
InfoChartQA: A Benchmark for Multimodal Question Answering on Infographic Charts

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Abstract

Understanding infographic charts with pictorial visual elements (*e.g.*, pictograms and icons) requires both visual recognition and reasoning, posing challenges for multimodal large language models (MLLMs). However, existing visual question answering benchmarks fall short in evaluating these capabilities of MLLMs due to the lack of paired plain charts and visual-element-based questions. To bridge this gap, we introduce **InfoChartQA**, a benchmark for evaluating MLLMs on infographic chart understanding. It includes 5,948 pairs of infographic and plain charts, each sharing the same underlying data but differing in visual presentations. We further design visual-element-based questions to capture their unique visual designs and communicative intent. Evaluation of 20 MLLMs reveals a substantial performance decline on infographic charts, particularly for visual-element-based questions related to metaphors. The paired infographic and plain charts enable fine-grained error analysis and ablation studies, which highlight new opportunities for advancing MLLMs in infographic chart understanding. We release **InfoChartQA** at <https://github.com/thu-vis/InfoChartQA>.

1 Introduction

Infographic charts enrich standard chart types such as bar, pie, and line charts by integrating pictorial visual elements such as pictograms, thematic icons, and metaphorical imagery. These elements serve not only to convey data but also to enhance visual engagement, reinforce the chart’s narrative or emotional tone, and communicate abstract concepts through symbolic visuals. Unlike plain charts that present data in a neutral and standardized way, infographic charts often adopt creative pictorial visual elements that reflect their communicative intent. As a result, understanding infographic charts requires more than basic visual recognition. It demands reasoning about heterogeneous visual elements, symbolic metaphors, and the underlying data relationships. This poses new challenges for multimodal large language models (MLLMs), whose ability to integrate visual and textual information is still under development. A comprehensive benchmark is therefore needed to enable systematic

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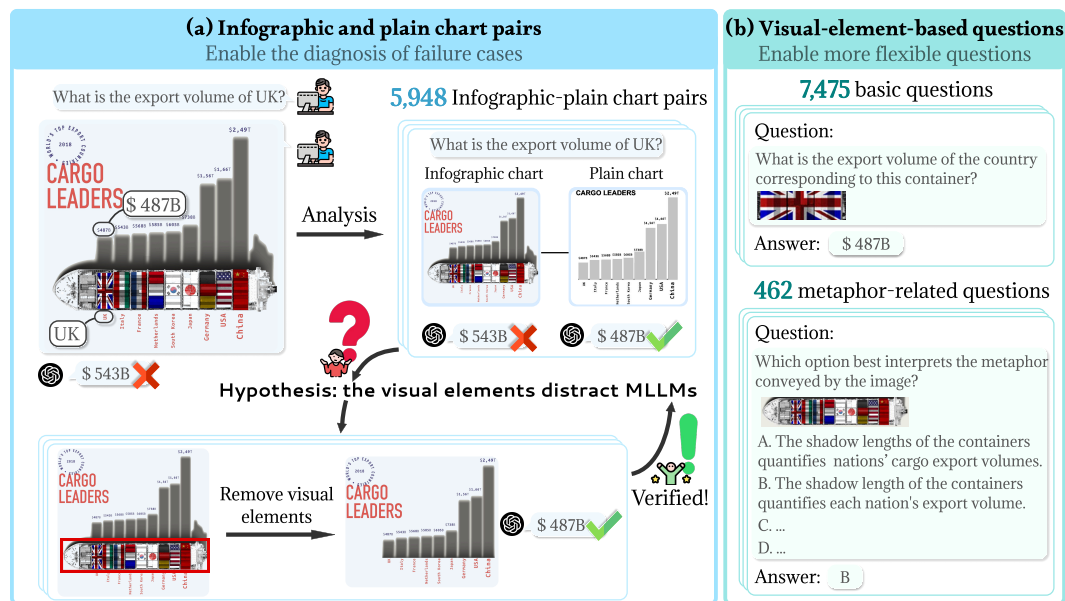


Figure 1: Overview of InfoChartQA.

evaluation and guide model improvement, capturing the unique features of infographic charts and supporting controlled comparisons with plain charts.

Many visual question answering benchmarks have been developed to assess the capabilities of MLLMs to jointly understand and reason over both visual and textual information [1, 2]. However, existing benchmarks face two limitations when it comes to evaluating infographic chart understanding. First, they lack paired infographic charts and plain chart counterparts constructed from the same underlying data. Such pairs are essential for disentangling whether a model's failure stems from the complexity of the data itself or from the additional visual elements used in infographic designs. For example, the MLLM in Figure 1(a) answers wrongly on the infographic chart but correctly on the associated plain chart. By removing the ship image in the infographic chart, the MLLM answers correctly, indicating that the ship image was the main cause of the MLLM's incorrect answer. Second, most benchmarks do not include visual-element-based questions that specifically target the visual elements in infographic charts, such as pictograms, thematic icons, and metaphorical imagery (e.g., the flag and ship elements in Figure 1(b)). These visual elements are often crucial for conveying data (e.g., the associated value of an icon) or high-level semantics metaphors (e.g., the metaphor conveyed by the ship). The absence of such visual-element-based questions limits the benchmarks' ability to capture the challenges posed by infographic-specific design.

To address these two limitations, we built InfoChartQA, a benchmark for multimodal question answering on infographic charts. InfoChartQA comprises 5,948 paired infographic and plain charts, where each pair shares the same underlying data but differs in visual representation (Figure 1). We built this dataset by collecting a high-quality set of infographic charts, extracting their underlying tabular data, and creating corresponding plain chart counterparts. These paired charts enable the creation of shared questions based on textual descriptions and tabular data. In addition to these shared questions, we also design visual-element-based questions. Such questions include basic ones that target the understanding of visual elements commonly used in infographic charts, and metaphor-related ones that reflect the higher-level semantics conveyed through visual elements.

We conduct a comprehensive evaluation of 6 proprietary and 14 open-source MLLMs on the InfoChartQA. The results indicate a significant performance decline on infographic charts compared with plain charts. For example, Claude 3.5 Sonnet scores 81.37% on plain charts but only 62.80% on infographic charts. MLLMs perform even poorer (e.g., Claude 3.5 Sonnet only scores 55.33%) on metaphor-related questions. The paired infographic and plain charts allow us to diagnose this poor performance through detailed error analysis and ablation studies. The analysis shows that the proximity between icons and corresponding data values plays a critical role in supporting accurate reasoning. Moreover, model accuracy tends to decline as visual complexity increases,

particularly when more visual elements are present in the infographic chart. These findings highlight new opportunities for advancing MLLMs in infographic chart question answering.

The key contributions of this paper are:

- We present **InfoChartQA**, the first benchmark containing paired infographic and plain charts that share the same underlying data but differ in visual representation.
- We introduce a rich set of visual-element-based QAs specifically designed for infographic charts to capture their unique visual elements and intended purpose.
- We identify and analyze the performance gap of current MLLMs when interpreting infographic charts versus plain charts, despite both being derived from the same data.

2 Related Works

Many benchmarks have been developed for chart question answering (QA) [1, 2, 3, 4, 5]. According to the types of charts, they can be categorized into plain and infographic chart QA benchmarks.

Plain chart QA benchmarks. An initial benchmark along this line is FigureQA [6]. FigureQA synthesized 100,000 charts across five types and generated one million binary questions based on 15 predefined templates, where answers are either "Yes" or "No". Subsequently, DVQA expanded the answer options to a fixed vocabulary of 1,000 words or extracted text from the charts [7]. Additionally, the question templates were extended to 74, derived from 7,000 crowd-sourced questions [8]. Since the synthesized charts and generated questions from templates cannot represent the real-world charts well, later efforts shifted toward collecting real-world charts with open-ended questions. OpenCQA collected 7,724 charts from Pew Research (pewresearch.org) and asked crowdworkers from Amazon Mechanical Turk to create open-ended questions and answers [9]. ChartQA gathered 20,882 charts from four distinct online sources, along with human-authored QA pairs created through Amazon Mechanical Turk [1]. Since OpenCQA and ChartQA primarily focus on three chart types, ChartBench extended them to nine chart types, resulting in a total of 2,100 charts [10]. Later efforts have been dedicated to collecting more diverse charts and more complex questions. ChartX covers 18 chart types and questions from 22 disciplinary topics [11]. ChartXiv includes 2,323 real-world charts selected from scientific papers across eight primary subjects published on arXiv [4]. ChartInsights found that most benchmarks focus on high-level chart QA tasks, with less attention given to low-level tasks, leading them to collect 2,000 charts and 22,000 QA for low-level chart QA tasks [12].

Although these plain chart QA benchmarks are effective in evaluating MLLMs, they overlook infographic charts, which are an important category of charts with the composition of data and pictorial visual elements presenting unique challenges to visual understanding and reasoning. In response, infographic chart QA benchmarks have been proposed.

Infographic chart QA benchmarks. The first benchmark in this category is InfographicVQA [2], which consists of 30,035 questions across 5,485 infographic charts. The questions in this dataset are based on tables, figures, and visualizations, as well as those that require combining multiple cues. This makes it particularly challenging for MLLMs. ChartQAPro [3] contains 1,341 charts from 157 diverse online sources, including 190 infographic charts. It features 1,948 questions in various formats, such as multiple-choice, conversational, hypothetical, and unanswerable questions, to better reflect real-world challenges.

Although these benchmarks collect a large number of infographic charts, they do not include the associated plain charts. These plain charts, which display the same data in simpler visual forms, are crucial for diagnosing the root causes behind the failure of MLLMs. Moreover, an important characteristic of infographic charts is that they convey rich information by combining a variety of visual elements [13]. However, the existing benchmarks do not provide such QAs specifically designed to evaluate the understanding of the visual elements in infographic charts. To fill these gaps, we developed **InfoChartQA**, a benchmark for multimodal QAs that includes pairs of infographics and plain charts, covering both data-fact-based and visual-element-based questions.

3 The InfoChartQA Benchmark

The **InfoChartQA** benchmark is constructed by three main steps: infographic chart dataset construction, paired infographic and plain chart generation, and multimodal question and answer construction

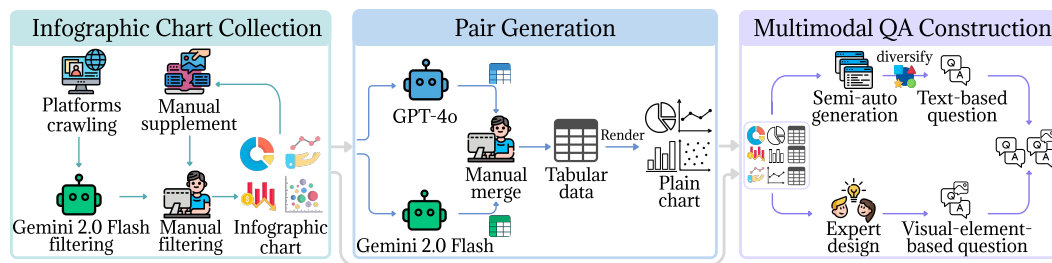


Figure 2: The InfoChartQA benchmark construction pipeline.

(Figure 2). First, the infographic chart dataset construction step collects a diverse set of infographic charts. Next, the paired infographic and plain chart generation step creates the corresponding plain chart for each infographic chart. Finally, the multimodal question and answer construction step creates both text-based and visual-element-based questions that focus on data-related facts and the interpretation of visual elements.

3.1 Infographic Chart Dataset Construction

Infographic chart source. InfoChartQA is collected from 11 real-world mainstream visualization platforms, such as Pinterest, Visual Capitalist, Statista, Behance, and iStock, as well as a large-scale infographic chart dataset, ChartGalaxy [5]. For platforms with high data quality, such as Statista and Visual Capitalist, we collected all publicly available infographic charts up to March 2025. For platforms with varying data quality, such as Pinterest and iStock, we manually selected high-quality infographic charts as seeds and utilized the recommendation systems of the associated platforms for identifying more infographic charts. For ChartGalaxy, we selected several high-quality infographic charts from it, following the recommendations of its authors.

