MMCOMPOSITION: Revisiting the Compositionality of Pre-trained Vision-Language Models

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Abstract

The advent of large Vision-Language Models (VLMs) has significantly advanced multimodal understanding, enabling more sophisticated and accurate integration of visual and textual information across various tasks, including image and video captioning, visual question answering, and cross-modal retrieval. Despite VLMs' superior capabilities, researchers lack a comprehensive understanding of their compositionality – the ability to understand and produce novel combinations of known visual and textual components. Prior benchmarks provide only a relatively rough compositionality evaluation from the perspectives of objects, relations, and attributes while neglecting deeper reasoning about object interactions, counting, and complex compositions. However, compositionality is a critical ability that facilitates coherent reasoning and understanding across modalities for VLMs. To address this limitation, we propose **MMComposition**, a novel human-annotated benchmark for comprehensively and accurately evaluating VLMs' compositionality. With MMCOMPOSITION, we can quantify and explore the compositionality of the mainstream VLMs. Surprisingly, we find GPT-4o's compositionality inferior to the best open-source model, and we analyze the underlying reasons. Our experimental analysis reveals the limitations of VLMs in fine-grained compositional perception and reasoning, and points to areas for improvement in VLM design and training. [1]

1 Introduction

Pre-trained vision-language models, such as GPT-4o (Achiam et al., 2023), LLaVA (Liu et al., 2024b), InternVL (Chen et al., 2024b), and VILA (Lin et al., 2024), have demonstrated impressive capabilities in complex reasoning, and have achieved remarkable results in various vision-language (VL) tasks. Despite these advancements, contemporary state-of-the-art VLMs still struggle with understanding fine-grained multimodal compositional information (Yuksekgonul et al., 2022; Thrush et al., 2022). For instance, VLMs often fail at counting objects in images, especially when the objects are mixed with other items or occluded, while humans can handle this task easily. This reveals a compositionality gap between humans and models. However, *compositionality* is recognized as a core capability for VLMs (Yuksekgonul et al., 2022), referring to the ability to understand and produce a potentially infinite number of novel combinations of known visual and textual components, i.e., to make "infinite use of finite means" (Chomsky, 2014). Compositionality is essential for tackling challenging questions in image captioning, visual question answering (VQA), and scene understanding, where complex interactions between objects and attributes need to be communicated in natural language.

In recent years, there has been a growing focus on evaluating the comprehensive capabilities of large VL models, such as MMBench (Liu et al., 2023b), MMMU (Yue et al., 2023), MMVet (Yu et al., 2024a;b), MME (Fu et al., 2023), Seed-bench (Li et al., 2023a), MMStar (Chen et al., 2024a), MathVista (Lu et al., 2023), and LLaVA-Bench (Liu et al., 2024b). These benchmarks evaluate VLMs' capabilities in recognition, OCR, knowledge, language generation, spatial awareness, and mathematical reasoning. While some of these benchmarks include visual compositional question-answering (QA) pairs (Fu et al., 2024; Li et al., 2023a; Tong et al., 2024b), none are specifically designed to comprehensively evaluate the models' fine-grained VL

[1] All data and code will be released upon publication of this paper.

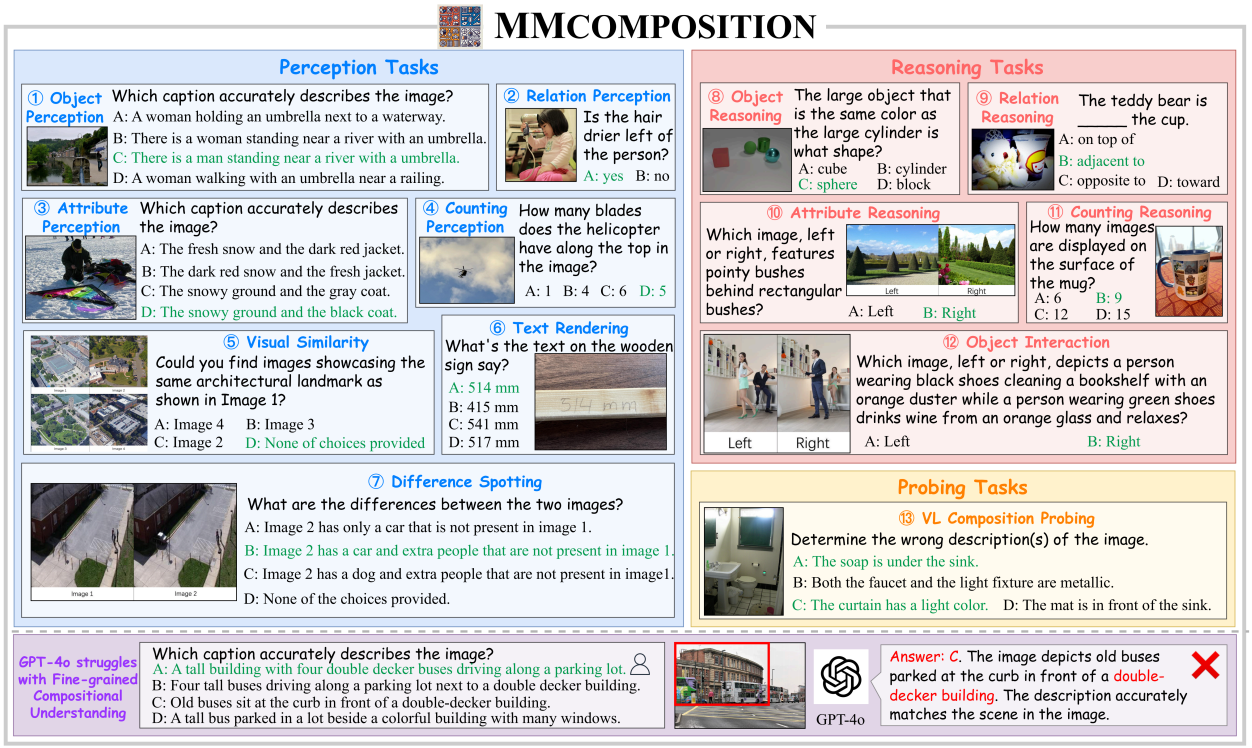

Figure 1: MMCOMPOSITION comprises 13 categories of high-quality VL composition QA pairs, covering a wide range of complex compositions. In the example, GPT-4o failed to understand the compositional aspects of the visual and textual components, misidentifying a three-story building as a double-decker structure. This misinterpretation highlights the limitations of current VLMs.

compositional perception and reasoning abilities. Additionally, some existing benchmarks (Yuksekgonul et al., 2022; Hsieh et al., 2024; Zhao et al., 2022; Thrush et al., 2022; Ray et al., 2023; Ma et al., 2023) evaluate models' compositionality roughly from the perspective of attribute, relation, and object perception. These benchmarks have limitations in evaluating fine-grained visual composition and reasoning. They mainly focus on image-to-text retrieval tasks, assessing basic object, relation, and attribute recognition but neglecting deeper reasoning about object interactions, counting, and complex compositions. As a result, researchers currently have an incomplete understanding of VLMs' compositionality.

