HakushoBench: A Japanese Chart and Table VQA Benchmark from Governmental White Papers

Anonymous ACL submission

Abstract

Understanding chart and table images is essential for applying vision-language models (VLMs) to real-world document understanding. While English benchmarks have advanced rapidly, non-English counterparts remain scarce, leaving it unclear whether this progress generalizes across languages. A key obstacle is the difficulty of collecting realistic and diverse non-English chart and table images at scale. To address this, we leverage governmental white papers as a scalable source for benchmark construction beyond English, as they contain naturally occurring charts and tables across diverse formats and domains and are freely accessible in many countries. As a first instantiation, we introduce HakushoBench, a challenging Japanese chart and table VQA benchmark built from 33 governmental white papers. HakushoBench contains 2,053 images spanning over 10 image types, with manually annotated QA pairs, designed to assess deep and holistic understanding of charts and tables, rather than local visual cues alone. Experiments across a broad range of VLMs demonstrate that HakushoBench remains challenging for open-weight models: the best open-weight model achieves only 58.6% accuracy, and a 34.9-point gap between open-weight and proprietary models highlights substantial room for improvement in complex chart and table understanding. We release our dataset and code.

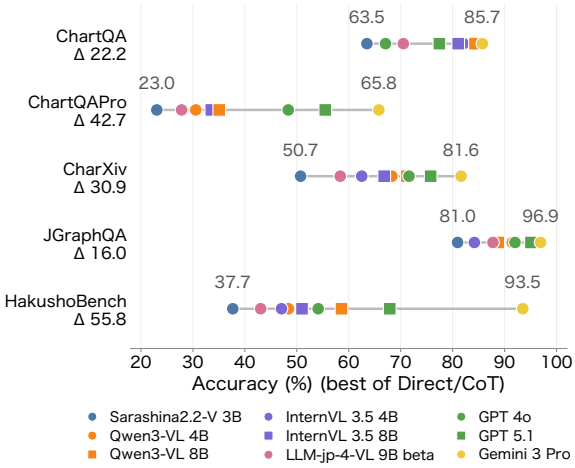

Figure 1: Score spread across models on each benchmark. HakushoBench is more challenging than the existing Japanese benchmark JGraphQA for all evaluated open-weight models and reveals a large performance gap between open-weight and proprietary models.

1 Introduction

Vision-language models (VLMs) (Liu et al., 2023; OpenAI, 2024; Qwen Team, 2025; Kimi Team, 2025) have rapidly advanced as general-purpose models capable of solving a wide range of vision-language tasks (Antol et al., 2015; Masry et al., 2022; Lu et al., 2024; Xie et al., 2024). Among these tasks, chart and table visual question answering (VQA) represents a fundamental capability for VLMs, as charts and tables are ubiquitous across a wide range of real-world documents, including public reports, financial documents, and scientific articles, often conveying information that cannot be expressed in text alone (Masry et al., 2022; Kantharaj et al., 2022).

To evaluate chart and table understanding in VLMs, numerous benchmarks have been developed. Early datasets such as ChartQA (Masry et al., 2022) and PlotQA (Methani et al., 2020) mainly focused on relatively simple chart types and questions requiring straightforward extraction of numerical values or labels. As VLM performance rapidly improved, these benchmarks became increasingly saturated and less effective at distinguishing model capabilities (Ho et al., 2025). More recent benchmarks, such as ChartQAPro (Masry et al., 2025) and CharXiv (Wang et al., 2024), address this limitation by introducing more diverse real-world chart images and more challenging question-answer pairs.

However, existing chart and table benchmarks

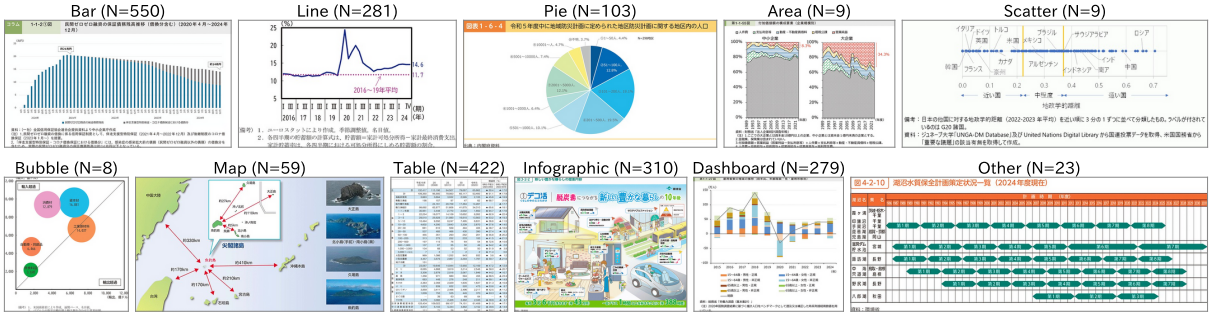

Figure 2: Diversity of image types in HakushoBench. One randomly sampled example is shown for each image type included in HakushoBench. HakushoBench contains diverse, well-designed chart and table images that present rich information in an accessible and visually understandable manner for general readers of government white papers.

are heavily biased toward English-centric visual conventions and document styles (Masry et al., 2022; Wang et al., 2024; Masry et al., 2025). Real-world chart understanding varies across languages and cultures, affecting visual composition, textual structure, and reasoning requirements (Tang et al., 2025; Xu et al., 2026). For example, chart and table images may differ in geographic conventions used in map-based figures, language-specific terminology in tables, writing direction (e.g., mixed vertical and horizontal text), and overall information density and layout structure (Wei et al., 2025; Sasagawa et al., 2025; Onami et al., 2024). As a result, strong performance on existing English benchmarks does not imply robust multilingual chart understanding (Pouget et al., 2024).

In Japanese, JGraphQA (Kinoshita, 2025) is currently the primary benchmark for chart and table understanding. However, it consists of only around 200 instances with limited visual diversity and relatively simple questions, leading to performance saturation where even 3B-scale VLMs already achieve over 80% accuracy (Figure 1).

To address these limitations, we leverage governmental white papers (*Hakusho* in Japanese) as an underexplored yet valuable source for chart and table benchmark construction. These reports contain large amounts of real-world charts and tables spanning diverse domains and visual formats, and are publicly available across many countries and languages (Japanese Digital Agency, 2026; U.S. Government Publishing Office, 2026).

As a first instantiation of this approach, we introduce **HakushoBench**, a challenging benchmark for Japanese chart and table understanding constructed from 33 white papers published by Japanese governmental agencies. The benchmark contains 2,053 unique images spanning more than 10 image types,

Benchmark	Real	Image Types	Lang.
PlotQA (Methani et al., 2020)	✗	3	EN
ChartQA (Masry et al., 2022)	✓	3	EN
ChartQAPro (Masry et al., 2025)	✓	>10	EN
CharXiv (Wang et al., 2024)	✓	>10	EN
JGraphQA (Kinoshita, 2025)	✓	5	JA
HakushoBench (Ours)	✓	>10	JA

Table 1: Comparison of chart and table VQA benchmarks. "Real" indicates that images are collected from real-world sources rather than programmatically generated. HakushoBench provides realistic and visually diverse Japanese chart and table VQA.

with manually annotated QA pairs designed to be challenging, including questions that require integrating information across the entire image and multi-hop reasoning beyond simple data extraction.