Chart type identification. To ensure the diversity of the collected infographic charts, one practical way is to ensure the collected charts encompass all major chart types. Although many existing studies [10, 11, 14, 15] classify charts into around 10 coarse-grained types, large visual differences persist within each type. For example, the radial bar chart and polar bar chart are both considered bar charts, yet they differ substantially in appearance. Therefore, we invited three visualization experts to identify more fine-grained chart types. Specifically, we first derived a set of over 150 potential types from the Data Viz Project [16]. However, we found that some of these types were not commonly used in infographic charts, such as multi-level donut charts. Therefore, we used the name of each type to search for infographic charts in all 11 visualization platforms mentioned above. If the total number of searched infographic charts of one type in all 11 platforms was less than 10, and the visualization experts believed it was not common in infographic charts, we removed it from our benchmark. During our search, we found that, although rare, some infographic charts contain multiple panels (sub-charts) [17, 18]. For such charts, questions involving cross-panel reasoning are more challenging than those for single-panel charts. To highlight these more challenging cases, we added two data types of multi-panel charts: homogeneous ones, where all panels share the same chart type, and heterogeneous ones, where panels belong to different chart types. Finally, a total of 54 chart types were identified, with details shown in Appendix A.1.

Infographic chart selection. Since the majority of the infographic charts were crawled from various platforms automatically, some irrelevant data, such as diagrams, illustrations, and natural images, were also included. Moreover, the number of infographic charts for certain chart types was limited, which led to an imbalanced benchmark. To mitigate the low quality and imbalance issues, we developed a semi-automatic selection pipeline. First, we applied Gemini 2.0 Flash, one of the most powerful MLLMs, to identify infographic chart candidates. The prompts can be found in Appendix A.2. Then, we recruited two experienced graduate students to select infographic charts from the candidate set. After the selection, we analyzed the distribution of the infographic charts by the 54 chart types. For each chart type, if the number of the associated infographic charts was less than 30, we used the chart type name to search for additional infographic charts on the platforms. The newly added infographic charts were also processed through the semi-automatic pipeline. This process was repeated until the number of charts for each type exceeds 30. The final dataset comprises 5,948 infographic charts.

3.2 Paired Infographic and Plain Chart Generation

Infographic charts enrich plain charts with rich pictorial visual elements to better convey information and metaphors. Comparing the performance of MLLMs in understanding these two types of charts can provide deeper insights into their visual recognition capabilities. Therefore, we generate the corresponding plain chart for each infographic chart. The generation consists of two steps: chart-to-table translation and plain chart rendering.

Chart-to-table translation. Since only a few platforms provide the associated tabular data for infographic charts, we utilize chart-to-table translation to extract the associated tabular data from the infographic charts. To ensure more reliable table extraction, we ensembled two MLLMs and invited four experts for verification. Specifically, for each infographic chart, we employed both Gemini 2.0 Flash and GPT-4o to extract the associated tabular data. Then, the experts merged the tables extracted by the two models and corrected any errors they found to ensure accuracy.

Plain chart rendering. Once the tabular data is extracted, the associated plain charts can be rendered easily according to their chart types. For example, for the vertical bar chart, we directly utilize APIs in Python, including plotly, matplotlib, and seaborn, for rendering when the tabular data is given.

3.3 Multimodal Question and Answer Construction

We construct the multimodal question and answer pairs by incorporating generic text-based questions, which are shared between plain and infographic charts, as well as visual-element-based questions unique to infographic charts, as shown in Table 1.

Text-based questions. We curate high-quality text-based questions to facilitate comparative analysis of MLLMs’ performance on infographic charts and their plain chart counterparts. The questions of existing chart understanding benchmarks are designed based on heuristics or experience, which may not ensure that all the information conveyed by the chart is covered. To address this issue, we propose using data facts to guide the design of questions. Data facts refer to the numerical or statistical results that the chart is intended to convey. According to the analysis by Wang *et al.* [19], there are eleven types of data facts: value, categorization, aggregation, extreme, rank, proportion, distribution, trend, difference, outlier, and association. Different types of data facts may be suitable for different chart types. For example, line charts are suitable for showing the trends of the data, but not for showing ranking results.

Based on the data facts, we utilize a semi-automated method to ensure the difficulty and diversity of questions while minimizing human efforts. Firstly, four visualization experts manually wrote 1,376 general questions based on 405 infographic samples, covering all chart types and data facts in the dataset. Then, for each infographic chart, we selected the suitable templates according to the chart type and data facts to generate questions and their answers, with more detail shown in Appendix A.3. Finally, we employed Gemini-2.5-Flash and GPT-4o to rewrite all template questions using the experts’ questions as reference to ensure both difficulty and linguistic diversity.

While the majority of questions can be reliably generated through our semi-automated method, we observed that the generated questions of multi-panel infographic charts tend to be inaccurate, especially the co-referential ones that require linking entities in different panels to answer. Therefore, for multi-panel infographic charts, instead of using semi-automatically generated questions, we invited the four visualization experts to design 780 complex co-referential questions.

Table 1: Comparison of InfoChartQA and existing benchmarks.

Dataset	Chart type	Infographic charts	Text-based questions	Visual-element-based questions	HD-D	SD
ChartQA	3	×	2.5K	×	0.769	0.805
ChartBench	42	×	16.8K	×	0.630	0.743
ChartQAPro	9	✓	1.9K	×	0.828	0.864
InfographicVQA	11	✓	3.2K	1.1K	0.837	0.823
InfoChartQA	54	✓	50.9K	7.9K	0.817	0.802

In total, we create 50,920 text-based questions for 54 different chart types. As shown in Table 1, our text-based questions surpass existing benchmarks in both scale and chart type diversity, enabling a more comprehensive comparison. Moreover, our dataset demonstrates a comparable level of semantic diversity, as measured by the **Semantic Diversity** score [20] (**SD**), and vocabulary richness, as measured by the **Hypergeometric Distribution-based Divergence** [3] (**HD-D**), to that of purely human-generated questions in existing benchmarks (*e.g.*, InfographicVQA).

Visual-element-based questions. The visual-element-based questions are a unique type of question we introduce for infographic charts to evaluate more sophisticated visual understanding and reasoning capabilities. As shown in Figure 1(b), it includes basic questions and metaphor-related questions.

- **Basic questions.** The basic questions enable intuitive reference to visual elements (*e.g.*, the flag in Figure 1(b)) related to data even in the absence of text annotations. It is an extension of text-based questions by multimodal inputs with infographic-specific elements. To construct these questions, we first combine InternImage [21], a SOTA detection model, with human verification to extract the visual elements. Subsequently, two types of basic questions are derived. The first type (2,073 questions) asks about the correspondence between the visual element and the data item (*e.g.*, Figure 1(b)). The second type (5,402 questions) examines the function of the visual elements (*e.g.*, highlighting trends or conveying themes) through multiple-choice. Similar to generating text-based questions, we generated the basic questions with templates and MLLMs in a semi-automated manner. The templates can be found in Appendix A.4.
- **Metaphor-related questions.** A more subtle type of visual-element-based question is the metaphor-related one. Specifically, the metaphor of infographic charts combines visual elements to convey narratives or evoke emotional responses. For example, as shown in Figure 1(b), the ship visual element conveys a metaphor for the export volume. Due to the challenge of recognizing metaphors within these charts, it is not feasible to generate metaphor-related questions automatically. Therefore, we invited two visualization experts experienced in metaphor analysis for infographic charts. Initially, the two experts reviewed all the infographic charts and identified 143 that convey metaphors. Then, each chart was annotated by one expert who designed metaphor-related questions and the corresponding answers in multiple-choice format. Since an infographic chart may contain multiple metaphors, the experts could provide one or more questions. After the annotation, the questions and answers of each infographic chart were reviewed by the other expert to ensure the correctness and neutrality (*e.g.*, avoiding ambiguous or culturally sensitive interpretations). Through this process, we obtained 462 metaphor-related questions.

In total, we construct over 7K visual-element-based questions, which is significantly more than those in InfographicVQA (Table 1). We show more examples of such questions in Appendix B.3.

4 Experiments

4.1 Experimental Setup

Models. We evaluated a diverse set of open-source and proprietary models on [InfoChartQA](#). For open-source models, we tested both general-purpose and domain-specific (in chart understanding) models, including: Qwen2.5-VL [22], Llama 4 [23], Intern-VL3 [24], Janus Pro [25], DeepSeek VL2 [26], Phi-4 [27], LLaVA OneVision [28], Pixtral [29], Ovis [30], ChartGemma [31], TinyChart [32], and ChartInstruct [33]. For proprietary models, we tested: OpenAI O4-mini [34], GPT-4.1 [35], GPT-4o [36], Claude 3.5 Sonnet [37], Gemini 2.5 Pro Preview [38], and Gemini 2.5 Flash Preview [39]. We provide test configurations for all these models in Appendix B.1.

Human baseline. We recruited 15 human participants with expertise in deep learning and visualization and report their performance (*i.e.*, Human) on [InfoChartQA](#) as a baseline (see Appendix B.5 for more information of human evaluation). To enable a fair comparison between humans and models, we presented the participants with the same questions and instructions and evaluated their responses using the same criteria as those applied to the models. Given the substantial time and cost involved, human performance was evaluated on a 10% subset of text-based and basic visual questions, while all metaphor-related questions were included due to their limited number.

Evaluation metric. InfoChartQA consists of multiple forms of questions with textual, numeric, and option answers. For textual answers, answers were considered correct if the ANLS score exceeded 0.8. The ANLS score evaluates the similarity between the model-generated answer and the ground truth based on the number of edits needed to convert one text into the other [40, 41]. For numeric answers, we employed the commonly used relaxed accuracy metric in chart question answering benchmarks [8]. To avoid errors introduced by different forms of numbers (*e.g.*, “1K” and “1,000”), we normalized the numbers into a unified form, *e.g.*, from “1K” to “1,000”. For option answers, we considered an answer correct if it exactly matched the ground truth. The pseudocode of the evaluation process can be found in Appendix B.2.

4.2 Quantitative MLLM Evaluation Results on the InfoChartQA Benchmark

We present our main result in Table 2. The detailed breakdowns, sampled questions, answers, and model responses can be found in Appendix B.3. Key observations include:

The performance of MLLMs degrades on infographic charts compared to plain charts. As shown in Table 2, the top-performing models demonstrated impressive performance on plain chart benchmarks, sometimes on a par with human performance. For example, Gemini 2.5 Pro Preview achieved 91.16% on plain charts while the human baseline was 95.44%. This result is also consistent with existing studies [4, 34]. However, the performance of all models deteriorated significantly when on infographic charts. It shows that there is significant potential for improvement in the infographic chart understanding abilities of MLLMs.

Strong performance on text-based questions is foundational to strong performance on visual-element-based questions. Visual-element-based questions evaluate not only a model’s ability to understand charts but also its visual alignment capability (*e.g.*, align the cropped element with the whole image). If a model lacks strong chart understanding ability, it is likely to perform poorly on visual-element-based questions. As shown in Table 2, models that performed well on visual-element-based questions, such as GPT-4.1 and Gemini 2.5 Pro Preview, generally exhibited strong performance on text-based questions. Conversely, models that performed poorly on visual-element-based questions, such as ChartGemma and TinyChart, tended to have weaker performance on text-based questions.

Table 2: Evaluation results on InfoChartQA in terms of accuracy. The best one (except human) is **bold**, and the runner-up is underlined. Results with (*) are tested on a randomly sampled 10% subset.