To address these issues, we propose MMCOMPOSITION, a novel, human-annotated, high-quality benchmark for the comprehensive evaluation of VLMs' compositionality. MMCOMPOSITION evaluates the compositionality of VLMs in three main dimensions: VL compositional perception, reasoning, and probing, which are further divided into 13 distinct categories of questions, as illustrated in Figure 1. While previous evaluation benchmarks have primarily focused on text-to-image retrieval, single-choice questions, and open-ended text generation, MMCOMPOSITION introduces a more diverse and challenging set of tasks. The benchmark encompasses 4,122 questions, covering both single-image and multi-image scenarios, as well as single-choice and multi-correct multi-choice formats. This expanded range of tasks is designed to evaluate the complex interplay between vision and language in VLMs more effectively. By incorporating a wider variety of complex composition questions, MMCOMPOSITION provides a more comprehensive and in-depth assessment of models' capabilities in cross-modal compositionality, surpassing the evaluations offered by earlier benchmarks like ARO (Yuksekgonul et al., 2022) and Winoground (Thrush et al., 2022). Table 11 highlights the differences between MMCOMPOSITION and other existing datasets that focus on VL compositionality.

In addition to the new benchmark, we also provide a comprehensive analysis of the models' capabilities in fine-grained VL compositional perception and reasoning. Our experiments show that most SOTA VLMs exhibit deficiencies in compositional understanding. Even GPT-4o, despite its advanced capabilities, struggles with

Table 1: Comparison with related VL compositional benchmarks: "Yes/No Ratio" refers to the proportion of yes/no questions, "Fine-grained" indicates whether the data provide detailed breakdowns of VL compositional information, and "IT Mismatch Detec." means "Image Text Mismatch Detection".

Dataset	Yes/No Ratio	Size	Human Annotation	Multi-Image	Multi-Correct MCQ	Task	Fine-grained
Winoground (Thrush et al., 2022)	-	400	✓	✓	-	Compositional Reasoning	✗
ARO (Yuksekgonul et al., 2022)	-	50k	✗	✗	-	T2I Retrieval	✗
Sugarcrepe (Hsieh et al., 2024)	-	7,512	✗	✗	-	T2I Retrieval	✗
VL-Checklist (Zhao et al., 2022)	-	410k	✗	✗	-	T2I Retrieval	✗
Cola (Ray et al., 2023)	-	1,200	✗	✗	-	T2I Retrieval	✗
FineMatch (Hua et al., 2024a)	-	49.9k	✓	✗	-	IT Mismatch Detec.	✓
GQA (Hudson & Manning, 2019)	0.7774	22M	✗	✗	✗	Compositional QA	✓
MMComposition (ours)	0.0483	4,122	✓	✓	✓	Compositional QA	✓

tasks requiring nuanced compositional reasoning. These findings highlight the need for further research and development to enhance the compositional abilities of VLMs. Our benchmark serves as a tool for identifying these gaps and inspiring future improvements in VLM design and training. Moreover, we analyze the critical factors in VLM architecture and training that may influence the compositionality of VLMs. According to the empirical results, we reach three findings: **(1) Visual Encoder Design**: While a mixture-of-encoder architecture can enhance compositionality, adding more encoders does not necessarily improve performance. Moreover, models that encode images with minimal degradation of image quality – preserving the original high resolution and aspect ratio – exhibit superior compositionality compared to those that utilize downsampling during the encoding process. **(2) Language Decoder Size**: Larger language decoders are associated with improved compositionality. **(3) The Volume of Training Data**: Fine-tuning models on more diverse datasets helps mitigate some compositionality limitations, driving more robust compositional understanding. In addition, although GPT-4o includes a powerful language model, we find that **for relatively simple QA tasks, only a small portion of its language capabilities are utilized** (compared to the models outperform GPT-4o, whose language model size is only 70B). **Once the language decoder size reaches a certain threshold (e.g., 34B, 70B), the visual encoder has a more significant impact on the model's compositionality**. We demonstrate in Figure 14 that the downsampling image processing in GPT-4o contributes to its inferior performance. Our experimental analysis highlights the limitations of large-scale VLMs in fine-grained compositional perception and reasoning. Our empirical analysis provides a systematic framework for evaluating and enhancing models' capability, pinpointing areas where large models still struggle.

Our main contributions are three-fold:

- We introduce **MMComposition**, a novel, human-annotated, high-quality benchmark designed to evaluate the compositionality of pre-trained VLMs. MMComposition assesses compositionality across three dimensions: compositional perception, reasoning, and probing, which are further divided into 13 distinct categories of questions. The benchmark comprises 4,122 questions, including 2,371 multi-hop reasoning questions, spanning both single-image and multi-image scenarios, as well as single-choice and multi-correct multi-choice formats. This broad coverage ensures a comprehensive and robust evaluation framework for VLMs.

- We comprehensively evaluate 77 well-known VLMs with MMComposition. The empirical results highlight the challenging nature of MMComposition, as the highest model accuracy reached only 68.16%, compared to 90.31% for human performance. This evaluation reveals a **substantial gap** between state-of-the-art VLMs and human capabilities and provides insights into the limitations of current VLMs.

- We systematically analyze critical factors in VLM architecture that may influence the compositionality of VLMs, including the size of language decoders, the volume of training data, and the visual encoder design. Furthermore, we provide an interpretable analysis of models' limitations in complex compositional understanding. This analysis identifies critical areas for model improvement and suggests directions for future advancements.

2 Related Work

VLM Evaluation Benchmarks. The advent of large-scale VLMs has led to the development of numerous benchmarks designed to evaluate various model capabilities. Among the most commonly evaluated are image captioning (Lin et al.; Onoe et al., 2024; Masry et al., 2022), which tests a VLM's ability to generate natural language descriptions of images; VQA (Antol et al., 2015; Marino et al., 2019; Mathew et al., 2020), which assesses the model's capacity to answer image-based questions by integrating visual perception with language understanding or external knowledge; and Visual Reasoning (Johnson et al., 2017; Suhr et al., 2017), which evaluates a model's understanding of spatial relationships and logical reasoning based on visual input. In recent years, researchers have built benchmarks that aim to evaluate the comprehensive capabilities of VLMs (Li et al., 2023a; Liu et al., 2023b; Yue et al., 2023; Fu et al., 2023; Yu et al., 2024a; Lu et al., 2023; Guan et al., 2024). Although some benchmarks include QA pairs related to compositional reasoning, such as BLINK (Fu et al., 2024), MMVP (Tong et al., 2024b), and Seed-bench (Li et al., 2023a), these are often mixed with other types of QA pairs, making it challenging to assess a model's compositionality precisely. In contrast, MMComposition consolidates and refines existing categories of VL compositionality, offering a diverse set of compositional QA pairs that provide a more precise evaluation of model performance.

