
GenAI-Bench: Evaluating and Improving Compositional Text-to-Visual Generation

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Abstract

While text-to-visual models now produce photo-realistic images and videos, they struggle with *compositional* text prompts involving attributes, relationships, and higher-order reasoning such as logic and comparison. In this work, we conduct an extensive human study on **GenAI-Bench** to evaluate the performance of leading image and video generation models in various aspects of compositional text-to-visual generation. We also compare automated evaluation metrics against our collected human ratings and find that **VQAScore** – a metric measuring the likelihood that a VQA model views an image as accurately depicting the prompt – significantly outperforms previous metrics such as CLIPScore. In addition, VQAScore can improve generation in a black-box manner (without finetuning) via simply ranking a few (3 to 9) candidate images. **Ranking by VQAScore** is 2x to 3x more effective than other scoring methods like PickScore, HPSv2, and ImageReward at improving human alignment ratings for DALL-E 3 and Stable Diffusion, especially on compositional prompts that require advanced visio-linguistic reasoning. We will release a new **GenAI-Rank** benchmark with over 40,000 human ratings to evaluate scoring metrics on ranking images generated from the same prompt. Lastly, we discuss promising areas for improvement in VQAScore, such as addressing fine-grained visual details. We will release all human ratings (over 80,000) to facilitate scientific benchmarking of both generative models and automated metrics.

1 Introduction

State-of-the-art text-to-visual models like Stable Diffusion [60], DALL-E 3 [2], Gen2 [18], and Sora [67] generate images and videos with exceptional realism and quality. Due to their rapid advancement, traditional evaluation metrics and benchmarks (e.g., FID scores on COCO [24, 40] and CLIPScores on PartiPrompt [23, 85]) are becoming insufficient [43, 53]. For instance, benchmarks should include more *compositional* text prompts [46] that involve attribute bindings, object relationships, and logical reasoning, among other visio-linguistic reasoning skills (Figure 1). Moreover, it’s crucial for automated evaluation metrics to measure how well the generated images (or videos) *align* with such compositional text prompts. Yet, widely used metrics like CLIPScore [23] function as *bag-of-words* [42, 73, 86] and cannot produce reliable alignment (faithfulness [26]) scores. Therefore, to guide the scientific benchmarking of generative models, we conduct a comprehensive evaluation of compositional text-to-visual generation alongside automated alignment metrics [6, 23].

Evaluating text-to-visual generation. We evaluate generative models using our collected **GenAI-Bench** benchmark, which consists of 1,600 challenging real-world text prompts sourced from professional designers. Compared to benchmarks [26, 31, 48] such as PartiPrompt [85] and T2I-

*Co-first authors; †Co-senior authors. Datasets and code are open-sourced on our website. This manuscript is an extended version of the CVPR workshop paper [37] and provides additional details on benchmark curation.

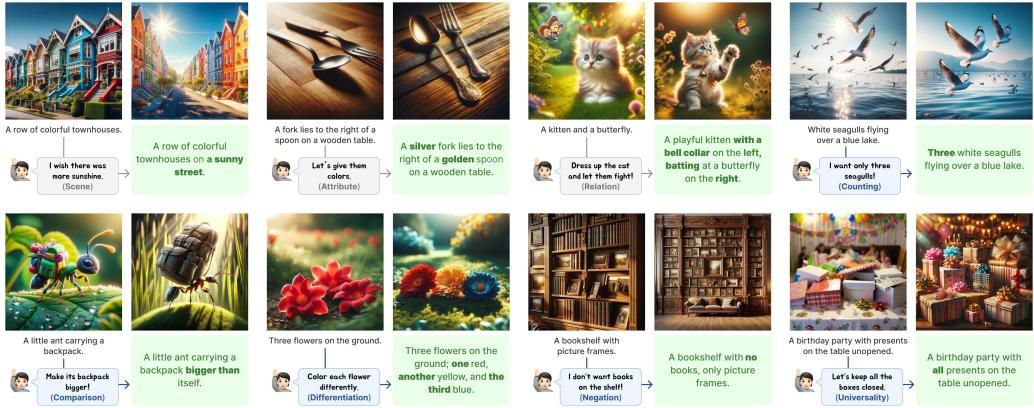


Figure 1: **Compositional text prompts of our GenAI-Bench (highlighted in green)** reflect how real-world users (e.g., designers) seek precise control in text-to-visual generation. For example, users often write detailed prompts that specify compositions of basic visual entities and properties (highlighted in gray), such as scenes, attributes, and relationships (spatial/action/part). Moreover, user prompts may require advanced visio-linguistic reasoning (highlighted in blue), such as counting, comparison, differentiation, and logic (negation/universality). Appendix B provides skill definitions with more examples. Table 1 compares GenAI-Bench with previous benchmarks [27, 31, 62, 85].

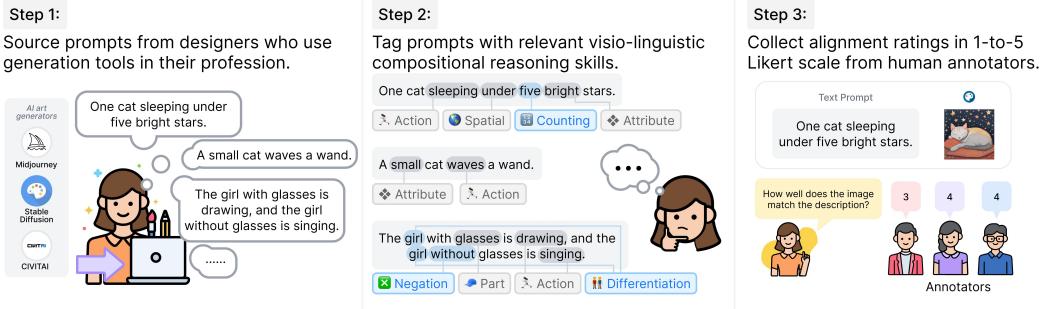


Figure 2: **Collecting GenAI-Bench.** To reliably evaluate generative models, we source prompts from professional designers who use tools such as Midjourney [51] and CIVITAI. This ensures the prompts encompass practical skills relevant to real-world applications and are free of subjective or inappropriate content. Each GenAI-Bench prompt is carefully tagged with all its evaluated skills. We then generate images and videos using state-of-the-art models like SD-XL [60] and Gen2 [18]. We follow the recommended annotation protocol [53] to collect 1-to-5 Likert scale ratings for how well the generated visuals align with the input text prompts.

CompBench [27] (see Table 1), GenAI-Bench captures a wider range of aspects in compositional text-to-visual generation [36], ranging from **basic** (scene, attribute, relation) to **advanced** (counting, comparison, differentiation, logic). We collect a total of 38,400 human alignment ratings (1-to-5 Likert scales [53]) on images and videos generated by ten leading models, such as Stable Diffusion [60], DALL-E 3 [2], Midjourney v6 [51], Pika v1 [55], and Gen2 [18]. Figure 2 illustrates the evaluation process. Our human study shows that while these models can often accurately generate basic compositions (e.g., attributes and relations), they still struggle with advanced reasoning (e.g., logic and comparison). For instance, for “basic” prompts that do not require advanced reasoning, the state-of-the-art DALL-E 3 (most preferred by humans) achieves a remarkable average rating of 4.3, meaning its images range from having “*a few minor discrepancies*” to ‘*matching exactly*’ with the prompts. However, its rating on “advanced” prompts drops to 3.4, indicating “*several discrepancies*”.

Evaluating automated metrics. We also use the human ratings to benchmark automated metrics (e.g., CLIPScore [23], PickScore [31], and Davidsonian [6]) that measure the alignment between an image and a text prompt. Specifically, we show that a simple metric, **VQAScore**, which computes the likelihood of generating a “Yes” answer to a question like “Does this figure show {text}?” from a VQA model [43], significantly surpasses previous metrics in correlating with human judgments. VQAScore can be calculated end-to-end from off-the-shelf VQA models, without finetuning on

human feedback [31, 83] or decomposing prompts into QA pairs [6, 84]. VQAScore is strong because it leverages the compositional reasoning capabilities of recent multimodal large language models (LLMs) [10, 44] trained for VQA. For instance, our study adopts the leading **CLIP-FlanT5** model [43], which follows the best training practices in the literature [9], e.g., using a bidirectional encoder that allows the image and question embeddings to “see” each other. VQAScore based on CLIP-FlanT5 sets a new state-of-the-art on both GenAI-Bench and previous benchmarks like TIFA160 [26] and Winoground [73]. As such, we recommend VQAScore over the “bag-of-words” CLIPScore, which has been widely misused in our community [29, 86]. We will release all human ratings to facilitate the development of automated metrics.