Model	Text-based			Visual-element-based		
	Infographic	Plain	Δ	Basic	Metaphor	Avg.
Baselines						
Human	94.63*	95.44*	0.81	92.89*	88.69	90.79
Proprietary Models						
OpenAI O4-mini	76.23	89.62	13.39	91.42	54.76	73.09
GPT-4.1	71.29	80.81	9.52	87.52	50.87	69.20
GPT-4o	64.59	80.60	16.01	81.05	47.19	64.12
Claude 3.5 Sonnet	62.80	81.37	18.57	<u>89.22</u>	55.33	72.28
Gemini 2.5 Pro Preview	79.23	91.16	11.93	<u>88.91</u>	60.42	74.67
Gemini 2.5 Flash Preview	72.40	80.56	8.16	81.25	<u>56.28</u>	68.77
Open-Source Models						
Qwen2.5-VL-72B	61.08	77.92	16.84	76.71	54.64	65.68
Llama-4 Scout	63.68	78.84	15.16	81.69	51.89	66.79
Intern-VL3-78B	63.42	81.41	17.99	78.80	51.52	65.16
Intern-VL3-8B	46.45	61.67	15.22	73.62	49.57	61.60
Janus Pro	27.89	35.88	7.99	41.22	42.21	41.72
DeepSeek VL2	40.40	44.44	4.04	58.59	44.54	51.57
Phi-4	35.47	54.68	19.21	61.63	38.31	49.97
LLaVA OneVision Chat 72B	44.69	58.51	13.82	61.82	50.22	56.02
LLaVA OneVision Chat 7B	36.45	50.47	14.02	60.56	45.67	53.12
Pixtral	46.61	59.29	12.68	64.00	50.87	57.44
Ovis1.6-Gemma2-9B	51.69	58.66	6.97	60.81	34.42	47.62
ChartGemma	22.42	33.33	10.91	30.75	33.77	32.26
TinyChart	24.32	42.97	18.65	15.35	9.03	12.19
ChartInstruct-LLama2	19.95	26.87	6.92	34.15	33.12	33.64

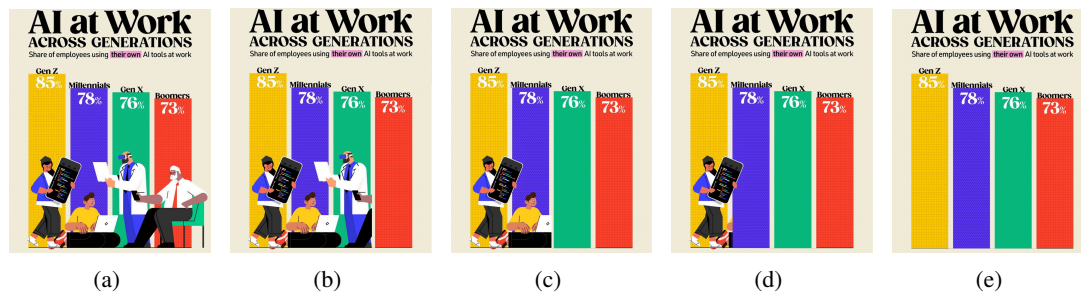


Figure 3: Example of **progressively** removing visual elements from infographic charts.

This observation was further supported by a high and statistically significant Spearman correlation between the two sets of results ($\rho = 0.895$, $p < 0.01$).

Metaphor-related questions are challenging for MLLMs. We found that understanding visual metaphors in infographic charts was still challenging for current MLLMs. Even though some models achieved approximately 80% accuracy on text-based questions in infographic charts (e.g., 79.23% for Gemini 2.5 Pro Preview), their performance dropped by around 20% on metaphor-related questions, down to 60.42%. On the other side, the human baseline showed a smaller drop, from 94.63% to 88.69%. This gap indicates that the alignment between abstract concepts and visual elements (e.g., a rising balloon symbolizing hope) needs to be enhanced in current MLLMs.

4.3 Analysis on Performance Degradation for Infographic Charts

Since InfoChartQA processes paired infographic and plain charts sharing the same underlying data, it enables us to perform ablation studies to analyze the performance degradation for infographic charts.

4.3.1 Visual elements primarily contribute to the performance degradation

Unlike plain charts, infographic charts often incorporate a wider variety and higher density of visual elements, such as metaphorical imagery, to convey information. To understand how these elements affect model performance, we grouped infographic charts by the number of visual elements and compared their performance. We observed that models performed worse on infographic charts with more visual elements compared to those with fewer elements. For example, infographic charts with 100 visual elements had 10% lower accuracy than those with 20 visual elements (details are provided in Appendix B.3). This suggests that these elements substantially increase the visual complexity of infographic charts, posing challenges for current MLLMs.

Since the experiment results above may be influenced by other factors, we conducted a controlled experiment to distangle the impact of visual elements from these other factors. As illustrated in Figure 3, we manually selected 300 infographic charts from our dataset that feature rich visual elements. These charts were then edited to **progressively** remove visual elements, resulting in versions of the **same** infographic with **different** numbers of visual elements, ranging from 0 to n , where n denotes the original number of visual elements. Text-based QA was then evaluated on these charts, selecting only those remaining answerable even after all visual elements were removed. This allowed us to observe changes in model performance on the **same** infographic chart but with **different** numbers of visual elements.

The results of GPT-4.1 and TinyChart are shown in Figure 4(a) and (b). Results of other models are provided in Appendix B.3.2. As we can see, after removing all visual elements, the model's accuracy nearly aligned with that on plain charts. Our results validate that the visual elements are the primary cause of the observed performance drop on infographic charts.

To further validate this conclusion, we conducted an experiment for model improvement. We revised the prompt instruction to explicitly guide the model to focus on visualization components rather than decorative elements. The performance of GPT-4.1 is improved by 2.93%. More details about this experiment can be found in Appendix B.6.

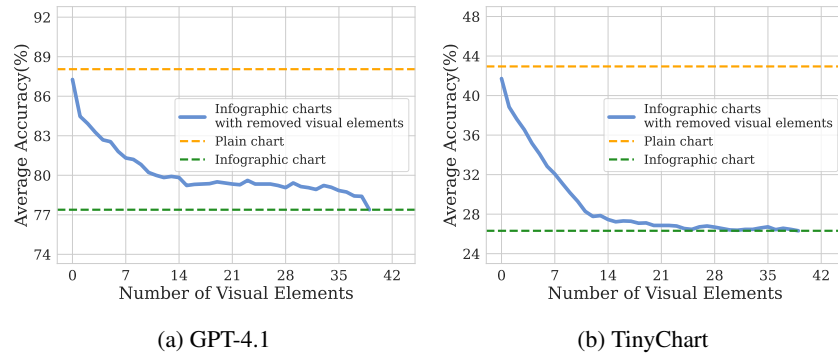


Figure 4: Model's performance change on the **same** infographic chart but with **different** number of visual elements.

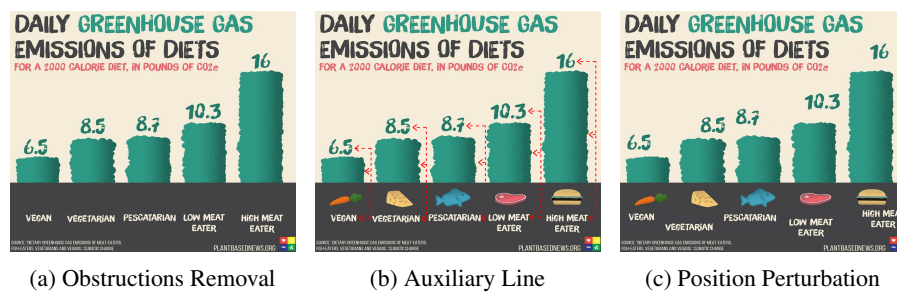


Figure 5: Different modifications on charts.

4.3.2 Clearer connections between text and visual elements improve understanding

Knowing that the visual elements affect the model's performance, we further investigated how they affect it. We discovered that the more visual elements were overlaid onto the charts, the lower the performance became. Since the overlay disturbs the **connections** between labels, visualization elements (e.g., bars in bar charts), and numerical annotations, we hypothesized that the model's ability to understand charts relies on such connections. Ambiguities in the connections, like occlusions or positional misalignments, can degrade model performance.

To validate this hypothesis, we randomly selected 200 images and applied three different types of modifications to introduce varying levels of perturbation to the connections. As shown in Figure 5:

1) **Obstructions Removal**. We eliminated obstructions that hinder the connections. 2) **Auxiliary Lines**. We introduced auxiliary lines to explicitly connect texts with their associated visual elements and chart components. 3) **Position Perturbation**. We randomly shifted the positions of the bars, labels, and annotations to disrupt the connections.

The result is shown in Table 3. Notably, even simple modifications, as shown in Figure 5(a) and (b), to highlight the connection can lead to comparably better performance and vice versa.

4.3.3 MLLMs are sensitive to the orders of text labels

Since the majority of QAs in InfoChartQA are designed based on data facts, we further analyzed how different data facts affect model performance. The accuracy across different data facts is shown in Appendix B.3.1. We observed that only the *rank* and *outlier* questions exhibited accuracies below 50%. To better understand the underlying causes, we focused on analyzing these two categories.

Model	Obstructions Removal	Auxiliary Line	Position Perturbation
GPT-4.1	↑ 0.79	↑ 0.85	↓ 2.95
TinyChart	↑ 3.23	↑ 3.08	↓ 2.78

Table 3: Performance changes (%) of GPT-4.1 and TinyChart under three types of modifications.

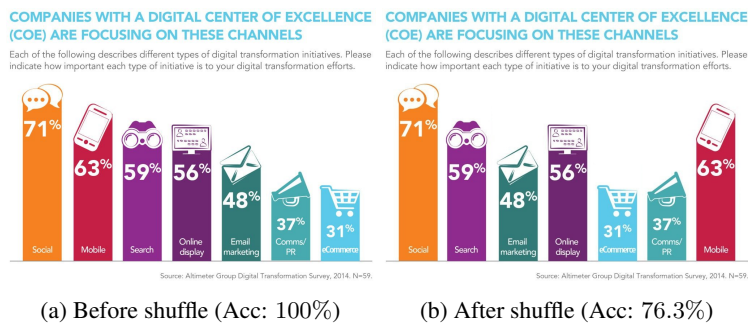


Figure 6: Sample charts before/after shuffle and corresponding performance.

For *rank* questions, we found that MLLMs tended to answer the questions based on the order of the text labels rather than the actual data values. Based on this observation, we hypothesized that MLLMs were sensitive to label order. To validate this, we randomly select 200 charts on which the model (GPT-4.1) originally achieved correct rankings and apply random spatial permutations to the text labels within each chart, while preserving their semantic content, as shown in Figure 6(a) and (b). When re-evaluated on these shuffled samples, the model's accuracy dropped from 100% to 76.3%. This substantial decline strongly suggests that the model relies heavily on superficial cues such as label order, rather than developing a robust understanding of ranking.

For *outlier* questions, answering correctly primarily requires the ability to perceive spatial relationships and contextual dependencies. Our results indicate notable limitations in this aspect, suggesting that the model lacks a fine-grained understanding of spatial configurations. This observation is consistent with prior work [42], which has also identified shortcomings in MLLMs regarding spatial and relational reasoning capabilities.

5 Limitations and Conclusion

Limitations. While InfoChartQA presents a comprehensive benchmark dedicated to infographic charts understanding with special visual-element-based questions, it still has some limitations, which highlight areas for further research. First, the difficulty in constructing metaphor-related questions limits the scale of testing for this subtle type of multimodal understanding. Increasing the amount of such questions and performing more fine-grained metaphor analysis may elicit more insights into the challenges of infographic charts. Second, although we actively involved human experts in the creation and verification of questions, some parts of our question generation pipeline rely on templates or large language models. This may limit the out-of-distribution diversity regarding the textual part of the questions, although the visual part of our questions exhibits superior diversity compared to existing benchmarks with complex real-world infographic charts and a wider range of chart types. Third, the participants in our user study consist of 15 students of similar ages, all with expertise primarily in deep learning and visualization. As a result, they may not fully represent the broader population with varying ages and areas of expertise. Moreover, although we briefly discussed how prompt engineering can enhance model performance on infographic charts based on the findings in our ablation studies, exploring how to better leverage these findings to improve MLLMs remains an important direction for future work.

Conclusion. In this paper, we present InfoChartQA, a novel benchmark for infographic chart understanding, with particular focus on evaluating MLLMs' reasoning ability on complicated multimodal questions. It involves a combination of heterogeneous pictorial visual elements or metaphors and the underlying data relationships. In this benchmark, we first construct paired infographic charts and their plain chart counterparts to pinpoint the source of model failure in either data complexity itself or additional infographic elements. InfoChartQA also extends the QA space by introducing visual-element-based questions unique to infographic charts, enabling more detailed analysis of visual reasoning capabilities. Experimental results highlight the special challenges of infographics, especially in visual-element-based questions, with further analysis revealing three performance degradation factors, including the impact of visual elements, the ambiguous connection between text and visual elements, and orders of text labels. We hope that InfoChartQA can provide a new perspective and a reliable foundation for evaluating more complex chart reasoning capabilities.