Compositionality for Vision-Language Models. Compositional understanding of images and text is a critical capability for VLMs. Research indicates that VLMs struggle to distinguish hard negative examples, i.e., image-text pairs that mismatch in at least one aspect (e.g., attribute, relation, object), as there is little incentive for them to learn compositionality during contrastive pre-training (Yuksekgonul et al., 2022). Hsieh et al. (2024) illustrate that contrastive pre-training with generated hard negative examples can improve models' performance on downstream tasks. Various benchmarks have been proposed to assess the capabilities of VLMs in compositional vision-language perception, including VL-Checklist (Zhao et al., 2022), ARO (Yuksekgonul et al., 2022), FineMatch (Hua et al., 2024a), Sugarcrepe (Hsieh et al., 2024), Crepe (Ma et al., 2023), Cola (Ray et al., 2023), CheckList (Zhao et al., 2022), etc. However, these benchmarks often evaluate models' capabilities from limited perspectives, such as object, attribute, and relation perception, and primarily focus on simple tasks like binary image-to-text retrieval, where models need to select the correct caption from pairs containing a correct and a hard negative caption. Moreover, the aforementioned benchmarks often contain a limited range of relations or attributes (e.g., ARO includes 48 relations and 117 attributes). GQA (Hudson & Manning, 2019) includes a diverse set of QA pairs focused on compositional reasoning, but the majority of the questions (77.74%) are simple Yes/No format. In contrast, MMComposition offers a more comprehensive assessment with various compositional scenarios, including multi-image and multi-correct multi-choice questions, providing a more comprehensive assessment. Furthermore, MMComposition evaluates the robustness in detecting complex relationships, including subtle scene composition, object interactions, and higher-order concepts beyond basic perception.

Pre-trained Vision-Language Models. Vision-language models (Radford et al., 2021; Liu et al., 2024a; Hua et al., 2024b; Ye et al., 2023; Tang et al., 2024; Chen et al., 2024b; Bi et al., 2024; Li et al., 2022; Tong et al., 2024a) aim to achieve multimodal intelligence by jointly understanding and generating visual and language information. Inspired by the remarkable success of recent large language models (LLMs) (Touvron et al., 2023; Chiang et al., 2023; Hua et al., 2021), researchers are now exploring large VLMs that combine pre-trained visual encoders and language decoders to tackle complex multimodal tasks. Flamingo (Alayrac et al., 2022) and BLIP-2 (Li et al.) are two of the early works that explore the integration of LLMs into vision-language pre-training. These models are trained as VL foundation models. Beginning with LLaVA (Liu et al., 2024a), researchers have used LLM-synthesized instruction-following chat data in VQA format for instruction tuning, achieving significantly improved results (Hua et al., 2024a). Subsequent studies have expanded to explore the broader capabilities of multimodal LLMs (Hu et al., 2023; Guan et al., 2024; Lin et al., 2023; Yu et al., 2024c; Tang et al., 2023). However, these efforts place less emphasis on improving the models' ability to fine-grained compositional perception and reasoning.

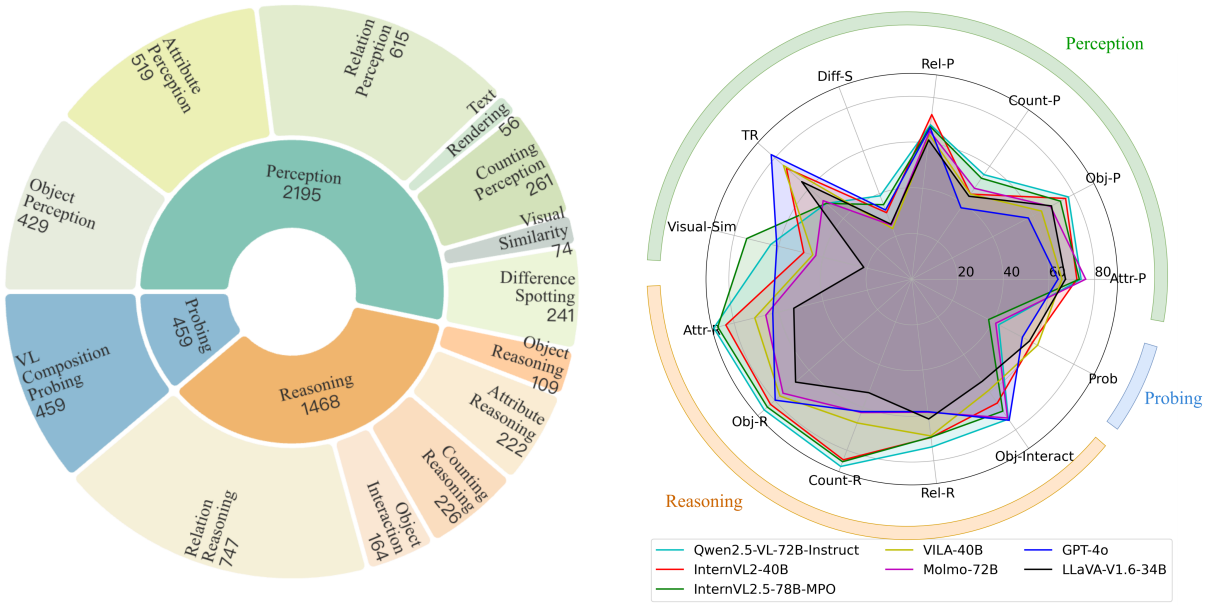

Figure 2: The statistics of 13 distinct categories of QA pairs in MMCOMPOSITION and some models' performance on each category.

3 MMComposition

3.1 Data Curation

To ensure a comprehensive and high-quality benchmark, we develop an efficient pipeline for curating VQA data that accurately reflects compositional information.

Data Collection. We use various datasets with the potential to construct VL compositional QA pairs as our seed data. This collection includes datasets that contain the description of objects, attributes, relations, and counting, such as VL-CheckList (Zhao et al., 2022), Sugar-Crepe (Hsieh et al., 2024), ARO (Yuksekgonul et al., 2022), Crepe (Ma et al., 2023), and DOCCI (Onoe et al., 2024). Additionally, we incorporate sources that are well-suited for constructing VL compositional reasoning QA pairs, including SVO-Probes (Hendricks & Nematzadeh, 2021), VSR (Liu et al., 2023a), BLINK (Fu et al., 2024), GQA (Hudson & Manning, 2019), Visual Genome (Krishna et al., 2016), and CLVER (Johnson et al., 2017). It also contains datasets with multiple images in each sample, such as Winoground (Thrush et al., 2022), MuriBench (Wang et al., 2024) and NLVR2 (Suhr et al., 2017).

Question and Answer Construction. We obtain QA pairs from the seed data in through several methodologies:

For the seed data that only contain positive and negative captions (e.g., ARC (Yuksekgonul et al., 2022)), we first generate sentence embeddings for each caption using Sentence-BERT (Reimers & Gurevych, 2019). We then utilize these embeddings to retrieve the most similar captions from the Visual Genome (Krishna et al., 2016) dataset. This process results in four captions per image in each sample, forming four answer options per question.

For data samples containing multiple images – such as those in the image difference spotting task, which includes two images per question – we concatenate the two images side by side and label them *Left* and *Right* beneath each sub-image. This setup allows for two types of question-answer options: *Left* and *Right* for questions asking which sub-image is described by a caption, and *True* and *False* for questions determining the accuracy of a caption describing the image difference. For tasks that include more than two images per question (e.g., visual similarity assessments), we concatenate all images into a single composite image and label each sub-image as $\text{Image}_1, ..., \text{Image}_i$.

For the probing task, we select several captions from the dense captions in Visual Genome (Krishna et al., 2016) as the correct options and write the misaligned captions manually for the image. Manual construction allows us to deliberately introduce specific compositional violations, ensuring that each incorrect option tests a particular compositional factor. Then, we randomly select $x \in \{1, 2, 3, 4\}$ captions from the set of accurate captions for a given image and complement these with $4 - x$ incorrect options drawn from a set of conflict captions. With this approach, we can obtain the multi-correct multi-choice QA pairs.

