DSH-BENCH: A DIFFICULTY- AND SCENARIO-AWARE BENCHMARK WITH HIERARCHICAL SUBJECT TAXONOMY FOR SUBJECT-DRIVEN TEXT-TO-IMAGE GENERATION

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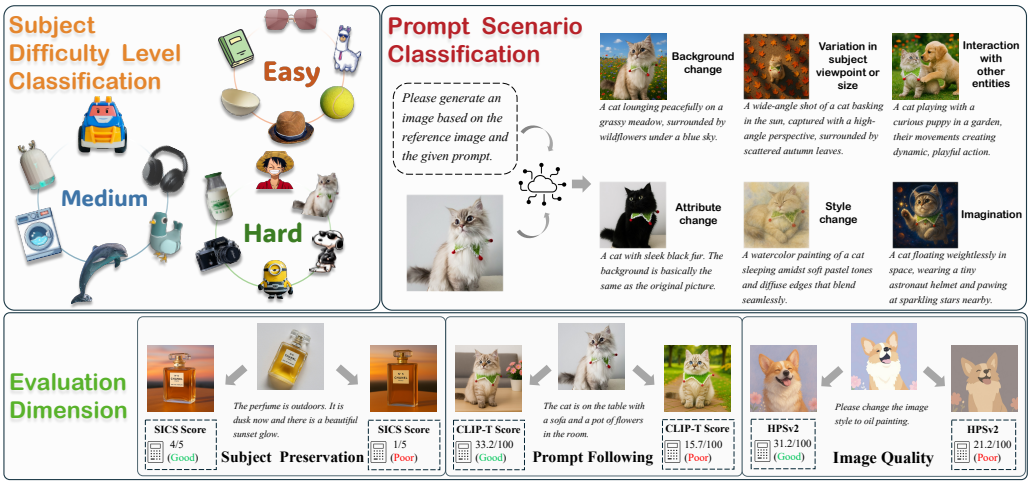


Figure 1: **Overview of DSH-Bench**. We curate a diverse dataset of subject images and categorize them into three difficulty levels—**easy**, **medium**, and **hard**—based on the complexity of preserving subject details. Leveraging GPT-4o's capabilities, we systematically generate contextually appropriate prompts for various scenarios. The generated images are then rigorously evaluated across three key dimensions: **Subject Preservation**, **Prompt Following**, and **Image Quality**.

ABSTRACT

Significant progress has been achieved in subject-driven text-to-image (T2I) generation, which aims to synthesize new images depicting target subjects according to user instructions. However, evaluating these models remains a significant challenge. Existing benchmarks exhibit critical limitations: 1) insufficient diversity and comprehensiveness in subject images, and 2) inadequate granularity in assessing model performance across different subject difficulty levels and prompt scenarios. To address these limitations, we propose DSH-Bench, a comprehensive benchmark that enables systematic multi-perspective analysis of subject-driven T2I models through three principal innovations: 1) a hierarchical taxonomy sampling mechanism ensuring comprehensive subject representation across 58 fine-grained categories, 2) an innovative classification scheme categorizing both subject difficulty level and prompt scenario for granular model capability assessment, and 3) a novel Subject Identity Consistency Score (SICS) metric demonstrating 9.4% higher correlation with human evaluation compared to existing measures in quantifying subject preservation. Through empirical evaluation of 15 subject-driven T2I models, DSH-Bench uncovers previously obscured limitations in current approaches while establishing concrete directions for future research.

1 INTRODUCTION

Subject-driven text-to-image (T2I) generation aims to generate images conditioned on both textual prompts and specific reference images. It has become feasible due to significant advancements in large-scale T2I generative models (Ding et al., 2021; Gafni et al., 2022; Saharia et al., 2022; Rombach et al., 2022a; Balaji et al., 2022; Chang et al., 2023; Kang et al., 2023; Dong et al., 2024). In subject-driven T2I generation, aside from image quality considerations, two other fundamental criteria must be satisfied: Subject Preservation and Prompt Following. Subject Preservation requires that the generated image maintain the details of the reference subject. Prompt Following demands that the generated image consistently reflects the content in the prompt. For example, a user might request an image of "his dog traveling around the world". In this scenario, the generated image must depict a dog identical to the reference image while illustrating the act of traveling as described.

Significant progress has been made in subject-driven T2I generation in recent years (Ruiz et al., 2023; Gal et al., 2022; Kumari et al., 2023; Wang et al., 2024a; Li et al., 2023a; Ye et al., 2023; Gal et al., 2023b; Wei et al., 2023; Hu et al., 2024b; Qiu et al., 2023). One approach involves fine-tuning general T2I models to create specialized models that reproduce specific subjects present in the training datasets. Alternatively, encoder-based methods achieve subject preservation by adapting features to incorporate reference subject into a general T2I model. Despite these advancements, challenges remain in comprehensively and effectively evaluating the actual performance of these models. An effective evaluation method should not only provide a comprehensive and unbiased assessment, but also align with human perception to ensure reliable measurement. Furthermore, the evaluation method is expected to provide valuable insights for future research. However, current benchmarks (Ruiz et al., 2023; Kumari et al., 2023; Chen et al., 2023a; Wang et al., 2024b; Peng et al., 2025) are limited by insufficient diversity and comprehensiveness in subject image collection, which restricts the thoroughness of model evaluation. In addition, they do not facilitate a detailed understanding of subject difficulty and prompt scenarios, thus constraining the depth of insights obtainable from the evaluation. As shown in Figure 3, our analysis of numerous model-generated instances reveals that different subject images and prompts place varying demands on a model's ability. For example, although subject-driven T2I models are capable of effectively preserving the details of relatively simple objects (e.g., a tennis ball), they often struggle to accurately reproduce objects with more intricate features (e.g., a camera). This observation highlights the importance of categorizing the subject difficulty and prompt scenario to better assess model performance. To address these requirements, we introduce DSH-Bench, a novel benchmark offers three notable advantages:

1. ***The diversity of subject images in DSH-Bench is substantially greater*** To mitigate evaluation bias caused by low diversity of subject images, we employ a hierarchical taxonomy in image collection. We referenced COCO (Lin et al., 2014) and ImageNet (Deng et al., 2009) in the hierarchical taxonomy construction. As shown in Figure 4(a), the widely used DreamBench includes only 6 categories and 30 subjects. In contrast, our benchmark expands the dataset to 48 categories and 459 subjects—representing an increase of **8**× and **15**×, respectively. Although DreamBench++ (Peng et al., 2025) offers 150 subjects, its diversity is constrained by its image collection. Notably, **33%** of our categories are not represented in DreamBench++. Therefore, benefiting from DSH-Bench's greater subject diversity, we enable more comprehensive evaluation of models.

2. ***An innovative classification scheme for subject difficulty level and prompt scenario*** Figure 3 shows the model's performance varies significantly with different samples, highlighting the necessity for a classification of both subject image and prompt. Although DreamBench++ categorizes prompts based on their perceived difficulty, the criteria underlying this classification are not clearly defined. Additionally, DreamBench++ does not analyze the difficulty levels associated with different subjects. To address these limitations, we categorize subjects into three difficulty levels (easy, medium, and hard) according to the difficulty of preserving visual appearance and classify prompts into six scenarios (background change, variation in subject viewpoint or size, interaction with other entities, attribute change, style change, imagination). As a result, our approach enables a more comprehensive and granular analysis of the challenges faced by current models.

3. ***A human-aligned and more efficient metric for subject preservation*** DreamBench++ replaces CLIP (Radford et al., 2021) and DINO (Caron et al., 2021) with GPT-4o (OpenAI, 2024) for evaluation, resulting in improved alignment with human evaluation. However, our benchmark reveals that per-model evaluation under this paradigm requires approximately 20,000 API calls to

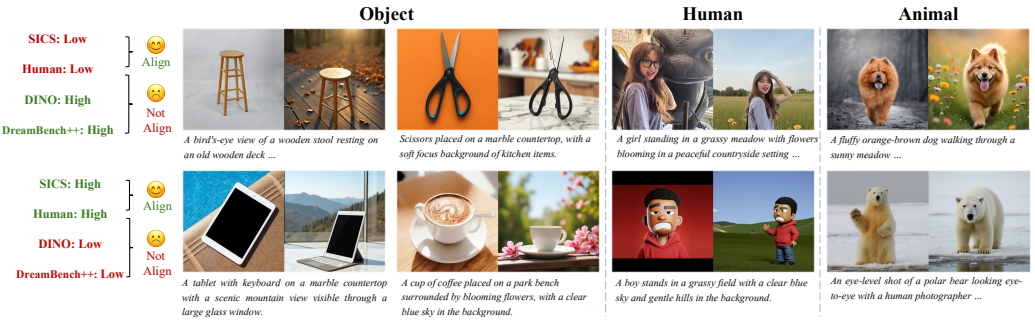


Figure 2: Qualitative comparison of subject preservation between SICS and the other methods.

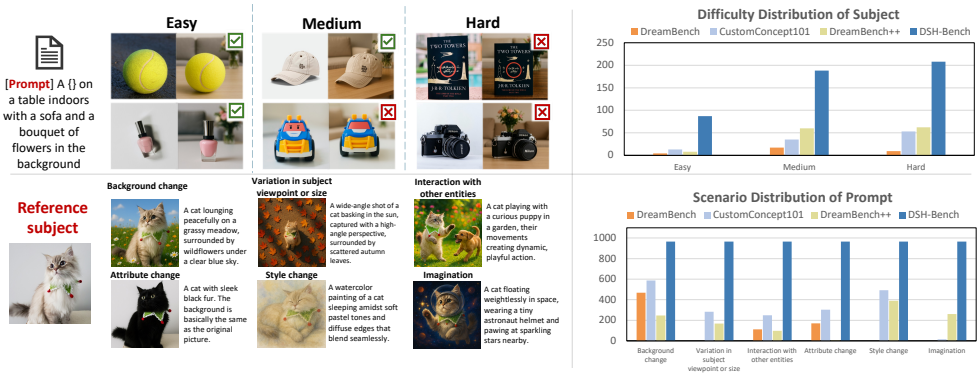
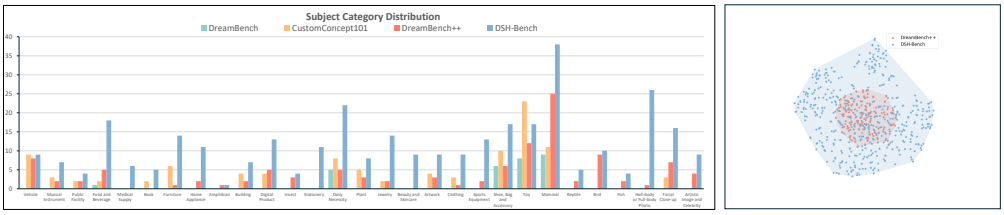


Figure 3: Qualitative comparison of generated images under different difficulty levels and scenarios.

GPT-4o, incurring prohibitive computational costs exceeding $400 for each evaluation. To address the limitation, we introduce **Subject Identity Consistency Score** (SICS), which innovatively focuses on subject-level consistency rather than merely relying on embedding comparisons. Firstly, five annotators label a training dataset containing 5,000 image-text pairs, focusing on subject preservation evaluation. We then fine-tune Qwen2.5-VL-7B (Bai et al., 2025) on this dataset, which leads the model to focus on core visual attributes rather than high-level semantics. Finally, we use Kendall's τ value to quantify the alignment between model outputs and human evaluation. Experimental results demonstrate that SICS achieves a statistically significant improvement, outperforming Dreambench++ by 9.4% in human evaluation correlation metrics. Figure 2 presents a partial qualitative comparison of concept preservation between SICS and the other assessment methods.

Takeaways We present some insightful findings from evaluating fifteen methods: i) Our evaluation reveals that no single method demonstrates consistently robust performance across all categories. Therefore, implementing hierarchical taxonomy sampling of subject images is critical for mitigating potential evaluation biases. ii) All methods exhibit degraded performance on hard subject images. It is crucial to enhance models' ability to encode and reconstruct complex subject details more effectively in future research. iii) The subject-driven T2I model's capability for different prompt scenarios is not robust. Future research on subject-driven T2I generation should focus on optimizing for adaptation to a variety of prompt scenarios.

In summary, our contributions are as follows: 1) We employ a hierarchical taxonomy in image collection to ensure both the diversity and comprehensiveness of subject images. 2) We propose an innovative classification scheme to categorize subject difficulty levels and prompt scenarios. This scheme enables us to obtain valuable insights. 3) We propose a human-aligned metric to evaluate subject preservation, which offers greater efficiency compared to DreamBench++. We are open-sourcing DSH-Bench, including subject images, prompts, generated images and related code.



(a) Distribution of Subject Images Across Different Categories (Under Photorealistic Category)

(b) t-SNE Visualization of DreamBench++ vs. DSH-Bench

Figure 4: **Distribution of subject images.** (a) Category-wise image distribution for our benchmark versus prior benchmarks. (b) t-SNE comparison of images between DSH-Bench and DreamBench++.

2 DSH-BENCH

This section provides an overview of the primary components of DSH-Bench. Section 2.1 outlines the data construction process. Section 2.2 introduces the definitions and evaluation methods for three evaluation dimensions. *A detailed explanation is available in the supplementary materials.*

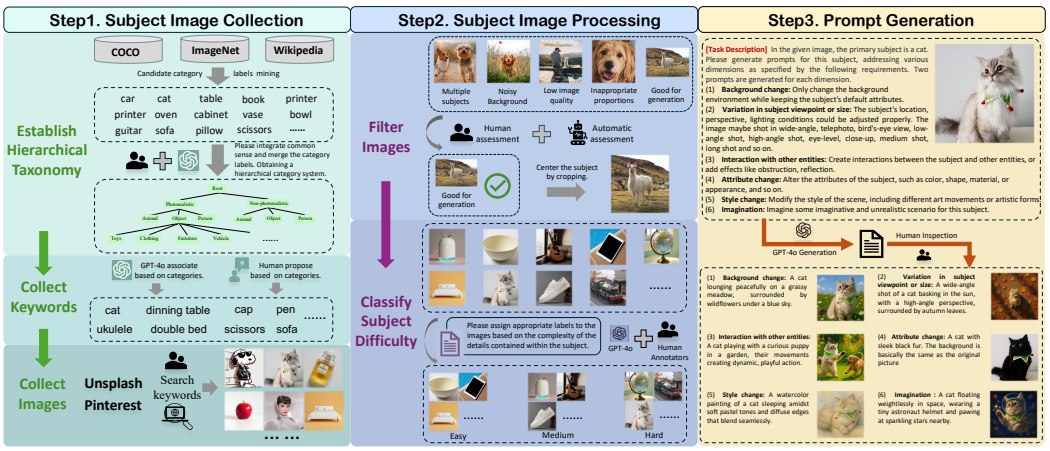


Figure 5: **Dataset construction process of DSH-Bench.** We construct a hierarchical taxonomy to obtain a comprehensive set of keywords. Then we collect web images using these keywords. After performing both manual review and automated filtering of the images, we classify the difficulty of subject images and use GPT-4o to generate prompts for each subject image.