Acknowledgments

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Justification: We provide an equivalent approval/review based on the requirements of our country or institution in the supplementary materials.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigor, or originality of the research, declaration is not required.

Answer: [\[Yes\]](#)

Justification: Our benchmark is designed for multimodal large language models (MLLMs), so it requires conducting experiments on MLLMs and analyzing the results.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Dataset Construction

This section provides more detail on our dataset construction, including specific chart types A.1, infographic chart selection prompts A.2, text-based question template A.3, and visual-element-based question template and examples A.4.

A.1 Chart Types

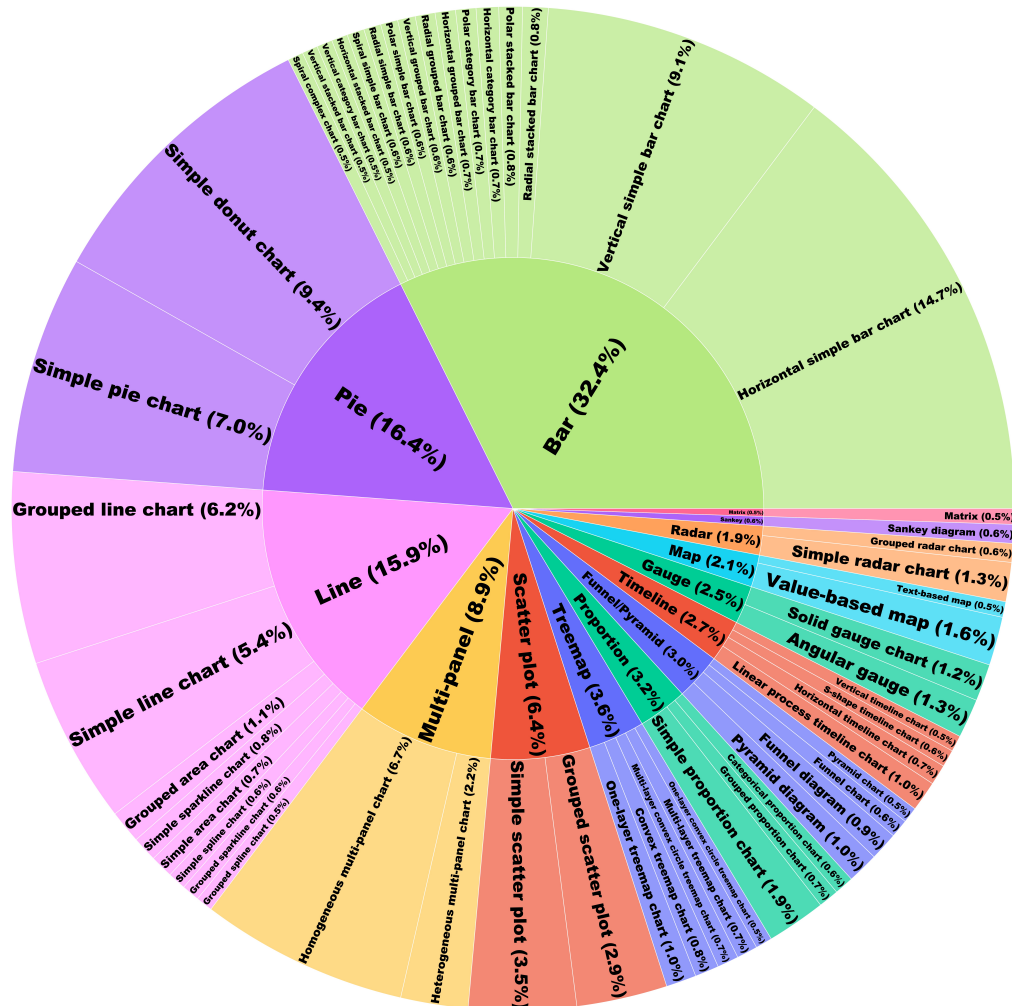


Figure 7: Distribution of 54 chart types

Table 4: Chart Type and Their Frequencies

No.	Chart Type	Note	Count
1	Vertical simple bar chart	Bar	543
2	Vertical category bar chart	Bar	30
3	Vertical grouped bar chart	Bar	34
4	Vertical stacked bar chart	Bar	30
5	Horizontal simple bar chart	Bar	877
6	Horizontal category bar chart	Bar	43
7	Horizontal grouped bar chart	Bar	39
8	Horizontal stacked bar chart	Bar	31
9	Polar simple bar chart	Bar	33
10	Polar category bar chart	Bar	39
11	Polar stacked bar chart	Bar	45
12	Radial simple bar chart	Bar	33
13	Radial grouped bar chart	Bar	38
14	Radial stacked bar chart	Bar	49
15	Spiral simple bar chart	Bar	33
16	Spiral complex chart	Bar	30
17	Simple line chart	Line	322
18	Grouped line chart	Line	367
19	Simple area chart	Line	44
20	Grouped area chart	Line	63
21	Simple sparkline chart	Line	48
22	Grouped sparkline chart	Line	34
23	Simple spline chart	Line	35
24	Grouped spline chart	Line	32
25	Simple donut chart	Pie	560
26	Simple pie chart	Pie	417
27	Simple proportion chart	Proportion	113
28	Grouped proportion chart	Proportion	39
29	Categorical proportion chart	Proportion	37
30	Funnel chart	Funnel/Pyramid	35
31	Funnel diagram	Funnel/Pyramid	54
32	Pyramid chart	Funnel/Pyramid	30
33	Pyramid diagram	Funnel/Pyramid	60
34	Angular gauge	Gauge	75
35	Solid gauge chart	Gauge	71
36	Text-based map	Map	30
37	Value-based map	Map	93
38	Matrix	Matrix	30
39	Simple radar chart	Radar	75
40	Grouped radar chart	Radar	36
41	Sankey diagram	Sankey	36
42	Simple scatter plot	Scatter plot	206
43	Grouped scatter plot	Scatter plot	174
44	Linear process timeline chart	Timeline	58
45	Vertical timeline chart	Timeline	31
46	Horizontal timeline chart	Timeline	39
47	S-shape timeline chart	Timeline	33
48	Convex treemap chart	Treemap	46
49	One-layer convex circle treemap chart	Treemap	32
50	Multi-layer convex circle treemap chart	Treemap	41
51	One-layer treemap chart	Treemap	58
52	Multi-layer treemap chart	Treemap	40
53	Homogeneous multi-panel chart	Multi-panel	398
54	Heterogeneous multi-panel chart	Multi-panel	129
Total			5,948

A.2 Infographic Chart Selection Prompts

Infographic Chart Selection Prompt

You are a professional infographic designer with extensive expertise in infographics and data visualization. Your task is to analyze the given infographic image and provide a detailed assessment in the specified format.

Definitions:

****Please keep in mind the following definitions.****

1. Visualization types:

Funnel Chart, Pyramid Chart, Line Graph, Sankey Diagram, Area Chart, Radar Chart, Radial Bar Chart, Bar Chart, Icicle Diagram, Heat Map, Treemap, Pie Chart, Donut Chart, Scatter Plot, Dot Chart, Bubble Chart, Map, Arc Diagram, Chord Diagram, Matrix Diagram, Boxplot, Timeline, Gauge, Parallel Coordinates, Set Visualization, Contour Plot, Node-link Diagram, Dendrogram.....

2. Data types of a visualization include the following:

- Single value: only a single value is displayed, such as a gauge or a single proportion or quantity
- Tabular data: structured data, such as a bar chart, line chart, or scatter plot
- Network data: data that represents relationships between entities, often visualized by a node-link diagram
- Hierarchical data: data with a hierarchical structure, primarily a tree structure
- Set data: data that represents sets and their relationships, such as a set visualization or a Venn diagram
- Geographic data: data that is presented by a map
- Descriptive (Textual) data: data that is primarily text-based, such as a word cloud, a timeline, or instructions (steps) for a process

3. Composite visualizations combine multiple visual representations of data into a cohesive and aesthetically meaningful layout, utilizing techniques such as juxtaposition, overlay, or nesting. Infographics or posters with multiple titles + charts are often not composite visualizations unless they are in the form of shared axes, connecting lines, cell arrangements, repeating styles, and so on.

Task:

Please analyze the image and output the results based on the following JSON format.

Output Format:

Reply in the following JSON format:

```
{
  "title": , // title of the infographic, if no visible title, summarize one for it
  "description": , // describe the infographic
  "keywords": [kw1, ...], // give a maximum of five keywords that best describe the detailed
  theme of the infographic
  "domain": , // one-word domain of the infographic
  "language": , // language of the infographic
  "style": , // design style of the infographic
  "vis_type": ["vis_type1", ...], // give the different visualization types present in the image:
  you need to choose from the visualization types given, and can only choose a maximum of
  **three** answers if there are more than one, answer other if you cannot classify as any of
  the provided visualization types
  "data_type": ["data_type1", ...], // give the different data types present in data visualization(s):
  you need to choose from the data types given
  "composite": "yes/no", // analyze if this image contains a composite visualization
}
```

Additional Guidelines:

Ensure your evaluation is concise and follows the format for consistency and accuracy.

A.3 Text-based Question Template

We designed question templates based on data facts, as shown in Table 5, which are suitable for charts with different data formats, including simple, stacked, grouped, and with-category.

Table 5: Templates for text-based questions

Data fact	Question type	Question template	Instructions
Value	value_single_element	What is the {y_label} of {ith_label}?	* Your response should only contain the value of {y_label} corresponding to {ith_tick}. * If there is an explicit answer in the chart, answer in the same format.
Value	value_element_of_group	What is the {y_label} of {ith_label}'s {jth_group}?	* Your response should only contain the value of {y_label} corresponding to {ith_label}'s {jth_group}. * If there is an explicit answer in the chart, answer in exactly the same format.
Difference	difference_elements	What is the difference between the {y_label} of {ith_label} and {jth_label}?	* Your response should only contain the value of the difference between the {y_label} corresponding to {ith_label} and {jth_label}. * The answer you give me should be the absolute value. * The format of the difference you provide must be consistent with the corresponding data format in the chart.
Difference	difference_group	What is the difference between the {y_label} of {ith_label}'s {kth_group} and {jth_label}'s {kth_group}?	* Your response should only contain the value of the difference between the {y_label} of {ith_label}'s {kth_group} and {jth_label}'s {kth_group}. * The answer you give me should be the absolute value. * The format of the difference you provide must be consistent with the corresponding data format in the chart.
Difference	difference_two_group	What is the difference between the {y_label} of {ith_label}'s {jth_group} and {ith_label}'s {kth_group}?	* Your response should only contain the value of the difference between the {y_label} of {ith_label}'s {jth_group} and {ith_label}'s {kth_group}. * The answer you give me should be the absolute value. * The format of the difference you provide must be consistent with the corresponding data format in the chart.
Difference	difference_yesno	Is the {y_label} in {ith_label} less than that in {jth_label}?	* If the {y_label} in {ith_label} is less than that in {jth_label}, your response should be 'Yes', otherwise 'No'. * Your response should only be 'Yes' or 'No'.
Difference	difference_in_group_yesno	Is the {y_label} in {ith_label}'s {kth_group} less than that in {jth_label}'s {kth_group}?	* If the {y_label} in {ith_label}'s {kth_group} is less than that in {jth_label}'s {kth_group}, your response should be 'Yes', otherwise 'No'. * Your response should only be 'Yes' or 'No'.

continued ...