For compositional probing, each incorrect option is constructed by modifying exactly one compositional factor while keeping all other aspects unchanged. This controlled design ensures that each distractor targets a specific failure mode, preventing models from eliminating options using superficial cues. As a result, correctly answering these questions requires precise verification of individual compositional components rather than coarse semantic matching.

Quality control for distractor retrieval. We retrieve the top-k (k=10) most similar captions from Visual Genome using Sentence-BERT cosine similarity, then apply a similarity threshold to filter out distractors that are either too easy (cosine similarity < 0.3) or potentially ambiguous (cosine similarity > 0.95). Candidate distractors are also required not to describe the same image as the query.

Deduplication. To address potential leakage concerns, we performed exact-match and near-duplicate checks between MMComposition's final QA items and the original seed datasets. For exact match, we compared question-answer strings directly; for near-duplicate detection, we computed Sentence-BERT cosine similarity between all MMComposition questions and their corresponding seed source questions, flagging pairs with similarity > 0.95 for manual review. This analysis confirmed that 96.5% of MMComposition items have undergone substantial transformation from their seed sources (format change from retrieval to MCQ, addition of retrieved distractors, or manual rewriting). Only 3.5% items were identified as near-duplicates and subsequently removed or revised.

Ambiguity control. Annotators verify that each single-choice item has exactly one unambiguously correct answer, and each multi-correct item has exactly one unambiguous correct answer set.

Data Filtering and Difficulty Classification. We divide the data into different difficulty levels: easy, medium, hard, and super hard. To achieve this, we use a voting system with six models, ranging from weaker to stronger, including LLaVA-1.5-13B (Liu et al., 2024b), LLaVA-1.6-Mistral-7B (Liu et al., 2024a), LLaVA-1.6-Vicuna-13B (Liu et al., 2024a), Phi-3-Vision-128K-Instruct (Abdin et al., 2024), InternVL-Chat-V1.5 (Chen et al., 2024b), and Qwen-VL-Chat (Bai et al., 2023). Based on the accuracy of model predictions for each question, questions are categorized into different difficulty levels. Questions with zero correct predictions are classified as super hard, those with one or two correct predictions are labeled as hard, questions with three or four correct predictions are considered medium, and those with more than five correct predictions are categorized as easy. The overall difficulty of the dataset is then controlled by adjusting the ratio of questions at each difficulty level. We note that the difficulty labels are not used in any reported evaluation metric; they serve solely as a curation tool to control the question difficulty distribution during dataset construction.

Human Annotation. The annotation process follows three stages: (1) **QA creation**: Annotators author QA pairs from scratch following compositional aspect-specific prompts, or receive GPT-synthesized candidates for manual verification; (2) **Verification**: Each QA pair is independently reviewed by at least two annotators for image–question alignment, answer correctness, and option plausibility, with disagreements resolved by a senior annotator; (3) **Quality review**: A final review checks for ambiguity, option correctness, and deduplication. A post-hoc audit on 20% of the dataset shows an error rate below 1.2%.

Multi-hop Identification. A sample is labeled as *multi-hop* if solving it requires two or more sequential reasoning steps where the output of one step is required for the next. We identify multi-hop samples using a two-stage pipeline: (1) GPT-assisted pre-labeling under a structured rubric, and (2) human verification by annotators. Using this procedure, we identify 2,371 multi-hop questions in MMComposition, arising from scene-graph reasoning (e.g., CLEVR/GQA), cross-image comparison, and distractor disambiguation in compositional MCQs.

3.2 Evaluation Metric

Let $\mathcal{D} = \{\mathcal{D}_m = \{\mathcal{T}_t\}_{t=1}^{T_d}\}_{m=1}^{|D|}$ denotes our dataset , where each catagory $\mathcal{D}_m$ consists of $\mathcal{T}_d$ subtasks. For each subtask, we calculate the accuracy across all annotations. For each question $q \in \mathcal{D}$, let $\mathcal{A}_q$ be the set of correct options, $\mathcal{P}_q$ be the set of predicted (selected) options. The score for question q, denoted as s_q, is calculated as:

$$s_q = \begin{cases} 1, & \text{if } \mathcal{P}_q = \mathcal{A}_q \\ \frac{|\mathcal{P}_q|}{|\mathcal{A}_q|}, & \text{if } \mathcal{P}_q \subset \mathcal{A}_q \\ 0, & \text{otherwise} \end{cases}$$

Here, $|\cdot|$ denotes the number of options selected by the participant and the number of correct options, $\mathcal{P}_q \subset \mathcal{A}_q$ means all selected options are correct, but some correct options are missing (under-selection). The "otherwise" case covers instances where incorrect options are selected (wrong or over-selection). This equation applies to both the single-choice and multi-correct multi-choice questions. The final weighted average accuracy across all categories is calculated as $\text{ACC} = \sum_{m=1}^{|D|} \sum_{t=1}^{T_d} s_q \times |\mathcal{T}_t|/|\mathcal{D}_d|$, where $|\cdot|$ is the question number in one set.

3.3 Quantitative Analysis

MMComposition evaluates VL compositional capabilities across three overarching and complementary hypertasks: (1) **Perception**, including Attribute Perception (**Attr-P**), Object Perception (**Obj-P**), Counting Perception (**Count-P**), Relation Perception (**Rel-P**), Difference Spotting (**Diff-S**), Text Rendering (**TR**), and Visual Similarity (**Visual-Sim**); (2) **Reasoning**, comprising Attribute Reasoning (**Attr-R**), Object Reasoning (**Obj-R**), Counting Reasoning (**Count-R**), Relation Reasoning (**Rel-R**), and Object Interaction (**Obj-Interact**); and (3) **Probing**, consisting of Compositional Probing (**Prob**). We use GPT-4o to label each question category via in-context learning, followed by manual verification for accuracy. Figure 5 illustrates the difficulty distribution of MMComposition, highlighting the challenging nature of our dataset. Figure 6 depicts the distribution of option counts per question, with over half of the data containing more than four options. To analyze the impact of input resolution on model performance, we further display the resolution distribution of images in Figure 7, which reflects the image quality of our data. For textual analysis, we visualize the phrase distribution of questions using a word cloud diagram in Figure 3, clearly depicting the word frequency and distribution across the questions. We also provide a detailed explanation for these 13 categories in Section A.2.

4 Revisiting the Compositionality of Pre-trained Vision-Language Models

In this section, we quantify and explore the compositionality of state-of-the-art VLMs and provide a comprehensive evaluation of VLMs. For all experiments, we use a consistent prompt template and the official default hyperparameters for each model.

Overall Performance. The overall performance indicates that models struggle with perceiving and reasoning about fine-grained VL compositional information. The best human expert achieves an accuracy of 90.31%, significantly outperforming all the models reported in the table. This demonstrates the still existing gap between human expertise and the performance of current models on the MMComposition benchmark. This reflects the benchmark's rigorous standards. The open-source InternVL2 (Chen et al., 2024c) series models secured first and second place on the leaderboard. InternVL2-40B performs better than InternVL2-76B. Among the API-based models, Qwen2-VL and GPT-4o achieved the best and second best performance. The superior performance of open-source models with relatively smaller language models compared to GPT-4o, which has a larger language model, is due to their more effective visual encoders. The mean accuracy of 7B and 13B open-source VLMs hovers around 36–38%. For reference, we provide the random guess accuracy (29.90%) as a lower bound for the benchmark.