Improving generation with VQAScore. We show that text-to-image generation can be improved by selecting the candidate image with the highest VQAScore (from a set of candidates). This ranking-based approach does not require any finetuning and can operate in a fully black-box manner [47], needing only an image generation API. Notably, simply ranking between 3 to 9 images can already enhance the average human ratings for DALL-E 3 and SD-XL by 0.2 to 0.3 (on a 1-to-5 Likert scale), setting the new closed-source and open-source SOTAs on GenAI-Bench. VQAScore significantly outperforms other metrics; for instance, using CLIPScore for ranking often leads to the same or lower human ratings. We present qualitative examples in Figure 7. Overall, VQAScore emerges as the most effective ranking metric, surpassing other metrics that rely on costly human feedback (e.g., PickScore [31] or ChatGPT for prompt decomposition (e.g., Davidsonian [6]) by 2x to 3x.

Limitations. Lastly, we explore the implications of Goodhart’s Law [19], particularly limitations of VQAScore in detecting fine-grained visual details and resolving linguistic ambiguity. Despite these mild limitations, we strongly urge the research community to adopt VQAScore as a reproducible supplement to non-reproducible human studies [53], or as a more reliable alternative to CLIPScore, which has ceased to be effective [29, 42, 86].

Table 1: Comparing GenAI-Bench to existing text-to-visual benchmarks. GenAI-Bench covers more essential aspects of compositional text-to-visual generation, emphasizing advanced reasoning skills (highlight in blue) that are required to parse complex user prompts. Moreover, GenAI-Bench tags each prompt with all its evaluated skills, whereas most benchmarks assign no tags or only one or two per prompt (even when multiple skills are involved). GenAI-Bench also provides human ratings for both image and video generative models to benchmark automated metrics.

Benchmarks	Skills Covered in Compositional Text-to-Visual Generation								Tagging	Human Annotation
	Scene	Attribute	Relation	Count	Negation	Universal	Compare	Differ		
PartiPrompt (P2) [85]	✓	✓	✓	✓	✓	✗	✗	✗	2 Tags	✗
DrawBench [62]	✓	✓	✓	✓	✗	✗	✗	✗	1 Tag	✗
EditBench [76]	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗
TIFAv1 [26]	✓	✓	✓	✓	✗	✗	✗	✗	All Tags	Images
Pick-a-pic [31]	✓	✓	✓	✓	✗	✗	✗	✗	✗	Images
T2I-CompBench [27]	✓	✓	✓	✓	✗	✗	✗	✗	1 Tag	Not Released
HPDv2 [81]	✓	✓	✓	✗	✗	✗	✗	✗	✗	Images
EvalCrafter [48]	✓	✓	✓	✓	✗	✗	✗	✗	✗	Videos
GenAI-Bench (Ours)	✓	✓	✓	✓	✓	✓	✓	✓	All Tags	Images & Videos

Contribution summary.

1. We conduct an extensive human study on compositional text-to-visual generation using **GenAI-Bench**, revealing limitations of leading open-source and closed-source models.
2. We present a simple black-box approach that improves generation by **ranking** images with VQAScore, significantly surpassing other scoring methods by 2x to 3x.
3. We will release **GenAI-Rank** with over 40,000 human ratings to benchmark methods that rank images generated from the same prompt.

2 Related Works

Text-to-visual benchmarks. Early benchmarks mostly rely on captions from existing datasets like COCO [7, 26, 40, 59], focusing on generating simple objects, attributes, and scenes. Other benchmarks, such as HPDv2 [81] and Pick-a-pic [31], primarily evaluate image quality (aesthetic) using simpler text prompts. Recently, benchmarks like DrawBench [62], PartiPrompt [85], and

T2I-CompBench [27] have shifted the focus to compositional text-to-image generation with an emphasis on attribute bindings and object relationships. Our GenAI-Bench escalates the challenge by incorporating more practical prompts that require “advanced” reasoning (e.g., logic and comparison) to benchmark next-generation text-to-visual models.

Automated metrics. Perceptual metrics like IS [63], FID [24] and LPIPS [87] use pre-trained networks to assess the quality of generated imagery using reference images. To evaluate vision-language alignment (also referred to as faithfulness or consistency [11, 26, 49]), recent studies [5, 16, 17, 30, 33, 50, 61, 65, 78] primarily report CLIPScore [23], which measures (cosine) similarity of the embedded image and text prompt. However, CLIP cannot reliably process compositional text prompts due to its “bag-of-words” encoding [29, 42, 86]. Human preference models like ImageReward [83], PickScore [31], and HPSv2 [81] further leverage human feedback to improve models like CLIP by finetuning on large-scale human ratings. Another popular line of works [8, 26, 27, 66, 79] uses LLMs like ChatGPT to decompose texts into simpler components for analysis, e.g., via question generation and answering (QG/A) [6]. For example, Davidsonian Scene Graph [6] decomposes a text prompt into simpler QA pairs and outputs a score as the accuracy of answers generated by a VQA model. However, Lin et al. [42, 43] show that such methods still struggle with complex text prompts and propose VQAScore, an end-to-end metric that better correlates with human judgments.

3 GenAI-Bench for Text-to-Visual Evaluation

In this section, we present **GenAI-Bench**, a challenging benchmark featuring practical user prompts that cover essential aspects of compositional text-to-visual generation.

Skill taxonomy. Prior literature on text-to-visual generation [27, 62, 85] focuses on generating “basic” objects, attributes, relations, and scenes. However, as illustrated in Figure 1, user prompts often require “advanced” compositional reasoning, including comparison, differentiation, counting, and logic. These “advanced” compositions extend beyond the “basic” ones. For example, user prompts may involve counting not just objects, but also attribute-object pairs and even object-relation-object triplets, e.g., “three white seagulls flying over a blue lake”. Also, users often want to generate multiple objects of the same category but differentiate them with varied properties, e.g., “three flowers on the ground; one red, another yellow, and the third blue”. To this end, we collaborate with designers who use text-to-image tools [51] in their profession to design a taxonomy that includes both “basic” (objects, scenes, attributes, and spatial/action/part relations) and “advanced” skills (counting, comparison, differentiation, negation, and universality). Table 1 shows that GenAI-Bench uniquely covers all these essential skills. Appendix B provides definitions and more examples.

GenAI-Bench. We also collect 1,600 prompts from these professional designers. Importantly, sourcing prompts from actual designers ensures that they are free from subjective or toxic contents. For example, we observe that ChatGPT-generated prompts from T2I-CompBench [27] can include subjective (e.g., non-visual) phrases like “a natural symbol of rebirth and renewal”. We also find that the Pick-a-pic [31] dataset contains inappropriate prompts (e.g., those suggesting NSFW images of celebrities) created by malicious web users. To avoid legal issues and test general model capabilities, we advise designers to create prompts with generic characters and subjects (e.g., food, vehicles, humans, pets, plants, household items, and mythical creatures) instead of celebrities or copyrighted characters. Appendix C details our collection procedure and discuss how we avoid these issues. For a fine-grained analysis, we tag each prompt with *all* its evaluated skills. This contrasts with previous benchmarks that either provide no tags [31, 48, 81] or overly simplify by assigning only one or two tags per prompt [27, 62, 85]. In total, GenAI-Bench provides over 5,000 human-verified tags with an approximately balanced distribution of skills. Specifically, about half of the prompts involve only “basic” compositions, while the other half poses greater challenges by incorporating both “basic” and “advanced” compositions.

4 Human Evaluation via GenAI-Bench

We now present an extended human study of ten popular image and video generative models.