Data fact	Question type	Question	Instructions
Difference	difference_groups_yesno	Is the {y_label} in {ith_label}'s {jth_group} less than that in {ith_label}'s {kth_group}?	* If the {y_label} in {ith_label}'s {jth_group} is less than that in {ith_label}'s {kth_group}, your response should be 'Yes', otherwise 'No'. * Your response should only be 'Yes' or 'No'.
Proportion	proportion_element	What is the proportion of {ith_label} in {father_name}?	* Your response should only contain the proportion of {ith_tick} in {father_name}. * If there is an explicit answer in the chart, answer in the same format.
Trend	trend_description	What is the trend of {ith_group} in this chart?	* Your response must be a sequence of trends in chronological order. * Possible trend values: 'increase', 'decrease', 'stable', 'oscillating', 'cyclical-ity', 'complex'. * Example format: 'increase, decrease, stable'
Categorization	categorization_target	Which {x_label}(s) {'less than {ith_label}', 'greater than {ith_label}'}?	* Your response should only contain the {x_label} which have {y_label} {'less than {ith_label}', 'greater than {ith_label}'} * Separate the answers with commas. * If there is no answer that meets the condition, respond with an empty string.
Categorization	categorization_in_group	What is/are the {x_label} which have {ith_group} {'less', 'greater'} than {jth_label}?	* Your final answer should only contain the {x_label} which have {ith_group} {'less', 'greater'} than {jth_label}. * Please provide your answer in the order from left to right, top to bottom, as they appear in the chart. * If there is no answer that meets the condition, respond with an empty string.
Categorization	categorization_groups	Which {x_label} have {ith_group} {'less', 'greater'} than {jth_group}?	* Your response should only contain the {x_label} which have {ith_group} {'less', 'greater'} than {jth_group}. * Please provide your answer in the order from left to right, top to bottom, as they appear in the chart. * If there is no answer that meets the condition, respond with an empty string.
Categorization	categorization_category	Which {x_label} in {ith_category} have {y_label} {'less', 'greater'} than {bound_value} ?	* Your response should only contain the {x_label} in the {ith_category} with {y_label} {'less', 'greater'} than {bound_value}. * Please provide your answer in the order from left to right, top to bottom, as they appear in the chart. * If there is no answer that meets the condition, respond with an empty string.
Categorization	categorization_in_category	What is/are the {x_label} which is/in {ith_category} ?	* Your response should only contain the {x_label} is/in {ith_category}. * Please provide your answer in the order from left to right, top to bottom, as they appear in the chart. * If there is no answer that meets the condition, respond with an empty string.

continued ...

Data fact	Question type	Question	Instructions
Aggregation	aggregation_sum	What is the sum of {y_label}?	* Your response should only contain the value of the sum of {y_label}.
Aggregation	aggregation_average	What is the average {y_label} per {x_label}?	* Your response should only contain the value of the average of {y_label} per {x_label}.
Aggregation	aggregation_median	What is the median {y_label}?	* Your response should only contain the value of the median of {y_label}.
Aggregation	aggregation_count	How many data points are there?	* Your response should only contain the value of the number of data points in the chart.
Association	association_correlation	What is the correlation between the {y_label} of {ith_group} and {jth_group}?	* Your final response should be within a few words, such as "positively correlated", "negatively correlated", or "irrelevant". * "positively correlated" if the correlation coefficient > 0.5, * "negatively correlated" if the correlation coefficient < -0.5, * "irrelevant" if the correlation coefficient is between -0.5 and 0.5.
Association	association_groups	Do the distributions of the {y_label} of {ith_group} and {jth_group} exhibit any distinct characteristics?	* Your final answer should be within a few words, such as "less", "greater", or "Not Applicable". * If {ith_group} generally less than {jth_group}, Your final answer should be 'less'. * If {ith_group} generally greater than {jth_group}, Your final answer should be 'greater'. * Otherwise, your final answer should be 'Not Applicable'.
Extreme	extreme_element	In which {x_label} is the {y_label} of {'minimum', 'maximum'}?	* Your response should only contain the {x_label} where {y_label} is {'minimum', 'maximum'}. * If there is an explicit answer in the chart, answer in exactly the same format.
Extreme	extreme_value	What is the {'minimum', 'maximum'} value of {y_label}?	* Your response should only contain the numerical value of the {'minimum', 'maximum'} {y_label}. * If there is an explicit answer in the chart, answer in exactly the same format.
Rank	rank_by_value	What is the order of {x_label} on {y_label} in ['increasing', 'decreasing'] order?	* Your final answer should only contain {x_label} on {y_label} in ['increasing', 'decreasing'] order. * Separate the answers with commas. * If there is an explicit answer in the chart, answer in exactly the same format.
Outlier	outlier_identification	Is there an outlier in this chart? If yes, what is its name?	* Respond with 'No' if there is no outlier, otherwise provide the outlier's name." * Your response should only be 'No' or the name of the outlier.
Distribution	distribution_identification	Does the chart data show a significant statistical distribution? If yes, what type?	* Your response should be either 'No' if there's no significant distribution, or '[Distribution Type]' if there is one. * Possible distribution types include: Uniform Distribution, Normal Distribution.

A.4 Visual-element-based Question Template and Examples

In this section, we provide additional information about our visual-element-based questions, including the template for generating visual-element-based basic questions (Table 6) and more examples of both basic and metaphor-related questions.

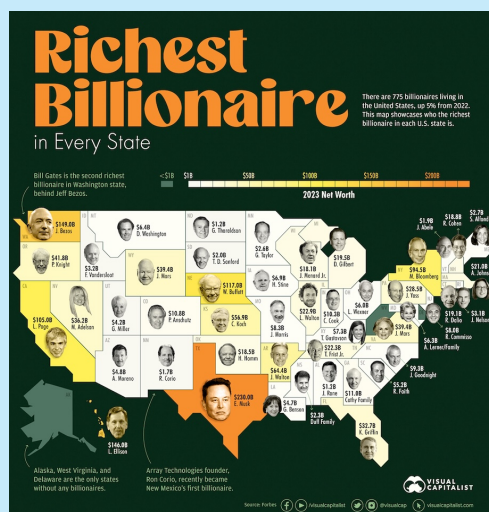
Table 6: Templates for visual-element-based basic questions

Question type	Question	Instructions
visual_basic_data_value	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon in Figure 2. Identify the icon specified and provide the corresponding data point value based on the information from Figure 1. What is the value of the data point in Figure 1 corresponding to the specified icon in Figure 2? [Figure 1: origin chart] [Figure 2: cropped icon]	* Your response should only contain the value of the data point corresponding to the icon specified in this chart. * If there is an explicit answer in the chart, answer in exactly the same format.
visual_basic_data_name	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon in Figure 2. Identify the icon specified and provide the corresponding data point based on the information from Figure 1. What is the name of the data point in Figure 1 corresponding to the specified icon in Figure 2? [Figure 1: origin chart] [Figure 2: cropped icon]	* Your response should only contain the name of the data point corresponding to the icon specified in this chart. * If there is an explicit answer in the chart, answer in exactly the same format.
visual_basic_group_value	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon in Figure 2. Identify the icon specified and the corresponding data group based on the information from Figure 1. What is the {ith_label} value of the data group in Figure 1 that corresponds to the specified icon in Figure 2? [Figure 1: origin chart] [Figure 2: cropped icon]	* Your response should only contain the value on/in/at {ith_label} of the data group corresponding to the icon specified in this chart. * If there is an explicit answer in the chart, answer in exactly the same format.
visual_basic_difference	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon1 and icon2 in Figure 2 and Figure 3. Identify the icons specified and provide the corresponding data point based on the information from Figure 1. What is the difference between the {y_label} corresponding to icon1 and icon2? [Figure 1: origin chart] [Figure 2: cropped icon1] [Figure 3: cropped icon2]	* Your response should only contain the value of the difference between the {y_label} corresponding to icon1 and icon2. * Your answer should be the absolute value of the difference, and its format must match the corresponding data format shown in the chart.
visual_basic_difference_yesno	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon1 and icon2 in Figure 2 and Figure 3. Identify the icons specified and provide the corresponding data point based on the information from Figure 1. Is the {y_label} of the icon corresponding to Figure 2 less than that in of the icon corresponding to Figure 3? [Figure 1: origin chart] [Figure 2: cropped icon1] [Figure 3: cropped icon2]	* If the {y_label} of the icon corresponding to Figure 2 is less than that of of the icon corresponding to Figure 3, your response should be 'Yes', otherwise 'No'. * Your response should only contain 'Yes' or 'No'.

continued ...

Question type	Question	Instructions
visual_basic_data_icon	Which one of the four icons above best matches {ith_label} based on the chart content? [Figure 1: origin chart], [Figure 2: cropped icon1] [Figure 3: cropped icon2] [Figure 4: cropped icon3] [Figure 5: cropped icon4]	* Think carefully based on the chart and the icons. * Only output the final answer in the following format: [Number of the best matching icon] * Do not output anything else besides the answer in the specified format.
visual_basic_imagery	Read and understand the information presented in Figure 1 (a chart). Then, locate the specified icon and Figure 2. What is the correct role of this icon in the chart? (A) [...] (B) [...] (C) [...] (D) [...]	* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Example of visual-element-based (basic) questions



Question:

Examine Figure 1 to familiarize yourself with the chart's details. Next, observe the icon highlighted in Figure 2. Using the information from Figure 1, determine the value associated with this specific icon. What is the data value linked to the icon shown in Figure 2 according to Figure 1?

* Your response should only contain the value of the data point corresponding to the icon specified in this chart.

* If there is an explicit answer in the chart, answer in exactly the same format.

Answer: \$230.0B

Example of visual-element-based (basic) questions



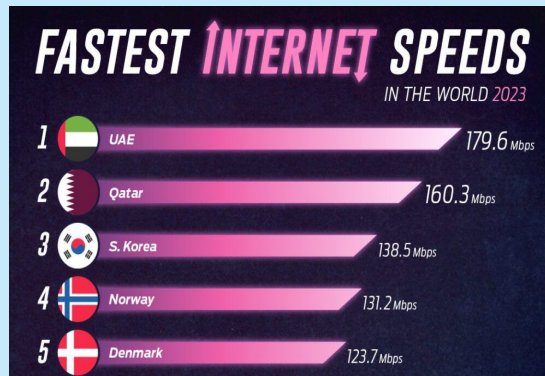
Question:

Carefully examine the chart shown in Figure 1. Next, observe the icon illustrated in Figure 2 and find its match within Figure 1. What is the data value from Figure 1 that corresponds to the icon presented in Figure 2?

- * Your response should only contain the value of the data point corresponding to the icon specified in this chart.
- * If there is an explicit answer in the chart, answer in exactly the same format.

Answer: one hour per week

Example of visual-element-based (basic) questions



Question:

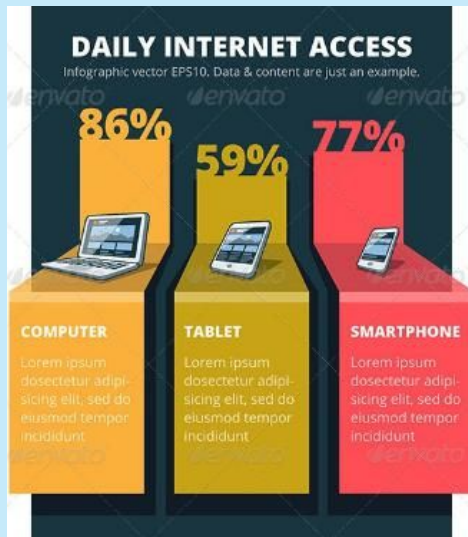
Review the chart in Figure 1 and examine the icon displayed in Figure 2. Match the icon from Figure 2 to its position in Figure 1, then state the data value associated with it as shown in the chart.

* Your response should only contain the value of Speed (Mbps) corresponding to the icon specified.

* If there is an explicit answer in the chart, answer in exactly the same format.

Answer: 123.7

Example of visual-element-based (basic) questions



Question:

First, examine Figure 1 to interpret the chart details. Next, review Figure 2 to find the highlighted icon. Using the chart in Figure 1, determine the data value that matches the icon shown in Figure 2.

* Your response should only contain the value of Daily Internet Access (%) corresponding to the icon specified.