2.1 BENCHMARK DATASET CONSTRUCTION

2.1.1 SUBJECT IMAGE COLLECTION

Hierarchical Taxonomy Establishment As shown in Figure 5, we establish a hierarchical taxonomy. For the first- and second-level categories, we primarily refer to existing benchmarks from prior studies (Ruiz et al., 2023; Kumari et al., 2023; Peng et al., 2025), resulting in two first-level categories and six second-level categories. For the third-level categories, we first reference COCO and ImageNet to compile a list of candidate category labels, then utilize GPT-4o to consolidate them into 58 refined categories. The final hierarchical taxonomy is confirmed and refined through co-authors' discussion. The detailed process and the category contents are provided in Appendix A.

Keyword Collection & Internet Image Collection In DreamBench++, keywords collection relies on GPT-4o and human input. The approach does not adequately ensure the diversity of the obtained keywords, potentially introducing bias during the image collection process. In contrast, DSH-Bench derives keywords from a hierarchical taxonomy. For each third-level category, we use GPT-4o to generate associated keywords, which are further supplemented by humans. All keywords are

then consolidated and deduplicated, resulting in a final set of **400** unique keywords—surpassing DreamBench++'s 300. The specific keywords are provided in the Appendix B. Given a set of selected keywords, we retrieve images from Unsplash (uns) and Pinterest (pin). Keywords without suitable images are discarded. *Each image's copyright status has been verified for academic suitability*.

2.1.2 Subject Image Processing

Image Filtering To filter unsuitable images, human annotators remove images with multiple subjects and noisy backgrounds. We use aesthetic score (Xu et al., 2024) and SAM (Kirillov et al., 2023) to filter images with low image quality and inappropriate proportions of subject regions. The curated images are subsequently cropped to centralize the reference subject.

Subject Difficulty Level Classification As illustrated in Figure 3, the model's performance varies considerably across different samples. To derive meaningful insights, we classify the subject images according to the difficulty level that the model experiences in preserving details of the reference subject. We define three subject difficulty levels, including (1) **Easy:** Subjects characterized by minimal surface complexity and homogeneous textural properties, exemplified by smooth-surfaced objects such as a ceramic mug with uniform coloration. These cases present negligible challenges for detail preservation due to their structural regularity. (2) **Medium:** Subjects containing discernible high-frequency features while maintaining global structural coherence, such as cylindrical containers with legible typographic elements. These cases require intermediate detail preservation capabilities. (3) **Hard:** Subjects exhibiting non-uniform texture distributions and multi-scale geometric details, typified by objects like book covers containing fine-grained calligraphic elements. Such cases expose model limitations in maintaining structural fidelity and textural granularity under complex topological constraints. We utilize GPT-4o to classify the subject images according to the aforementioned criteria. Subsequently, all images are reviewed by five human annotators to ensure accuracy and consistency.

2.1.3 Prompt Generation

Although DreamBench++ categorizes prompts based on their perceived difficulty, it does not provide empirical evidence to substantiate the criterion. To address this limitation, we organize the prompts according to specific application scenarios, dividing them into six categories, including (1) **Background change (BC):** scenarios involving changes in background elements. (2) **Variation in subject viewpoint or size (VS):** scenarios that entail changes in camera angle, which may include variations in subject size, lighting, or shadows. (3) **Interaction with other entities (IE):** scenarios requiring complex interactions with additional entities, potentially resulting in occlusion and necessitating adherence to physical plausibility. (4) **Attribute change (AC):** scenarios involving modifications to certain attributes of the subject, such as color or shape. (5) **Style change (SC):** scenarios involving alterations in the artistic or visual style of the subject. (6) **Imagination (IM):** scenarios where the target image depicts an imagined or fictional scene. We generate two prompts for each scenario. The specific instructions are depicted in Figure 5. All prompts are reviewed by five human annotators to ensure they are ethical and free from defects. For the specific verification procedure, please refer to the Appendix E.3. Finally, we obtain a total of **459** high-quality images and **5,508** prompts. Figure 3 shows the distribution of subject image difficulty levels and prompt scenarios. We visualize the t-SNE of images from our benchmark and DreamBench++ in Figure 4(b). The results indicate that our benchmark achieves superior diversity.

2.2 Evaluation Dimension

Previous notable works (Ruiz et al., 2023; Gal et al., 2022; Kumari et al., 2023; Wang et al., 2024a) evaluate the performance of subject-driven T2I models from two perspectives: Subject Preservation and Prompt Following. Mao et al. (2024) also uses ImageReward (Xu et al., 2023) to evaluate image quality. Therefore, DSH-Bench evaluates from the three aforementioned dimensions.

Subject Preservation DreamBench++ utilizes GPT-4o for evaluation to improve alignment with human assessments. However, the GPT-4o-based method is prohibitively expensive. To address this limitation, we propose a novel metric—**Subject Identity Consistency Score** (SICS). Firstly, we establish a scoring criterion for assessing subject preservation, the details are provided in Appendix E.2. Five annotators label the collected image pairs according to the criterion. During the annotation process, each image pair is not only assigned a score but also accompanied by an explanation. Previous

work (Wei et al., 2022) has indicated that labeled data with explanatory reasoning can help models better understand the underlying logic and reasoning behind the labels. We then perform meticulous fine-tuning of the model using this annotated dataset. During fine-tuning, SICS leverages prompts to explicitly prioritize subject consistency rather than global semantics, mitigating background and style artifacts that commonly bias CLIP-based approaches and yielding closer alignment with the goals of subject-consistency evaluation. Although GPT-4o demonstrates outstanding performance across a wide range of tasks, it has not been specifically optimized for subject preservation evaluation. More details of the SICS metric can be found in Appendix E.2.

Prompt Following Prompt following primarily evaluates whether a model can generate images that accurately correspond to textual prompts. DreamBench++ has demonstrated that the CLIP-T score is highly consistent with human annotations. Therefore, we also adopt CLIP-T score as the evaluation metric for prompt following.

Image Quality HPSv2 (Wu et al., 2023) utilizes professionally annotated data to more accurately reflect human aesthetic preferences for generated images. Previous studies (Sun et al., 2025) demonstrate that models optimized with HPSv2 achieve superior performance in image quality assessment compared to existing approaches. Therefore, we adopt HPSv2 for image quality evaluation.

3 Experiment

3.1 Experiment Setup

Implementation Details We conduct experiments on two mainstream approaches: ***i) Finetuning-based:*** 1) Textual Inversion(TI) (Gal et al., 2023a), 2) DreamBooth, 3) Custom Diffusion, 4) Hiper (Han et al., 2023), 5) NeTI (Alaluf et al., 2023). ***ii) Encoder-based:*** 1) BLIP-Diffusion (Li et al., 2023a), 2) IP-Adapter (Ye et al., 2023), 3) MS-Diffusion (Wang et al., 2024b), 4) Emu2 (Sun et al., 2024), 5) OminiControl (Tan et al., 2024), 6) SSR-Encoder (Zhang et al., 2024), 7) RealCustom++ (Mao et al., 2024), 8) OmniGen (Xiao et al., 2024), 9) λ-Eclipse (Patel et al., 2024), 10) UNO (Wu et al., 2025). Our experiments are conducted using the official implementations to guarantee reliability and fairness. More details can be found in Appendix E.

Human Annotation All annotation tasks, including labeling of the SICS training datasets, were conducted by the same five human annotators. We provide the annotators with detailed labeling guidelines and sufficient training to ensure they fully understand the subject-driven T2I generation task and could provide unbiased and discriminative scores. For additional details regarding the human annotation process, please see the Appendix E.4.

Table 1: The human alignment degree among different metrics, measured by **Kendall's τ value** and **Spearman correlation coefficient value**. H: Human, G: GPT-4o, D: DINO, Dv2: DINOv2, CB: CLIP-B, CL: CLIP-L, S: SICS. Bold font is used to denote the maximum value in a row.

Method	Kendall↑						Spearman↑					
	H-CB	H-CL	H-D	H-Dv2	H-G	H-S	H-CB	H-CL	H-D	H-Dv2	H-G	H-S
BLIP-Diffusion	0.228	0.176	0.285	0.167	0.354	**0.531**	0.285	0.215	0.350	0.206	0.383	**0.554**
IP-Adapter	0.294	0.296	0.258	0.290	0.419	**0.622**	0.364	0.371	0.325	0.364	0.459	**0.657**
MS-Diffusion	0.158	0.090	0.116	0.122	0.119	**0.178**	**0.194**	0.109	0.144	0.156	0.131	0.189
OminiControl	0.375	0.371	0.337	0.348	0.650	**0.713**	0.490	0.486	0.441	0.453	0.729	**0.764**
SSR-Encoder	0.264	0.338	0.295	0.348	0.504	**0.664**	0.328	0.421	0.368	0.434	0.549	**0.697**
UNO	0.249	0.218	0.299	0.240	0.236	**0.385**	0.340	0.297	0.390	0.312	0.268	**0.426**
RealCustom++	0.181	0.128	0.206	0.241	0.291	**0.464**	0.229	0.162	0.266	0.303	0.325	**0.511**
OmniGen	0.465	0.396	0.344	0.349	0.617	**0.621**	0.579	0.497	0.440	0.456	**0.697**	0.667
λ-Eclipse	0.143	0.233	0.084	0.103	0.325	**0.375**	0.176	0.287	0.103	0.127	0.352	**0.393**
Custom Diffusion	0.316	0.336	0.382	0.425	0.487	**0.642**	0.388	0.409	0.470	0.519	0.512	**0.654**
DreamBooth	0.639	0.591	0.537	0.429	0.647	**0.692**	0.733	0.721	0.661	0.537	0.705	**0.740**
Textual Inversion	0.482	0.459	0.447	0.438	0.541	**0.568**	0.587	0.559	0.545	0.534	0.582	**0.590**
HiPer	0.338	0.387	0.351	0.404	0.584	**0.625**	0.417	0.469	0.430	0.496	0.629	**0.655**
NeTI	0.469	0.456	0.431	0.417	0.617	**0.728**	0.573	0.561	0.529	0.512	0.682	**0.778**
ALL	0.416	0.411	0.350	0.376	0.619	**0.677**	0.529	0.522	0.451	0.483	0.697	**0.734**

3.2 Main Results

SICS Results Table 1 presents a rigorous study of human alignment using *Kendall's τ value* (KDV) and *Spearman correlation coefficient value* (SCV) (metric selection rationale in Appendix E.2). Our experimental results demonstrate that **SICS achieves superior alignment with human evaluations**

Table 2: **Evaluation of Subject-driven T2I generation.** DB: DreamBench, DB++: DreamBench++, HB: DSH-Bench. All scores are normalized to 0-1. Bold indicates the minimum value in each row for a given evaluation dimension..

Method	Subject Preservation			Prompt Following			Image Quality		
	DB	DB++	HB	DB	DB++	HB	DB	DB++	HB
BLIP-Diffusion	0.229	0.216	**0.204**	0.291	0.278	**0.277**	0.267	0.254	**0.223**
IP-Adapter	0.230	0.244	**0.229**	0.321	0.318	**0.315**	0.291	0.296	**0.266**
MS-Diffusion	**0.316**	0.346	0.352	**0.332**	0.339	0.338	0.311	0.314	**0.294**
OminiControl	0.279	0.268	**0.258**	**0.325**	0.337	0.334	0.312	0.308	**0.290**
SSR-Encoder	0.231	**0.202**	**0.202**	0.290	**0.287**	0.295	0.273	0.270	**0.247**
UNO	**0.409**	0.410	**0.409**	**0.317**	0.322	0.323	0.304	0.297	**0.278**
Emu2	0.360	0.343	**0.341**	**0.291**	0.309	0.304	0.272	0.278	**0.260**
RealCustom++	0.377	0.380	**0.375**	**0.325**	0.329	0.332	0.316	0.314	**0.298**

Table 3: **DSH-Bench leaderboard.** The models are ranked by the final score S_h. We only present the top models; the complete ranking can be found in the Appendix D.2.

Method	T2I Model	Subject Preservation	Prompt Following	Image Quality	$S_h\uparrow$
UNO	FLUX.1-dev	**0.409**	0.323	0.278	**0.252**
RealCustom++	SDXL	0.375	0.332	**0.294**	0.251
MS-Diffusion	SDXL	0.352	**0.338**	**0.294**	0.248
Emu2	SDXL	0.341	0.304	0.260	0.228
OminiControl	FLUX.1-schnell	0.258	0.334	0.290	0.218
IP-Adapter	SDXL	0.256	0.292	0.266	0.199
λ-Eclipse	SDXL	0.229	0.315	0.242	0.198
OmniGen	SD v1.5	0.202	0.295	0.265	0.183
SSR-Encoder	SDXL	0.188	0.322	0.247	0.181
NeTI	SD v1.4	0.192	0.301	0.234	0.176
BLIP-Diffusion	SD v1.5	0.204	0.277	0.223	0.174
DreamBooth	SD v1.5	0.158	0.321	0.245	0.164
HiPer	SD v1.4	0.135	0.318	0.247	0.151
Textual Inversion	SD v1.5	0.109	0.299	0.225	0.129
Custom Diffusion	SD v1.4	0.062	0.323	0.240	0.091

compared to existing methods, showing consistently higher agreement across both correlation metrics in most experimental settings. Although SICS attains second-highest correlation scores in MS-Diffusion and OmniGen, it significantly outperforms GPT-4o (*GPT-4o refers to the evaluation method used in DreamBench++*) by **9.37%** (KDV) and **5.31%** (SCV). This performance gap strongly suggests SICS's enhanced capability in modeling human evaluation. Notably, GPT-4o exhibits greater consistency with human evaluation than CLIP and DINO, aligning with DreamBench++ findings. Importantly, our proposed SICS metric surpasses all existing metrics in human judgment consistency.