Human evaluation. We evaluate six text-to-image models: Stable Diffusion [60] (SD v2.1, SD-XL, SD-XL Turbo), DeepFloyd-IF [13], Midjourney v6 [51], DALL-E 3 [2]; along with four text-

to-video models: ModelScope [75], Floor33 [15], Pika v1 [55], Gen2 [18]. Next, we hire three annotators to collect 1-to-5 Likert scale human ratings for image-text or video-text alignment using the recommended annotation protocol of [53]:

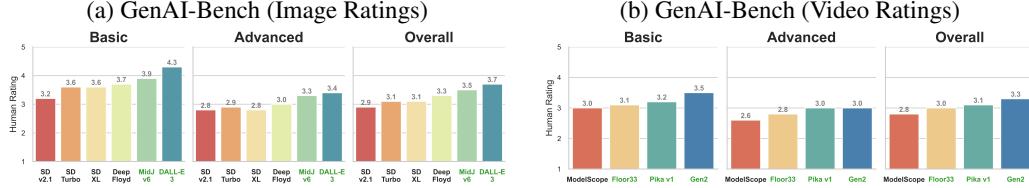
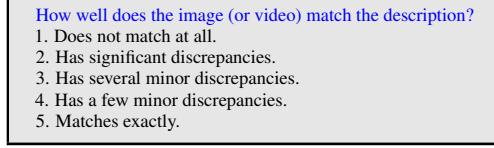


Figure 3: **Human evaluation on GenAI-Bench.** We show the average human alignment ratings on ten popular image and video generative models. We highlight closed-source models (e.g., DALL-E 3 [2]) in green. We find that (1) “advanced” prompts that require higher-order reasoning (e.g., negation and comparison) challenge all models more, (2) models using better text embeddings or captions (DeepFloyd-IF [13] and DALL-E 3 [2]) outperform others (SD-XL [60]), (3) open-source and video-generative models [18, 60] still lag behind their closed-sourced and image-generative counterparts, suggesting room for improvement.

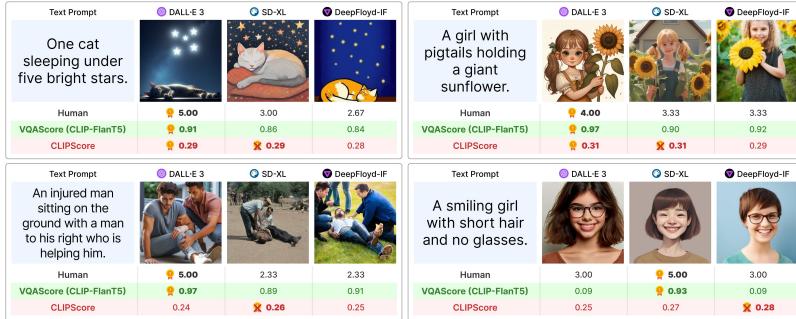


Figure 4: **VQAScore (based on CLIP-FlanT5 [43]) versus CLIPScore** on samples from GenAI-Bench. VQAScore shows a significantly stronger agreement with human ratings compared to CLIPScore [23], making it a more reliable tool for automatic text-to-visual evaluation, especially on user prompts that involve complex compositional reasoning.

Our collected human ratings indicate a high level of inter-rater agreement, with Krippendorff’s Alpha reaching 0.72 for image ratings and 0.70 for video ratings, suggesting substantial agreement [26]. The use of the Likert scale also makes the final rating interpretable. For example, a score near 5 implies that the model’s generated images almost always “match exactly” with the input prompts.

Analysis. Figure 3 presents human ratings for basic, advanced, and overall prompts. Notably, advanced prompts that require complex visio-linguistic reasoning are much harder. For example, the top-performing DALL-E 3 scores 4.3 on basic prompts, indicating “*a few minor discrepancies*”. However, on advanced prompts, its score drops to 3.4, indicating “*several minor discrepancies*”. Interestingly, models (e.g., DeepFloyd-IF and DALL-E 3) using stronger text embeddings from LLMs (e.g., T5 [58]) outperform those using CLIP text embeddings (e.g., SD-XL). Lastly, we observe that open-source and video-generative models lag behind their closed-source and image-generative counterparts, suggesting room for future innovation. In Appendix C, we detail model performance across various skills, highlighting challenges in higher-order reasoning like negation and comparison.

5 Evaluating Automated Metrics

We use our human ratings to benchmark automated alignment metrics [6, 23, 84] on GenAI-Bench.

Table 2: **Evaluating the correlation of automated metrics with human ratings on GenAI-Bench.** We report Pairwise accuracy [14], Pearson, and Kendall, with higher scores indicating better performance for all. **VQAScore** based on the CLIP-FlanT5 model [43] (detailed in Appendix E) achieves the strongest agreement with human ratings on images and videos, significantly surpassing popular metrics like CLIPScore [23], PickScore [31], and Davidsonian [6].

Method	GenAI-Bench (Image)			GenAI-Bench (Video)		
	Pairwise	Pearson	Kendall	Pairwise	Pearson	Kendall
CLIPScore [23]	50.3	15.1	10.8	53.6	25.3	18.0
BLIPv2Score [23]	52.1	23.0	13.4	54.6	25.3	20.1
ImageReward [83]	55.7	30.0	22.2	60.0	42.9	31.4
PickScore [31]	56.2	31.8	23.1	56.8	34.6	24.8
HPSv2 [81]	49.3	12.6	9.0	51.5	18.4	13.7
VQ2 [84]	51.3	12.3	11.7	52.8	18.0	15.5
Davidsonian [6]	53.1	28.7	21.4	55.9	32.3	23.5
VQAScore [43]	62.8	46.0	37.2	63.2	50.6	38.2

VQAScore. Given an image and text, we calculate the probability of a “Yes” answer to a simple question like “Does this figure show ‘{text}’? Please answer yes or no.”:

$$P(\text{"Yes"} | \text{image}, \text{question}) \quad (1)$$

We implement VQAScore using the state-of-the-art **CLIP-FlanT5** model [43] trained on 665K public VQA data [44]. For video-text pairs, we average the scores across all video frames following prior work [65]. Appendix D includes implementation details and pseudocode for reference.

Evaluation setup. To evaluate automated metrics on GenAI-Bench, we follow TIFA160 [26] to report the Pearson and Kendall coefficients, which reflect the correlation of the metric score with human judgment. However, Deutsch et al. [14] (EMNLP’23 outstanding paper) note several issues with these metrics. For example, Pearson assumes a linear relationship between metric and human scores, while Kendall ignores ties common in 1-to-5 Likert scales. As such, we also report **Pairwise** accuracy [14], designed to address these issues. We direct readers to [14] for equations and provide a brief overview below. For a dataset with M items (e.g., image-text pairs), there are two M -size score vectors: one for human ratings and one for metric scores. Pairwise accuracy (a value between 0 and 1) evaluates the percentage of agreement across all $M \times M$ pairs of items, i.e., if one item scores higher, lower, or ties with another item in both human and metric scores. Additionally, we apply the tie calibration technique from [14] to find the optimal tie threshold for each metric.

Results. Table 2 shows that VQAScore significantly outperforms previous metrics such as CLIPScore [23], models trained with extensive human feedback [31, 81, 83], and QG/A methods that use the same CLIP-FlanT5 VQA model [6, 84]. Appendix G shows that VQAScore achieves the state-of-the-art performance on seven more alignment benchmarks such as TIFA160 [26] and Winoground [73]. Figure 4 qualitatively compare VQAScore against CLIPScore on random samples from GenAI-Bench. The strong performance of VQAScore makes it a more reliable tool for the future automated evaluation of text-to-visual models.

6 Improving Text-to-Visual Generation

VQAScore’s superior performance in evaluating text-to-visual generation suggests its potential to improve generation as well. We now show that VQAScore can improve the alignment of DALL-E 3 [2] and SD-XL [60] by simply ranking candidate images. We also collect a **GenAI-Rank** benchmark to evaluate scoring metrics on ranking images from the same prompt.

Ranking images by VQAScore. Given the same prompt, most text-to-visual models produce vastly different images with each run. As such, we adopt a *black-box* method [47] that improves text-to-image generation by selecting the highest-VQAScore image from a few generated candidates. This ranking-based approach is simple yet surprisingly effective. For instance, despite SD-XL’s weaker prompt alignment compared to DALL-E 3, Figure 5 shows how VQAScore can select the best SD-XL images (from three candidates) that outperform DALL-E 3’s. Figure 7 shows that VQAScore can also improve the closed-source (*black-box*) DALL-E 3 by correctly selecting the most prompt-aligned images from three candidates.

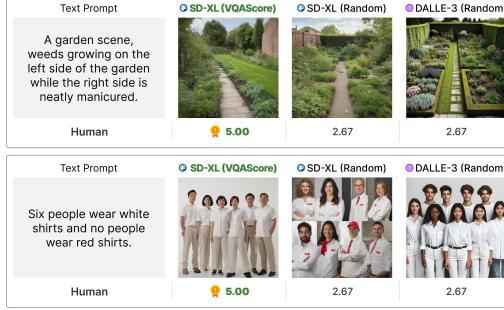


Figure 5: VQAScore can select images generated by SD-XL [60] that outperform DALL-E 3’s [2]. Although less powerful in prompt alignment than DALL-E 3, SD-XL [60] can still be improved by selecting the highest VQAScore image from merely three candidates. We provide examples of how VQAScore ranks SD-XL images in Appendix A.