We evaluate a broad suite of open-weight and proprietary VLMs on HakushoBench and compare against both existing Japanese and English chart and table benchmarks. The results show that HakushoBench is more challenging than JGraphQA, with the best-performing open-weight model, Qwen3-VL 8B (Qwen Team, 2025), reaching only 58.6% accuracy. HakushoBench reveals a 34.9-point accuracy gap between the best proprietary and open-weight models, suggesting that open-weight VLMs still fall short on complex chart and table understanding. Manual error analysis on Gemini 3 Pro, the best-performing model, further reveals that even state-of-the-art models exhibit diverse errors including perception, external knowledge, and counting failures.

2 Related Work

Chart and table VQA benchmarks. As vision-language models have become increasingly capable and general-purpose (Liu et al., 2023; Qwen Team,

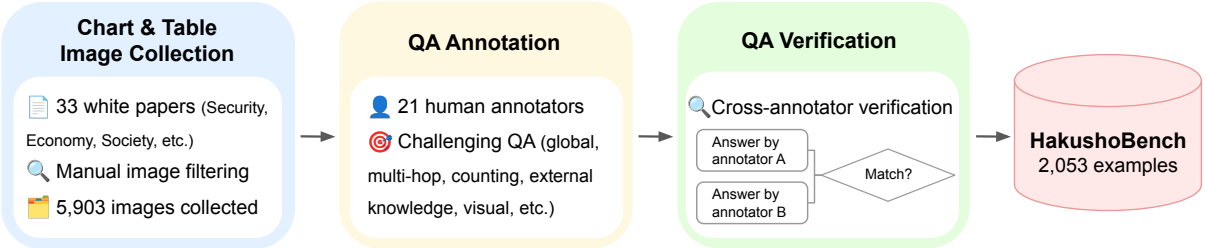

Figure 3: Construction pipeline of HakushoBench. Chart and table images are collected from 33 Japanese white papers and filtered to 5,903 candidates. Annotators then create one high-difficulty QA pair per image, followed by independent verification, yielding 2,053 VQA pairs.

2025), chart and table VQA benchmarks have also evolved toward greater diversity and more challenging reasoning tasks.

Early datasets such as FigureQA (Kahou et al., 2018) and DVQA (Kafle et al., 2018) focused on synthetic bar charts, while later work such as PlotQA (Methani et al., 2020) expanded chart types and task complexity. To bridge the gap with real-world documents, ChartQA (Masry et al., 2022) introduced human-annotated QA pairs on real chart images collected from online platforms such as Statista (Statista, 2026) and Our World in Data (OWID, 2026), which present diverse topics across a broad range of domains.

More recent benchmarks have further expanded the scope of image sources: ChartQAPro (Masry et al., 2025) collected charts from a larger set of online platforms, covering more varied types such as dashboards and infographics, while CharXiv (Wang et al., 2024) extracted chart images from papers across eight arXiv categories (including Computer Science, Economics, and Physics) to construct a natural and challenging benchmark. Despite these advances, chart and table benchmark development has primarily focused on English, and non-English evaluation remains limited.

Japanese chart and table VQA benchmarks. In Japanese, several benchmarks have been proposed for document understanding. JDocQA (Onami et al., 2024) built a document VQA benchmark from diverse PDFs published by Japanese public institutions such as municipal offices, and BusinessSlideVQA (Stockmark, 2025) constructed a slide understanding benchmark from business slides released by Japanese companies.

The most closely related prior work, JGraphQA (Kinoshita, 2025), focuses on Japanese chart and table question answering and is constructed from IR presentation slides of Japanese companies. However, this source domain is relatively narrow, and the benchmark contains only around 200 examples. Furthermore, following the QA design of ChartQA, questions are comparatively simple and focused primarily on data extraction and basic arithmetic rather than complex reasoning. As a result, even 3B-scale VLMs already achieve over 80% accuracy, suggesting that the benchmark is becoming saturated.

Table 1 summarizes existing chart and table VQA benchmarks alongside HakushoBench. In contrast to prior work, HakushoBench leverages governmental white papers as an image source, enabling a realistic, visually diverse, and challenging Japanese chart and table VQA benchmark.

3 Construction of HakushoBench

HakushoBench is constructed through a three-stage pipeline, illustrated in Figure 3.

3.1 Chart and Table Image Collection from Japanese White Papers

White papers as a data source. White papers published by Japanese governmental agencies summarize official statistics and policy analyses on national topics such as defense, energy, welfare, and education for a general readership. As a result, the images they contain are professionally designed, information-dense, and visually diverse across a wide range of domains, making them a valuable source for evaluating the generalizability of VLMs across heterogeneous chart and table types. Furthermore, since many governments around the world similarly publish official white papers (U.S. Government Publishing Office, 2026), our data collection methodology can be readily extended to other languages, facilitating the construction of multilingual benchmarks in future work.

Scope and edition selection. We collect chart and table images from such white papers, which are publicly available through the Japanese government's e-Gov portal (Japanese Digital Agency, 2026). Each Japanese governmental agency publishes its own annual white paper spanning a broad range of policy domains. While these are primarily distributed as PDFs, accurately extracting figures and tables from PDFs remains challenging even for current OCR models (Wei et al., 2025; Cui et al., 2025). We therefore restrict our dataset to white papers that also provide HTML editions, from which chart and table images can be collected directly via their URLs. Since different yearly editions of the same white paper often contain highly similar charts and tables (e.g., annual updates of population statistics), we use only the most recent edition from each white paper series. This choice also helps reduce potential contamination risk (Oren et al., 2024). As a result, our benchmark is constructed from 33 distinct governmental white paper series. The full list is provided in Appendix C.

Image filtering and candidate selection. From these white papers, we initially collect 18,539 images. However, many of them are unsuitable for chart and table QA annotation, including photographs such as group pictures, low-resolution images whose contents are difficult to read, and near-duplicate images appearing across multiple pages. We therefore manually remove such inappropriate images and retain 5,903 candidate chart and table images for annotation.

3.2 QA Annotation

Building on the collected chart and table images, we annotate them with question-answer pairs as follows. QA annotation is carried out by 21 native Japanese-speaking annotators hired through a professional annotation agency. Each annotator is given a set of images and writes one QA pair per image, following the requirements below.

QA requirements. Questions are required to (a) be unanswerable from the question text alone, requiring the image to resolve; (b) be natural and well-posed; and (c) admit a single, unambiguous answer expressible in a word, phrase, or short sentence. These constraints follow prior work showing that ambiguous questions make evaluation difficult and hinder fair assessment of model capabilities (Chen et al., 2024; Joshi et al., 2026).