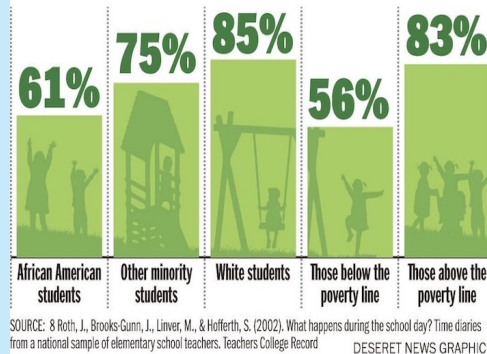
* If there is an explicit answer in the chart, answer in exactly the same format.

Answer: 86

Example of visual-element-based (basic) questions

Who gets recess?

In randomly selected schools on a randomly selected day in 2002, who had recess?



Question:

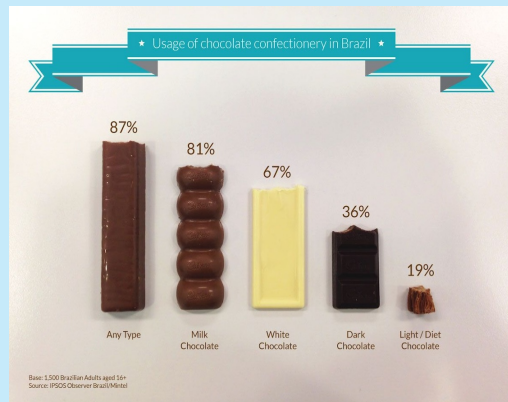
The left image is a chart, and the right is an image cropped from that chart. What role does this image primarily play within the chart?

- (A) To emphasize the chart's central theme concerning disparities in children's access to playtime.
- (B) To serve primarily as a decorative background, enhancing the overall visual appeal of the graph.
- (C) To visually clarify the concept of 'recess' that the 83% statistic represents for this student group.
- (D) To symbolically represent the social interaction and group activities common during school recess.

* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Answer: C

Example of visual-element-based (basic) questions



Question:

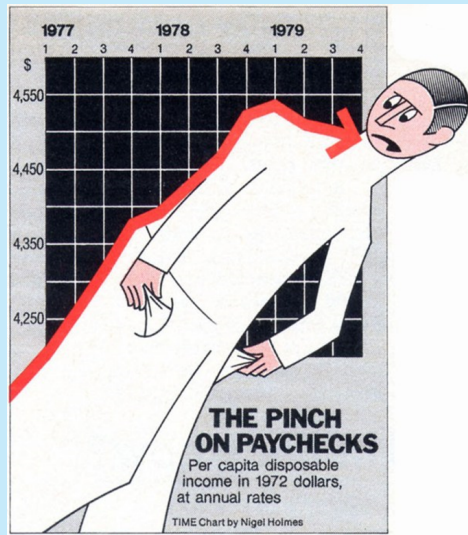
The sequence above presents a chart followed by a crop of that chart; within the chart, what primary function does this cropped image serve?

- (A) To provide purely aesthetic enhancement and make the chart more visually engaging.
- (B) To serve as a direct visual representation for the 'Any Type' category, clarifying the data point.
- (C) To establish a specific brand association for the most popular chocolate category.
- (D) To create an emotional connection by emphasizing the universal appeal of a classic chocolate bar.

* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Answer: B

Example of visual-element-based (metaphor) questions



Question:

Answer this question and choose the most appropriate answer (A, B, C, D).

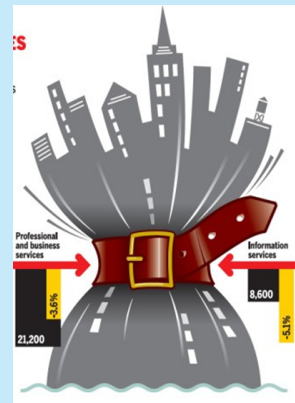
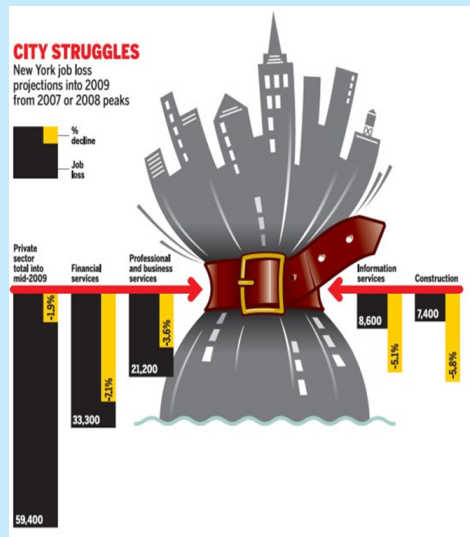
Why might the person in the chart be wearing an unhappy facial expression?

- (A) To show the person's anger because his packet has been stolen.
- (B) To show the person's embarrassment because his packet is empty.
- (C) To convey the anxiety associated with decreasing disposable income.
- (D) To make the chart look more friendly.

* Your response should only contain 'A'/'B'/'C'/'D'. If your response contains multiple options, you should separate them by ','. Do not include any explanation, analysis, or repeat the option text.

Answer: C

Example of visual-element-based (metaphor) questions



Question:

Answer this question and choose the most appropriate answer (A, B, C, D).

According to the chart, by drawing the buildings in the chart, what is the main idea the chart tries to convey?

- (A) The job loss in New York is making it struggle.
- (B) New York City is trying to ignore the damage caused by the job loss.
- (C) The job loss is being solved due to the city's effort.
- (D) "Private sector total into mid-2009" is facing the most job loss.

* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Answer: A

B Additional Experimental Settings and Results

B.1 Test Configurations for MLLMs

We present our running configurations for each MLLM in Table 7. We conduct all experiments on a single server equipped with $8 \times$ NVIDIA RTX 4090 GPUs.

Table 7: Running configurations for different MLLMs. Temp. denotes temperature.

Model	Version/HF Checkpoint	Do Sample	Max New Tokens	Temp.	Top-P
GPT-4.1	gpt-4.1		1024	0	1
GPT-4o	gpt-4o-2024-08-06		1024	0	1
Claude 3.5 Sonnet	claude-3-5-sonnet-20241022		1024	0	1
Gemini 2.5 Pro Preview	gemini-2.5-pro-preview-03-25		1024	0	1
Gemini 2.5 Flash Preview	gemini-2.5-flash-preview-04-17		1024	0	1
Qwen2.5-VL-72B	Qwen/Qwen2.5-VL-72B-Instruct	False	1024	0	1
Llama-4 Scout	meta-llama/Llama-4-Scout-17B-16E-Instruct	False	1024	0	1
Intern-VL3 78B	OpenGVLab/InternVL3-78B	False	1024	0	1
Intern-VL3 8B	OpenGVLab/InternVL3-8B	False	1024	0	1
Janus Pro	deepseek-ai/Janus-Pro-7B	False	512	0	1
DeepSeek VL2	deepseek-ai/deepseek-vl2	False	512	0	1
Phi-4	microsoft/Phi-4-multimodal-instruct	False	1000	0	1
LLaVA OneVision Chat 78B	llava-hf/llava-onevision-qwen2-72b-ov-chat-hf	False	1024	0	1
LLaVA OneVision Chat 7B	llava-hf/llava-onevision-qwen2-7b-ov-chat-hf	False	1024	0	1
Pixtral	mistralai/Pixtral-12B-2409	False	8192	0	1
Ovis1.6-Gemma2-9B	AIDC-AI/Ovis1.6-Gemma2-9B	False	1024	0	1
ChartGemma	ahmed-masry/chartgemma	False	512	0	1
TinyChart	mPLUG/TinyChart-3B-768	False	512	0	1
ChartInstruct-LLama2	ChartInstruct-LLama2	False	512	0	1

B.2 Pseudocode for Evaluation

We provide the pseudocode for answer validation in this section, as shown in Algorithm 1.

B.3 Additional Results

In this section, we present additional experimental results, including detailed breakdowns of the quantitative MLLM evaluation results (B.3.1) and more performance degradation results when removing visual elements (B.3.2).

B.3.1 Detailed Breakdowns of the Quantitative MLLM Evaluation Results

In this section, we provide detailed breakdowns of the quantitative MLLM evaluation results. We first categorize the infographic charts into three difficulty levels based on the average accuracy of Gemini 2.5 Pro Preview and GPT-4.1: Easy (above 80%), Moderate (40–80%), and Hard (below 40%). The difficulty level of each sample is provided in the metadata of the dataset card. This yields 46.7% easy, 32.4% moderate, and 20.9% hard charts. Table 8 and Table 9 report the performance of each model across the three difficulty levels. As shown, all models perform poorly on hard charts, while even domain-specific models such as ChartInstruct-LLama2 struggle to achieve strong results on the easy charts.

We also provide quantitative MLLM evaluation results by answer types and data-fact types. For the answer types, we divide the answers into three categories: textual, numeric, and multiple-choice. The corresponding results are presented in Table 10. For the data-fact types, we provide the performance of GPT4.1 on different data-fact types as shown in Table 11.

B.3.2 Additional Performance Results When Removing Visual Elements

We calculate the average accuracy of GPT-4.1 and TinyChart with respect to the number of visual elements, as shown in Figure 8 (Left: GPT-4.1, right: TinyChart). Both models exhibit a clear performance drop as the number of visual elements increases. For example, GPT-4.1’s accuracy decreases by more than 10% once the number of such elements exceeds 100, and a similar trend is observed in TinyChart.

Algorithm 1 Answer Normalization and Evaluation

Require: Predicted answer a_{pred} , ground truth a_{gt} **Ensure:** Correct / Incorrect

```
1: if  $a_{pred}$  is text then
2:   Convert all characters to lowercase
3:   Standardize special symbols (e.g., replace single quotes with double quotes)
4:   Remove leading, trailing, and consecutive whitespace
5:   Compute ANLS score between  $a_{pred}$  and  $a_{gt}$ 
6:   if ANLS > 0.8 then
7:     return Correct
8:   else
9:     return Incorrect
10:  end if
11: else if  $a_{pred}$  is numeric then
12:   Extract the numerical part
13:   Remove units (e.g., "$")
14:   Convert into unified numerical format
15:   Compute relative error  $\frac{|a_{pred} - a_{gt}|}{a_{gt}}$ 
16:   if relative error < 0.05 then
17:     return Correct
18:   else
19:     return Incorrect
20:   end if
21: else if  $a_{pred}$  is multiple-choice then
22:   if  $a_{pred}$  option =  $a_{gt}$  option then
23:     return Correct
24:   else
25:     return Incorrect
26:   end if
27: end if
```

Table 8: Evaluation result of text-based questions on [InfoChartQA](#).