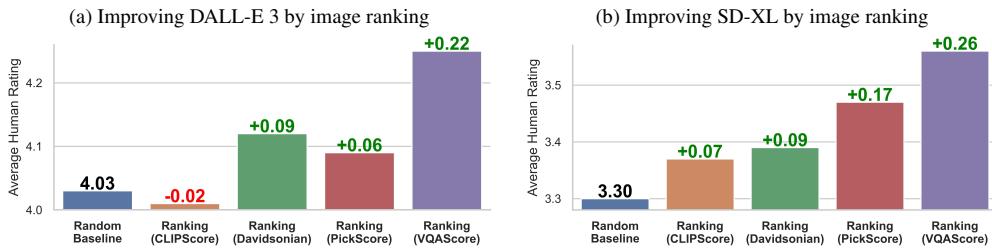


Figure 6: Improving text-to-visual generation by ranking nine candidate images. We show the performance gains over the *Random* baseline (no ranking) in green and decreases in red. Notably, selecting the highest VQAScore images from nine candidates significantly boosts the overall human alignment ratings. In contrast, ranking by CLIPScore [23] results in the same or lower performance. Overall, VQAScore is 2x to 3x more effective than other methods that rely on costly human feedback (PickScore [31]) or decompose texts using ChatGPT (Davidsonian [6]). Table 3 reports more scoring methods.

A benchmark for ranking. To compare against other ranking metrics (e.g., CLIPScore and PickScore), we hire three annotators to rate nine generated images for each prompt. In this study, we randomly select 800 prompts from GenAI-Bench and collect 43,200 human ratings for 14,400 images generated by DALL-E 3 and SD-XL. We will release this benchmark (termed **GenAI-Rank**) for reproducibility and to facilitate the evaluation of future ranking metrics.

VQAScore achieves superior performance gains. Figure 6 confirms that ranking by VQAScore delivers the most significant improvements in human ratings. While ranking by CLIPScore [23] results in the same or even lower performance, VQAScore consistently improves with more images to rank. VQAScore is also 2x to 3x more effective than other ranking metrics that rely on expensive human feedback (e.g., PickScore [31]) or decompose texts via ChatGPT (e.g., Davidsonian [6]). Table 3 details the performance gains for ranking 3 to 9 images across basic, advanced, and all prompts. VQAScore notably improves the prompt alignment of DALL-E 3 and SD-XL by about 0.3 on “advanced” prompts that require complex visio-linguistic reasoning, such as counting, comparison, and logic.

							
VQAScore (Ours)	9.97	0.73	0.51	VQAScore (Ours)	8.89	0.82	0.60
Human	5.00	4.00	3.00	Human	5.00	3.33	2.00
CLIPScore	0.29	0.30	0.30	CLIPScore	0.27	0.28	0.24
							
VQAScore (Ours)	9.96	0.53	0.22	VQAScore (Ours)	9.95	0.89	0.75
Human	5.00	3.33	2.33	Human	5.00	3.33	2.67
CLIPScore	0.29	0.29	0.25	CLIPScore	0.25	0.31	0.22
							
VQAScore (Ours)	9.87	0.74	0.48	VQAScore (Ours)	9.87	0.68	0.27
Human	5.00	3.33	2.33	Human	5.00	3.33	2.67
CLIPScore	0.30	0.32	0.29	CLIPScore	0.25	0.26	0.24
							
VQAScore (Ours)	9.95	0.82	0.60	VQAScore (Ours)	9.95	0.81	0.62
Human	5.00	2.67	2.00	Human	5.00	3.33	2.33
CLIPScore	0.30	0.30	0.27	CLIPScore	0.25	0.26	0.23

Figure 7: **Ranking DALL-E 3 generated images with VQAScore or CLIPScore.** VQAScore outperforms CLIPScore in ranking candidate images generated by DALL-E 3, particularly for prompts that involve attributes, relationships, and higher-order reasoning. This indicates that VQAScore can already improve text-to-image generation using only an image generation API [47].

Table 3: **Comparing scoring methods for image ranking on GenAI-Rank.** We present the average human ratings of 7 popular scoring methods across basic, advanced, and all prompts. Performance gains over the *Random* baseline (no ranking) are highlighted in green, while decreases are marked in red. We first note that ranking by CLIPScore [23] can lead to a performance drop. For instance, CLIPScore results in a 0.04 drop when given more images to rank (from 3 to 9). In contrast, VQAScore demonstrates consistent and significant improvements with more images. VQAScore improves performance on the more challenging “advanced” prompts that require complex visio-linguistic reasoning skills like counting, comparison, and logic. For these “advanced” prompts, VQAScore boosts DALL-E 3 by 0.30 and SD-XL by 0.27 by ranking nine images, outperforming the second-best method PickScore [31] by 2x to 3x. For reference, we include human (oracle) performance (ranking by ground-truth human ratings). GenAI-Rank will release over 40,000 human ratings to aid in the development of future ranking metrics.

Method	Basic		Advanced		Overall	
	3 Imgs	9 Imgs	3 Imgs	9 Imgs	3 Imgs	9 Imgs
Random	4.51	4.51	3.77	3.77	4.03	4.03
Human Oracle	4.77 _{+.26}	4.89 _{+.38}	4.18 _{+.41}	4.46 _{+.69}	4.39 _{+.36}	4.61 _{+.58}
CLIPScore [23]	4.54 _{+.03}	4.53 _{+.02}	3.79 _{+.02}	3.73 _{-.04}	4.05 _{+.02}	4.01 _{-.02}
ImageReward [83]	4.56 _{-.05}	4.52 _{+.01}	3.82 _{+.05}	3.83 _{+.06}	4.08 _{+.05}	4.08 _{+.05}
PickScore [31]	4.58 _{-.07}	4.60 _{+.09}	3.82 _{+.05}	3.81 _{+.04}	4.09 _{+.06}	4.09 _{+.06}
HPSv2 [81]	4.57 _{-.06}	4.60 _{+.09}	3.80 _{+.03}	3.78 _{+.03}	4.07 _{+.04}	4.07 _{+.04}
VQ2 [84]	4.54 _{+.03}	4.55 _{+.04}	3.79 _{+.02}	3.79 _{+.02}	4.05 _{+.02}	4.06 _{+.03}
Davidsonian [6]	4.56 _{-.05}	4.61 _{+.10}	3.83 _{+.05}	3.84 _{+.07}	4.09 _{+.06}	4.12 _{-.09}
VQAScore	4.59_{-.08}	4.62_{+.11}	3.92_{+.15}	4.05_{+.28}	4.16_{+.13}	4.25_{+.22}

(a) Improving DALL-E 3 by image ranking

Method	Basic		Advanced		Overall	
	3 Imgs	9 Imgs	3 Imgs	9 Imgs	3 Imgs	9 Imgs
Random	3.80	3.80	3.02	3.02	3.30	3.30
Human (Oracle)	4.17 _{+.37}	4.41 _{+.61}	3.38 _{+.36}	3.70 _{+.68}	3.66 _{+.36}	3.95 _{+.65}
CLIPScore [23]	3.86 _{+.06}	3.92 _{+.12}	3.06 _{+.04}	3.06 _{+.04}	3.34 _{+.04}	3.37 _{+.07}
ImageReward [83]	3.94_{+.14}	3.96 _{+.16}	3.10 _{+.08}	3.15 _{+.13}	3.40 _{+.10}	3.44 _{+.14}
PickScore [31]	3.94 _{+.14}	4.02 _{+.22}	3.13 _{+.11}	3.17 _{+.15}	3.42 _{+.12}	3.47 _{+.17}
HPSv2 [81]	3.91 _{+.11}	3.99 _{+.19}	3.11 _{+.08}	3.15 _{+.13}	3.39 _{+.09}	3.45 _{+.15}
VQ2 [84]	3.83 _{+.03}	3.88 _{+.08}	3.06 _{+.03}	3.08 _{+.06}	3.33 _{+.03}	3.37 _{+.07}
Davidsonian [6]	3.85 _{+.05}	3.88 _{+.08}	3.06 _{+.04}	3.11 _{+.09}	3.34 _{+.04}	3.39 _{+.09}
VQAScore	3.94_{+.14}	4.06_{+.26}	3.15_{+.13}	3.29_{+.27}	3.43_{+.13}	3.56_{+.26}

(b) Improving SD-XL by image ranking

7 Goodhart’s Law Still Applies

When a measure becomes a target, it ceases to be a good measure.