Quantitative & Qualitative Results Table 2 shows overall evaluation results. The results show that: **i) DSH-Bench poses more significant challenges than existing benchmarks.** For subject preservation and image quality, the majority of methods consistently yield lower scores on DSH-Bench. The result can be attributed to the hierarchical taxonomy sampling method employed, which allows our dataset to more accurately represent the true data distribution. Moreover, it highlights that benchmarks derived from true distributions present greater challenges. **ii)** For prompt following, DreamBench yields slightly lower scores than DSH-Bench for certain methods. In DreamBench, prompts requiring attribute change constitute 22.7%, which is higher than the 16.7% observed in DSH-Bench. Figure 7(b) indicates that all methods exhibit relatively poor average performance on prompts involving attribute change. **iii)** Table 3 shows that there exists a trade-off between subject preservation and prompt following. We plot the Pareto frontier (see in Appendix D.1) using the data presented in Table 3. The primary objective is to identify a Pareto optimal solution that effectively balances the two objectives. *Additional results and discussions can be found in Appendix D.2.*

Leaderboard In order to assess a model's overall capability, we define the final score as:

$$\mathcal{S}_{\mathrm{h}} = \frac{3}{\frac{\lambda}{\mathrm{SP}} + \frac{\gamma}{\mathrm{PF}} + \frac{\mu}{\mathrm{IQ}}} \tag{1}$$

SP, PF, and IQ represent the scores for Subject Preservation, Prompt Following, and Image Quality, respectively. λ, γ, μ are the weights assigned to the importance of each corresponding dimension. In this study, we set $\lambda = 1.5, \gamma = 1.5, \mu = 1$, as subject preservation and prompt following are of paramount importance in subject-driven T2I generation. The harmonic mean requires strong

performance across all dimensions to yield a high overall score. We rank models by S_h scores in Table 3. UNO exhibits relatively strong overall performance. We attribute this improvement to the novel architectural design of UNO and the minimal yet effective modifications implemented in DiT.

4 Analysis

In this section, we conduct a detailed analysis of the performance of all methods based on the hierarchical category, the subject difficulty level classification, and the prompt scenario classification:

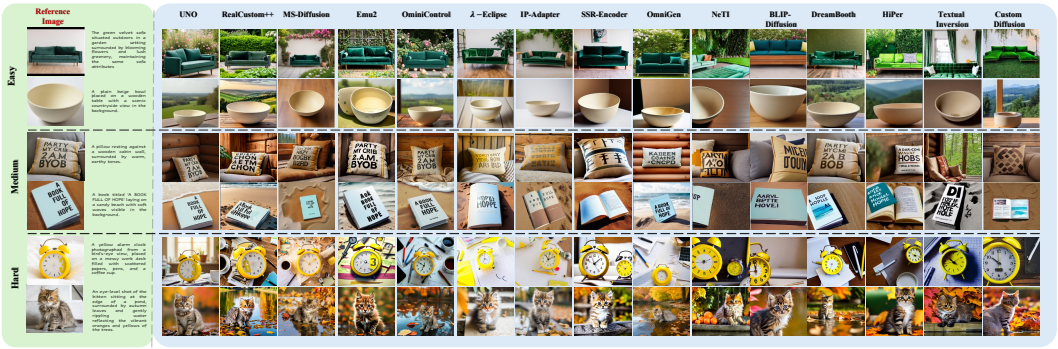


Figure 6: Examples generated by methods listed in the leaderboard. Best viewed when zoomed in.

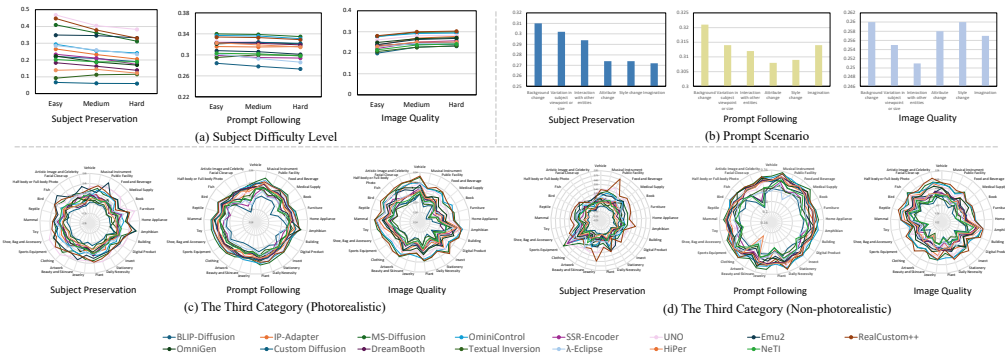


Figure 7: Comparison for DSH-Bench scores in different evaluation dimensions. The specific metric values are provided in the Appendix D.2. Best viewed when zoomed in.

A scientific and comprehensive subject image sampling method is necessary Figure 7(c) and Figure 7(d) present the performance of various methods in the third-level categories. The results reveal that model robustness varies considerably among categories. For example, performance in categories "*artwork*" (both photorealistic and non-photorealistic) is substantially lower. This disparity suggests that the absence of subject images from specific categories can lead to biased evaluation results, highlighting the importance of data diversity. Furthermore, Figure 7 also demonstrates that none of the current models perform well across all categories. We hypothesize that this may be related to the varying complexity of the subjects within different categories. A more detailed analysis of model performance in different categories can be found in Appendix D.1.

Current subject-driven T2I models exhibit performance degradation on hard level subjects As illustrated in Figure 7(a), the model exhibits substantial variation in performance across different difficulty levels: 1) For subject preservation, there is a pronounced decline in performance as the difficulty of the subject images increases. The model achieves significantly better results on images classified as simple compared to those categorized as hard. This observation supports the validity of our image difficulty classification scheme. 2) For prompt following, Figure 7(a) shows that the capability of the models is minimally influenced by the subject difficulty level. This could be explained by the fact that CLIP-T primarily emphasizes overall semantic information. Consequently,

as long as the generated image correctly represents the general category and overall shape, the evaluation score is unlikely to be substantially reduced, even if finer details are not perfectly captured. *Given these findings, it is crucial to enhance models' ability to encode and reconstruct complex subject details more effectively in future research endeavors.*

The subject-driven T2I capability for different prompt scenarios is not robust Figure 7(b) shows the average performance of all models across six prompt scenarios. The results show that: 1) In BC, VS, and IE scenarios, the model's performance consistently declines across all evaluation dimensions. This trend suggests that the difficulty of the scenarios increases progressively from BC to IE. Notably, the finding that the IE scenario is more challenging than the BC scenario aligns with intuitive expectations. 2) For subject preservation, the model's average performance across the AC, SC, and IM prompt scenarios remains relatively low. This could be because the generated subjects undergo partial modifications relative to the original subjects in these three scenarios. *Given these findings, more emphasis should be placed on enhancing methods for IE prompt scenario. For instance, increasing the volume of training data tailored to these specific contexts.*

5 Related Work

5.1 Subject-Driven Text-to-Image Generation

In recent years, subject-driven T2I generation has attracted significant research attention (Ruiz et al., 2023; Gal et al., 2022; Kumari et al., 2023; Wang et al., 2024a; Li et al., 2023a; Gal et al., 2023b;a; Wei et al., 2023; Hu et al., 2024b; Qiu et al., 2023). Within the context of diffusion models, optimization-based model (Voynov et al., 2023; Liu et al., 2023; Hua et al., 2023; Hao et al., 2023) enables subject-driven generation by introducing lightweight parameters and performs parameter-efficient fine-tuning for each subject. In contrast, the encoder-based methods (Shi et al., 2023; Ma et al., 2024; Chen et al., 2023b; Li et al., 2023b; Le et al., 2024; Rowles et al., 2024; Zeng et al., 2024; Hu et al., 2024a; Huang et al., 2025a; Xiong et al., 2025; Patashnik et al., 2025; Wu et al., 2025; Huang et al., 2025b; He et al., 2025) leverage additional image encoders and network layers to encode the reference image of the subject. IP-Adapter (Ye et al., 2023) introduces cross-attention through an additional image encoder to incorporate control signals. Furthermore, SSR-Encoder (Zhang et al., 2024) enhances identity preservation without necessitating further fine-tuning when introducing new concepts. The Diffusion Transformers (Peebles & Xie, 2023; Podell et al., 2023; Rombach et al., 2022b) uses transformer as a denoising network to iteratively refine noisy image tokens. Based on these foundation models, approaches like OminiControl (Tan et al., 2024) and UNO (Wu et al., 2025) explore the inherent image reference capabilities of transformers.

5.2 Subject-Driven T2I Generation Benchmark

Evaluation of subject-driven T2I relies on diverse metrics. For image quality, several notable studies (Xu et al., 2023; Kirstain et al., 2023; Wu et al., 2023; Alaluf et al., 2023; Xu et al., 2024; Wang et al., 2025) have been proposed. Subject preservation is typically measured by learning-based metrics that compare deep feature distances, often using embeddings from large vision models such as CLIP (Radford et al., 2021) and DINO (Caron et al., 2021), as well as image-retrieval scores (Liu et al., 2021). To better align with human perception, DreamSim (Fu et al., 2023) emphasizes foreground objects when assessing image similarity. Semantic consistency is commonly measured with the CLIP score. DreamBench lacks diversity in subjects and prompts, and although DreamBench++ expands to 150 subjects, it still lacks systematic categorization, hindering meaningful analysis.

6 Conclusion

This paper introduces a novel benchmark called DSH-Bench, designed specifically for subject-driven T2I generation. Key features include: 1) a hierarchical category system in image collection to ensure both the diversity and comprehensiveness of subject images; 2) an innovative classification scheme for categorizing subject difficulty levels and prompt scenarios to obtain valuable insights; and 3) a human-aligned and more efficient metric for subject preservation. The benchmark will be publicly available to support the advancement in the subject-driven T2I generation era.

REFERENCES

Yuval Alaluf, Elad Richardson, Gal Metzer, and Daniel Cohen-Or. A neural space-time representation for text-to-image personalization. *ACM Transactions on Graphics (TOG)*, 42(6):1–10, 2023.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, Humen Zhong, Yuanzhi Zhu, Mingkun Yang, Zhaohai Li, Jianqiang Wan, Pengfei Wang, Wei Ding, Zheren Fu, Yiheng Xu, Jiabo Ye, Xi Zhang, Tianbao Xie, Zesen Cheng, Hang Zhang, Zhibo Yang, Haiyang Xu, and Junyang Lin. Qwen2.5-vl technical report, 2025. URL https://arxiv.org/abs/2502.13923.

Yogesh Balaji, Seungjun Nah, Xun Huang, Arash Vahdat, Jiaming Song, Qinsheng Zhang, Karsten Kreis, Miika Aittala, Timo Aila, Samuli Laine, et al. ediff-i: Text-to-image diffusion models with an ensemble of expert denoisers. *arXiv preprint arXiv:2211.01324*, 2022.

Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 9650–9660, 2021.

Huiwen Chang, Han Zhang, Jarred Barber, Aaron Maschinot, Jose Lezama, Lu Jiang, Ming-Hsuan Yang, Kevin Patrick Murphy, William T Freeman, Michael Rubinstein, et al. Muse: Text-to-image generation via masked generative transformers. In *International Conference on Machine Learning*, pp. 4055–4075. PMLR, 2023.

Wenhu Chen, Hexiang Hu, Yandong Li, Nataniel Ruiz, Xuhui Jia, Ming-Wei Chang, and William W Cohen. Subject-driven text-to-image generation via apprenticeship learning. *Advances in Neural Information Processing Systems*, 36:30286–30305, 2023a.

Zhuowei Chen, Shancheng Fang, Wei Liu, Qian He, Mengqi Huang, Yongdong Zhang, and Zhendong Mao. Dreamidentity: Improved editability for efficient face-identity preserved image generation, 2023b. URL https://arxiv.org/abs/2307.00300.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pp. 248–255. Ieee, 2009.

Ming Ding, Zhuoyi Yang, Wenyi Hong, Wendi Zheng, Chang Zhou, Da Yin, Junyang Lin, Xu Zou, Zhou Shao, Hongxia Yang, et al. Cogview: Mastering text-to-image generation via transformers. *Advances in neural information processing systems*, 34:19822–19835, 2021.

Runpei Dong, Chunrui Han, Yuang Peng, Zekun Qi, Zheng Ge, Jinrong Yang, Liang Zhao, Jianjian Sun, Hongyu Zhou, Haoran Wei, et al. Dreamllm: Synergistic multimodal comprehension and creation. In *ICLR*, 2024.

Stephanie Fu, Netanel Tamir, Shobhita Sundaram, Lucy Chai, Richard Zhang, Tali Dekel, and Phillip Isola. Dreamsim: Learning new dimensions of human visual similarity using synthetic data. In *Advances in Neural Information Processing Systems*, volume 36, pp. 50742–50768, 2023.

Oran Gafni, Adam Polyak, Oron Ashual, Shelly Sheynin, Devi Parikh, and Yaniv Taigman. Make-a-scene: Scene-based text-to-image generation with human priors. In *European Conference on Computer Vision*, pp. 89–106. Springer, 2022.

Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H. Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion, 2022. URL https://arxiv.org/abs/2208.01618.

Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit Haim Bermano, Gal Chechik, and Daniel Cohen-or. An image is worth one word: Personalizing text-to-image generation using textual inversion. In *The Eleventh International Conference on Learning Representations*, 2023a. URL https://openreview.net/forum?id=NAQvF08TcyG.

Rinon Gal, Moab Arar, Yuval Atzmon, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. Encoder-based domain tuning for fast personalization of text-to-image models. *ACM Transactions on Graphics (TOG)*, 42(4):1–13, 2023b.

Inhwa Han, Serin Yang, Taesung Kwon, and Jong Chul Ye. Highly personalized text embedding for image manipulation by stable diffusion. *arXiv preprint arXiv:2303.08767*, 2023.

Shaozhe Hao, Kai Han, Shihao Zhao, and Kwan-Yee K Wong. Vico: Plug-and-play visual condition for personalized text-to-image generation. *arXiv preprint arXiv:2306.00971*, 2023.

Junjie He, Yuxiang Tuo, Binghui Chen, Chongyang Zhong, Yifeng Geng, and Liefeng Bo. Anystory: Towards unified single and multiple subject personalization in text-to-image generation, 2025. URL https://arxiv.org/abs/2501.09503.