The tasks where VLMs exhibit relative strengths and weaknesses. From Table 2, we observe that VLMs perform relatively better on tasks such as Attribute, Object, and Relation Perception, as well as Attribute, Object, and Count Reasoning, where they perform much better than other categories. However,

Table 2: The comprehensive performance of 54 representative VLMs on Acc, including open source models and API-based models . The **best** and second best results are in bold and underlined, respectively. The full table containing comprehensive performance of 93 VLMs is shown in Appendix Table 16.

Method	Perception↑							Reasoning↑					Probing↑	Overall ↑
	Attr-P	Obj-P	Count-P	Rel-P	Diff-S	TR	Visual-Sim	Attr-R	Obj-R	Count-R	Rel-R	Obj-Interact	Prob	
Human	97.94	98.04	93.06	92.00	79.02	85.71	86.54	91.20	78.83	100.00	77.35	88.00	91.84	90.31
GPT-5 (OpenAI, 2025)	77.13	77.16	**75.86**	72.00	71.37	58.93	**87.84**	86.04	86.24	88.94	**78.18**	**92.07**	38.34	**73.73**
Claude-Opus-4.5-thinking (Anthropic, 2025)	73.41	73.66	74.33	70.24	74.27	57.14	75.68	**93.24**	87.16	**93.36**	77.91	85.98	34.82	72.44
Claude-Opus 4.6-thinking (Anthropic, 2025)	73.38	75.06	71.65	70.11	**74.69**	53.57	75.68	92.34	86.24	87.17	75.77	84.76	36.89	71.75
Claude-Opus-4.6 (Anthropic, 2025)	73.38	75.52	65.13	72.17	74.27	57.14	75.68	88.74	86.24	92.04	74.30	79.27	37.62	71.38
Claude-Sonnet-4.6-thinking (Anthropic, 2025)	74.82	71.79	74.71	64.91	**74.69**	58.93	72.97	90.54	81.65	88.50	74.83	82.32	34.31	70.33
Gemini-3.0-Flash (Google, 2025)	**78.23**	**78.32**	68.20	71.44	54.36	50.00	77.03	77.03	83.49	75.66	73.90	81.71	40.81	69.91
Claude-Opus-4.5 (Anthropic, 2025)	71.74	77.86	60.15	68.86	59.75	51.79	72.97	88.29	83.49	92.92	70.82	77.44	36.60	68.77
Qwen2.5-VL-72B-Instruct (team, 2024)	74.05	77.39	55.56	68.01	39.00	50.00	63.51	89.19	86.24	87.61	73.90	74.39	42.92	68.16
Claude-Sonnet-4.5-thinking (Anthropic, 2025)	72.03	67.60	70.11	63.12	70.54	53.57	59.46	92.79	85.32	90.71	71.35	77.44	35.77	68.10
InternVL2-40B (Chen et al., 2024b)	72.22	75.99	45.21	**72.53**	31.12	73.21	48.65	83.78	82.57	84.51	69.75	65.85	59.59	67.60
Qwen3-VL-235B-A22B-Instruct (Bai et al., 2025)	76.20	75.52	59.00	64.84	45.64	53.57	75.68	91.44	**88.99**	85.84	73.90	75.61	32.06	67.57
Qwen2-VL-72B-Instruct (team, 2024)	59.57	63.87	52.49	62.52	45.23	**82.14**	67.57	87.84	84.40	84.51	71.49	70.12	**69.57**	66.86
Claude-Sonnet-4.6 (Anthropic, 2025)	74.15	72.49	57.09	62.66	54.36	51.79	68.92	87.39	80.73	90.71	71.75	77.44	34.75	66.73
InternVL2-76B (Chen et al., 2024b)	70.65	75.52	48.28	70.00	19.09	78.57	48.65	85.14	83.49	85.40	70.01	67.07	58.46	66.65
Qwen3-VL-32B-Instruct (Bai et al., 2025)	75.24	75.52	52.49	65.91	39.00	51.79	72.97	86.94	88.07	84.96	72.96	70.12	30.76	65.89
InternVL2.5-78B-MPO (Chen et al., 2024b)	73.28	73.43	53.64	67.25	34.85	50.00	74.32	87.39	84.40	85.40	69.61	70.12	37.98	65.61
Qwen3-VL-30B-A3B-Instruct (Bai et al., 2025)	73.89	72.73	50.96	63.47	25.31	46.43	56.76	87.84	85.32	80.53	68.94	70.12	33.84	63.15
InternVL2.5-78B (Chen et al., 2024b)	70.07	66.90	47.13	64.23	32.37	48.21	60.81	85.59	82.57	80.09	68.27	73.17	37.58	62.64
Qwen2-VL-7B-Instruct (team, 2024)	68.30	71.79	41.38	64.63	32.37	39.29	52.70	81.08	76.15	80.53	67.34	69.51	41.43	62.09
VILA-40B (Lin et al., 2024)	65.70	64.10	45.21	63.65	23.65	75.00	44.59	70.72	77.06	67.26	69.08	59.15	62.16	61.83
InternVL2.5-38B (Chen et al., 2024b)	66.51	67.60	46.74	60.28	30.29	53.57	59.46	84.23	83.49	80.97	65.19	71.95	41.68	61.43
Qwen3-VL-4B-Instruct (Bai et al., 2025)	71.77	70.40	47.89	61.38	31.54	39.29	63.51	84.68	79.82	76.55	68.27	67.68	29.92	61.34
Qwen3-VL-8B-Instruct (Bai et al., 2025)	71.29	70.63	48.66	60.35	30.29	30.36	66.22	86.94	82.57	74.78	66.27	69.51	32.28	61.12
Ovis1.6-Gemma2-27B (Lu et al., 2024)	66.25	61.07	49.04	60.13	28.22	42.86	54.05	81.53	80.73	80.53	68.81	57.93	41.14	60.27
Qwen2.5-VL-7B-Instruct (team, 2024)	69.91	66.90	43.30	59.74	22.41	41.07	48.65	82.88	81.65	80.09	64.39	68.29	40.41	60.06
Molmo-72B (Deitke et al., 2024)	76.08	68.53	48.28	65.20	25.31	51.79	43.24	65.77	75.23	62.39	58.63	73.78	41.47	59.59
GPT-4o (Achiam et al., 2023)	63.97	57.58	37.93	66.76	32.37	**82.14**	60.81	62.61	79.82	61.95	58.37	75.00	54.65	59.03
POINTS1.5-7B-Chat (Liu et al., 2024c)	70.13	61.54	39.46	60.39	24.90	46.43	44.59	76.13	77.06	76.11	60.24	69.51	45.21	58.66
InternVL2.5-8B-MPO (Chen et al., 2024b)	65.64	66.20	45.21	58.12	21.99	41.07	56.76	78.83	80.73	76.55	65.19	59.76	37.44	58.49
Claude-Sonnet-4.5 (Anthropic, 2025)	62.52	50.12	57.47	53.01	41.49	39.29	55.41	82.88	80.73	87.61	65.06	69.51	31.92	58.10
InternVL2-8B (Chen et al., 2024b)	62.68	59.21	31.80	59.54	25.31	73.21	33.78	78.83	75.23	73.89	60.37	62.20	54.10	57.76
Llama-3.2-90B-Vision-Instruct	68.85	69.46	39.85	62.87	23.65	53.57	41.89	64.86	69.72	54.87	57.56	64.63	46.84	57.23
MiniCPM-V2.6 (Yao et al., 2024)	65.19	58.04	41.00	61.80	21.99	73.21	37.84	63.96	73.39	68.14	52.07	60.98	54.43	56.07
InternLM-XComposer2-4KHD-7B (Dong et al., 2024b)	62.24	55.24	39.08	58.36	23.65	67.86	27.03	70.72	74.31	60.18	55.82	59.15	60.02	55.35
Qwen-VL-Max (Bai et al., 2023)	53.76	53.15	36.40	58.67	22.82	80.36	41.89	53.60	65.14	53.98	60.91	62.80	63.87	54.75
Qwen3-VL-2B-Instruct (Bai et al., 2025)	66.18	67.83	43.68	57.70	24.07	41.07	27.03	68.02	76.15	63.27	53.68	59.76	35.69	54.44
Hunyuan-Vision	61.95	61.31	37.16	58.58	26.97	76.79	36.49	61.26	72.48	56.19	52.21	59.15	45.03	53.67
Gemini-1.5-Pro (Reid et al., 2024)	55.30	53.50	39.46	57.11	24.48	67.86	55.41	59.91	74.31	50.44	56.29	65.24	49.60	53.27
Mini-Gemini-34B (Li et al., 2023b)	58.35	55.01	37.93	53.70	25.31	73.21	39.19	54.50	73.39	58.41	55.82	61.59	41.79	51.96
Molmo-7B-D (Deitke et al., 2024)	68.02	55.71	37.16	52.40	24.90	48.21	40.54	56.76	67.89	46.02	53.41	60.98	42.70	51.61
MiniCPM-Llama3-V2.5 (Yao et al., 2024)	51.93	50.12	36.40	49.88	19.92	76.79	20.27	69.37	77.06	68.14	56.49	62.20	41.79	50.95
Bunny-Llama-3-8B-V (He et al., 2024)	58.16	51.05	34.87	54.07	21.58	50.00	12.16	45.95	66.06	53.10	48.73	57.32	59.44	49.93
Mini-Monkey (Huang et al., 2024)	52.25	56.64	26.82	52.53	26.56	73.21	18.92	68.92	65.14	59.29	50.60	50.00	42.37	49.46
Phi3.5-Vision-Instruct (Abdin et al., 2024)	55.01	45.69	30.27	52.61	21.16	66.07	31.08	45.05	63.30	53.10	53.95	53.66	54.65	49.12
Yi-VL-34B (AI et al., 2024)	53.02	38.23	30.27	50.33	26.14	64.29	17.57	50.45	56.88	55.31	51.00	52.44	53.88	47.38
Step-1V-32K	46.11	39.86	26.44	46.25	25.31	67.86	43.24	66.67	66.97	62.83	50.60	59.76	45.46	47.12
ConvLLaVA-1024-7B (Ge et al., 2024)	51.73	44.29	32.57	44.96	28.22	69.64	21.62	55.41	65.14	53.10	49.53	54.88	40.89	46.21
LLaVA-HR-13B (Luo et al., 2024)	50.32	41.26	35.25	39.81	32.37	66.07	27.03	45.50	60.55	45.58	48.46	57.32	48.80	45.12
Monkey-Chat (Li et al., 2024)	49.20	47.55	24.14	47.13	16.60	69.64	13.51	51.35	58.72	44.25	44.18	51.22	48.91	44.10
SliME-7B (Zhang et al., 2024b)	45.70	44.52	28.74	40.76	31.12	62.50	20.27	43.24	59.63	48.23	50.74	53.05	30.03	42.52
INF-LLaVA* (Ma et al., 2024)	43.19	44.76	32.95	41.92	24.48	57.14	20.27	50.00	66.06	55.31	45.65	54.27	31.41	42.41
DeepStack-L-HD-Vicuna-7B (Meng et al., 2024)	43.29	34.97	28.74	35.74	18.67	60.71	17.57	46.85	60.55	45.13	42.97	59.15	35.88	39.21
mPLUG-Owl2 (Ye et al., 2024)	40.04	36.83	28.74	42.93	26.97	30.36	12.16	41.89	60.55	38.94	44.58	50.61	30.36	38.77
InstructBLIP-13B (Dai et al., 2023)	39.21	40.56	22.99	38.86	24.07	35.71	33.78	40.54	48.62	37.17	41.23	51.83	25.24	36.76
Random Choice	23.12	24.01	21.84	25.85	29.46	35.71	25.68	36.94	46.79	38.50	34.00	47.65	28.61	29.90