Model	Text-based								
	Infographic				Plain				Δ
	Easy	Moderate	Hard	Overall	Easy	Moderate	Hard	Overall	
Proprietary Models									
OpenAI O4-mini	85.68	63.45	29.00	76.23	97.46	81.81	46.66	89.62	13.39
GPT-4.1	83.17	60.38	14.28	71.29	89.24	71.42	40.11	80.81	9.52
GPT-4o	74.27	48.35	24.41	64.59	87.91	73.83	38.33	80.60	16.01
Claude 3.5 Sonnet	75.32	44.16	26.67	62.80	91.01	67.89	45.71	81.37	18.57
Gemini 2.5 Pro Preview	87.53	69.34	32.75	79.23	98.30	84.52	57.33	91.16	11.93
Gemini 2.5 Flash Preview	84.81	57.14	19.98	72.40	87.91	75.13	31.67	80.56	8.16
Open-Source Models									
Qwen2.5-VL-72B	74.70	47.84	22.64	61.08	85.30	67.93	39.59	77.92	16.84
Llama-4 Scout	70.80	48.67	27.32	63.68	85.71	72.50	28.18	78.84	15.16
Intern-VL3-78B	69.68	49.71	29.25	63.42	90.91	72.96	31.14	81.41	17.99
Intern-VL3-8B	56.25	37.80	18.29	46.45	71.36	54.84	33.73	61.67	15.22
Janus Pro	32.97	21.20	20.33	27.89	40.80	29.17	24.27	35.88	7.99
DeepSeek VL2	44.94	36.36	13.33	40.40	49.37	40.26	13.33	44.44	4.04
Phi-4	40.80	25.27	16.67	35.47	62.35	42.53	29.77	54.68	19.21
LLaVA OneVision Chat 78B	54.91	33.19	21.91	44.69	66.58	49.57	39.66	58.51	13.82
LLaVA OneVision Chat 7B	43.63	27.92	21.84	36.45	57.56	42.86	36.03	50.47	14.02
Pixtral	56.64	34.86	26.05	46.61	59.85	58.00	35.00	59.29	12.68
Ovis1.6-Gemma2-9B	63.09	39.21	25.02	51.69	67.50	49.75	34.52	58.66	6.97
ChartGemma	25.51	18.18	18.26	22.42	36.23	29.22	19.60	33.33	10.91
TinyChart	28.23	18.38	21.66	24.32	48.34	35.55	36.05	42.97	18.65
ChartInstruct-LLama2	22.18	16.10	20.20	19.95	31.22	20.44	22.95	26.87	6.92

To better understand which elements contribute most to this degradation, we further analyze the effect of element removal strategies. Specifically, elements are removed either in descending order of size—since larger elements typically carry more prominent information—or in a randomly shuffled order. As shown in Table 12, both strategies lead to similar degradation trends, suggesting that the removal order plays only a minor role. Building on these observations, we further evaluate models on de-decorated infographic charts, where visual elements are removed while preserving the core chart structure. We test GPT-4.1, Gemini-2.5 Pro Preview, TinyChart, and Qwen2.5-VL-72B under these settings and compare their performance against both infographic and plain charts. The results in Table 13 align with the findings in Section 4.3.1, further confirming that removing unnecessary visual elements consistently improves model performance.

Table 9: Evaluation result of visual-element-based basic questions on [InfoChartQA](#).

Model	Easy	Moderate	Hard
Proprietary Models			
OpenAI O4-mini	92.07	91.83	90.33
GPT-4.1	88.25	87.69	86.84
GPT-4o	82.39	79.45	78.92
Claude 3.5 Sonnet	90.45	89.12	89.98
Gemini 2.5 Pro Preview	90.56	89.39	89.36
Gemini 2.5 Flash Preview	82.03	81.54	80.91
Open-Source Models			
Qwen2.5-VL-72B	79.09	77.95	75.50
Llama-4 Scout	82.32	79.86	76.88
Intern-VL3-78B	79.82	81.33	77.66
Intern-VL3-8B	77.71	74.99	71.93
Janus Pro	40.77	40.22	46.39
DeepSeek VL2	63.33	60.06	56.71
Phi-4	63.27	61.66	59.81
LLaVA OneVision Chat 72B	62.12	62.08	58.53
LLaVA OneVision Chat 7B	60.78	60.54	56.55
Pixtral	60.07	67.36	73.09
Ovis1.6-Gemma2-9B	62.42	60.89	57.61
ChartGemma	30.96	28.28	36.45
TinyChart	17.47	13.71	15.69
ChartInstruct-LLama2	32.80	33.10	40.36

Table 10: Evaluation result on [InfoChartQA](#) with different answer types.

Model	Numeric	Textual	Multiple-choice
Proprietary Models			
OpenAI O4-mini	83.38	78.75	73.36
GPT-4.1	74.51	67.85	70.29
GPT-4o	65.01	58.00	63.71
Claude 3.5 Sonnet	61.52	64.65	72.26
Gemini 2.5 Pro Preview	80.79	81.17	72.58
Gemini 2.5 Flash Preview	73.04	70.71	62.25
Open-Source Models			
Qwen2.5-VL-72B	62.85	57.48	62.48
Llama-4 Scout	60.03	68.83	56.49
Intern-VL3-78B	65.12	59.22	66.21
Intern-VL3-8B	51.79	38.74	62.94
Janus Pro	31.55	19.81	36.96
DeepSeek VL2	43.28	35.35	47.72
Phi-4	23.29	43.88	48.43
LLaVA OneVision Chat 72B	48.91	35.48	57.04
LLaVA OneVision Chat 7B	41.58	26.28	57.17
Pixtral	52.37	34.38	59.69
Ovis1.6-Gemma2-9B	49.74	54.63	57.31
ChartGemma	28.01	11.13	30.51
TinyChart	30.58	11.17	13.75
ChartInstruct-LLama2	24.73	9.59	32.29

Table 11: Models' performance on different data-fact types.

Model	Outlier	Extreme	Association	Trend	Value	Rank	Difference	Categorization	Distribution	Aggregation	Proportion
GPT-4.1	28.1	75.2	51.0	53.8	81.6	37.6	84.1	58.6	93.3	64.2	95.9

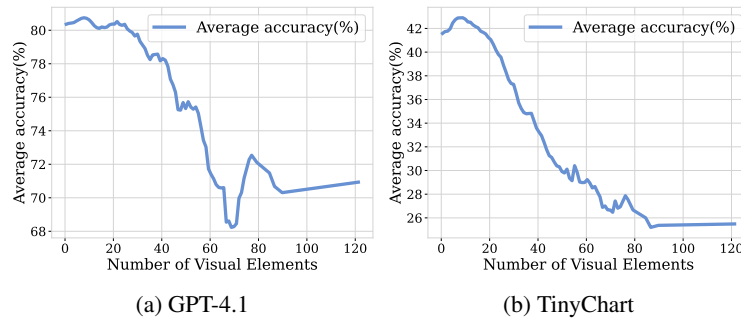


Figure 8: Average accuracy with respect to the number of visual elements.

B.4 Interface for Human Answering

We provide a screenshot of the interface for human answering (Figure 9).

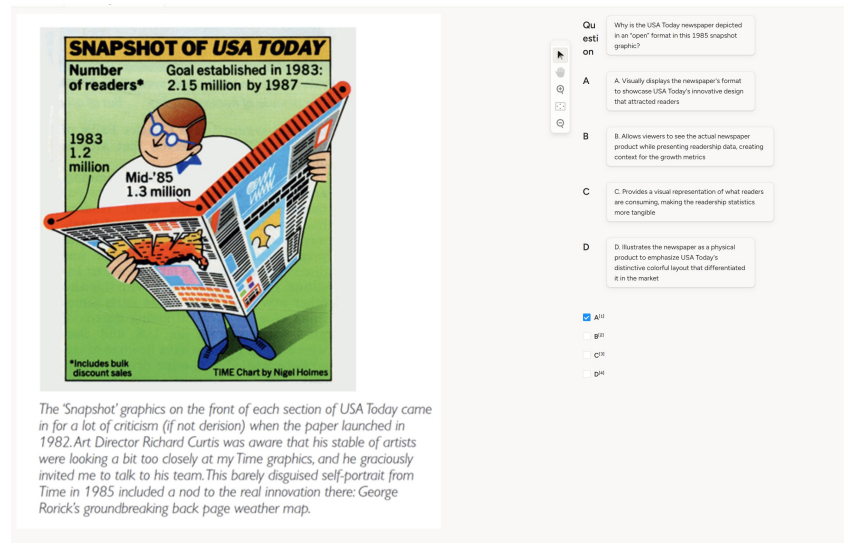


Figure 9: The interface for human answering.

B.5 More Detailed Information for Human Evaluation

We provide more detailed information for human evaluation. Our human evaluation involved 15 participants, including 14 males and 1 female, all of whom are native Chinese speakers. They were graduate students (aged 20–30) from universities in China, with expertise in deep learning and visualization. None of the participants is the author of this paper.

B.6 Model Improvement Based on the Performance Degradation Analysis

In Sec. 4.3.1, we found that the visual elements primarily contributed to the infographic chart degradation. Therefore, we revised the prompt instruction to explicitly guide the model to focus on visualization components rather than decorative elements:

Table 12: GPT-4.1’s performance under different removal orders and numbers of visual elements.

Removal order / # of visual elements	0	5	10	15	20	25	30	35	40
By Size	87.27	82.55	80.22	79.42	78.34	79.35	79.14	78.84	77.39
Random	87.27	82.11	80.56	78.99	78.87	78.99	78.12	78.01	77.39

Table 13: Performance comparison on infographic, de-decorated infographic, and plain charts.

Model	Infographic Chart	De-decorated Infographic Chart	Plain Chart
GPT-4.1	77.39	82.27	83.05
Gemini-2.5 Pro Preview	81.31	90.36	91.28
TinyChart	26.32	41.72	42.94
Qwen2.5-VL-72B	60.51	76.34	79.32

Instruction prompting: "Hint: Please be aware that this is an infographic chart. To obtain a more accurate answer, do not be influenced by its decorative elements; ignore such elements and focus your attention on the data visualization components."

We conducted this experiment on GPT-4.1 with 20% of the dataset for quick evaluation. Table 14 shows that performance improves when such instructions are added.

Table 14: Performance comparison of GPT-4.1 under different prompting strategies.

Model	Vanilla prompting	Instruction prompting
GPT-4.1	70.97	73.90

B.7 Finetuning Evaluation

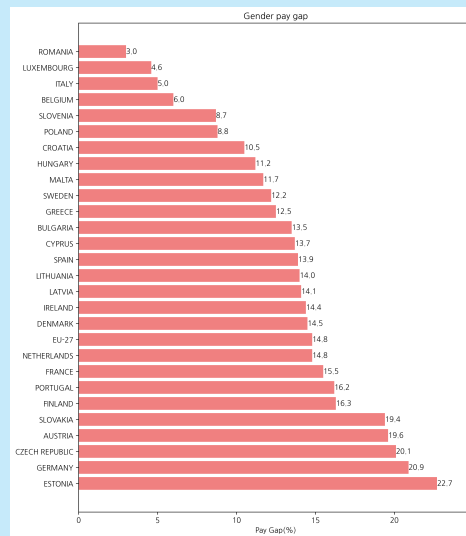
We randomly selected 30k questions from the synthetic portion as the training set and used the remaining questions as the test set. The training set was then used to fine-tune the LLaVA OneVision Chat 7B model with LoRA. The experimental results show that its performance on text-based questions improved from the original 38.41% to 50.19% on the test set, which demonstrates the usefulness of the synthetic portion.

B.8 Sample Questions and Answers

We provide sample answers for text-based B.8.1, visual-element-based basic B.8.2 and metaphor B.8.3 questions in this section.

B.8.1 Sample Answers of Text-based Questions

Example of text-based questions



Question:

By how much does the Pay Gap(%) of MALTA differ from that of POLAND?

* If the Pay Gap(%) of MALTA is less than the Pay Gap(%) of POLAND, your response should be Yes, otherwise 'No'.

* Your response should only contain 'Yes' or 'No'.

Answer: No

Model's answers

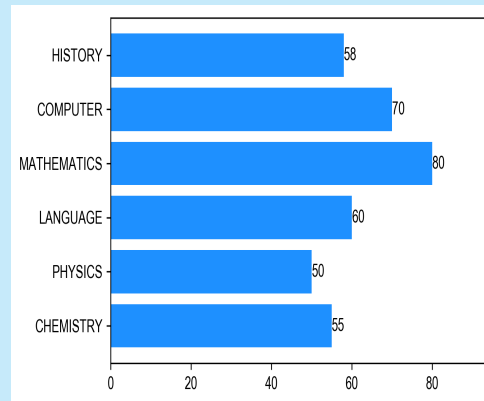
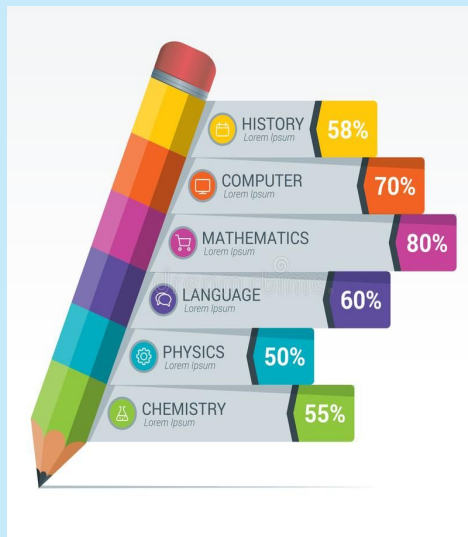
o4-mini: Yes (Info)
No (Plain)

Gemini 2.5 pro preview: No (Info)
No (Plain)

InternVL 3 78B: Yes (Info)
No (Plain)

TinyChart: No (Info)
No (Plain)

Example of text-based questions



Question:

What is the result if we sum up all Percentage(%)?