Hexiang Hu, Kelvin C. K. Chan, Yu-Chuan Su, Wenhu Chen, Yandong Li, Kihyuk Sohn, Yang Zhao, Xue Ben, Boqing Gong, William Cohen, Ming-Wei Chang, and Xuhui Jia. Instruct-imagen: Image generation with multi-modal instruction, 2024a. URL https://arxiv.org/abs/2401.01952.

Hexiang Hu, Kelvin CK Chan, Yu-Chuan Su, Wenhu Chen, Yandong Li, Kihyuk Sohn, Yang Zhao, Xue Ben, Boqing Gong, William Cohen, et al. Instruct-imagen: Image generation with multi-modal instruction. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 4754–4763, 2024b.

Miao Hua, Jiawei Liu, Fei Ding, Wei Liu, Jie Wu, and Qian He. Dreamtuner: Single image is enough for subject-driven generation, 2023. URL https://arxiv.org/abs/2312.13691.

Linyan Huang, Haonan Lin, Yanning Zhou, and Kaiwen Xiao. Flexip: Dynamic control of preservation and personality for customized image generation, 2025a. URL https://arxiv.org/abs/2504.07405.

Zhipeng Huang, Shaobin Zhuang, Canmiao Fu, Binxin Yang, Ying Zhang, Chong Sun, Zhizheng Zhang, Yali Wang, Chen Li, and Zheng-Jun Zha. Wegen: A unified model for interactive multi-modal generation as we chat, 2025b. URL https://arxiv.org/abs/2503.01115.

Minguk Kang, Jun-Yan Zhu, Richard Zhang, Jaesik Park, Eli Shechtman, Sylvain Paris, and Taesung Park. Scaling up gans for text-to-image synthesis. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10124–10134, 2023.

Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4015–4026, 2023.

Yuval Kirstain, Adam Polyak, Uriel Singer, Shahbuland Matiana, Joe Penna, and Omer Levy. Pick-a-pic: An open dataset of user preferences for text-to-image generation. *Advances in Neural Information Processing Systems*, 36:36652–36663, 2023.

Nupur Kumari, Bingliang Zhang, Richard Zhang, Eli Shechtman, and Jun-Yan Zhu. Multi-concept customization of text-to-image diffusion. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 1931–1941, 2023.

Duong H. Le, Tuan Pham, Sangho Lee, Christopher Clark, Aniruddha Kembhavi, Stephan Mandt, Ranjay Krishna, and Jiasen Lu. One diffusion to generate them all, 2024. URL https://arxiv.org/abs/2411.16318.

Dongxu Li, Junnan Li, and Steven Hoi. Blip-diffusion: Pre-trained subject representation for controllable text-to-image generation and editing. *Advances in Neural Information Processing Systems*, 36:30146–30166, 2023a.

Zhen Li, Mingdeng Cao, Xintao Wang, Zhongang Qi, Ming-Ming Cheng, and Ying Shan. Photomaker: Customizing realistic human photos via stacked id embedding, 2023b. URL https://arxiv.org/abs/2312.04461.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer vision–ECCV 2014: 13th European conference, zurich, Switzerland, September 6-12, 2014, proceedings, part v 13*, pp. 740–755. Springer, 2014.

Zheyuan Liu, Cristian Rodriguez-Opazo, Damien Teney, and Stephen Gould. Image retrieval on real-life images with pre-trained vision-and-language models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2125–2134, 2021.

Zhiheng Liu, Yifei Zhang, Yujun Shen, Kecheng Zheng, Kai Zhu, Ruili Feng, Yu Liu, Deli Zhao, Jingren Zhou, and Yang Cao. Cones 2: Customizable image synthesis with multiple subjects, 2023. URL https://arxiv.org/abs/2305.19327.

Jian Ma, Junhao Liang, Chen Chen, and Haonan Lu. Subject-diffusion:open domain personalized text-to-image generation without test-time fine-tuning, 2024. URL https://arxiv.org/abs/2307.11410.

Zhendong Mao, Mengqi Huang, Fei Ding, Mingcong Liu, Qian He, and Yongdong Zhang. Realcustom++: Representing images as real-word for real-time customization. *arXiv preprint arXiv:2408.09744*, 2024.

OpenAI. Introducing gpt-4o and more tools to chatgpt free users, 2024. URL https://openai.com/index/gpt-4o-and-more-tools-to-chatgpt-free/. Accessed: 2024-06-15.

Or Patashnik, Rinon Gal, Daniil Ostashev, Sergey Tulyakov, Kfir Aberman, and Daniel Cohen-Or. Nested attention: Semantic-aware attention values for concept personalization, 2025. URL https://arxiv.org/abs/2501.01407.

Maitreya Patel, Sangmin Jung, Chitta Baral, and Yezhou Yang. λ-eclipse: Multi-concept personalized text-to-image diffusion models by leveraging clip latent space. *arXiv preprint arXiv:2402.05195*, 2024.

William Peebles and Saining Xie. Scalable diffusion models with transformers, 2023. URL https://arxiv.org/abs/2212.09748.

Yuang Peng, Yuxin Cui, Haomiao Tang, Zekun Qi, Runpei Dong, Jing Bai, Chunrui Han, Zheng Ge, Xiangyu Zhang, and Shu-Tao Xia. Dreambench++: A human-aligned benchmark for personalized image generation. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=4GSOESJrk6.

pin. https://www.pinterest.com/. https://www.pinterest.com/.

Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis, 2023. URL https://arxiv.org/abs/2307.01952.

Zeju Qiu, Weiyang Liu, Haiwen Feng, Yuxuan Xue, Yao Feng, Zhen Liu, Dan Zhang, Adrian Weller, and Bernhard Schölkopf. Controlling text-to-image diffusion by orthogonal finetuning. *Advances in Neural Information Processing Systems*, 36:79320–79362, 2023.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PmLR, 2021.

Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10684–10695, 2022a.

Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2022b. URL https://arxiv.org/abs/2112.10752.

Ciara Rowles, Shimon Vainer, Dante De Nigris, Slava Elizarov, Konstantin Kutsy, and Simon Donné. Ipadapter-instruct: Resolving ambiguity in image-based conditioning using instruct prompts, 2024. URL https://arxiv.org/abs/2408.03209.

Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 22500–22510, 2023.

Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in neural information processing systems*, 35:36479–36494, 2022.

Jing Shi, Wei Xiong, Zhe Lin, and Hyun Joon Jung. Instantbooth: Personalized text-to-image generation without test-time finetuning, 2023. URL https://arxiv.org/abs/2304.03411.

Quan Sun, Yufeng Cui, Xiaosong Zhang, Fan Zhang, Qiying Yu, Yueze Wang, Yongming Rao, Jingjing Liu, Tiejun Huang, and Xinlong Wang. Generative multimodal models are in-context learners. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 14398–14409, 2024.

Shangkun Sun, Bowen Qu, Xiaoyu Liang, Songlin Fan, and Wei Gao. Ie-bench: Advancing the measurement of text-driven image editing for human perception alignment. *arXiv preprint arXiv:2501.09927*, 2025.

Zhenxiong Tan, Songhua Liu, Xingyi Yang, Qiaochu Xue, and Xinchao Wang. Ominicontrol: Minimal and universal control for diffusion transformer. *arXiv preprint arXiv:2411.15098*, 2024.

uns. https://unsplash.com/. https://unsplash.com/.

Andrey Voynov, Qinghao Chu, Daniel Cohen-Or, and Kfir Aberman. P+: Extended textual conditioning in text-to-image generation, 2023. URL https://arxiv.org/abs/2303.09522.

Haofan Wang, Matteo Spinelli, Qixun Wang, Xu Bai, Zekui Qin, and Anthony Chen. Instantstyle: Free lunch towards style-preserving in text-to-image generation. *arXiv preprint arXiv:2404.02733*, 2024a.

Xierui Wang, Siming Fu, Qihan Huang, Wanggui He, and Hao Jiang. Ms-diffusion: Multi-subject zero-shot image personalization with layout guidance. *arXiv preprint arXiv:2406.07209*, 2024b.

Yibin Wang, Yuhang Zang, Hao Li, Cheng Jin, and Jiaqi Wang. Unified reward model for multimodal understanding and generation. *arXiv preprint arXiv:2503.05236*, 2025.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.

Yuxiang Wei, Yabo Zhang, Zhilong Ji, Jinfeng Bai, Lei Zhang, and Wangmeng Zuo. Elite: Encoding visual concepts into textual embeddings for customized text-to-image generation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 15943–15953, 2023.

Shaojin Wu, Mengqi Huang, Wenxu Wu, Yufeng Cheng, Fei Ding, and Qian He. Less-to-more generalization: Unlocking more controllability by in-context generation. *arXiv preprint arXiv:2504.02160*, 2025.

Xiaoshi Wu, Keqiang Sun, Feng Zhu, Rui Zhao, and Hongsheng Li. Human preference score: Better aligning text-to-image models with human preference. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 2096–2105, 2023.

Shitao Xiao, Yueze Wang, Junjie Zhou, Huaying Yuan, Xingrun Xing, Ruiran Yan, Chaofan Li, Shuting Wang, Tiejun Huang, and Zheng Liu. Omnigen: Unified image generation. *arXiv preprint arXiv:2409.11340*, 2024.

Zhexiao Xiong, Wei Xiong, Jing Shi, He Zhang, Yizhi Song, and Nathan Jacobs. Groundingbooth: Grounding text-to-image customization, 2025. URL https://arxiv.org/abs/2409.08520.

Jiazheng Xu, Xiao Liu, Yuchen Wu, Yuxuan Tong, Qinkai Li, Ming Ding, Jie Tang, and Yuxiao Dong. Imagereward: Learning and evaluating human preferences for text-to-image generation. *Advances in Neural Information Processing Systems*, 36:15903–15935, 2023.

Jiazheng Xu, Yu Huang, Jiale Cheng, Yuanming Yang, Jiajun Xu, Yuan Wang, Wenbo Duan, Shen Yang, Qunlin Jin, Shurun Li, Jiayan Teng, Zhuoyi Yang, Wendi Zheng, Xiao Liu, Ming Ding, Xiaohan Zhang, Xiaotao Gu, Shiyu Huang, Minlie Huang, Jie Tang, and Yuxiao Dong. Visionreward: Fine-grained multi-dimensional human preference learning for image and video generation, 2024. URL https://arxiv.org/abs/2412.21059.

Hu Ye, Jun Zhang, Sibo Liu, Xiao Han, and Wei Yang. Ip-adapter: Text compatible image prompt adapter for text-to-image diffusion models. *arXiv preprint arXiv:2308.06721*, 2023.

Yu Zeng, Vishal M. Patel, Haochen Wang, Xun Huang, Ting-Chun Wang, Ming-Yu Liu, and Yogesh Balaji. Jedi: Joint-image diffusion models for finetuning-free personalized text-to-image generation, 2024. URL https://arxiv.org/abs/2407.06187.

Yuxuan Zhang, Yiren Song, Jiaming Liu, Rui Wang, Jinpeng Yu, Hao Tang, Huaxia Li, Xu Tang, Yao Hu, Han Pan, et al. Ssr-encoder: Encoding selective subject representation for subject-driven generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8069–8078, 2024.

A Details of Hierarchical Category Establishing

The First-level Category We observed the composition of existing benchmark data. From a more abstract and higher-level perspective perspective, images in these datasets could be categorized into two types: photorealistic and non-photorealistic. Theoretically, the specific image categories represented within these two types can be identical. To maintain consistency with previous work and to ensure comprehensive data sampling, we designated photorealistic and non-photorealistic as the first-level categories. Furthermore, we ensure that the specific subcategories under both photorealistic and non-photorealistic types are fully aligned.

The Second-level Category We examined both the DreamBench and DreamBench++ datasets. In DreamBench, the dataset is divided into two categories: living subjects and objects. DreamBench++ further refines this categorization by introducing three categories: living subjects, objects, and style. We construct our secondary subcategories based on them. We define our secondary categories as objects, humans, and animals. Specifically, we subdivide the "living subjects" category into "humans" and "animals," as humans exhibit significantly different visual characteristics compared to animals. For the human category, we place particular emphasis on the accuracy of facial feature reconstruction, acknowledging the existence of dedicated research domains focused on facial preservation. In contrast, animals generally display greater variability in appearance than human faces. In comparison to DreamBench++, we exclude the "style" category. This decision is motivated by the focus of our task on subject-driven T2I generation, where "style" does not constitute a tangible entity. Moreover, including the style category would complicate the calculation of subject consistency, whereas our work is primarily concerned with the customization of entities.

The Third-level Category For the third-level categories, our objective was to strike a balance between granularity and generality. Categories that are too broad may result in insufficient keyword retrieval, potentially introducing bias into the final image sampling. Conversely, overly fine-grained categories may hinder subsequent experimental analysis by diluting meaningful insights. To address this, we consulted existing large-scale datasets such as COCO and ImageNet, as well as Wikipedia, to compile a list of candidate category labels. The specific labels are listed in Table 4. This comprehensive set of labels ensured broad coverage. However, many of these labels were excessively detailed, so we employ GPT-4o to merge them, followed by manual review to ensure the rationality and coherence of the final categories. The correspondence between the third-level categories and the candidate category labels is presented in Table 4. For the "human" category, we introduced a specific distinction by dividing it into "celebrities & artistic figures," "facial close-ups," and "half-body or full-body photo". We observed that models tend to perform significantly better on celebrities, which we hypothesize is due to the inclusion of celebrity data in the training sets of text-to-image foundation models. Table 14 provides empirical support for our hypothesis to some extent. The rationale for distinguishing between facial close-ups and non-facial close-ups is that the former focuses exclusively on the facial details of the individual in the reference image, whereas the latter also requires attention to the body details.

Through the aforementioned steps, we constructed a hierarchical category system. The resulting category hierarchy is presented in Figure 8.