they struggle with tasks such as Count Perception, Difference Spotting, Visual Similarity, and Probing (see illustrations in Fig. 1). These tasks often involve multiple images, some with extreme aspect ratios, and the probing tasks include multi-correct multi-choice questions, which pose additional challenges for the models. GPT-4o performs relatively weaker on Obj-P, Count-P, Attr-R, Count-R, and Rel-R tasks compared to smaller models that outperform it, aligning with the limitations outlined in the official GPT-4o documentation. Overall, the models perform relatively well on mid-level perception and reasoning tasks.

5 Diagnostic Analysis of Factors Influencing Model Compositionality

In this section, we analyze the factors that may influence the compositionality of VLMs. We focus on three dominant factors: visual encoder design, language decoder size, and training data volume.

5.1 Visual Encoder Design

High-Resolution Visual Encoders. A common strategy to enhance a model's perception of fine-grained visual content is to incorporate higher-resolution encoders. In this study, we adopt a controlled experimental setup, varying only the input resolution of the visual encoders while keeping the training data and text

decoders fixed. As shown in Table 3, models equipped with higher-resolution encoders generally achieve better performance in multimodal compositional perception and reasoning. However, for the Mini-Gemini series, introducing a high-resolution encoder with a patch information mining mechanism surprisingly led to a performance drop. We attribute this to Mini-Gemini's dual encoder architecture, which combines high- and low-resolution encoders. The patch info mining mechanism fuses high-resolution features into the compressed low-resolution representation, limiting overall representational capacity. In contrast, other models benefit from longer visual token sequences enabled by higher resolutions, which enhance the expressiveness of their visual encoders.

Table 3: Performance comparison of models with and without high-resolution encoders (Avg. refers to average resolution).