— Marilyn Strathern [68]

This quote conveys the essence of Goodhart’s Law [19, 20]: an over-optimized metric inevitably loses its effectiveness. This phenomenon is well-documented in fields such as machine learning [25, 72], economics [12, 20], and education [3, 32]. Acknowledging that VQAScore is also subject to this law, we examine its limitations as an automated metric and suggest avenues for future improvements.

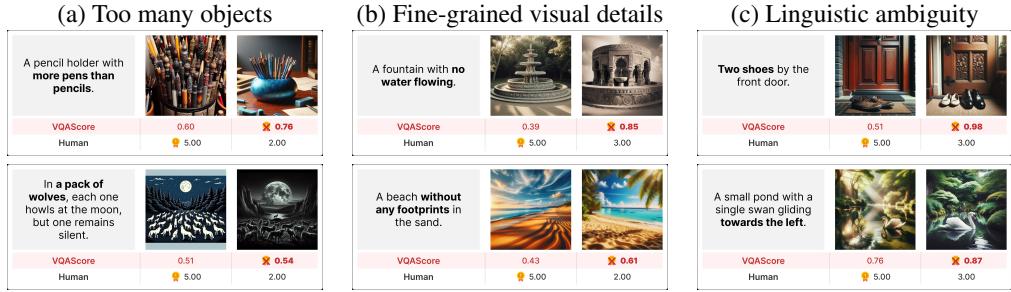


Figure 8: **Limitations of VQAScore (please zoom into the figures for a detailed view).** We identify three failure cases of VQAScore. (a) While VQAScore can reasonably count objects in small quantities, it struggles with larger numbers. (b) VQAScore can overlook small visual details, such as entities that occupy only a small portion of the image. (c) VQAScore may not understand ambiguous prompts, misinterpreting “two shoes” as “two pairs of shoes”, or “towards the left (of the viewer)” as “towards the left (of the swan)”.

Limitations of VQAScore. We conduct a qualitative study by manually examining samples where VQAScore and human ratings disagree. Figure 8 identifies three failure cases: (1) miscounting when there are too many objects, (2) overlooking fine-grained visual details, and (3) misinterpreting linguistic ambiguity. We posit that VQA models with higher image resolution [64] and more capable language models [52, 71] may improve on these challenging aspects. Despite these mild limitations, we strongly recommend adopting VQAScore as a more reliable alternative to CLIPScore, which has already ceased to be an effective metric [29, 42, 86]. We believe VQAScore also serves well as a reproducible supplement to non-reproducible human studies [53].

8 Conclusion

Limitations and future work. Currently, GenAI-Bench does not evaluate several vital aspects of generative models [35, 48, 54, 80], such as toxicity, bias, aesthetics, and video motion. Although our ranking-based approach is effective, future work may explore white-box finetuning techniques [4, 56, 82] for more efficient inference.

Summary. We have conducted an extensive human study with GenAI-Bench, focusing on both compositional text-to-visual generation and automated evaluation metrics. We show a straightforward ranking-based method that improves the prompt alignment of black-box generative models. By discussing Goodhart’s Law, we hope to encourage further research into automated evaluation techniques, which is essential to the scientific progression of this field.

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GenAI-Bench: Evaluating and Improving Compositional Text-to-Visual Generation

Supplementary Material

Outline

This document supplements the main paper with benchmark and method details. Below is the outline:

- **Section A** presents additional qualitative studies.
- **Section B** details GenAI-Bench’s skill taxonomy.
- **Section C** describes how we collect GenAI-Bench.
- **Section D** describes how we compute VQAScore.
- **Section E** describes how CLIP-FlanT5 is trained.
- **Section F** discusses other baseline methods.
- **Section G** discusses other alignment benchmarks.

A Additional Examples

Ranking SD-XL images by VQAScore. Figure 9 shows that ranking by VQAScore can also improve the prompt alignment of SD-XL using only its image generation API. We encourage future work to explore other white-box techniques for finetuning [22, 34, 39, 41, 61, 70, 74].

<p>A red bicycle against a blue wall.</p>  <p>VQAScore (Ours)  0.99 Human  5.00 CLIPScore  0.28</p>	<p>In the pond, two ducks swim near each other: the larger one has a bright green head, while the smaller one is all brown.</p>  <p>VQAScore (Ours)  0.92 Human  5.00 CLIPScore  0.29</p>	<p>A hammock strung between two palm trees on a beach.</p>  <p>VQAScore (Ours)  0.98 Human  5.00 CLIPScore  0.29</p>	<p>A runner in blue shoes speeds past another in red shoes.</p>  <p>VQAScore (Ours)  0.79 Human  5.00 CLIPScore  0.30</p>	<p>A person types on an old typewriter.</p>  <p>VQAScore (Ours)  0.98 Human  5.00 CLIPScore  0.27</p>	<p>six people wear white shirts and no people wear red shirts.</p>  <p>VQAScore (Ours)  0.94 Human  5.00 CLIPScore  0.28</p>	<p>A dog, a cat and a chicken on a table.</p>  <p>VQAScore (Ours)  0.98 Human  5.00 CLIPScore  0.34</p>	<p>At the party, a pineapple is flanked by beers on each side.</p>  <p>VQAScore (Ours)  0.93 Human  5.00 CLIPScore  0.27</p>
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Figure 9: **Ranking SD-XL generated images with VQAScore and CLIPScore.** VQAScore outperforms CLIPScore in ranking candidate images generated by SD-XL, particularly for advanced prompts that involve complex visio-linguistic reasoning.

B Skill taxonomy of GenAI-Bench

We now detail the evaluated skills of GenAI-Bench.

Skill definitions. Most literature on text-to-visual generation [7, 26, 27, 62, 85] primarily focuses on generating *basic* objects, attributes, relations, and scenes. While these “basic” visual compositions still pose challenges, real-world user prompts often introduce greater complexity. Such prompts require higher-order reasoning beyond basic compositions, including comparison, differentiation, counting, and logic. For example, while existing benchmarks focus only on counting objects [26, 85], real-world prompts often require counting attribute-object pairs or even object-relation-object triplets, like “one person wearing a white shirt and the other five wearing blue shirts”. To this end, after reviewing relevant literature [27, 51, 73, 85] and discussing with professional designers, we define a set of compositional reasoning skills and categorize them into “basic” and “advanced”, where the latter can build upon the former. For logical reasoning, we focus on “negation” and “universality”, which are the two most common types of logic observed in user prompts. Other logical operators such as conjunction [46] are not included; the logical “AND” is usually implied in prompts that involve multiple objects, and “OR” is rarely useful as designers tend to specify their requirements explicitly. Lastly, we leave it to future work to evaluate image styles. We provide detailed definitions for “basic” skills in Table 4 and “advanced” skills in Table 5.

Table 4: Skill definitions and examples for basic compositions.

Skill Type	Definition	Examples
Basic Compositions		
Object	Basic entities within an image, such as person, animal, food, items, vehicles, or text symbols (e.g., “A”, “1+1”).	a dog , a cat and a chicken on a table ; a young man with a green bat and a blue ball ; a ‘ No Parking ’ sign on a busy street .
Attribute	Visual properties of entities, such as color, material, emotion, size, shape, age, gender, state, and so on.	a silver spoon lies to the left of a golden fork on a wooden table ; a green pumpkin is smiling happily , a red pumpkin is sitting sadly .
Scene	Backgrounds or settings of an image, such as weather and location.	A child making a sandcastle on a beach in a cloudy day ; a grand fountain surrounded by historic buildings in a town square .
Spatial Relation	Physical arrangements of multiple entities relative to each other, e.g., on the right, on top, facing, towards, inside, outside, near, far, and so on.	a bustling city street , a neon ‘ Open 24 Hours ’ sign glowing above a small diner; a teacher standing in front of a world map in a classroom; tea steams in a cup, next to a closed diary with a pen resting on its cover.
Action Relation	Action interactions between entities, e.g., pushing, kissing, hugging, hitting, helping, and so on.	a dog chasing a cat ; a group of children playing on the beach; a boat glides across the ocean, dolphins leaping beside it and seagulls soaring overhead.
Part Relation	Part-whole relationships between entities – one entity is a component of another, such as body part, clothing, and accessories.	a pilot with aviator sunglasses ; a baker with a cherry pin on a polka dot apron ; a young lady wearing a T-shirt puts her hand on a puppy’s head .