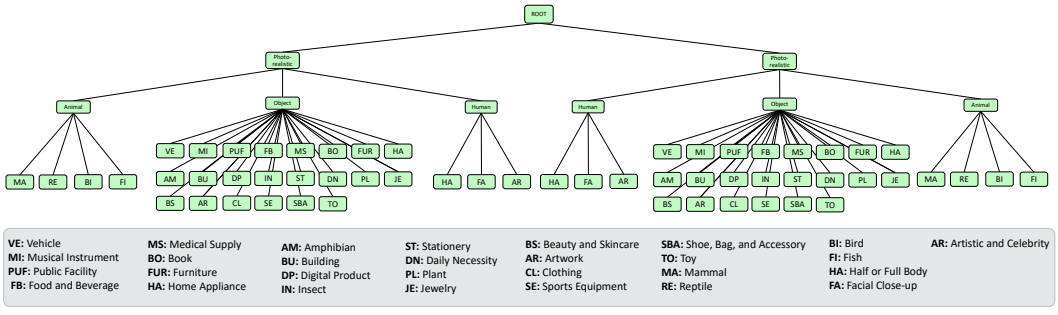


Figure 8: **The hierarchical category system.** We developed a three-level category hierarchy by integrating data from existing large-scale datasets and open-source encyclopedic resources.

Table 4: The correspondence between the third-level categories and the candidate category labels

Candidate Category Labels							The Third-level Category
reptile	lizard	dinosaur	turtle	crocodile	chameleon	gecko	Reptile
fly	firefly	ant	butterfly	ladybug	locust	dragonfly	Insect
amphibian	frog	bullfrog	toad	salamander			Amphibian
fish	goldfish	seahorse	shark	tilapia			Fish
bird hen	chicken turkey	duck swallow	owl crow	swan pigeon	goose	rooster	Bird
mammal bear goat whale	cat squirrel pig aardvark	dog giraffe kangaroo rabbit	horse lion rhinoceros zebra	sheep monkey deer mouse	cow tiger hippo	elephant bunny platypus	Mammal
street field goal post	fountain soccer net	fire hydrant basketball court	traffic light bus stop sign	sign	parking meter	goal net	Public Facility
furniture table window	dining table coffee table door	sofa side table chandelier	chair bench table lamp	couch cabinet gate	bed mirror	desk carpet	Furniture
flower	potted plant	tree	sunflower	cactus	lavender		Plant
cookie pineapple bread cheese	milk carrot sandwich cupcake	pancake broccoli cake donut	pasta banana pizza hot dog	grape orange soup bacon	cereal strawberry meat egg	bean apple pumpkin tomato	Food and Beverage
dryer blender	fridge hair drier	refrigerator fan (ceil/floor)	microwave printer	oven fax machine	toaster copier	washer	Home Appliance
necklace	bracelet	ring	pendant	brooch	anklet		Jewelry
wheelchair	gauze	crutch	stethoscope	syringe			Medical Supply
pants shorts	jacket scarf	long sleeve shirt tie	short sleeve shirt super hero costume	pajamas sock	underpants	shirt	Clothing
book	magazine	textbook	dictionary	biography			Book
bat sports ball	skis basketball	snowboard football	tennis racket tennis net	basketball hoop hoop	baseball glove	soccer ball	Sports Equipment
flip flop	handbag	glove	shoe	backpack			Shoe, Bag, and Accessory
pen	pencil	fax machine	stapler				Stationery
vehicle sailboat unicycle	car raft motorcycle	van airplane motorbike	truck helicopter skateboard	bus hot air balloon	train rocket	boat bicycle	Vehicle
house	building	roof	bridge	church			Building
picture frame	movie (disc)	playing cards	table cloth				Artwork
musical instrument	guitar	drum	flute	violin			Musical Instrument
telephone remote	laptop mouse	computer keyboard	tablet printer	ipad desktop	iphone copier	cell phone radio	Digital Product
kite	toy cars	toy	legos	robot	doll		
hair brush	toner	blush	serum	emulsion	sunscreen		Beauty and Skincare
bottle spoon box	plate clock chopping board	cup toothbrush ladder	bowl vase basket	teapot towel pillow	fork candle power outlet	knife balloon light switch	Daily Necessity
person							Person

B Details of Keywords Collection

The keywords utilized during the image collection process are presented in Table 5. During the keyword collection process, we utilized the following prompt for GPT-4o:

"You are a researcher with extensive knowledge of various real-world entity classifications. Given a specific category, please generate detailed, non-redundant instances relevant to this category. The category is {}.
The corresponding instances are as follows:"

Table 5: Based on the categories, we employ GPT-4o to generate keyword associations and further enhanced the results by incorporating manually curated keywords.

The Third-level Category	Keywords						
Vehicle	van pickup truck	steam locomotive bicycle	car boat	airplane taxi	UFO motorcycle	hot air balloon subway	oil tanker
Musical Instrument	guitar pick suona	electronic drum saxophone	digital piano harmonica	guitar cello	snare drum violin	flute pipa	african drum erhu
Public Facility	fire extinguisher	traffic sign	street lamp	street	station		
Food and Beverage	edible oil pineapple apple vegetable	instant noodles milk donut chicken	water orange durian noodles	pastries avocado sports drink hamburger	coffee can canned health products salad	biscuits juice egg chocolate	edible salt milk powder rice yogurt
Medical Supply	band-aid blood glucose meter	medicine crutch	wheelchair stethoscope	disinfectant syringe	first aid kit	medication	medicine bottle
Book	yearbook book	almanac notebook	workbook magazine	comic dictionary	encyclopedia	atlas	pamphlet
Furniture	shelf barber chair ottoman	makeup mirror office chair bookcase	stool bathroom mirror wardrobe	bathroom cabinet chair nightstand	cabinet sofa dresser	bean bag chair dining table	children's chair bed
Home Appliance	beauty device microphone television	kettle refrigerator oven	speaker hair dryer juicer	massage chair humidifier dishwasher	vacuum cleaner washing machine	rice cooker microwave oven	robot vacuum curling iron
Amphibian	newt frog	olm toad	bullfrog caecilian	wood frog salamander	Surinam toad	alpine newt	glass frog
Building	house hut	apartment building leaning tower of pisa	duplex house pyramid	church statue of liberty	temple of heaven eiffel tower	castle	golden gate bridge
Digital Product	smart robot printer smartwatch	headphones camcorder vintage camera	e-book reader camera monitor	desktop computer smart camera drone	roll of film laptop projector	router mobile phone fitness tracker	tablet walkie-talkie
Insect	shrimp	crab	ant	grasshopper	butterfly		
Stationery	glue stick stapler	globe crayon	calculator ballpoint pen	floppy disk eraser	tape measure	scissors	compass
Daily Necessity	hammer birdcage glass jar electric saw	candle alarm clock vase mop	mug spoon hanger broom	teapot bowl soap dish comb	berry bowl toothbrush frying pan	curtain shower gel baby bottle	pillow clock kitchen knife
Plant	cactus mint	coconut tree rose	tree sunflower	potted plant tulip	peony cactus	willow tree lavender	maple leaf
Jewelry	earrings tiara gold bar	ring crown necklace	crystal stud pendant	bracelet chain brooch	watch gemstone anklet	hair accessory choker locket	beaded bracelet hairpin
Beauty and Skincare	perfume blush	makeup brush eye shadow	lotion facial serum	sunscreen spray emulsion	face cream serum	nail polish mascara	toner lipstick
Artwork	bouquet of flowers sculpture	clay sculpture ceramic craft	wood carving mural	classical bust relief	stone carving	catstatue	mugskulls
Clothing	dress pants	baby clothes shirt	clothing down jacket	jeans coat	sweatshirt skirt	T-shirt shorts	socks vest
Sports Equipment	tennis adjustable bench treadmill	ball knee pad skateboard	tent backpack barbell	trekking poles soccer dumbbell	yoga mat sleeping bag	billiard baseball	badminton flamingo float
Shoe, Bag and Accessory	suitcase glasses hat	slippers sandals backpack	sunglasses shoes cap	canvas shoes luggage purse tie	high-top shoes fancy boot handbag	sports shoes belt sandals	scarf sneaker
Toy	actionfigure robot minion	monster toy motorbike toy smart robot	car magic cube robot toy	egg poop emoji toy	duck toy sloth plushie wolf plushie	teddy bear bear plushie doll	balloon red cartoon Eevee figurine
Mammal	rabbit panda alpaca	fox elephant puppy	wolf llama monkey	Siamese cat tiger kitten	polar bear dog dolphin	cat raccoon French bulldog	deer lion
Reptile	cobra turtle	gecko sea turtle	rattlesnake soft-shelled turtle	crocodile snake	chameleon lizard	alligator	iguana
Bird	heron woodpecker peacock bird	pigeon nightingale swallow canary	toucan duck owl sparrow	parrot turkey kingfisher rooster	stork chicken hawk	flamingo crow dove	penguin eagle anchovy
Fish	shark skate	tropical fish swordfish	jellyfish herring	goldfish sardine	perch carp	eel salmon	monkfish tuna
Person	person						

C Details of Prompt Generation

The specific instructions used in prompt generation are detailed in Figure 5. During the actual generation process, some of the prompts produced by GPT-4o did not meet the required criteria. Therefore, we instructed GPT-4o to generate multiple prompts for each image, and then manually selected those that best matched the intended scenarios. Figure 14 presents the results generated by different methods in this study, along with their corresponding prompts.

D Additional Discussions and Details of Model Performance

D.1 Additional Discussions

Analysis of The First-Level Category The primary categories are divided into photorealistic and non-photorealistic. Table 6 and Figure 9 present the performance of different methods on these two categories across three evaluation dimensions. The results show that: *(1) Subject Preservation:* Almost all methods perform better on photorealistic categories than on non-photorealistic ones. We speculate that this is because, when referencing subjects from non-photorealistic categories, these methods tend to generate photorealistic images based on the prompt, which results in lower subject consistency. *(2) Prompt Following:* The performance gap between photorealistic and non-photorealistic categories is relatively small. This can be attributed to the fact that CLIP-T focuses primarily on the semantic information of the image. As long as the generated subject matches the category and general appearance described in the prompt, the CLIP-T score will not be significantly reduced. *(3) Image quality:* There is little difference in performance between photorealistic and non-photorealistic categories. This indicates that the distinction between these two categories does not affect the quality of image generation, and the HPSv2 metric does not show a preference for either category.

Analysis of The Second-Level Category The secondary categories under both the realistic and non-realistic primary categories are further subdivided into objects, humans, and animals. Table 7 and Figure 10 present the performance of various methods across these three dimensions for both realistic and non-realistic categories. The results demonstrate that, irrespective of whether the primary category is realistic or non-realistic, the scores for the subject preservation dimension are consistently lower for the human category across nearly all models. As detailed in Table 8, this phenomenon can be attributed to the distribution of difficulty levels within the human category, where the proportions of simple, medium, and hard cases are 1.96%, 50.98%, and 47.06%, respectively. In contrast, the object and animal categories exhibit a higher proportion of subjects at the simple difficulty level and a lower proportion at the hard difficulty level, which likely contributes to their relatively higher subject preservation scores.

Implications for Technical Approaches (1) Figure 11 shows that, as base models and model architectures are updated, the performance boundary of these models consistently expands outward. Table 9 presents all the base models used by each method. It can be observed that the top-performing methods consistently employ relatively recent text-to-image base models. For instance, UNO utilizes FLUX as its foundational model. This observation suggests that the adoption of advanced text-to-image base models is a critical factor in enhancing performance on subject-driven T2I tasks. (2) Historically, fine-tuning methods have generally outperformed encoder-based approaches in terms of subject preservation. This advantage is attributed to their ability to better retain the original text-image conditional distribution by fine-tuning on images of the specified subject. In contrast, encoder-based methods often encounter interference during feature injection, which can hinder precise prompt alignment. However, with the development of more advanced encoding techniques, the adoption of larger and more powerful base models, and the availability of extensive training datasets, encoder-based methods have demonstrated significantly improved performance. From an application standpoint, fine-tuning methods require substantial computational resources for optimization and often exhibit limited generalization capabilities. In contrast, encoder-based methods are less constrained by these limitations, making them more practical for future applications. Nevertheless, our analysis indicates that current encoder-based methods still face challenges in accurately reconstructing subjects with high-frequency details in images. This limitation may stem from the characteristics of commonly used image encoders, such as CLIP, which tend to prioritize semantic information over fine-grained details. Consequently, future research should focus on enhancing the restoration of challenging subject details.

D.2 Details of Model Performance

In this section, we present the detailed evaluation results for each metric across all models. To comprehensively evaluate the effectiveness of different metrics for assessing subject consistency, we calculated multiple metrics for each method. The detailed results are presented in Table 10, 11, 12. In section 4, we present the performance of all methods across images with different difficulty

Figure 9: Comparison of bar charts for DSH-Bench scores in different first-level categories.

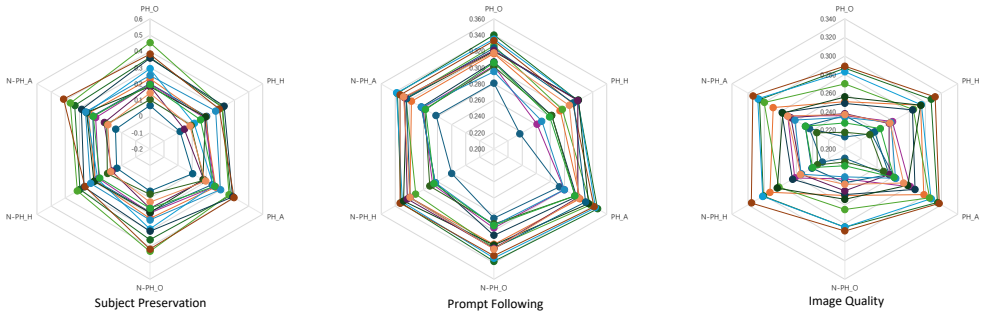


Figure 10: Comparison of radar charts for DSH-Bench scores in different second-level categories.

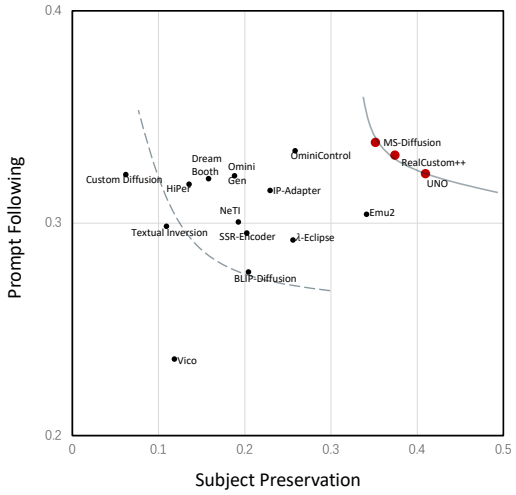


Figure 11: Pareto front diagram illustrating model performance across both subject and prompt dimensions. The red points in the diagram represent the current Pareto-optimal solutions.

levels, different prompt scenarios, and multiple categories. We show the specific metric values in Table 13, 14, 15, 16. Table 9 shows the full ranking among all methods.