We adopt a short answer format (Wang et al., 2024), avoiding multiple-choice and yes/no questions, which can be solved without the image or by random guessing (Chen et al., 2024). Answers are scored using an LLM-based judge that classifies each response as correct or incorrect, enabling robust evaluation that accommodates surface-level variations (e.g., "7" vs. "seven").

Difficulty dimensions. To encourage diverse and reasoning-intensive QA pairs, each accepted question must satisfy at least one of the following difficulty dimensions:

- **Global**: requiring integration of information spread across multiple regions of the image;
- **Multi-hop**: requiring multiple reasoning steps, such as extracting multiple values and then computing their ratio;
- **Counting**: requiring counting or indexing of objects;
- **External knowledge**: requiring knowledge beyond the image to answer correctly, such as knowledge of Japanese geography;
- **Visual**: requiring fine-grained visual perception, such as object color and shape;
- **Other**: covering difficult questions that did not fit the above categories.

Annotators assign one or more flags per QA pair.

Annotators are allowed to skip images for which no sufficiently challenging and well-defined question could be written, preventing the inclusion of artificially simple QA pairs.

3.3 QA Verification

QA annotation is prone to producing ambiguous questions and incorrectly annotated answers, and verification by independent annotators is widely used to improve benchmark quality (Chen et al., 2024; Masry et al., 2025). Following this practice, we introduce a separate verification stage for all annotated QA pairs.

For each QA pair, a second annotator (different from the original author) is given only the image and question and asked to independently answer it without access to the original answer. If the two answers match up to minor surface variations, the example is accepted; otherwise, the QA pair is revised or discarded. After completing the full pipeline, we obtained 2,053 QA pairs.

	Bar	Line	Pie	Area	Scatter	Bubble	Map	Table	Infographic	Dashboard	Other	Total
HakushoBench	550	281	103	9	9	8	59	422	310	279	23	**2,053**
JGraphQA	50	30	44	0	0	0	0	50	0	22	0	196
ChartQA	1,220	211	78	0	0	0	0	0	0	0	0	1,509
ChartQAPro	380	317	22	39	18	12	9	1	33	416	5	1,252
CharXiv	108	443	5	18	126	6	9	5	1	105	153	979

Table 2: Distribution of image types across benchmarks. Compared with JGraphQA, HakushoBench contains over ten times more examples and covers a broader range of image types, while remaining competitive with benchmarks such as ChartQAPro and CharXiv in both scale and diversity.

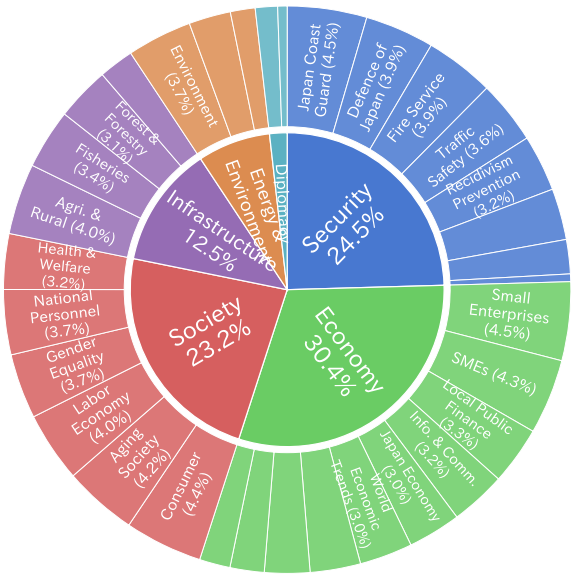

Figure 4: Distribution of QA pairs in HakushoBench. The inner ring represents the topic-wise distribution of examples, while the outer ring represents the white-paper-wise distribution.

Question Type	Examples
Global	1,743
Multi-hop	634
Counting	293
External-knowledge	148
Visual	897
Other	132

Table 3: Distribution of question-type flags over the 2,053 verified QA pairs in HakushoBench. Each QA pair may have multiple flags, so counts are not mutually exclusive and do not sum to 2,053.

4 Exploring HakushoBench

Statistics of HakushoBench. HakushoBench contains 2,053 examples collected from 33 white papers, grouped into six topics (Security, Economy, Society, Infrastructure, Energy & Environment, and Diplomacy). Figure 4 shows the distribution of QA pairs per topic and per white paper, and Appendix C lists the per-white-paper breakdown. The largest topic is Economy (30.4%), followed by Society (23.3%), while the number of QA pairs per white paper is relatively balanced. Table 3 reports the distribution of difficulty flags. Each type has at least 100 examples, and Global is the most frequent, as multiple flags are allowed per question and Global tends to overlap with other types.

Visual diversity. To analyze the visual diversity of HakushoBench, we categorize images from HakushoBench, JGraphQA, ChartQA (test), ChartQAPro, and CharXiv (val) into 11 visual-format categories: Bar, Line, Pie, Area, Scatter, Bubble, Map, Table, Infographic, Dashboard, and Other. Our taxonomy follows that of ChartQAPro (Masry et al., 2025), with the addition of Map and Table. We use Gemini 3 Pro (Google DeepMind, 2025) to classify image types by providing each image together with a classification prompt, which is described in Appendix D. Manual verification of 100 randomly sampled examples confirms that the classification aligns well with human judgment, with minor ambiguities acceptable given the diversity of real-world images. Table 2 shows the image types distribution for each benchmark. Compared to JGraphQA, HakushoBench contains more than 10× as many images and covers more than 10 image types, including types absent from JGraphQA such as Map and Infographic, enabling evaluation of more diverse visual understanding capabilities.

We further measure visual diversity using image embeddings extracted by the SigLIP2 vision encoder (`siglip2-so400m-patch16-512`) (Tschannen et al., 2025). Computing the mean pairwise cosine distance between embeddings shows that HakushoBench achieves higher diversity than JGraphQA (0.365 vs. 0.275).

Dataset showcase. Figure 2 presents a randomly selected image from each image type in HakushoBench, illustrating its diversity. As

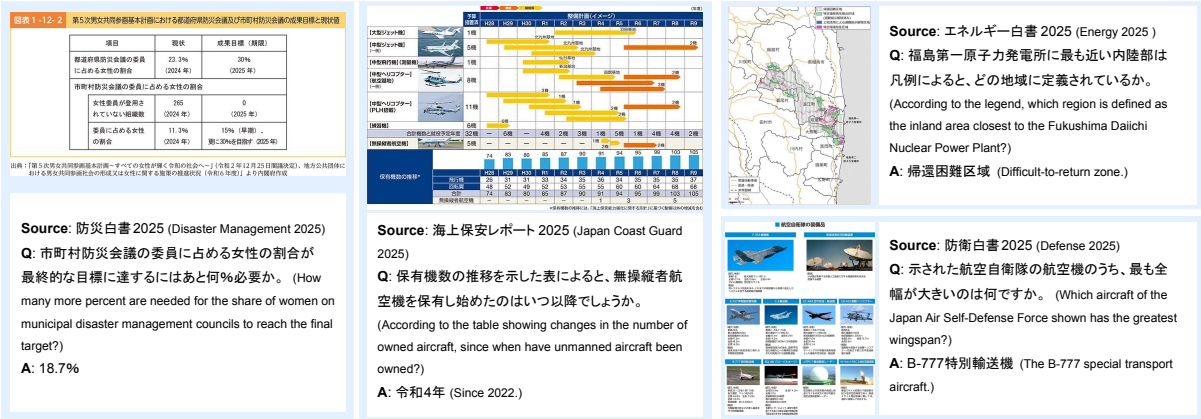

Figure 5: Representative VQA pairs in HakushoBench, requiring multi-hop reasoning and global image understanding rather than local visual cues alone.