Method	Resolution	Visual Tokens	Perception Avg. 1098*847	Reasoning Avg. 926*534	Probing Avg. 828*523	Overall
ConvLLaVA-768-7B (Ge et al., 2024)	768	144	36.07	51.02	37.11	41.51
ConvLLaVA-1024-7B (Ge et al., 2024)	1024	256	$42.96_{+6.89}$	$52.72_{+1.70}$	$40.89_{+3.78}$	$46.21_{+4.70}$
ConvLLaVA-1536-7B (Ge et al., 2024)	1536	576	$41.47_{+5.40}$	$52.25_{+1.23}$	$34.20_{-6.69}$	$44.50_{+2.99}$
LLaVA-1.5-13B (Liu et al., 2024a)	336	576	30.08	42.37	41.39	35.72
LLaVA-HR-13B (Luo et al., 2024)	1024	1024	$41.46_{+11.38}$	$49.46_{+7.09}$	$48.80_{+7.41}$	$45.12_{+9.40}$
DeepStack-L-Vicuna-7B (Meng et al., 2024)	672	2880	36.33	44.62	30.21	38.60
DeepStack-L-HD-Vicuna-7B (Meng et al., 2024)	1344	14400	$34.69_{-1.64}$	$47.00_{+2.38}$	$35.88_{+5.67}$	$39.21_{+0.61}$
Mini-Gemini-13B (Li et al., 2023b)	768	576	37.71	53.54	32.28	42.75
Mini-Gemini-13B-HD (Li et al., 2023b)	1536	576	$36.48_{-1.23}$	$49.73_{-3.81}$	$34.28_{+2.00}$	$40.95_{-1.80}$
Mini-Gemini-34B (Li et al., 2023b)	768	576	50.07	57.97	41.79	51.96
Mini-Gemini-34B-HD (Li et al., 2023b)	1536	576	$46.49_{-3.58}$	$60.63_{+2.66}$	$35.91_{-5.88}$	$50.35_{-1.61}$

Mixture-of-Encoder. Another approach to enhancing visual encoders is the use of a mixture-of-encoder architecture. In this setup, image features are extracted by a combination of high-resolution and low-resolution encoders, providing rich visual information to the language decoders. We analyze the relationship between the mixture-of-encoder architecture and model performance by aggregating different encoders while keeping the training data and decoders fixed. We use the LLaVA-1.5 pretraining data for stage-1 pretraining and the EAGLE 1.8M dataset (Bi et al., 2024) for stage-2 fine-tuning. The initial encoder is a CLIP model with 448 resolution (Radford et al., 2021), and the decoder is LLaMA-3-8B (Dubey et al., 2024). We scale up the encoders using: *(A)* ConvNeXt (Liu et al., 2022), *(B)* SAM (Kirillov et al., 2023), *(C)* DINOv2 (Oquab et al., 2023), and *(D)* Pix2Struct (Lee et al., 2023). The empirical results in Table 4 indicate that combining CLIP with encoder A improves the models' performance; however, as the number of visual encoders increases, the models' performance declines. The non-monotonic behavior observed in Table 4 suggests that adding more visual encoders does not necessarily improve compositionality. One possible explanation is feature redundancy between certain encoders, which may introduce overlapping representations rather than complementary information. In contrast, combinations of encoders with different inductive biases tend to produce more complementary visual features.

Table 4: A comparative analysis of various mixture-of-encoder architectures in relation to model compositionality.

Method	Visual Encoders	Relolution	Perception	Reasoning	Probing	Overall
LLaVA-1.5 (Liu et al., 2024a)	CLIP	448	44.43	53.07	53.34	48.50
LLaVA-1.5+A	CLIP+A	1024	$45.34_{+0.91}$	$52.25_{-0.82}$	$56.93_{+3.59}$	$49.13_{+0.63}$
LLaVA-1.5+A+B	CLIP+A+B	1024	$45.32_{+0.95}$	$51.23_{-1.84}$	$49.02_{-4.32}$	$47.83_{-0.67}$
LLaVA-1.5+A+B+C	CLIP+A+B+C	1024	$42.88_{-1.55}$	$50.34_{-2.73}$	$54.21_{+0.87}$	$46.80_{-1.70}$
LLaVA-1.5+A+C+D	CLIP+A+C+D	1024	$46.94_{+2.51}$	$50.34_{-2.73}$	$54.86_{+1.55}$	$49.04_{+0.54}$

Visual encoder has a more significant impact on the model's compositionality, while GPT-4o struggles with processing higher-resolution images. By summarizing the empirical results of this study, we find that for relatively simple QA tasks, only a small portion of its language capabilities are utilized (compared to the models outperforming GPT-4o, whose language model size is only 70B). Once the language

decoder size reaches a certain threshold (e.g., 34B, 70B), the visual encoder plays a more critical role in the models' performance. As discussed in Section A.4, Qwen2VL processes images by largely preserving their original resolution and aspect ratio. The Internvl-2 series models employ a dynamic 'any-resolution' encoding strategy: images are first mapped to an optimal aspect ratio from predefined ratios, then divided into 448 × 448 pixel tiles, with each tile converted into 256 image tokens. These approaches enable the encoders to handle images of any resolution and aspect ratio with minimal degradation of image quality. In contrast, GPT-4o processes images with downsampling when the image's longest side > 2048px or shortest side > 768px (our data contains 889 such examples), contributing to its inferior performance compared to other open-source models.

5.2 The Volume of Training Data

The volume of training data is a crucial factor influencing models' performance. In this study, we conduct a comparison analysis of this factor. In Table 5, we observe a significant performance increase when the training data is scaled up substantially. For instance, InternVL-Chat-V1.2 and InternVL-Chat-V1.2-Plus, which use 10 times more training data than the former, show significant performance improvements.

Table 5: The comparison of models with and without training data scale up.

Method	Dataset Size	Perception	Reasoning	Probing	Overall
INF-LLaVA (Ma et al., 2024)	1.25M	41.38	45.44	35.58	42.18
INF-LLaVA* (Ma et al., 2024)	2.56M	$39.45_{-1.93}$	$50.27_{+4.83}$	$31.41_{-4.17}$	$42.41_{+0.23}$
InternVL-Chat-V1.2 (Chen et al., 2024c)	1.2M	55.74	63.69	60.71	59.13
InternVL-Chat-V1.2-Plus (Chen et al., 2024c)	12M	$60.27_{+4.53}$	$70.64_{+6.95}$	$65.80_{+5.09}$	$64.58_{+5.45}$
InternVL-Chat-V1.5 (Chen et al., 2024b)	–	53.09	67.44	57.01	58.64
InternVL2-26B (Chen et al., 2024b)	–	$59.51_{+6.42}$	$69.48_{+2.04}$	$52.43_{-4.58}$	$62.27_{+3.63}$

5.3 Language Decoder Size

From Table 2, we observe that models with larger decoders demonstrate stronger performance. To analyze this relationship more accurately, we compare models with different decoder sizes while keeping the encoder and training data constant. The results are shown in Table 6, from which we can conclude that larger language decoders result in better performance.

Table 6: The comparison analysis of text decoder size and models' compositionality.