Comparing skills across benchmarks. We find the skill categorization in benchmarks like PartiPrompt [85] to be ambiguous or even confusing. For example, PartiPrompt introduces two categories “*complex*” and “*fine-grained detail*”. The former refers to “...*fine-grained, interacting details or relationships between multiple participants*”, while the latter refers to “...*attributes or actions of entities or objects in a scene*”. Upon closer examination, the categorization of spatial, action, and part relations into these categories appears arbitrary. To address this, we attempt to compare the skill coverage across all benchmarks by our unified set of skills. For benchmarks (PartiPrompt/T2I-CompBench) with pre-defined skill categories, we map their skills to our definitions. For benchmarks (TIFAv1/Pick-a-pic/DrawBench/EditBench/HPDv2/EvalCrafter) without a comprehensive skill set, we manually annotate a random subset of samples. Finally, we calculate the skill proportions in each benchmark, identifying skills that constitute more than 2% as genuinely present.

Table 5: Skill definitions and examples for advanced compositions.

Skill Type	Definition	Examples
Advanced Compositions		
Counting	Determining the quantity, size, or volume of entities, e.g., objects, attribute-object pairs, and object-relation-object triplets.	<i>two cats playing with a single ball; five enthusiastic athletes and one tired coach; one pirate ship sailing through space, crewed by five robots; three pink peonies and four white daisies in a garden.</i>
Differentiation	Differentiating objects within a category by their attributes or relations, such as distinguishing between “old” and “young” people by age, or “the cat on top of the table” versus “the cat under the table” by their spatial relations.	<i>one cat is sleeping on the table and the other is playing under the table; there are two men in the living room, the taller one to the left of the shorter one; a notebook lies open in the grass, with sketches on the left page and blank space on the right; there are two shoes on the grass, the one without laces looks newer than the one with laces.</i>
Comparison	Comparing characteristics like number, attributes, area, or volume between entities.	<i>there are more people standing than sitting; between the two cups on the desk, the taller one holds more coffee than the shorter one, which is half-empty; a small child on a skateboard has messier hair than the person next to him; three little boys are sitting on the grass, and the boy in the middle looks the strongest.</i>
Negation	Specifying the absence or contradiction of elements, as indicated by “no”, “not”, or “without”, e.g., entities not present or actions not taken.	<i>a bookshelf with no books, only picture frames.; a person with short hair is crying while a person with long hair is not; a smiling girl with short hair and no glasses; a cute dog without a collar.</i>
Universality	Specifying when every member of a group shares a specific attribute or is involved in a common relation, indicated by words like “every”, “all”, “each”, “both”.	<i>in a room, all the chairs are occupied except one; a bustling kitchen where every chef is preparing a dish; in a square, several children are playing, each wearing a red T-shirt; a table laden with apples and bananas, where all the fruits are green; the little girl in the garden has roses in both hands.</i>

C GenAI-Bench

This section describes how we collect GenAI-Bench.

Details of GenAI-Bench. GenAI-Bench consists of 1,600 diverse prompts that cover advanced skills not addressed in previous benchmarks [27, 62, 85]. To ensure our prompts reflect real-world applications, we collaborate with graphic designers who use text-to-visual tools like Midjourney [51] in their profession. First, we collaborate with them to refine our skill taxonomy, identifying practical skills that current models may struggle with. They then gather compositional prompts relevant to their professional needs. To avoid copyright issues, we advise them to write prompts featuring generic subjects. We provide designers with sample prompts from existing benchmarks like DrawBench and PartiPrompt for inspiration and encourage the use of ChatGPT to brainstorm prompt variants across diverse visual domains. Importantly, these designers ensure that the prompts are *objective*. This contrasts with T2I-CompBench [27], whose prompts are almost entirely auto-generated. For example, in T2I-CompBench’s “*texture*” category, an overwhelming 40% of the 1000 programmatically-generated prompts use “metallic” as the attribute, which limits their diversity. Other T2I-CompBench’s prompts generated by ChatGPT often contain subjective (non-visual) phrases. For instance, in the prompt “the delicate, fluttering wings of the butterfly signaled the arrival of spring, a natural symbol of rebirth and renewal”, the “rebirth and renewal” can convey different meanings to different people. Similarly, in “the soft, velvety texture of the rose petals felt luxurious against the fingertips, a romantic symbol of love and affection”, the “love and affection” is also open to diverse interpretations. Thus, we carefully guide the designers to avoid such prompts. Lastly, each prompt in GenAI-Bench is tagged with all its relevant skills. In total, we collect over 5,000 human-verified tags with a roughly balanced distribution of “basic” and “advanced” skills.

Collecting human ratings. We evaluate six text-to-image models: Stable Diffusion [60] (SD v2.1, SD-XL, SD-XL Turbo), DeepFloyd-IF [13], Midjourney v6 [51], DALL-E 3 [2]; along with four text-to-video models: ModelScope [75], Floor33 [15], Pika v1 [55], Gen2 [18]. Due to the lack of APIs for Floor33 [15], Pika v1 [55], and Gen2 [18], we manually download videos from their websites. For image generative models, we generate images using all 1,600 GenAI-Bench prompts. We use a coreset of 800 prompts to collect videos for the four video models. The same 800 prompts are used to collect the GenAI-Rank benchmark in the main paper. In total, we collect over 80,000 human ratings, greatly exceeding the scale of human annotations in previous work [6, 26], e.g., TIFA160 collected 2,400 ratings. We pay the local minimum wage of 12 dollars per hour for a total of about 800 annotator hours.

GenAI-Bench performance. We detail the performance of the ten image and video generative models across all skills in Table 6. Both humans and VQAScores rate DALL-E 3 [2] higher than the other models in nearly all skills, except for negation. In addition, prompts requiring “advanced” compositions are rated significantly lower by both humans and VQAScores, with negation being the most challenging skill. Lastly, current video models do not perform as well as image models, suggesting room for improvement.

Table 6: **Performance breakdown on GenAI-Bench.** We present the averaged human ratings and VQAScores (based on CLIP-FlanT5) for “basic” and “advanced” prompts. Human ratings use a 1-5 Likert scale, and VQAScore ranges from 0 to 1, with higher scores indicating better performance for both. Generally, both human ratings and VQAScores favor DALL-E 3 over other models, with DALL-E 3 preferred across almost all skills except for negation. We find that “advanced” prompts that require higher-order reasoning present significant challenges. For instance, the state-of-the-art DALL-E 3 receives a remarkable average human rating of 4.3 for “basic” prompts, indicating the images and prompts range from “*having a few minor discrepancies*” to “*matching exactly*”. However, it scores only 3.4 for “advanced” prompts, suggesting “*several minor discrepancies*”. In addition, video models receive significantly lower scores than image models. Overall, VQAScores closely match human ratings.

Method	Attribute	Scene	Relation			Avg
			Spatial	Action	Part	
<i>Image models</i>						
SD v2.1	3.2	3.4	3.1	3.2	2.9	3.2
SD-XL Turbo	3.5	3.6	3.4	3.4	3.2	3.5
DeepFloyd-IF	3.6	3.7	3.6	3.6	3.4	3.6
SD-XL	3.6	3.8	3.5	3.6	3.5	3.7
Midjourney v6	4.0	4.1	4.0	4.1	3.8	4.0
DALL-E 3	4.3	4.4	4.2	4.3	4.2	4.3
<i>Video models</i>						
ModelScope	3.1	3.1	2.8	3.0	3.1	3.0
Floor33	3.2	3.2	2.9	3.2	3.1	3.1
Pika v1	3.4	3.4	3.1	3.3	3.2	3.3
Gen2	3.6	3.7	3.4	3.6	3.6	3.6