shown, HakushoBench contains a wide variety of chart and table image types spanning diverse domains, reflecting the breadth of governmental white papers as a benchmark resource. Figure 5 shows representative VQA pairs, demonstrating that HakushoBench contains challenging questions over information-dense chart and table images. For example, some questions require extracting and computing multiple numerical values from a table, others demand understanding spatial relationships between map locations and legends, and still others involve reading and comparing textual descriptions embedded in figures. These examples illustrate that HakushoBench often requires multi-hop reasoning and holistic image understanding beyond simple value extraction.

5 Experiments

We evaluate a broad set of open-weight and proprietary models on HakushoBench, and compare its characteristics against existing benchmarks.

5.1 Experimental Settings

Models. We evaluate a diverse set of open-weight and proprietary VLMs. On the open-weight side, we include Qwen3-VL-4B, 8B (Qwen Team, 2025) and InternVL3.5-4B, 8B (InternVL Team, 2025) as general-purpose multilingual models, as well as Sarashina2.2-Vision-3B (SB Intuitions, 2025) and LLM-jp-4-VL 9B beta (Sugiura et al., 2026b) as Japanese-centric models. On the proprietary side, we evaluate GPT-4o (`gpt-4o-2024-11-20`) (OpenAI, 2024), GPT-5.1 (`gpt-5.1-2025-11-13`) (OpenAI, 2025), and Gemini 3 Pro (`gemini-3-pro-preview`) (Google DeepMind, 2025).

Prompt settings. To examine the effect of reasoning-oriented prompting, we evaluate two settings per model. The **Direct** setting asks models to answer the question accurately and concisely, while the **CoT** setting additionally instructs models to think step by step before producing the final answer (Wei et al., 2022; Kojima et al., 2022). Full prompts are provided in Appendix D.

Inference settings. We set the temperature to 0 for all models except GPT-5.1, which does not support temperature control, and use a maximum generation length of 8,192 tokens. Open-weight models are evaluated on NVIDIA A100 GPUs, while proprietary models are accessed through their official APIs. For reasoning settings, we use the `medium` reasoning mode for Gemini 3 Pro. For GPT-5.1, we use `none` for the Direct setting and `medium` for the CoT setting.

Evaluation metric. We use accuracy as the evaluation metric, where each model output is scored as correct or incorrect by GPT-5.1 (`gpt-5.1-2025-11-13`) as an LLM judge. This enables automatic evaluation at scale while tolerating minor surface-level variations in phrasing. The judge prompt is provided in Appendix D. To account for stochastic variation in both model outputs and LLM judgment, each evaluation is repeated three times, and we report the mean score.

Compared benchmarks. To better understand the characteristics of HakushoBench, we additionally evaluate the same set of models on four existing chart and table benchmarks: JGraphQA (Kinoshita, 2025), ChartQA (test) (Masry et al., 2022), ChartQAPro (Masry et al., 2025), and CharXiv

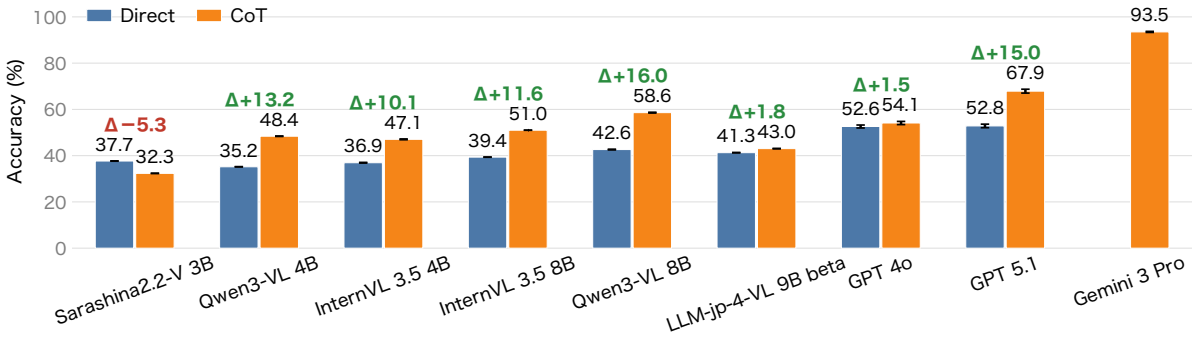

Figure 6: Performance of each model on HakushoBench under the Direct and CoT settings. Since Gemini 3 Pro is a thinking-only model, we report only its CoT score. Most open-weight models remain below 60% accuracy, highlighting the challenging nature of HakushoBench.

(val) (Wang et al., 2024). For JGraphQA, we use JGraphQA-Verified (Sugiura et al., 2026a), a cleaned and corrected version of the original benchmark.

6 Results

6.1 Main Results

Figure 6 shows model performance on HakushoBench.

Gemini 3 Pro outperforms open-weight models by a large margin. Gemini 3 Pro achieves the highest score of 93.5%. In contrast, GPT-5.1 scores only 67.9%, revealing a substantial performance gap among proprietary models in Japanese chart and table understanding. Open-weight models perform worse: even the best-performing open-weight model, Qwen3-VL 8B, reaches only 58.6%. The large gap between the best proprietary and open-weight models suggests that there remains considerable room for improvement in open-weight models on Japanese chart and table understanding.

CoT prompting effectiveness varies by model. CoT prompting improves accuracy for most models, with GPT 5.1, Qwen3-VL, and InternVL3.5 all gaining more than 10 points. In contrast, GPT-4o, LLM-jp-4-VL 9B beta, and Sarashina2.2-Vision 3B show limited gains or even degradation. Manual analysis suggests these models often fail to engage in reasoning or produce repetitive and incoherent chains, indicating limited reasoning ability.

6.2 Comparison with Existing Benchmarks

Table 4 reports the performance of each model on all benchmarks, and Figure 1 summarizes the score range across models.

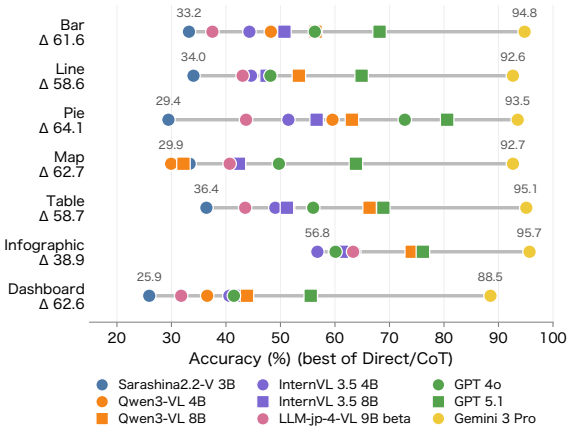

Figure 7: Accuracy spread across models on HakushoBench, grouped by image type. Categories with fewer than 50 examples (Area, Scatter, Bubble, and Other) are omitted.