Table 6: We evaluate the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **the first-level categories**. PH: Photorealistic. N-PH: Non-Photorealistic.

Method	**Subject Preservation↑**		**Prompt Following↑**		**Image Quality↑**	
	PH	N-PH	PH	N-PH	PH	N-PH
BLIP-Diffusion	0.209	0.190	0.276	0.279	0.225	0.220
IP-Adapter	0.232	0.220	0.315	0.318	0.266	0.266
MS-Diffusion	0.356	0.341	**0.338**	**0.336**	0.295	0.291
OminiControl	0.258	0.259	0.334	0.333	0.289	0.292
SSR-Encoder	0.209	0.185	0.295	0.296	0.248	0.245
UNO	**0.414**	**0.394**	0.324	0.320	0.279	0.275
Emu2	0.359	0.294	0.305	0.301	0.261	0.257
RealCustom++	0.371	0.383	0.332	0.331	**0.297**	**0.298**
OmniGen	0.183	0.201	0.323	0.321	0.266	0.264
Custom Diffusion	0.066	0.052	0.323	0.322	0.239	0.240
DreamBooth	0.165	0.138	0.320	0.323	0.243	0.250
Textual Inversion	0.117	0.088	0.301	0.293	0.226	0.222
λ-Eclipse	0.263	0.236	0.292	0.293	0.243	0.240
HiPer	0.144	0.112	0.317	0.323	0.247	0.247
NeTI	0.201	0.169	0.304	0.292	0.237	0.228
Aver.	0.236	0.217	0.313	0.312	0.257	0.256

E Implementation Details

E.1 Experimental Details of Existing Methods

The configurations for the training hyperparameters used in training-based methods on DSH-Bench are detailed in Table 17. To ensure a fair comparison in inference stage, we generated four images for each prompt of every image. The final evaluation metrics were calculated as the average score across these four images.

E.2 Details of SICS Implementation

How the SICS metric is computed Rather than relying on simple embedding distances, SICS instruction-tunes multimodal large language models to directly produce fine-grained subject-consistency scores (0–5) with accompanying explanations. These criteria align closely with human judgments. As illustrated in Figure 12, SICS employs prompts during fine-tuning that explicitly target subject consistency while de-emphasizing global image semantics. This design reduces background and style confounds that bias CLIP-like methods, yielding tighter alignment with the core requirements of subject-consistency evaluation. Consequently, SICS focuses on core visual attributes rather than high-level semantics. A further advantage of SICS is its scoring granularity, which mitigates the "score saturation" phenomenon commonly observed in the upper range of GPT-4o evaluations. Figure 2 shows representative cases in which SICS aligns more closely with human assessments.

Evaluation Instruction Figure 12 illustrates the annotation criteria of the training dataset as well as the training process.

Datasets We collected a substantial number of image pairs. To ensure data quality, we applied standardized filtering and preprocessing procedures, such as enforcing a minimum image resolution of 512 pixels. Additionally, we employed Qwen2.5-VL-72B to conduct preliminary screening. After this automated filtering, five annotators manually annotated the remaining image pairs according to the guidelines illustrated in Figure 12.

Training Details We fine-tuned Qwen2.5-VL-7B on the manually annotated dataset described above. All experiments were conducted using 8 GPUs. For the learning rate, we experimented with the set 1e5. The batch size per device was set to 4, with a gradient accumulation step of 8.

Table 7: We evaluate the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **the second-level categories**. PH: Photorealistic, N-PH: Non-Photorealistic, O: Object, A: Animal, H: Human.

Method	Subject Preservation					
	PH_O	**PH_H**	**PH_A**	**N-PH_O**	**N-PH_H**	**N-PH_A**
BLIP-Diffusion	0.202	0.201	0.24	0.186	0.189	0.206
IP-Adapter	0.232	0.193	0.267	0.226	0.188	0.237
MS-Diffusion	0.362	0.315	0.371	0.358	0.296	0.333
OminiControl	0.293	0.114	0.249	0.291	0.17	0.247
SSR-Encoder	0.199	0.186	0.26	0.193	0.162	0.185
UNO	**0.453**	0.312	0.361	**0.428**	**0.315**	0.365
Emu2	0.358	**0.326**	0.387	0.305	0.266	0.285
RealCustom++	0.383	0.291	**0.396**	0.415	0.26	**0.412**
OmniGen	0.183	0.194	0.176	0.19	0.196	0.249
Custom Diffusion	0.067	0.014	0.103	0.059	0.035	0.043
DreamBooth	0.188	0.044	0.184	0.164	0.07	0.124
Textual Inversion	0.104	0.091	0.184	0.078	0.101	0.105
λ-Eclipse	0.252	0.266	0.3	0.236	0.221	0.256
HiPer	0.143	0.083	0.195	0.126	0.079	0.098
NeTI	0.195	0.159	0.259	0.164	0.156	0.201
Aver.	0.241	0.186	0.262	0.228	0.180	0.223

Method	Prompt Following					
	PH_O	**PH_H**	**PH_A**	**N-PH_O**	**N-PH_H**	**N-PH_A**
BLIP-Diffusion	0.281	0.237	0.293	0.285	0.26	0.282
IP-Adapter	0.317	0.294	0.322	0.317	0.319	0.317
MS-Diffusion	**0.340**	0.319	**0.347**	**0.338**	0.332	0.337
OminiControl	0.335	0.319	0.344	0.334	0.33	**0.338**
SSR-Encoder	0.302	0.261	0.3	0.297	0.287	0.301
UNO	0.327	0.297	0.337	0.321	0.311	0.325
Emu2	0.307	0.282	0.317	0.306	0.283	0.303
RealCustom++	0.333	0.312	0.342	0.331	**0.333**	0.333
OmniGen	0.320	**0.320**	0.334	0.318	0.328	0.324
Custom Diffusion	0.324	0.313	0.33	0.322	0.319	0.324
DreamBooth	0.321	0.319	0.319	0.322	0.323	0.327
Textual Inversion	0.301	0.282	0.315	0.292	0.291	0.298
λ-Eclipse	0.295	0.268	0.3	0.294	0.283	0.303
HiPer	0.318	0.307	0.32	0.323	0.319	0.328
NeTI	0.306	0.279	0.315	0.294	0.285	0.297
Aver.	0.315	0.294	0.322	0.313	0.307	0.316

Method	Image Quality					
	PH_O	**PH_H**	**PH_A**	**N-PH_O**	**N-PH_H**	**N-PH_A**
BLIP-Diffusion	0.213	0.233	0.262	0.21	0.228	0.244
IP-Adapter	0.251	0.294	0.298	0.25	0.293	0.289
MS-Diffusion	0.287	0.307	0.315	0.284	0.301	0.306
OminiControl	0.283	0.295	0.307	0.284	0.302	0.308
SSR-Encoder	0.236	0.259	0.281	0.232	0.262	0.271
UNO	0.270	0.285	0.305	0.265	0.282	0.3
Emu2	0.249	0.284	0.287	0.249	0.265	0.278
RealCustom++	**0.289**	**0.312**	**0.317**	**0.288**	**0.316**	**0.314**
OmniGen	0.256	0.294	0.278	0.254	0.284	0.277
Custom Diffusion	0.236	0.237	0.255	0.236	0.241	0.249
DreamBooth	0.238	0.255	0.255	0.245	0.254	0.267
Textual Inversion	0.218	0.231	0.248	0.214	0.234	0.235
λ-Eclipse	0.234	0.257	0.263	0.23	0.254	0.262
HiPer	0.237	0.256	0.273	0.238	0.255	0.271
NeTI	0.228	0.244	0.261	0.218	0.24	0.249
Aver.	0.248	0.270	0.280	0.246	0.267	0.275

Table 8: Subject hard level distribution under the second category

Benchmark	Photorealistic								
	Object			Human			Animal		
	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Medium	Hard
DreamBench	3	10	7	0	0	0	0	7	2
DreamBench++	6	24	31	0	7	5	0	26	16
DSH-Bench	54	85	84	1	26	24	2	39	21
Benchmark	**Non-photorealistic**								
	Object			**Human**			**Animal**		
	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Medium	Hard
DreamBench	1	0	0	0	0	0	0	0	0
DreamBench++	2	1	1	0	1	7	0	1	2
DSH-Bench	28	32	15	1	4	20	3	11	8

Table 9: **The full DSH-Bench leaderboard.** The models are ranked by the final score S_h.

Method	T2I Model	Subject Preservation	Prompt Following	Image Quality	$S_h\uparrow$
RealCustom++	SDXL	0.375	0.332	**0.298**	**0.110**
UNO	FLUX.1-dev	**0.409**	0.323	0.278	0.109
MS-Diffusion	SDXL	0.352	**0.338**	0.294	0.107
Emu2	SDXL	0.341	0.304	0.260	0.089
OminiControl	FLUX.1-schnell	0.258	0.334	0.290	0.085
IP-Adapter	SDXL	0.229	0.315	0.266	0.071
λ-Eclipse	SDXL	0.256	0.292	0.242	0.069
OmniGen	SDXL	0.188	0.322	0.265	0.062
SSR-Encoder	SD v1.5	0.202	0.295	0.247	0.059
NeTI	SD v1.4	0.192	0.301	0.234	0.056
BLIP-Diffusion	SD v1.5	0.204	0.277	0.223	0.054
DreamBooth	SD v1.5	0.158	0.321	0.245	0.052
HiPer	SD v1.4	0.135	0.318	0.247	0.045
Textual Inversion	SD v1.5	0.109	0.299	0.225	0.035
ViCo	SD v1.4	0.118	0.236	0.186	0.029
Custom Diffusion	SD v1.4	0.062	0.323	0.240	0.023

Table 10: Evaluation of Subject-driven T2I generation model on **DreamBench**. C, D, Img, T and I represent CLIP, DINO, Image, Text and Image, respectively.

Method	Subject Preservation					Prompt Following		Image Quality		
	C-B-I↑	C-L-I↑	D-I↑	D-v2-I↑	SICS↑	C-B-T↑	C-L-T↑	ImageReward↑	PickScore↑	HPSv2↑
BLIP-Diffusion	0.824	0.784	0.684	0.640	0.229	0.291	0.239	0.420	0.599	0.267
IP-Adapter	0.836	**0.820**	0.684	0.648	0.230	0.321	0.263	0.616	0.600	0.291
MS-Diffusion	0.814	0.796	0.732	0.687	0.316	0.332	0.279	0.775	0.600	0.311
OminiControl	0.784	0.772	0.614	0.555	0.279	**0.336**	**0.284**	0.793	0.593	0.306
SSR-Encoder	0.830	0.802	0.732	0.677	0.231	0.302	0.251	0.535	0.600	0.282
UNO	0.827	0.801	0.744	**0.716**	**0.409**	0.317	0.259	0.725	**0.602**	0.304
Emu2	**0.838**	0.818	0.737	0.704	0.360	0.291	0.235	0.463	0.599	0.272
RealCustom++	0.794	0.770	**0.746**	0.698	0.377	0.325	0.278	**0.813**	0.601	**0.316**

Table 11: Evaluation of Subject-driven T2I generation model on **DreamBench++**. C, D, Img, T and I represent CLIP, DINO, Image, Text and Image, respectively.

Method	Subject Preservation					Prompt Following		Image Quality		
	C-B-I↑	C-L-I↑	D-I↑	D-v2-I↑	SICS↑	C-B-T↑	C-L-T↑	ImageReward↑	PickScore↑	HPSv2↑
BLIP-Diffusion	0.836	0.809	0.691	0.664	0.216	0.279	0.225	0.260	0.591	0.249
IP-Adapter	**0.846**	**0.845**	0.659	0.646	0.244	0.320	0.266	0.554	0.593	0.291
MS-Diffusion	0.812	0.823	0.666	0.653	0.346	**0.339**	**0.285**	0.729	0.593	0.309
OminiControl	0.761	0.780	0.551	0.566	0.268	0.336	0.284	**0.793**	0.593	0.308
SSR-Encoder	0.814	0.815	0.639	0.611	0.202	0.302	0.252	0.455	0.591	0.276
UNO	0.828	0.835	0.694	0.694	**0.410**	0.321	0.263	0.673	0.592	0.293
Emu2	0.833	0.823	0.665	0.632	0.343	0.309	0.255	0.460	0.593	0.275
RealCustom++	0.819	0.810	**0.714**	**0.706**	0.380	0.330	0.280	0.710	**0.594**	**0.314**

Table 12: Evaluation of Subject-driven T2I generation model on **DSH_Bench**. C, D, Img, T and I represent CLIP, DINO, Image, Text and Image, respectively.

Method	Subject Preservation					Prompt Following		Image Quality		
	C-B-I↑	C-L-I↑	D-I↑	D-v2-I↑	SICS↑	C-B-T↑	C-L-T↑	ImageReward↑	PickScore↑	HPSv2↑
BLIP-Diffusion	0.806	0.770	0.632	0.573	0.204	0.277	0.225	0.239	0.591	0.223
IP-Adapter	0.824	0.812	0.610	0.577	0.229	0.315	0.263	0.493	0.594	0.266
MS-Diffusion	0.786	0.783	0.623	0.600	0.352	**0.338**	0.287	0.705	**0.595**	0.294
OminiControl	0.721	0.736	0.462	0.461	0.258	0.334	**0.288**	**0.787**	0.594	0.290
SSR-Encoder	0.803	0.787	0.613	0.554	0.202	0.295	0.246	0.369	0.593	0.247
UNO	0.781	0.784	0.607	0.599	**0.409**	0.323	0.272	0.705	0.594	0.278
Emu2	0.815	0.804	0.631	0.606	0.341	0.304	0.256	0.441	0.594	0.260
RealCustom++	0.781	0.769	0.645	0.624	0.374	0.332	0.285	0.695	0.595	**0.298**
OmniGen	0.696	0.678	0.436	0.326	0.188	0.322	0.274	0.586	0.592	0.265
Custom Diffusion	0.648	0.648	0.283	0.230	0.062	0.323	0.282	0.481	0.590	0.239
DreamBooth	0.714	0.713	0.451	0.420	0.158	0.321	0.279	0.489	0.591	0.245
Textual Inversion	0.689	0.683	0.372	0.320	0.109	0.299	0.253	0.340	0.590	0.225
λ-Eclipse	0.852	**0.833**	**0.676**	**0.638**	0.256	0.292	0.239	0.349	0.594	0.242
HiPer	0.749	0.734	0.449	0.431	0.135	0.318	0.274	0.410	0.592	0.247
NeTI	0.762	0.743	0.525	0.491	0.192	0.301	0.256	0.338	0.592	0.234

Table 13: We evaluated the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **the third-level categories (under photorealistic)**. Subject preservation, prompt following, and image quality are evaluated using SICS, CLIP-T, and HPSv2, respectively. **VE**: Vehicle, **MI**: Musical Instrument, **PUF**: Public Facility, **FB**: Food and Beverage, **MS**: Medical Supply, **BO**: Book, **FUR**: Furniture, **HA**: Home Appliance, **AM**: Amphibian, **BU**: Building, **DP**: Digital Product, **IN**: Insect, **ST**: Stationery, **DN**: Daily Necessity, **PL**: Plant, **JE**: Jewelry, **BS**: Beauty and Skincare, **AR**: Artwork, **CL**: Clothing, **SE**: Sports Equipment, **SBA**: Shoe, Bag, and Accessory, **TO**: Toy, **MA**: Mammal, **RE**: Reptile, **BI**: Bird, **FI**: Fish, **HF**: Half or Full Body, **FA**: Facial Close-up, **AC**: Artistic and Celebrity.