(a) Human ratings on “basic” prompts	Method	Attribute	Scene	Relation			Avg
				Spatial	Action	Part	
<i>Image models</i>							
SD v2.1	0.75	0.77	0.72	0.72	0.69	0.74	
SD-XL Turbo	0.79	0.82	0.77	0.78	0.76	0.79	
DeepFloyd-IF	0.82	0.83	0.80	0.81	0.80	0.81	
SD-XL	0.82	0.84	0.80	0.81	0.81	0.82	
Midjourney v6	0.85	0.88	0.86	0.86	0.85	0.85	
DALL-E 3	0.91	0.91	0.89	0.89	0.91	0.90	
<i>Video models</i>							
ModelScope	0.69	0.69	0.65	0.65	0.70	0.66	
Floor33	0.70	0.71	0.64	0.66	0.67	0.67	
Pika v1	0.78	0.80	0.74	0.72	0.76	0.75	
Gen2	0.79	0.81	0.74	0.76	0.83	0.77	

(b) VQAScores on “basic” prompts	Method	Attribute	Scene	Relation			Avg
				Spatial	Action	Part	
<i>Image models</i>							
SD v2.1	0.66	0.63	0.61	0.50	0.57	0.58	
SD-XL Turbo	0.69	0.65	0.64	0.51	0.57	0.60	
DeepFloyd-IF	0.69	0.66	0.65	0.48	0.57	0.60	
SD-XL	0.71	0.67	0.64	0.49	0.57	0.60	
Midjourney v6	0.75	0.73	0.70	0.49	0.64	0.65	
DALL-E 3	0.78	0.76	0.70	0.46	0.65	0.65	
<i>Video models</i>							
ModelScope	0.58	0.61	0.57	0.52	0.52	0.55	
Floor33	0.60	0.64	0.59	0.53	0.55	0.57	
Pika v1	0.65	0.64	0.63	0.55	0.63	0.61	
Gen2	0.69	0.69	0.64	0.54	0.58	0.62	

(c) Human ratings on “advanced” prompts	Method	Count	Differ	Compare	Logical		Avg
					Negate	Universal	
<i>Image models</i>							
SD v2.1	2.8	2.5	2.6	2.9	3.2	2.9	
SD-XL Turbo	3.0	2.6	2.6	2.9	3.3	3.0	
DeepFloyd-IF	3.0	2.7	2.6	2.9	3.3	3.0	
SD-XL	3.2	2.9	2.9	2.9	3.5	3.1	
Midjourney v6	3.4	3.2	3.2	3.1	3.9	3.3	
DALL-E 3	3.6	3.5	3.4	3.0	3.8	3.4	
<i>Video models</i>							
ModelScope	2.4	2.4	2.2	2.6	2.8	2.5	
Floor33	2.7	2.7	2.5	2.8	3.2	2.8	
Pika v1	2.7	2.7	2.6	2.9	3.3	2.9	
Gen2	2.8	2.7	2.6	2.9	3.3	2.9	

(d) VQAScores on “advanced” prompts	Method	Count	Differ	Compare	Logical		Avg
					Negate	Universal	
<i>Image models</i>							
SD v2.1	0.66	0.63	0.61	0.50	0.57	0.58	
SD-XL Turbo	0.69	0.65	0.64	0.51	0.57	0.60	
DeepFloyd-IF	0.69	0.66	0.65	0.48	0.57	0.60	
SD-XL	0.71	0.67	0.64	0.49	0.57	0.60	
Midjourney v6	0.75	0.73	0.70	0.49	0.64	0.65	
DALL-E 3	0.78	0.76	0.70	0.46	0.65	0.65	
<i>Video models</i>							
ModelScope	0.58	0.61	0.57	0.52	0.52	0.55	
Floor33	0.60	0.64	0.59	0.53	0.55	0.57	
Pika v1	0.65	0.64	0.63	0.55	0.63	0.61	
Gen2	0.69	0.69	0.64	0.54	0.58	0.62	

Algorithm 1: PyTorch-style pseudocode for VQAScore.

```
# tokenize(): text tokenizer that converts texts to a list of token indices
# vqa_model(): VQA model returns logits for predicted answer

def vqa_score(image, text):
    # Format the text into the below QA pair
    question = f"Does this figure show '{text}'? Please answer yes or no."
    answer = "Yes"

    # Tokenize the QA pair into tokens
    question_tokens = tokenize(question)
    answer_tokens = tokenize(answer)

    # Extract logits for predicted answer of shape [len(answer_tokens), vocab_size]
    # answer_tokens is a required input for auto-regressive decoding
    logits = vqa_model(image, question_tokens, answer_tokens)

    # labels must skip the first BOS (Begin-Of-Sentence) token
    labels = answer_tokens[1:]
    # logits must skip the last EOS (End-Of-Sentence) token
    logits = logits[:-1]

    # Compute the log likelihood of the answer
    log_likelihood = -torch.nn.CrossEntropyLoss()(logits, labels)
    # (Optional) Cancel the log to obtain P("Yes" | image, question)
    score = log_likelihood.exp()
    return score
```

D Implementing VQAScore

In this section, we describe how we compute VQAScore to ensure this paper is self-contained. For a more thorough discussion, please refer to our VQAScore paper [43].

Computing VQAScore as an auto-regressive product. Recall that VQAScore calculates the alignment score of an image \mathbf{i} and text \mathbf{t} directly from a VQA model. We first use a simple QA template to convert the text \mathbf{t} to a question and an answer (denoted as $\mathbf{q}(\mathbf{t})$ and $\mathbf{a}(\mathbf{t})$), for example:

$$\mathbf{q}(\mathbf{t}) = \text{Does this figure show "\{t\}"? Please answer yes or no.} \quad (2)$$

$$\mathbf{a}(\mathbf{t}) = \text{Yes} \quad (3)$$

We find that such a straightforward question-answer pair is sufficient for good performance across all benchmarks. In language modeling [1], a piece of text is pre-processed (or tokenized) into a token sequence, e.g., $\mathbf{a}(\mathbf{t}) = \{a_1, \dots, a_m\}$. Although “Yes” usually counts as a single token, we include the EOS (end-of-sentence) token at the end of the text sequence for a simpler implementation. We find that the EOS token only marginally affects the VQAScore results. Next, the generative likelihood of the answer (conditioned on both the question and image) can be naturally factorized as an auto-regressive product [1]:

$$\text{VQAScore}(\mathbf{i}, \mathbf{t}) := P(\mathbf{a}(\mathbf{t})|\mathbf{i}, \mathbf{q}(\mathbf{t})) = \prod_{k=1}^m P(a_k|a_{<k}, \mathbf{i}, \mathbf{q}(\mathbf{t})) \quad (4)$$

The answer decoders of VQA models [10, 45] return back m softmax distributions corresponding to the m terms in the above expression. Computing VQAScore is more efficient than generating answer token-by-token. Since the entire sequence of tokens $\{a_k\}$ is already available as input for VQAScore, the above m terms can be efficiently computed in *parallel*. In contrast, answer generation as done by [6, 26] requires *sequential* token-by-token prediction, as token a_k must be generated before it can serve as input to generate the softmax distribution for the subsequent token a_{k+1} .

Pseudocode of VQAScore. To better explain how VQAScore works, we attach the pseudocode in algorithm 1. We will release a pip-installable API to compute VQAScore using one-line of Python code.

E CLIP-FlanT5

This section describes the training of CLIP-FlanT5.

CLIP-FlanT5. We adhere to the training recipe of the state-of-the-art LLaVA-1.5 [44]. We adopt the same (frozen) CLIP visual encoder (ViT-L-336) [57] and the 2-layer MLP projector for image tokenization. We also follow LLaVA-1.5’s two-stage finetuning procedure and datasets. In stage-1 training, we finetune the MLP projector on 558K captioning data (LAION-CC-SBU with BLIP captions [38]). To accommodate FlanT5’s encoder-decoder architecture, we adopt the split-text training method proposed in BLIPv2 [38]. This involves splitting a caption into two parts at a random position, with the first part sent to the encoder and the second part to the decoder. In stage-2 training, we finetune both the MLP projector and the language model (FlanT5) on 665K mixture of public VQA datasets (e.g., VQAv2 [21] and GQA [28]). To efficiently train the encoder-decoder architecture, we convert all multi-turn VQA samples into single-turn, resulting in 3.4M image-question-answer pairs. We also retrain LLaVA-1.5 on the same single-turn VQA samples and observe the same VQAScore results. We borrow hyperparameters of LLaVA-1.5 (see Table 7), such as the learning rate schedule, optimizer, number of epochs, and weight decay. We use 8 A100 (80Gbs) GPUs to train all our models. Our largest CLIP-FlanT5-XXL (11B) takes 5 hours for the stage-1 and 80 hours for the stage-2. For stage-2 training, we adhere to the system (prefix) prompt of LLaVA-1.5 during training ²:

A chat between a curious user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user’s questions.