HakushoBench is more challenging than JGraphQA. Compared to JGraphQA, HakushoBench is much harder for open-weight models: Qwen3-VL 8B reaches only 58.6% on HakushoBench versus 88.8% on JGraphQA, and Sarashina2.2-Vision 3B reaches 37.7% versus 81.0%. Figure 7 shows the accuracy spread across image types, and Appendix E provides a similar breakdown by question type. The spread is consistent across both dimensions, with infographics being a notable exception, suggesting that HakushoBench evaluates a broad range of model capabilities.

Large open-weight–proprietary gap on challenging benchmarks. As benchmarks become more diverse and challenging, the performance gap between proprietary and open-weight VLMs widens. On HakushoBench, the gap is 34.9 points (58.6 vs.

Model	HakushoBench		JGraphQA		ChartQA		ChartQAPro		CharXiv	
	Direct	CoT	Direct	CoT	Direct	CoT	Direct	CoT	Direct	CoT
Open-weight Models										
Sarashina2.2-V 3B	37.7 ± 0.1	32.3 ± 0.1	80.4 ± 0.3	81.0 ± 0.8	47.8 ± 0.2	63.5 ± 0.1	23.0 ± 0.0	23.0 ± 0.1	48.6 ± 0.0	50.7 ± 0.0
Qwen3-VL 4B	35.2 ± 0.1	48.4 ± 0.1	84.2 ± 0.5	91.5 ± 0.3	67.0 ± 0.1	83.7 ± 0.0	30.5 ± 0.0	30.5 ± 0.1	65.3 ± 0.0	68.3 ± 0.1
InternVL 3.5 4B	36.9 ± 0.1	47.1 ± 0.2	84.2 ± 0.0	84.2 ± 0.0	73.7 ± 0.1	82.1 ± 0.1	34.7 ± 0.1	34.8 ± 0.1	62.5 ± 0.0	61.9 ± 0.0
InternVL 3.5 8B	39.4 ± 0.0	51.0 ± 0.0	85.9 ± 0.3	88.4 ± 0.3	75.0 ± 0.2	81.1 ± 0.3	33.5 ± 0.0	33.5 ± 0.1	66.8 ± 0.0	65.7 ± 0.1
Qwen3-VL 8B	42.6 ± 0.2	58.6 ± 0.2	86.6 ± 0.3	88.8 ± 0.5	70.3 ± 0.0	84.3 ± 0.3	35.0 ± 0.1	35.1 ± 0.1	70.1 ± 0.1	71.2 ± 0.1
LLM-jp-4-VL 9B beta	41.3 ± 0.1	43.0 ± 0.1	87.8 ± 0.5	85.2 ± 0.0	70.5 ± 0.1	68.0 ± 0.1	27.8 ± 0.2	27.8 ± 0.1	58.4 ± 0.1	56.6 ± 0.1
Proprietary Models										
GPT 4o	52.6 ± 0.6	54.1 ± 0.7	92.0 ± 0.6	84.7 ± 1.0	62.1 ± 0.3	67.1 ± 0.3	44.1 ± 0.2	48.4 ± 0.1	71.6 ± 0.1	71.4 ± 0.2
GPT 5.1	52.8 ± 0.8	67.9 ± 0.8	95.1 ± 1.1	94.9 ± 1.0	64.9 ± 0.7	77.4 ± 0.3	42.0 ± 0.4	55.5 ± 0.7	68.9 ± 0.2	75.8 ± 0.1
Gemini 3 Pro	–	**93.5** ± 0.2	–	**96.9** ± 0.5	–	**85.7** ± 0.4	–	**65.8** ± 0.2	–	**81.6** ± 0.1

Table 4: Performance of each model on chart and table benchmarks under the Direct and CoT settings, reported as accuracy (%) averaged over three runs (mean ± standard deviation).

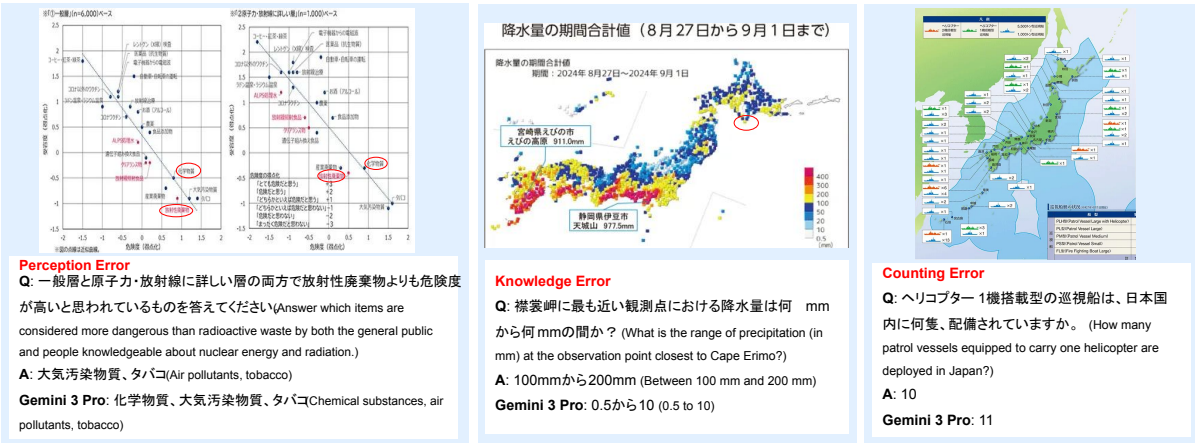

Figure 8: Representative failure cases of Gemini 3 Pro on HakushoBench. Left: a perception error in reading scatter plot conditions. Middle: a knowledge error in identifying the map location closest to Cape Erimo (襟裳岬). Right: a counting error resulting in an off-by-one prediction.

93.5), larger than on JGraphQA (8.1 points; 88.8 vs. 96.9) and ChartQA (1.4 points; 84.3 vs. 85.7), and comparable to ChartQAPro (30.7 points; 35.1 vs. 65.8), suggesting that open-weight VLMs still struggle with the advanced reasoning and visual understanding required for complex multilingual chart and table comprehension.

6.3 Error Analysis of Gemini 3 Pro

To better understand the remaining challenges in HakushoBench, we manually analyze 50 randomly sampled questions incorrectly answered by Gemini 3 Pro, the best-performing model on the benchmark. Figure 8 shows representative examples of three major error types: perception, knowledge, and counting. In the *Perception* example, the model fails to correctly interpret spatial relationships in a scatter plot. The *Knowledge* example requires external geographic knowledge to identify Cape Erimo on a thematic precipitation map. The *Counting* example illustrates an off-by-one error in fine-grained counting. These findings show that even the best-performing model still makes diverse errors, including perception, external knowledge, and counting failures.