Method	Decoder	Perception	Reasoning	Probing	Overall
InternVL2-1B (Chen et al., 2024b)	Qwen2-0.5B-Instruct	39.05	49.18	27.89	41.41
InternVL2-2B (Chen et al., 2024b)	InternLM2-Chat-1.8B	$41.57_{+2.52}$	$50.07_{+0.89}$	$38.10_{+10.21}$	$44.22_{+2.81}$
InternVL2-4B (Chen et al., 2024b)	Phi3-Mini-128K-Instruct	$45.79_{+6.74}$	$61.85_{+12.67}$	$41.18_{+13.29}$	$51.00_{+9.59}$
InternVL2-8B (Chen et al., 2024b)	InternLM2.5-Chat-7B	$52.64_{+13.59}$	$66.55_{+17.37}$	$54.10_{+26.21}$	$57.76_{+16.35}$
InternVL2-26B (Chen et al., 2024b)	InternLM2-Chat-20B	59.51	69.48	52.43	62.27
InternVL2-40B (Chen et al., 2024b)	Nous-Hermes-2-Yi-34B	$64.55_{+5.04}$	$74.66_{+5.18}$	$59.59_{+7.16}$	$67.60_{+5.33}$
InternVL2-76B (Chen et al., 2024b)	Hermes-2-Theta-Llama-3-70B	$62.56_{+3.05}$	$75.34_{+5.86}$	$58.46_{+6.03}$	$66.65_{+4.38}$
LLaVA-V1.6-Mistral-7B (Liu et al., 2024a)	Mistral-7B-Instruct	33.58	40.94	38.24	36.72
LLaVA-V1.6-Vicuna-13B (Liu et al., 2024a)	Vicuna-13B-V1.5	$30.98_{-2.60}$	$46.32_{+5.38}$	$38.16_{-0.08}$	$37.24_{+0.52}$
LLaVA-V1.6-34B (Liu et al., 2024a)	Nous-Hermes-2-Yi-34B	$56.91_{+23.33}$	$57.56_{+16.62}$	$58.17_{+19.93}$	$57.28_{+20.56}$
Mini-Gemini-13B (Li et al., 2023b)	Vicuna-13B-V1.5	37.71	53.54	32.28	42.75
Mini-Gemini-34B (Li et al., 2023b)	Nous-Hermes-2-Yi-34B	$50.07_{+12.36}$	$57.97_{+4.43}$	$41.79_{+9.51}$	$51.96_{+9.21}$
SliME-7B (Zhang et al., 2024b)	Vicuna-7B-V1.5	40.04	50.14	30.03	42.52
SliME-8B (Zhang et al., 2024b)	Llama-3-8B-Instruct	$40.00_{-0.04}$	$49.86_{-0.28}$	$29.96_{-3.07}$	$42.39_{-0.13}$
SliME-13B (Zhang et al., 2024b)	Vicuna-13B-V1.5	$39.18_{-0.86}$	$48.09_{-2.05}$	$33.55_{+3.52}$	$41.73_{-0.79}$
LLaVA-HR-7B (Luo et al., 2024)	Vicuna-7B-V1.5	38.94	48.57	33.04	41.71
LLaVA-HR-13B (Luo et al., 2024)	Vicuna-13B-V1.5	$41.46_{+2.52}$	$49.46_{+0.89}$	$48.80_{+15.25}$	$45.12_{+3.41}$
Yi-VL-6B (AI et al., 2024)	Yi-6B-Chat	43.34	50.07	48.76	46.34
Yi-VL-34B (AI et al., 2024)	Yi-34B-Chat	$42.81_{-0.53}$	$52.18_{+2.11}$	$53.88_{+5.12}$	$47.38_{+1.04}$

5.4 Effect of Enabling Thinking

To further examine whether explicit reasoning improves compositionality, we compare API-based models with and without thinking within the same model family. As shown in Table 7, enabling thinking consistently improves the overall performance across the latest Claude families. The improvements are primarily driven by gains in *Reasoning* categories, while *Perception* also shows noticeable improvements in most cases. In contrast, *Probing* does not consistently benefit from thinking and even shows slight decreases for several model variants. This pattern suggests that thinking mainly enhances multi-step compositional reasoning rather than exploiting potential regularities in the benchmark's option construction. If models were primarily leveraging latent benchmark rules, we would expect disproportionate gains in *Probing*, which is structurally closer to the option-selection mechanism. However, such gains are not observed. Overall, these results indicate that explicit thinking improves compositional reasoning ability, particularly for tasks requiring sequential visual inference, while offering limited advantage for probing-style compositional selection tasks.

Table 7: The comparison of models with and without thinking.

Method	Thinking	Perception	Reasoning	Probing	Overall
Claude-Opus-4.5 Anthropic (2025)	w/o	68.97	78.54	36.60	68.77
Claude-Opus-4.5 Anthropic (2025)	w/	$72.44_{+3.47}$	$84.20_{+5.66}$	$34.82_{-1.78}$	$72.44_{+3.67}$
Claude-Opus-4.6 Anthropic (2025)	w/o	72.24	80.65	37.62	71.38
Claude-Opus-4.6 Anthropic (2025)	w/	$72.30_{+0.06}$	$81.81_{+1.16}$	$36.89_{-0.73}$	$71.75_{+0.37}$
Claude-Sonnet-4.5 Anthropic (2025)	w/o	53.69	72.89	31.92	58.10
Claude-Sonnet-4.5 Anthropic (2025)	w/	$67.38_{+13.69}$	$79.29_{+6.40}$	$35.77_{+3.85}$	$68.10_{+10.00}$
Claude-Sonnet-4.6 Anthropic (2025)	w/o	65.66	78.34	34.75	66.73
Claude-Sonnet-4.6 Anthropic (2025)	w/	$70.96_{+5.30}$	$80.65_{+2.31}$	$34.31_{-0.44}$	$70.33_{+3.60}$

5.5 Interpretable Analysis of Model Deficiencies

We conduct a comprehensive error analysis to better understand the models' deficiencies in fine-grained compositional understanding. In this analysis, the models are required to answer questions and provide explanations in a multi-turn dialogue format. Figures 4, 15, and 16 in Section A.6 illustrate the reasons why the models fail to predict the correct answers for each task. For example, in the Obj-P task (example 3), while the "yellow colored outline" is easily detected by humans, the models struggle to accurately identify the target objects due to the outline being mixed with numerous other characters. Additionally, the models face difficulties with fine-grained object counting, especially when several similar objects are present. In the Count-R (example 6) task, for instance, humans can precisely count the number of triangles on a wheel, but the models confuse the six irregular polygons for triangles.

5.6 Failure Mode Analysis

To better understand the limitations of current VLMs on compositional reasoning, we conduct a structured failure mode analysis across representative task categories. We observe that models frequently fail in scenarios involving irregular object layouts or partial occlusions. In particular, models tend to rely on approximate visual patterns rather than precise enumeration, leading to systematic errors when objects are densely packed or visually ambiguous. Despite strong performance on standard QA tasks, all models exhibit significant degradation on compositional probing, where multiple options may simultaneously be correct. This suggests that current VLMs struggle to jointly verify multiple compositional constraints and are prone to accepting partially correct statements. Models often fail to identify target objects when they are embedded in cluttered scenes or mixed with visually similar distractors. These failures indicate limited robustness in isolating relevant compositional primitives under complex visual contexts. Overall, these failure patterns persist even in frontier models, highlighting that compositional understanding remains a fundamental bottleneck for current VLMs.

6 Conclusion

This paper introduces MMComposition, a novel high-quality benchmark for evaluating VLM compositionality. With MMComposition, we comprehensively evaluate the compositionality of notable VLMs. Our evaluation reveals a significant gap between these models and human performance, providing insights into the limitations of existing VLMs. Additionally, we systematically analyze factors that may influence compositionality, including visual encoder design, training data volume, and language decoder size. We find that for relatively simple QA tasks, only a small portion of the language model's capacity is utilized (as seen in models outperforming GPT-4o, whose language model has 70B parameters). Once the language decoder reaches a certain size threshold (e.g., 34B, 70B), the visual encoder has a more pronounced impact on compositionality. In summary, our work provides a comprehensive and precise framework for evaluating the compositionality of VLMs, identifies key areas for improvement, and suggests potential directions for future advancements. Our findings suggest that compositional understanding in VLMs cannot be fully captured by conventional benchmarks or improved solely through scaling or extended reasoning, underscoring the need for more targeted evaluation frameworks such as MMComposition.

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