Method	Subject Preservation																										
	VE	MI	PUF	FB	MS	BO	FUR	HA	AM	BU	DP	IN	ST	DN	PL	JE	BS	AR	CL	SE	SBA	TO	MA	RE	BI	FI	HF	FA	AC
BLIP-Diffusion	0.246	0.181	0.142	0.182	0.151	0.187	0.220	0.195	0.242	0.285	0.192	0.185	0.157	0.212	0.257	0.164	0.176	0.189	0.247	0.225	0.209	0.205	0.268	0.192	0.205	0.181	0.202	0.202	0.194
IP-Adapter	0.217	0.244	0.183	0.217	0.207	0.137	0.287	0.228	0.208	0.300	0.216	0.123	0.257	0.230	0.248	0.189	0.232	0.162	0.292	0.246	0.262	0.218	0.303	0.190	0.248	0.225	0.195	0.221	0.139
MS-Diffusion	0.293	0.368	0.292	0.313	0.378	0.290	0.451	0.361	0.592	0.327	0.346	0.244	0.353	0.353	0.397	0.386	0.307	0.287	0.449	0.396	0.433	0.336	0.374	0.345	0.415	0.337	0.337	0.302	0.273
OminiControl	0.187	0.329	0.333	0.312	0.314	0.172	0.292	0.335	0.275	0.252	0.296	0.225	0.296	0.311	0.300	0.227	0.296	0.293	0.258	0.297	0.336	0.324	0.246	0.208	0.308	0.208	0.135	0.082	0.107
SSR-Encoder	0.187	0.237	0.156	0.191	0.201	0.150	0.315	0.202	0.192	0.286	0.183	0.146	0.158	0.195	0.293	0.112	0.158	0.143	0.204	0.231	0.185	0.203	0.301	0.197	0.209	0.215	0.159	0.228	0.188
UNO	0.387	0.411	0.446	0.444	0.461	0.330	0.580	0.442	0.442	0.461	0.442	0.325	0.402	0.457	0.427	0.396	0.418	0.419	0.515	0.502	0.524	0.436	0.359	0.322	0.420	0.300	0.367	0.258	0.247
Emu2	0.324	0.281	0.546	0.326	0.382	0.302	0.444	0.394	0.583	0.379	0.378	0.344	0.318	0.319	0.355	0.290	0.418	0.348	0.365	0.385	0.429	0.300	0.370	0.310	0.443	0.510	0.308	0.311	0.404
RealCustom++	0.340	0.421	0.371	0.340	0.328	0.228	0.479	0.395	0.500	0.406	0.347	0.327	0.358	0.399	0.432	0.349	0.325	0.347	0.389	0.488	0.369	0.417	0.394	0.342	0.450	0.390	0.306	0.270	0.283
OmniGen	0.111	0.123	0.094	0.249	0.161	0.183	0.196	0.133	0.058	0.236	0.192	0.096	0.157	0.169	0.229	0.146	0.251	0.179	0.202	0.173	0.203	0.180	0.197	0.082	0.203	0.144	0.209	0.215	0.113
Custom Diffusion	0.075	0.083	0.060	0.086	0.058	0.037	0.058	0.051	0.083	0.181	0.048	0.063	0.063	0.074	0.097	0.030	0.082	0.038	0.074	0.079	0.054	0.055	0.108	0.107	0.115	0.060	0.014	0.015	0.009
DreamBooth	0.225	0.180	0.206	0.206	0.151	0.077	0.224	0.232	0.200	0.242	0.158	0.190	0.195	0.220	0.307	0.135	0.163	0.105	0.131	0.187	0.167	0.186	0.181	0.170	0.190	0.208	0.048	0.035	0.050
Textual Inversion	0.143	0.081	0.090	0.116	0.081	0.022	0.099	0.085	0.192	0.225	0.059	0.117	0.115	0.089	0.174	0.115	0.074	0.101	0.071	0.114	0.087	0.134	0.191	0.133	0.219	0.160	0.082	0.078	0.138
λ-Eclipse	0.280	0.215	0.117	0.215	0.214	0.170	0.346	0.248	0.283	0.312	0.253	0.156	0.211	0.249	0.275	0.243	0.211	0.193	0.298	0.283	0.309	0.238	0.340	0.227	0.272	0.231	0.261	0.273	0.268
HiPer	0.148	0.150	0.165	0.162	0.108	0.097	0.135	0.175	0.183	0.261	0.132	0.144	0.132	0.144	0.183	0.112	0.119	0.115	0.119	0.153	0.107	0.167	0.201	0.160	0.235	0.140	0.092	0.079	0.065
NeTI	0.199	0.154	0.140	0.193	0.179	0.123	0.235	0.200	0.292	0.275	0.144	0.196	0.182	0.225	0.264	0.176	0.152	0.188	0.145	0.193	0.193	0.226	0.262	0.252	0.282	0.233	0.152	0.139	0.218

Method	Prompt Following																										
	VE	MI	PUF	FB	MS	BO	FUR	HA	AM	BU	DP	IN	ST	DN	PL	JE	BS	AR	CL	SE	SBA	TO	MA	RE	BI	FI	HF	FA	AC
BLIP-Diffusion	0.271	0.283	0.279	0.282	0.275	0.244	0.269	0.286	0.307	0.285	0.273	0.299	0.283	0.286	0.294	0.280	0.273	0.272	0.281	0.296	0.281	0.294	0.291	0.287	0.301	0.287	0.241	0.223	0.245
IP-Adapter	0.315	0.332	0.310	0.318	0.314	0.301	0.306	0.324	0.331	0.312	0.320	0.319	0.320	0.317	0.316	0.306	0.307	0.310	0.319	0.325	0.321	0.333	0.325	0.303	0.327	0.306	0.291	0.291	0.311
MS-Diffusion	0.336	0.354	0.335	0.339	0.342	0.322	0.339	0.343	0.349	0.332	0.333	0.338	0.337	0.344	0.345	0.324	0.321	0.335	0.344	0.347	0.349	0.353	0.352	0.331	0.345	0.327	0.319	0.317	0.324
OminiControl	0.328	0.345	0.333	0.337	0.335	0.317	0.337	0.336	0.351	0.331	0.327	0.333	0.328	0.337	0.339	0.331	0.331	0.327	0.336	0.342	0.341	0.347	0.349	0.328	0.344	0.321	0.317	0.321	0.322
SSR-Encoder	0.290	0.315	0.289	0.301	0.295	0.291	0.291	0.311	0.303	0.294	0.297	0.291	0.306	0.304	0.311	0.300	0.307	0.298	0.304	0.307	0.299	0.309	0.302	0.281	0.309	0.293	0.267	0.249	0.266
UNO	0.322	0.343	0.330	0.328	0.325	0.312	0.326	0.331	0.349	0.322	0.319	0.331	0.321	0.330	0.330	0.320	0.320	0.315	0.328	0.336	0.334	0.333	0.340	0.324	0.337	0.321	0.295	0.299	0.297
Emu2	0.310	0.316	0.307	0.303	0.309	0.285	0.308	0.310	0.316	0.316	0.297	0.310	0.310	0.311	0.319	0.300	0.296	0.299	0.305	0.316	0.308	0.315	0.318	0.304	0.326	0.309	0.292	0.276	0.266
RealCustom++	0.327	0.339	0.332	0.336	0.333	0.322	0.331	0.337	0.352	0.326	0.326	0.336	0.323	0.338	0.335	0.322	0.323	0.326	0.340	0.338	0.339	0.344	0.346	0.328	0.343	0.325	0.312	0.315	0.309
OmniGen	0.318	0.318	0.312	0.333	0.312	0.307	0.316	0.313	0.357	0.316	0.314	0.316	0.310	0.322	0.330	0.316	0.325	0.317	0.314	0.327	0.327	0.328	0.340	0.311	0.331	0.317	0.324	0.317	0.315
Custom Diffusion	0.331	0.330	0.316	0.322	0.321	0.313	0.323	0.321	0.337	0.327	0.312	0.316	0.316	0.325	0.325	0.322	0.322	0.326	0.325	0.329	0.326	0.332	0.336	0.317	0.330	0.310	0.312	0.314	0.315
DreamBooth	0.315	0.330	0.315	0.321	0.320	0.314	0.319	0.325	0.299	0.316	0.312	0.306	0.318	0.320	0.324	0.313	0.320	0.321	0.320	0.327	0.325	0.330	0.323	0.303	0.326	0.301	0.319	0.319	0.316
Textual Inversion	0.310	0.307	0.294	0.308	0.304	0.275	0.293	0.306	0.323	0.312	0.296	0.307	0.300	0.292	0.309	0.292	0.302	0.294	0.299	0.309	0.305	0.307	0.320	0.301	0.316	0.283	0.276	0.290	0.286
λ-Eclipse	0.280	0.302	0.286	0.296	0.298	0.278	0.299	0.297	0.312	0.278	0.290	0.299	0.303	0.310	0.305	0.284	0.289	0.289	0.292	0.301	0.290	0.297	0.301	0.294	0.297	0.298	0.272	0.274	0.248
HiPer	0.313	0.335	0.316	0.316	0.316	0.304	0.316	0.316	0.308	0.312	0.311	0.307	0.311	0.319	0.319	0.313	0.317	0.301	0.326	0.331	0.333	0.324	0.324	0.313	0.320	0.305	0.305	0.312	0.302
NeTI	0.308	0.314	0.311	0.311	0.314	0.276	0.300	0.312	0.302	0.307	0.302	0.310	0.300	0.302	0.312	0.295	0.307	0.299	0.307	0.315	0.315	0.312	0.320	0.309	0.311	0.300	0.281	0.282	0.266

Method	Image Quality																										
	VE	MI	PUF	FB	MS	BO	FUR	HA	AM	BU	DP	IN	ST	DN	PL	JE	BS	AR	CL	SE	SBA	TO	MA	RE	BI	FI	HF	FA	AC
BLIP-Diffusion	0.253	0.203	0.213	0.222	0.175	0.168	0.189	0.190	0.274	0.235	0.196	0.256	0.195	0.204	0.236	0.206	0.205	0.235	0.216	0.214	0.227	0.243	0.263	0.246	0.265	0.263	0.234	0.229	0.233
IP-Adapter	0.296	0.248	0.241	0.252	0.218	0.224	0.239	0.242	0.305	0.276	0.247	0.277	0.232	0.239	0.256	0.231	0.245	0.279	0.255	0.246	0.259	0.284	0.305	0.266	0.299	0.294	0.290	0.293	0.306
MS-Diffusion	0.320	0.279	0.282	0.290	0.260	0.269	0.282	0.279	0.310	0.306	0.279	0.305	0.271	0.287	0.296	0.265	0.275	0.301	0.288	0.283	0.294	0.313	0.322	0.288	0.308	0.309	0.303	0.311	0.309
OminiControl	0.297	0.277	0.280	0.283	0.264	0.286	0.275	0.274	0.313	0.299	0.280	0.287	0.273	0.282	0.289	0.277	0.274	0.289	0.284	0.277	0.290	0.303	0.314	0.283	0.304	0.292	0.292	0.298	0.300
SSR-Encoder	0.275	0.226	0.239	0.239	0.202	0.204	0.216	0.225	0.290	0.264	0.223	0.263	0.221	0.230	0.255	0.232	0.225	0.250	0.243	0.236	0.242	0.259	0.286	0.262	0.281	0.282	0.261	0.254	0.264
UNO	0.295	0.266	0.277	0.272	0.248	0.256	0.252	0.260	0.308	0.275	0.266	0.289	0.260	0.270	0.280	0.254	0.262	0.275	0.272	0.272	0.279	0.293	0.313	0.284	0.298	0.296	0.282	0.287	0.287
Emu2	0.289	0.242	0.252	0.243	0.228	0.214	0.238	0.234	0.288	0.276	0.234	0.271	0.246	0.248	0.265	0.235	0.236	0.272	0.249	0.245	0.252	0.272	0.291	0.271	0.291	0.272	0.289	0.283	0.270
RealCustom++	0.325	0.279	0.294	0.291	0.277	0.275	0.277	0.275	0.307	0.308	0.285	0.313	0.275	0.287	0.294	0.264	0.272	0.297	0.299	0.290	0.302	0.305	0.321	0.301	0.319	0.309	0.311	0.313	0.311
OmniGen	0.278	0.239	0.253	0.263	0.237	0.240	0.251	0.242	0.265	0.286	0.253	0.255	0.251	0.251	0.271	0.243	0.258	0.271	0.241	0.256	0.260	0.266	0.286	0.249	0.281	0.263	0.300	0.292	0.281
Custom Diffusion	0.255	0.234	0.236	0.235	0.223	0.221	0.238	0.230	0.245	0.249	0.226	0.239	0.219	0.234	0.246	0.228	0.231	0.241	0.237	0.234	0.241	0.249	0.259	0.247	0.254	0.247	0.235	0.237	0.238
DreamBooth	0.266	0.236	0.236	0.239	0.215	0.226	0.233	0.229	0.222	0.251	0.228	0.250	0.222	0.236	0.253	0.226	0.223	0.252	0.240	0.237	0.247	0.250	0.260	0.233	0.252	0.251	0.253	0.255	0.257
Textual Inversion	0.253	0.214	0.219	0.226	0.212	0.178	0.208	0.214	0.261	0.248	0.205	0.233	0.206	0.205	0.234	0.207	0.211	0.233	0.218	0.217	0.228	0.231	0.252	0.234	0.249	0.236	0.227	0.232	0.244
λ-Eclipse	0.276	0.220	0.228	0.235	0.206	0.222	0.231	0.222	0.277	0.242	0.234	0.248	0.229	0.236	0.242	0.214	0.227	0.247	0.238	0.234	0.237	0.247	0.266	0.245	0.266	0.267	0.263	0.256	0.245
HiPer	0.269	0.238	0.242	0.237	0.218	0.211	0.232	0.222	0.287	0.253	0.229	0.256	0.219	0.230	0.253	0.225	0.224	0.239	0.243	0.242	0.251	0.255	0.277	0.264	0.271	0.267	0.257	0.255	0.254
NeTI	0.262	0.224	0.234	0.233	0.213	0.186	0.215	0.218	0.249	0.248	0.211	0.246	0.214	0.221	0.247	0.214	0.224	0.246	0.228	0.234	0.241	0.245	0.266	0.250	0.257	0.260	0.243	0.240	0.250

MLLM Projects *(1) Qwen2.5-VL-7B:* https://huggingface.co/Qwen/Qwen2.5-VL-7B-Instruct *(2) Implementation Framework:* https://github.com/hiyouga/LLaMA-Factory

Why we use *Kendall's τ value* and *Spearman correlation coefficient value*: The scenario is as follows: We have multiple metrics scoring the same dataset. These metrics may have different value ranges. The ground truth scores are provided by human annotators. We want to measure the correlation between each metric and the human scores. The following are some commonly used correlation evaluation metrics:

Table 14: We evaluated the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **the third-level categories (under non-photorealistic)**.