7 Conclusion

We presented HakushoBench, a Japanese chart and table VQA benchmark constructed from 33 governmental white papers, containing 2,053 VQA pairs over 10 distinct image types. We demonstrated that governmental white papers serve as a valuable source for benchmark construction, offering broad domain coverage and visual diversity. HakushoBench is more challenging than JGraphQA, with the best open-weight model reaching only 58.6% accuracy, and reveals a large open-weight–proprietary gap, suggesting that open-weight VLMs still fall short on complex chart and table understanding.

Limitations

Language and domain coverage. HakushoBench addresses the lack of challenging and visually diverse Japanese chart and table QA benchmarks. However, the dataset is currently limited to Japanese and does not directly address the scarcity of benchmarks for other low-resource languages. In addition, our dataset is constructed exclusively from governmental white papers, which may not fully cover the diversity of visual styles and domains found in other real-world documents. Nevertheless, because many countries publish analogous governmental reports and white papers (U.S. Government Publishing Office, 2026), our data construction approach can be naturally extended to other languages and cultural contexts.

Potential data contamination. We use the most recent edition of each white paper to mitigate contamination risk (Oren et al., 2024). However, we cannot completely rule out the possibility that some images or related information appeared in derivative web content included in model pretraining corpora. That said, all QA pairs in our benchmark were newly constructed through manual annotation, making it highly unlikely that they were included in any model's pretraining data.

Saturation at the frontier. While HakushoBench proves challenging for most models, Gemini 3 Pro achieves 93.5%, leaving limited headroom to discriminate among frontier models. A natural remedy is to construct a harder subset by filtering out questions solved by Gemini 3 Pro, following Phan et al. (2026), or to collect more demanding QA pairs targeting capabilities beyond current frontier models. However, increasing difficulty introduces a risk of producing unnatural questions that deviate from realistic use cases. Balancing difficulty and practical relevance is therefore a non-trivial design challenge that we leave for future work.

Ethical Considerations

Public data sources and safety. All images are collected from white papers publicly released by Japanese governmental agencies. Given this source, risks related to privacy, personally identifiable information, and NSFW (Not Safe For Work) content are negligible. This was further confirmed during manual filtering, where no problematic content was observed.

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A Licenses for Our Resources

HakushoBench and its evaluation code are released under the Apache 2.0 License. Note that we distribute only image URLs rather than the raw image data.

B Use of AI Assistants

We used AI assistants to correct typographical errors, improve the clarity and naturalness of expressions, and generate scripts for plotting figures.

C White Paper Sources

Table 5 lists the 33 Japanese governmental white papers used in HakushoBench.

D Prompt

We show the prompts used in the experiments below.

Image type classification prompt

You are an expert at classifying figures in documents. Look at the image and choose exactly ONE label from the following 11 categories that best describes the primary visualization type:
- Bar : Bar chart (vertical, horizontal, grouped, or stacked bars).
- Line : Line chart (including multi-line time series).
- Pie : Pie chart or donut chart.
- Area : Area chart or stacked-area chart.
- Scatter : Scatter plot.
- Bubble : Bubble chart.
- Map : Geographic / thematic / choropleth map.
- Table : A pure table with no charts.
- Infographic : Text-heavy figure with icons, illustrations, or flow elements; not a chart or table.
- Dashboard : A composite figure that combines two or more of the above in one image (e.g., a chart together with an inline table, or multiple charts of different types laid out together).
- Other : Does not fit any of the above.

Rules: - Choose EXACTLY ONE label.
- If the image contains multiple chart components (e.g., a bar chart and an inline table, or two different chart types side by side), use "Dashboard".
- Use "Other" only as a last resort.

Respond with ONLY the label (e.g., "Bar"). No explanation, no quotes.

Direct prompt

上記の質問に対して、正確かつ簡潔に答えてください。
(For the above question, answer accurately and concisely.)

CoT prompt

上記の質問に対して、ステップバイステップで考えてから答えてください。
最後の行は 'Answer: $ANSWER' の形式で、正確かつ簡潔に回答してください。
(For the above question, think step by step before answering.
The final line should be in the format 'Answer: $ANSWER', and provide the answer accurately and concisely.)

Judge prompt

Judge whether the following [response] to [question] is correct or not based on the precise and unambiguous [correct_answer] below.
When judging equivalence, allow variations in script or notation that convey the same meaning (e.g., '2羽' and '二羽' should be considered equivalent).
Treat the following cases as correct: - The extracted answer includes additional context (e.g., series name, author name, location, broader category) while still containing the correct_answer exactly or as its unambiguous, specific instance. (For example, "富嶽三十六景江戸日本橋" is correct if the correct_answer is "江戸日本橋".) - The extracted answer is more specific than the [correct_answer] while remaining consistent with it. - The extracted answer is an alternate name, synonymous phrasing, or another commonly accepted way to refer to the same concept, object, place, or artwork. - The extracted answer omits information that is not essential to the correctness of the question. - Allow minor variations in spacing, capitalization, or script, as long as the core correct_answer is unambiguously present.
[question]: question
[response]: response
Your judgement must be in the format and criteria specified below:

Japanese title	English title	Topic group	Examples
海上保安レポート2025	Japan Coast Guard 2025	Security	93
防衛白書2025	Defence of Japan 2025	Security	81
消防白書2024	Fire Service 2024	Security	81
交通安全白書2025	Traffic Safety 2025	Security	74
再犯防止推進白書2024	Recidivism Prevention 2024	Security	66
防災白書2025	Disaster Management 2025	Security	60
犯罪被害者白書2024	Crime Victims 2024	Security	40
警察白書2025	Police 2025	Security	9
小規模企業白書2025	Small Enterprises 2025	Economy	92
中小企業白書2025	Small and Medium Enterprises 2025	Economy	88
地方財政白書2025	Local Public Finance 2025	Economy	68
情報通信白書2025	Information & Communications 2025	Economy	65
日本経済レポート2024	Japan Economy 2024	Economy	62
世界経済の潮流2025-01	World Economic Trends 2025	Economy	62
通商白書2025	International Economy and Trade 2025	Economy	59
年次経済財政報告2025	Japanese Economy and Public Finance 2025	Economy	53
地域課題分析レポート2025-08	Regional Issues 2025	Economy	40
科学技術白書2025	Science & Technology 2025	Economy	36
消費者白書2023	Consumer 2023	Society	91
高齢社会白書2025	Aging Society 2025	Society	86
労働経済白書2024	Labor Economy 2024	Society	82
男女共同参画白書2025	Gender Equality 2025	Society	76
人事院白書2024	National Personnel 2024	Society	76
厚生労働白書2025	Health, Labour & Welfare 2025	Society	65
食料農業農村白書2024	Food, Agriculture and Rural Areas 2024	Infrastructure	83
水産白書2024	Developments in Japan's Fisheries 2024	Infrastructure	70
森林林業白書2024	Forest & Forestry 2024	Infrastructure	63
国土交通白書2024	Land, Infrastructure, Transport and Tourism 2024	Infrastructure	41
環境白書2025	Environment 2025	Energy & Environment	76
原子力白書2023	Nuclear Energy 2023	Energy & Environment	49
エネルギー白書2025	Energy 2025	Energy & Environment	29
開発協力白書2023	Development Cooperation 2023	Diplomacy	26
外交青書2025	Diplomatic Bluebook 2025	Diplomacy	11
Total			2,053