USER: image \n question ASSISTANT: answer

Table 7: **Training hyperparameters for CLIP-FlanT5.**

Hyperparameter	Stage-1	Stage-2
dataset size	558K	665K
batch size	256	96
lr	1e-2	2e-5
lr schedule	cosine decay	
lr warmup ratio	0.03	
weight decay	0	
epoch	1	
optimizer	AdamW	
DeepSpeed stage	2	3

F Details of Baseline Methods

In this section, we detail the implementation of the baseline methods. Note that Table 8 reports VQAScore performance on seven more benchmarks that measures correlation with human judgments.

CLIPScore and BLIPv2Score. To calculate CLIPScore, we use the same CLIP-L-336 model [23] of CLIP-FlanT5. To calculate BLIPv2Score, we use the ITM head of BLIPv2-vit-G [38]. For an in-depth analysis of how these discriminatively pre-trained VLMs behave as bag-of-words models, we refer readers to previous studies [29, 42, 73, 86].

Metrics finetuned on human feedback (PickScore/ImageReward/HPSv2). We use the official code and model checkpoints to calculate these metrics. Specifically, PickScore [31] and HPSv2 [81] finetune the CLIP-H model, and ImageReward [83] finetunes the BLIPv2 [38], using costly human feedback from either random web users or expert annotators. Our experiments on the Winoground and EqBen benchmarks (Table 8) show that these metrics perform no better than random chance, likely because the discriminative pre-trained VLMs bottleneck their performance due to bag-of-words encodings. In addition, their finetuning datasets may lack compositional texts. Finally, we observe that human annotations can be noisy or subjective, especially when these annotators are not well trained (e.g., random web users of the Pick-a-pic dataset [31]). We discuss these issues in Appendix G.

QG/A methods (VQ2/Davidsonian). We first note that these divide-and-conquer methods are the most popular in recent text-to-visual evaluation [2, 27, 69, 79]. VQ2 [84] uses a finetuned FlanT5 to generate free-form QA pairs and computes the average score of $P(\text{answer} | \text{image}, \text{question})$.

²By default, we also use the system prompt during inference. Interestingly, removing the system prompt (“A chat between a curious user ... answers to the user’s questions”) during inference does not affect CLIP-FlanT5 but will hurt LLaVA-1.5’s performance.

Table 8: **VQAScore on image-text alignment benchmarks.** We show Group Score for Winoground and EqBen; AUROC for DrawBench, EditBench, and COCO-T2I; pairwise accuracy [14] for TIFA160 and GenAI-Bench; and binary accuracy for Pick-a-Pick, with higher scores indicating better performance for all metrics. VQAScore (based on CLIP-FlanT5) outperforms all prior art across all benchmarks.

Method	Models	Winoground	EqBen	DrawBench	EditBench	COCO-T2I	TIFA160	Pick-a-Pic	GenAI-Bench
<i>Based on vision-language models</i>									
CLIPScore [23]	CLIP-L-14	7.8	25.0	49.1	60.6	63.7	54.1	76.0	50.3
<i>Finetuned on human feedback</i>									
PickScore [31]	CLIP-H-14 (finetuned)	6.8	23.6	72.3	64.3	61.5	59.4	70.0	56.2
ImageReward [83]	BLIPv2 (finetuned)	12.8	26.4	70.4	70.3	77.0	67.3	75.0	55.8
HPSv2 [81]	CLIP-H-14 (finetuned)	4.0	17.0	63.1	64.1	60.3	55.2	69.0	49.3
<i>QG/A methods</i>									
VQ2 [84]	FlanT5, LLaVA-1.5	10.0	20.0	52.8	52.8	47.7	48.7	73.0	51.3
Davidsonian [6]	ChatGPT, LLaVA-1.5	15.5	20.0	78.8	69.0	76.2	54.3	70.0	53.1
<i>VQAScore (ours) using open-source VQA models</i>									
VQAScore	InstructBLIP	28.5	38.6	82.6	75.7	83.0	70.1	83.0	62.3
VQAScore	LLaVA-1.5	29.8	35.0	82.2	70.6	79.4	66.4	76.0	61.6
<i>VQAScore (ours) using our VQA model</i>									
VQAScore	CLIP-FlanT5	46.0	47.9	85.3	77.0	85.0	71.2	84.0	62.8

Davidsonian uses a more sophisticated pipeline by prompting ChatGPT to generate yes-or-no QA pairs while avoiding inconsistent questions. For example, given the text “the moon is over the cow”, if a VQA model already answers “No” to “Is there a cow?”, it then skips the follow-up question “Is the moon over the cow?”. However, these methods often generate nonsensical QA pairs, as shown in Table 9 on real-world user prompts from GenAI-Bench.

Table 9: **Failure cases of divide-and-conquer methods (VQ2/Davidsonian).** We show generated question-and-answer pairs of VQ2 and Davidsonian on three GenAI-Bench prompts. These methods often generate irrelevant or erroneous QA pairs (highlighted in red), especially with more compositional texts.

Method	Generated questions	Candidate answers (correct answer choice in bold)
VQ2	Text: “a snowy landscape with a cabin, but no smoke from the chimney” What is the name of the landscape on which it’s a cabin? In this landscape what does the fire not go off?	a snowy landscape a cabin
Davidsonian	Is there a landscape? Is there no smoke from the chimney? Is the cabin in the landscape?	yes, no yes, no yes, no
VQ2	Text: “six people wear white shirts and no people wear red shirts” What does the average American wear? What kind of clothes do not all people wear?	white shirts red shirts
Davidsonian	Are there people? Are the shirts red? Are the shirts white?	yes, no yes, no yes, no
VQ2	Text: “in the classroom there are two boys standing together, the boy in the red jumper is taller than the boy in the white t-shirt” Where do two tall kids stand? Which color of jumper is the tallest?	the classroom the red jumper
Davidsonian	Is the boy in the red jumper wearing a red jumper? Is the boy in the white t-shirt wearing a white t-shirt? Are the boys standing together?	yes, no yes, no yes, no

G Details of Alignment Benchmarks

This section discusses other benchmarks.

TIFA160 [26]. TIFA160 collects 160 text prompts from four sources: MSCOCO captions [40], DrawBench [62], PartiPrompts [85], and PaintSkill [7]. Each text prompt is paired with five text-to-image models, generating a total of 800 image-text pairs. Furthermore, Davidsonian [6] labels these image-text pairs using 1-5 Likert scale for human evaluation.

Pic-a-pick [31]. We find that the text-to-image evaluation benchmark, Pic-a-pick, contains an excessive amount of NSFW (sexual/violent) content and incorrect labels, likely due to an inadequate automatic filtering procedure. Specifically, after manually reviewing the test set of 500 samples, we

find that 10% contain inappropriate content (e.g., “*zentai*” and “*Emma Frost as an alluring college professor wearing a low neckline top*”) and approximately 50% had incorrect labels. This may also account for the inferior performance of PickScore. As a result, we manually filter the test set to obtain a clean subset of 100 prompts paired with 200 images for evaluating binary accuracy. We also remove all tied labels due to their subjective nature. We will release this subset of Pick-a-pic for reproducibility.

SeeTrue [84] (DrawBench/EditBench/COCO-T2I). We utilize the binary match-or-not labels collected by SeeTrue [84] for the three benchmarks. These benchmarks consist of individual image-text pairs, where some pairs are correctly paired and others are not. We follow their original evaluation protocols to report the AUROC (Area Under the Receiver Operating Characteristic curve), taking into account all possible classification thresholds.

Winoground [73] and EqBen [77]. In our study, we use the entire Winoground dataset consisting of 400 pairs of image-text pairs. For EqBen, because the official test set includes low-quality images (e.g., very dark or blurry pictures), we analyze the higher-quality EqBen-Mini subset of 280 pairs of image-text pairs, as recommended by their official codebase. These two benchmarks evaluate image-text alignment via matching tasks: each sample becomes 2 image-to-text matching tasks with one image and two candidate captions, and 2 text-to-image matching tasks with one caption and two candidate images. The text (and image) score is awarded 1 point only if *both* matching tasks are correct. The final group score is awarded 1 point only if *all* 4 matching tasks are correct. Importantly, we discover that these benchmarks (especially Winoground) test advanced compositional reasoning skills crucial for understanding real-world prompts, such as counting, comparison, differentiation, and logical reasoning. These advanced compositions operate on basic visual entities, which themselves can be compositions of objects, attributes, and relations.