* Your response should only contain the value of the sum of Percentage(%) .

Answer:373

Model's answers

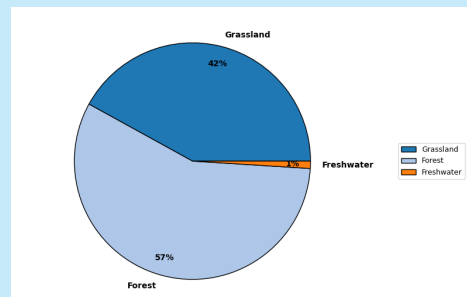
o4-mini: 373 (Info)
373 (Plain)

Gemini 2.5 pro preview: 373 (Info)
373 (Plain)

InternVL 3 78B: 383 (Info)
373 (Plain)

TinyChart: 85% (Info)
373 (Plain)

Example of text-based questions



Question:

What is the value difference between the Freshwater and Forest percentages?

* Your response should only contain the value of the difference between the Percentage corresponding to Freshwater and the Percentage corresponding to Forest.

* The answer you give me should be the absolute value.

Answer: 56%

Model's answers

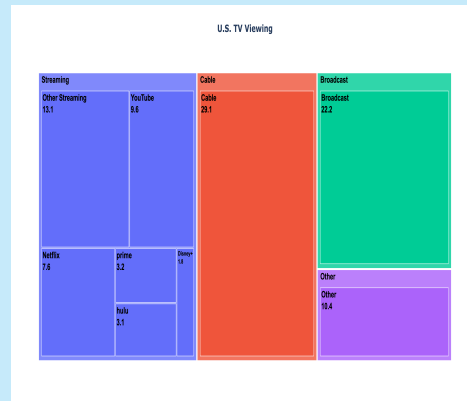
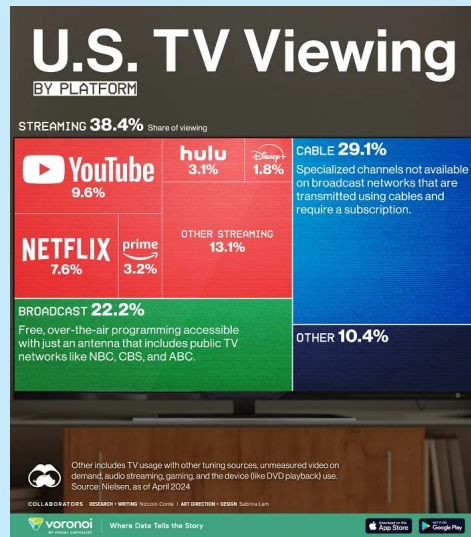
o4-mini: 56 (Info)
56 (Plain)

Gemini 2.5 pro preview: 56 (Info)
56 (Plain)

InternVL 3 78B: 56% (Info)
56% (Plain)

TinyChart: 10.0 (Info)
46% (Plain)

Example of Text-based questions



Question:

What are the nodes categorized as Streaming?

* Your response should only contain the node is/in Streaming.

*Please provide your answer in the order from left to right, top to bottom, as they appear in the chart.

*If there is no answer that meets the condition, respond with an empty string.

Answer: YouTube, Netflix, prime, hulu, Disney+, Other Streaming

Model's answers

o4-mini:

YouTube, Netflix, prime, hulu, Disney+, Other Streaming (Info)

YouTube, Netflix, prime, hulu, Disney+, Other Streaming (Plain)

Gemini 2.5 pro preview:

YouTube, Netflix, prime, hulu, Disney+, Other Streaming, **Streaming** (Info)

YouTube, Netflix, prime, hulu, Disney+, Other Streaming (Plain)

InternVL 3 78B: YouTube, Netflix, Hulu, Prime, Other Streaming (Info)

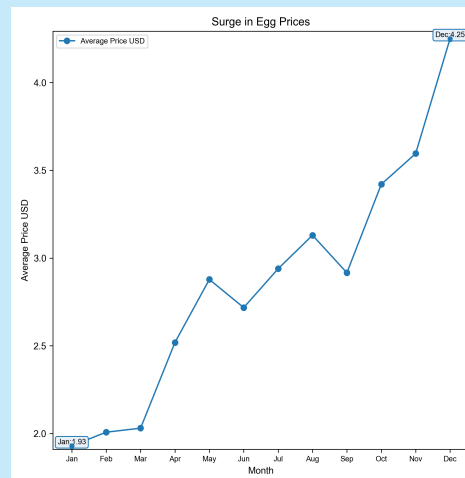
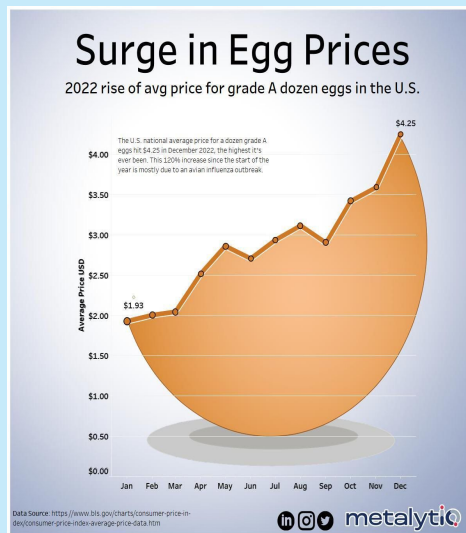
YouTube, Netflix, prime, hulu, Disney+, Other Streaming (Plain)

TinyChart:

Streaming (Info)

Streaming (Plain)

Example of text-based questions



Question:

What was the Average Price in USD during December?

* Your response should only contain the value of Average Price USD corresponding to Average Price USD in/on/at Dec.

* If there is an explicit answer in the chart, answer in exactly the same format.

Answer: 4.25

Model's answers

o4-mini: 4.25 (Info)

4.25 (Plain)

Gemini 2.5 pro preview: 4.25 (Info)

4.25 (Plain)

InternVL 3 78B: 4.25 (Info)

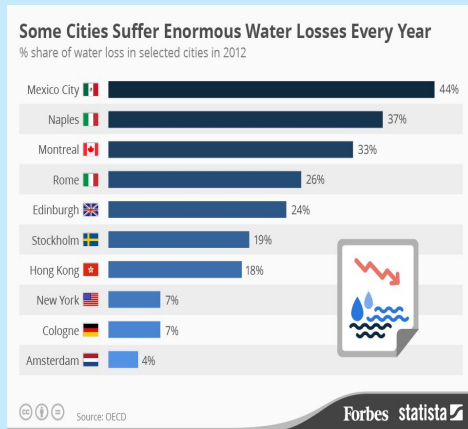
4.25 (Plain)

TinyChart: 4.25 (Info)

4.25 (Plain)

B.8.2 Sample Answers of Visual-element-based (Basic) Questions

Example of visual-element-based (basic) question



Question:

Beginning with a chart and followed by its cropped segment, the images above are arranged from left to right. What is the primary reason for incorporating this imagery into the chart?

- (A) To visually emphasize the chart's central theme regarding the frequency and importance of media citations.
- (B) To serve primarily as a decorative background element, enhancing the overall visual appeal of the infographic.
- (C) To specifically highlight the data column showing the number of citations, aiding in data interpretation.
- (D) To use symbolism (water representation, downward arrow) to represent the abstract concept of 'water loss'.

* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Answer: D

Model's answers

o4-mini: D

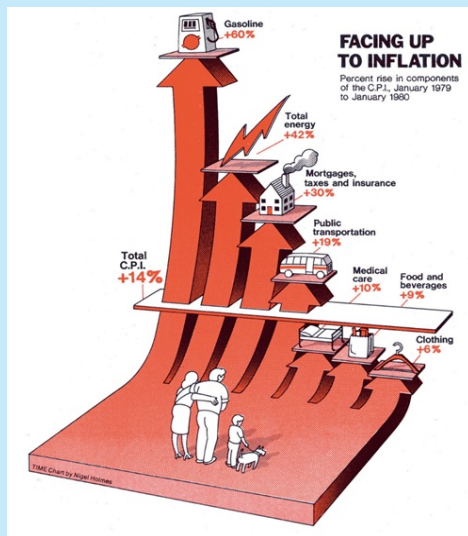
Gemini 2.5 pro preview: A

InternVL 3 78B: A

TinyChart: 0.7

B.8.3 Sample Answers of Visual-element-based (Metaphor) Questions

Example of visual-element-based (metaphor) question



Question:

Answer this question and choose the most appropriate answer (A, B, C, D).

According to Figure 1, the overall visual presentation aims to convey which idea, especially by drawing the figures in Figure 2:

- A) The challenge of the increasing inflation needs to be addressed.
- B) Addressing the increasing inflation needs to effort of families.
- C) The total inflation of C.P.I is growing higher and higher over time.
- D) High inflation is becoming a challenge for people.

* Your response should be the letter only (e.g., 'C'). Do not include any explanation or repeat the option text.

Answer: A

Model's answers

o4-mini: D

Gemini 2.5 pro preview: (A) The challenge of the increasing inflation needs to be addressed. The title "FACING UP TO INFLATION" suggests confronting a problem, which implies recognizing its severity and the need to deal with it. ... The final answer is A.

InternVL 3 78B: D

TinyChart: A, B, C, D

C Licenses

In this section, we provide licenses for data and models used in our experiments.

C.1 Licenses for Data

We provide the data licenses of each platform in Table 15. Since some platforms adopt license policies that may restrict data redistribution, we release our dataset in the form of URLs to mitigate copyright risks.

Table 15: Data license.

Platform	Data License
Pinterest	Custom
Visual Capitalist	Custom
Statista	Custom
iStock	Custom
Behance	Custom
PNGEgg	Custom
information is beautiful	Custom
coolinfographics	Not Applicable
designweek	Custom
marketing-partners	Custom
datavizproject	Not Applicable
ChartGalaxy	Apache-2.0 license

C.2 Licenses for Model

Table 16: Model license.

Model	Model License	Code Licenses
OpenAI O4-mini	Proprietary	Proprietary
GPT-4.1	Proprietary	Proprietary
GPT-4o	Proprietary	Proprietary
Claude 3.5 Sonnet	Proprietary	Proprietary
Gemini 2.5 Pro Preview	Proprietary	Proprietary
Gemini 2.5 Flash Preview	Proprietary	Proprietary
Qwen2.5-VL-72B	Custom	Apache 2.0 License
Llama-4 Scout	Custom	Custom
Intern-VL3 78B	MIT	MIT
Intern-VL3 8B	MIT	MIT
Janus Pro	Custom	MIT
DeepSeek VL2	Custom	MIT
Phi-4	MIT	MIT
LLaVA OneVision Chat 72B	Apache 2.0	Apache 2.0
LLaVA OneVision Chat 7B	Apache 2.0	Apache 2.0
Pixtral	Apache-2.0	Apache-2.0
Ovis1.6-Gemma2-9B	Apache-2.0	Apache-2.0
ChartGemma	GPL-3.0	MIT
TinyChart	MIT	MIT
ChartInstruct-LLama2	GPL-3.0	MIT

C.3 Institutional review board (IRB) approvals

清华大学科技伦理委员会
人工智能委员会伦理审查批件

伦理批件编号：THU-03-2025-1001

项目名称：InfoChartQA：基于信息图表的视觉问答数据集

项目负责人：刘世霞

所在院系：410 软件学院

项目来源：自然科学基金委

审查评议意见：

经伦理委员会通过对送审材料的审阅和讨论，该研究设计和研究方案充分考虑了安全性、公平性及可信可控原则，研究内容不构成对研究参与者的伤害和风险，研究参与者的招募安全且基于自愿和知情同意原则，并尽最大限度保护研究参与者的隐私，研究内容和结果不存在利益冲突，同意该研究按计划进行。

主任签字：
清华大学科技伦理委员会

2025 年 11 月 11 日

Figure 10: Institutional review board (IRB) approvals.