Table 5: The 33 Japanese white papers used in HakushoBench.

extracted_final_answer: The final exact answer extracted from the [response]. Put the extracted answer as 'None' if there is no exact, final answer to extract from the response.
[correct_answer]: correct_answer
reasoning: Explain why the extracted_final_answer is correct or incorrect based on [correct_answer], focusing only on if there are meaningful differences between [correct_answer] and the extracted_final_answer. Do not comment on any background to the problem, do not attempt to solve the problem, do not argue for any answer different than [correct_answer], focus only on whether the answers match.
correct: Answer 'yes' if extracted_final_answer matches the [correct_answer] given above, or is within a small margin of error for numerical problems. Answer 'no' otherwise, i.e. if there if there is any inconsistency, ambiguity, non-equivalency, or if the extracted answer is incorrect.

confidence: The extracted confidence score between 0% and 100% from [response]. Put 100 if there is no confidence score available.

E Accuracy Spread by Question Type on HakushoBench

Figure 9 shows the accuracy spread across models on HakushoBench, grouped by question type.

F Evaluation Results on Existing Chart and Table Benchmarks

Figures 10,11,12, and13 visualize the per-model Direct and CoT accuracy on ChartQA, ChartQAPro, CharXiv, and JGraphQA as bar charts.

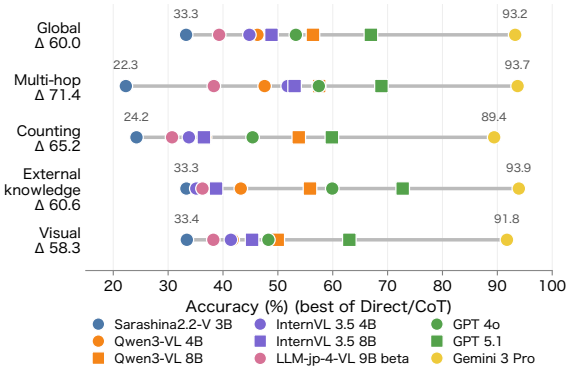

Figure 9: Accuracy spread across models on HakushoBench, grouped by question type.

G Image Showcases for Comparison Benchmarks

Figures 14, 16, 17, and 15 show one randomly sampled image per image-type category for each benchmark.

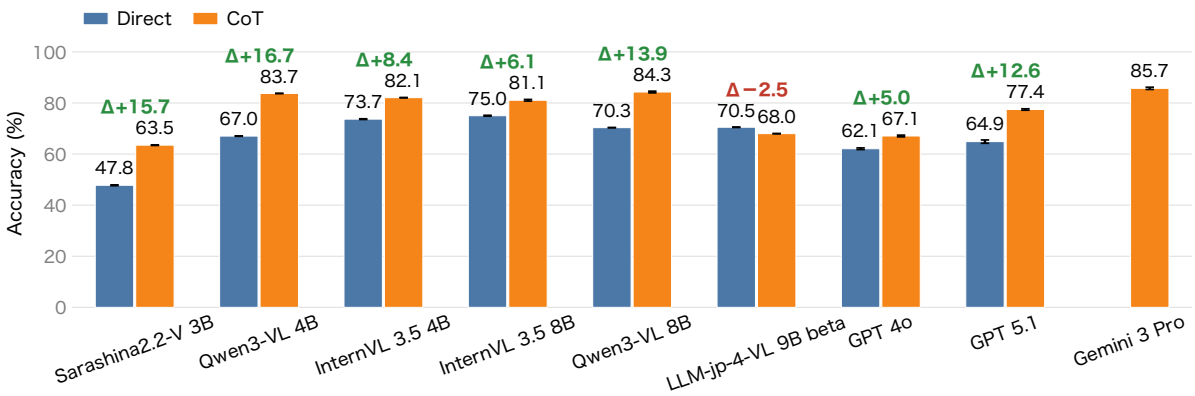

Figure 10: Performance of each model on ChartQA.

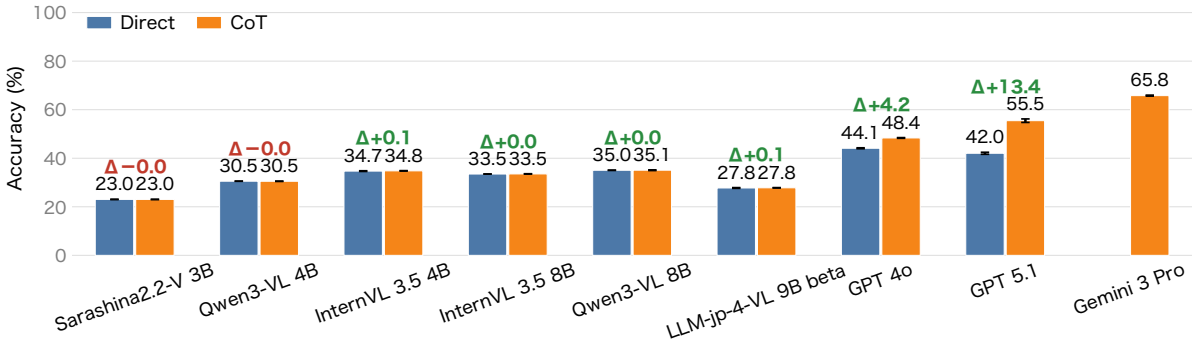

Figure 11: Performance of each model on ChartQAPro.

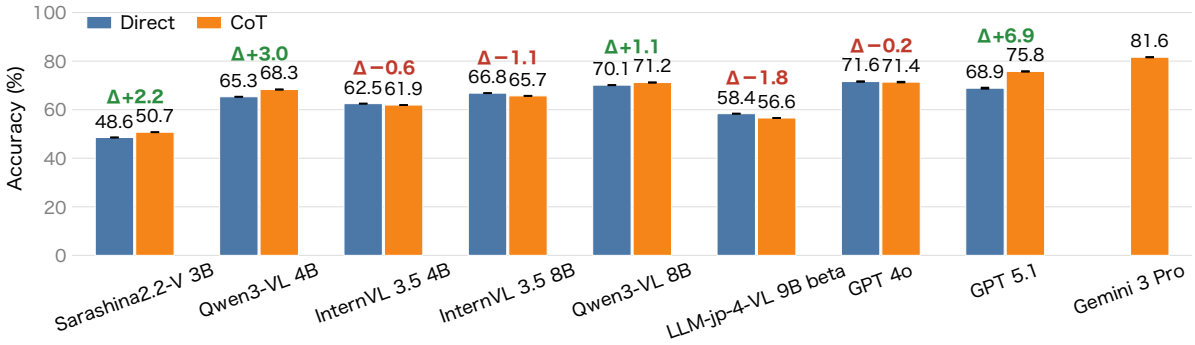

Figure 12: Performance of each model on CharXiv.

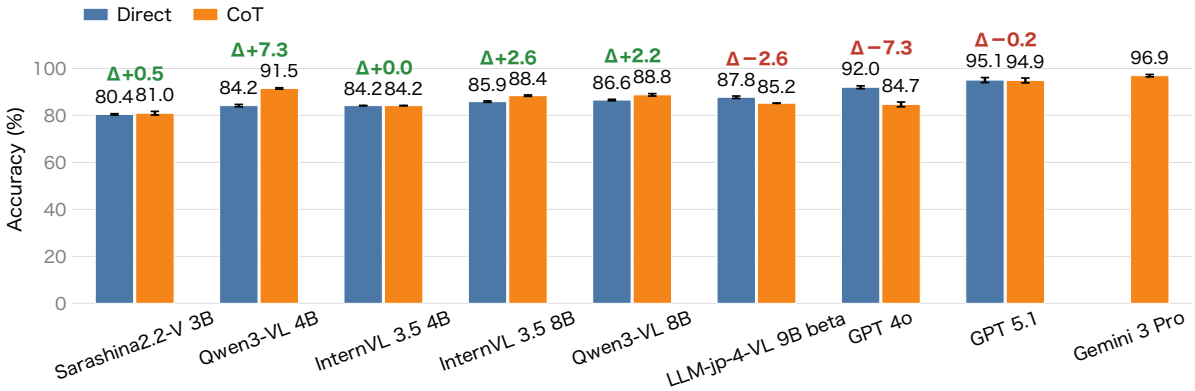

Figure 13: Performance of each model on JGraphQA.

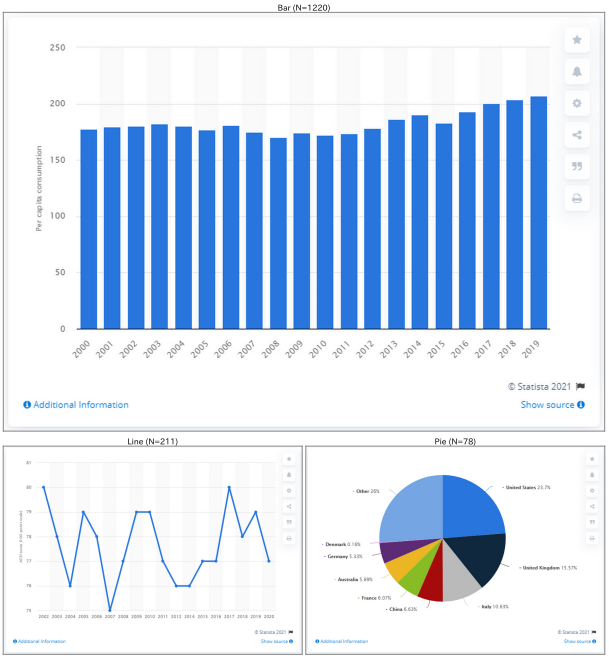

Figure 14: ChartQA: one randomly sampled image per image type.

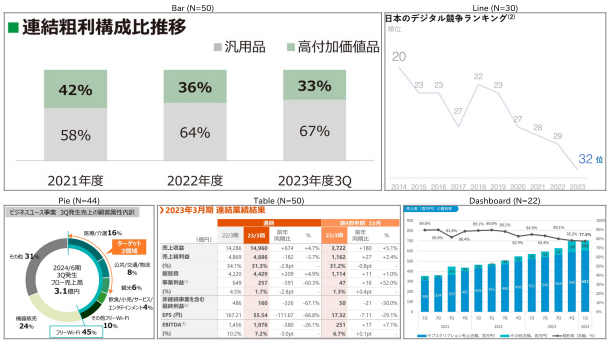

Figure 15: JGraphQA: one randomly sampled image per image type.

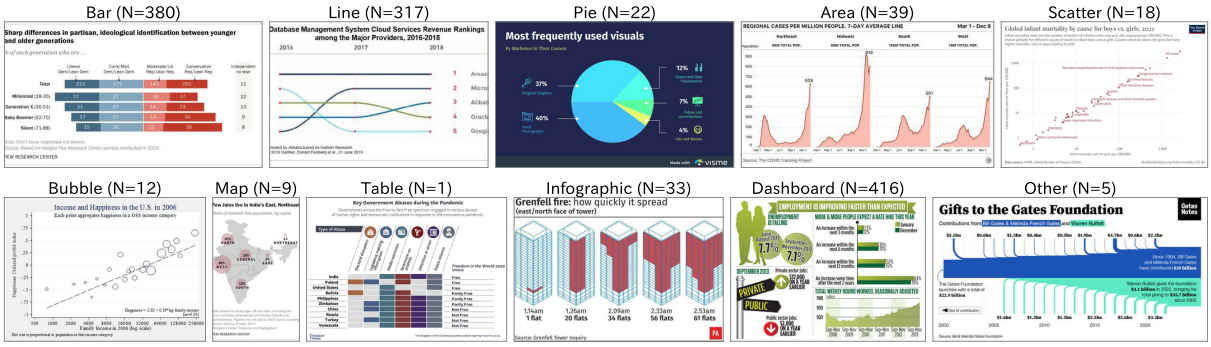

Figure 16: ChartQAPro: one randomly sampled image per image type.

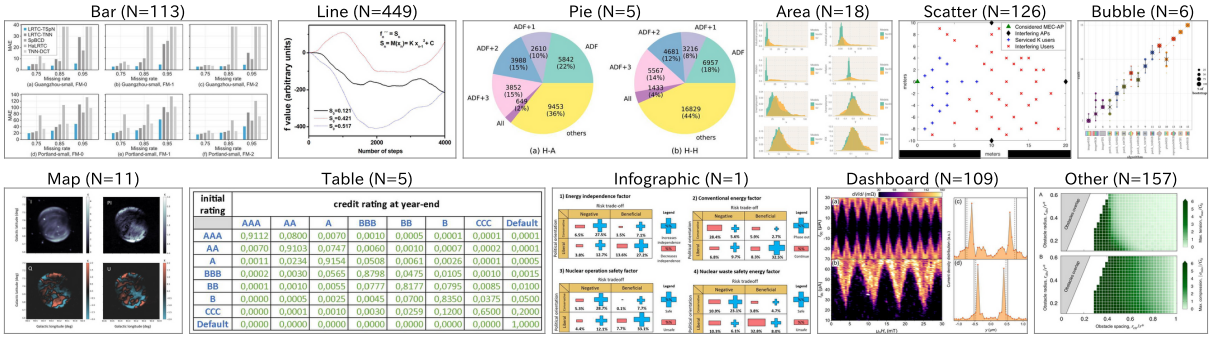

Figure 17: CharXiv: one randomly sampled image per image type.