Method	VE	MI	PUF	FB	MS	BO	FUR	HA	AM	BU	DP	IN	ST	DN	PL	JE	BS	AR	CL	SE	SBA	TO	MA	RE	BI	FI	HF	FA	AC
Subject Preservation																													
BLIP-Diffusion	0.227	0.170	0.175	0.208	0.146	0.153	0.210	0.180	0.133	0.185	0.139	0.175	0.108	0.208	0.183	0.171	0.181	0.125	0.188	0.375	0.221	0.177	0.219	0.247	0.192	0.183	0.180	0.221	0.194
IP-Adapter	0.240	0.248	0.175	0.283	0.212	0.281	0.178	0.210	0.208	0.223	0.164	0.188	0.192	0.248	0.183	0.217	0.227	0.175	0.250	0.683	0.243	0.144	0.250	0.233	0.245	0.208	0.177	0.200	0.201
MS-Diffusion	0.362	0.410	0.387	0.375	0.396	0.361	0.363	0.345	0.342	0.292	0.272	0.292	0.233	0.438	0.250	0.296	0.310	0.367	0.438	0.742	0.426	0.235	0.325	0.342	0.363	0.300	0.302	0.233	0.300
OminiControl	0.290	0.370	0.367	0.333	0.377	0.275	0.181	0.252	0.292	0.265	0.269	0.213	0.237	0.342	0.075	0.254	0.362	0.217	0.300	0.633	0.342	0.217	0.273	0.261	0.190	0.283	0.158	0.092	0.202
SSR-Encoder	0.187	0.168	0.221	0.260	0.183	0.219	0.179	0.198	0.208	0.201	0.103	0.079	0.146	0.173	0.179	0.133	0.154	0.175	0.170	0.667	0.260	0.131	0.219	0.156	0.177	0.208	0.145	0.208	0.176
UNO	0.440	0.448	0.537	0.365	0.467	0.428	0.415	0.399	0.433	0.377	0.367	0.308	0.342	0.471	0.317	0.462	0.481	0.458	0.530	0.675	0.438	0.335	0.350	0.431	0.358	0.375	0.315	0.208	0.338
Emu2	0.350	0.310	0.337	0.315	0.412	0.303	0.303	0.257	0.192	0.267	0.186	0.212	0.379	0.448	0.100	0.333	0.333	0.158	0.305	0.433	0.350	0.187	0.294	0.314	0.280	0.375	0.251	0.250	0.288
RealCustom++	0.435	0.425	0.763	0.431	0.508	0.472	0.436	0.380	0.525	0.300	0.331	0.404	0.208	0.469	0.337	0.646	0.398	0.433	0.317	0.450	0.493	0.342	0.419	0.406	0.392	0.367	0.265	0.179	0.271
OmniGen	0.235	0.130	0.108	0.246	0.348	0.231	0.232	0.180	0.292	0.152	0.094	0.200	0.158	0.175	0.067	0.158	0.256	0.100	0.243	0.375	0.169	0.083	0.263	0.242	0.253	0.183	0.178	0.142	0.231
Custom Diffusion	0.071	0.072	0.067	0.048	0.073	0.094	0.017	0.052	0.033	0.154	0.019	0.037	0.050	0.077	0.050	0.029	0.038	0.000	0.047	0.150	0.042	0.002	0.042	0.017	0.055	0.092	0.025	0.000	0.056
DreamBooth	0.171	0.245	0.179	0.215	0.181	0.211	0.111	0.170	0.233	0.208	0.089	0.096	0.163	0.231	0.050	0.196	0.154	0.050	0.172	0.308	0.112	0.040	0.120	0.089	0.118	0.233	0.065	0.017	0.087
Textual Inversion	0.144	0.090	0.108	0.090	0.104	0.067	0.033	0.052	0.075	0.164	0.033	0.083	0.063	0.054	0.054	0.058	0.083	0.058	0.058	0.267	0.040	0.040	0.112	0.097	0.122	0.058	0.092	0.050	0.122
λ-Eclipse	0.279	0.237	0.225	0.317	0.244	0.261	0.194	0.218	0.250	0.226	0.214	0.192	0.092	0.235	0.221	0.192	0.219	0.450	0.227	0.517	0.250	0.196	0.270	0.294	0.232	0.267	0.215	0.196	0.234
HiPer	0.162	0.167	0.163	0.192	0.142	0.142	0.057	0.114	0.108	0.162	0.053	0.079	0.075	0.156	0.054	0.067	0.133	0.200	0.135	0.333	0.126	0.021	0.109	0.031	0.107	0.183	0.061	0.046	0.108
NeTI	0.181	0.200	0.237	0.146	0.194	0.164	0.189	0.150	0.275	0.181	0.142	0.154	0.117	0.210	0.146	0.125	0.148	0.317	0.093	0.192	0.135	0.137	0.210	0.231	0.182	0.150	0.158	0.175	0.151
Prompt Following																													
BLIP-Diffusion	0.290	0.287	0.291	0.293	0.291	0.279	0.275	0.284	0.281	0.280	0.292	0.277	0.278	0.296	0.259	0.282	0.287	0.259	0.286	0.285	0.292	0.277	0.283	0.291	0.274	0.289	0.256	0.222	0.272
IP-Adapter	0.317	0.336	0.316	0.321	0.335	0.304	0.307	0.319	0.326	0.304	0.313	0.320	0.321	0.332	0.267	0.320	0.331	0.293	0.320	0.319	0.320	0.312	0.321	0.317	0.311	0.309	0.314	0.308	0.327
MS-Diffusion	0.337	0.355	0.334	0.339	0.354	0.326	0.335	0.340	0.332	0.326	0.332	0.329	0.328	0.348	0.310	0.341	0.344	0.322	0.346	0.342	0.344	0.321	0.344	0.332	0.333	0.334	0.328	0.324	0.338
OminiControl	0.330	0.348	0.341	0.335	0.340	0.321	0.334	0.333	0.341	0.330	0.324	0.334	0.330	0.344	0.321	0.329	0.336	0.309	0.339	0.334	0.334	0.326	0.338	0.328	0.342	0.333	0.326	0.313	0.337
SSR-Encoder	0.289	0.317	0.287	0.304	0.305	0.287	0.291	0.305	0.301	0.285	0.293	0.302	0.298	0.305	0.270	0.292	0.308	0.291	0.304	0.298	0.299	0.293	0.300	0.303	0.302	0.296	0.288	0.251	0.294
UNO	0.316	0.343	0.319	0.325	0.334	0.305	0.321	0.324	0.314	0.309	0.313	0.327	0.302	0.338	0.289	0.318	0.333	0.294	0.333	0.316	0.330	0.300	0.329	0.317	0.327	0.309	0.308	0.297	0.317
Emu2	0.309	0.337	0.303	0.311	0.326	0.303	0.293	0.305	0.313	0.298	0.307	0.317	0.301	0.318	0.291	0.309	0.304	0.276	0.308	0.323	0.312	0.273	0.297	0.312	0.304	0.297	0.292	0.243	0.279
RealCustom++	0.319	0.351	0.326	0.328	0.340	0.328	0.331	0.331	0.317	0.326	0.309	0.332	0.320	0.350	0.301	0.325	0.329	0.298	0.346	0.336	0.338	0.317	0.338	0.319	0.339	0.333	0.330	0.321	0.338
OmniGen	0.322	0.321	0.313	0.328	0.341	0.318	0.308	0.305	0.332	0.317	0.301	0.322	0.309	0.321	0.299	0.298	0.338	0.305	0.326	0.336	0.314	0.323	0.329	0.327	0.309	0.333	0.326	0.315	0.333
Custom Diffusion	0.315	0.336	0.330	0.326	0.326	0.313	0.324	0.323	0.322	0.323	0.308	0.302	0.311	0.326	0.314	0.324	0.323	0.318	0.321	0.329	0.321	0.317	0.331	0.320	0.325	0.313	0.316	0.312	0.326
DreamBooth	0.322	0.337	0.329	0.331	0.330	0.317	0.322	0.317	0.327	0.322	0.310	0.317	0.309	0.322	0.314	0.319	0.316	0.295	0.325	0.334	0.325	0.325	0.334	0.328	0.323	0.303	0.324	0.315	0.324
Textual Inversion	0.290	0.304	0.287	0.293	0.303	0.287	0.291	0.293	0.302	0.301	0.281	0.288	0.291	0.290	0.272	0.286	0.304	0.266	0.301	0.314	0.282	0.282	0.299	0.304	0.298	0.292	0.290	0.289	0.294
λ-Eclipse	0.280	0.313	0.256	0.300	0.293	0.290	0.295	0.292	0.301	0.278	0.281	0.304	0.302	0.310	0.273	0.293	0.306	0.241	0.311	0.335	0.304	0.288	0.305	0.297	0.306	0.296	0.286	0.283	0.279
HiPer	0.321	0.339	0.317	0.334	0.325	0.317	0.324	0.320	0.327	0.324	0.311	0.317	0.320	0.325	0.318	0.324	0.319	0.220	0.323	0.336	0.322	0.333	0.336	0.330	0.320	0.310	0.319	0.313	0.319
NeTI	0.297	0.327	0.305	0.306	0.317	0.292	0.274	0.291	0.302	0.295	0.272	0.300	0.301	0.305	0.257	0.286	0.300	0.256	0.291	0.325	0.288	0.270	0.299	0.290	0.295	0.301	0.285	0.227	0.296
Image Quality																													
BLIP-Diffusion	0.244	0.208	0.193	0.221	0.184	0.185	0.186	0.202	0.232	0.243	0.190	0.234	0.220	0.221	0.189	0.224	0.220	0.204	0.212	0.184	0.225	0.189	0.246	0.272	0.229	0.256	0.224	0.216	0.235
IP-Adapter	0.285	0.255	0.239	0.263	0.230	0.231	0.227	0.245	0.309	0.279	0.245	0.271	0.259	0.258	0.220	0.278	0.264	0.242	0.240	0.229	0.251	0.227	0.294	0.310	0.265	0.311	0.283	0.293	0.305
MS-Diffusion	0.304	0.287	0.268	0.296	0.269	0.273	0.269	0.276	0.308	0.304	0.267	0.286	0.288	0.294	0.267	0.299	0.298	0.267	0.284	0.283	0.289	0.255	0.307	0.321	0.296	0.332	0.293	0.307	0.311
OminiControl	0.295	0.290	0.265	0.287	0.269	0.274	0.278	0.278	0.314	0.298	0.277	0.281	0.284	0.295	0.288	0.298	0.285	0.265	0.282	0.281	0.287	0.270	0.312	0.309	0.307	0.325	0.297	0.291	0.309
SSR-Encoder	0.258	0.237	0.216	0.241	0.204	0.206	0.213	0.239	0.288	0.260	0.214	0.242	0.232	0.234	0.217	0.245	0.237	0.227	0.229	0.210	0.241	0.212	0.271	0.287	0.266	0.293	0.260	0.248	0.268
UNO	0.286	0.277	0.249	0.288	0.257	0.249	0.252	0.262	0.312	0.275	0.243	0.285	0.267	0.290	0.223	0.282	0.274	0.226	0.265	0.228	0.276	0.240	0.302	0.315	0.290	0.311	0.273	0.278	0.294
Emu2	0.278	0.261	0.239	0.259	0.236	0.239	0.227	0.235	0.294	0.269	0.242	0.278	0.246	0.265	0.254	0.252	0.252	0.247	0.244	0.255	0.254	0.223	0.269	0.296	0.275	0.302	0.268	0.256	0.264
RealCustom++	0.304	0.300	0.283	0.291	0.269	0.280	0.277	0.274	0.316	0.314	0.258	0.304	0.290	0.304	0.250	0.296	0.282	0.277	0.306	0.284	0.300	0.259	0.311	0.331	0.313	0.321	0.305	0.319	0.330
OmniGen	0.280	0.251	0.236	0.262	0.261	0.262	0.231	0.232	0.291	0.274	0.239	0.282	0.248	0.259	0.243	0.256	0.265	0.253	0.256	0.268	0.253	0.252	0.281	0.298	0.251	0.292	0.276	0.288	0.292
Custom Diffusion	0.240	0.239	0.238	0.235	0.227	0.221	0.241	0.228	0.240	0.257	0.221	0.228	0.215	0.241	0.247	0.240	0.231	0.229	0.235	0.245	0.235	0.240	0.253	0.245	0.255	0.250	0.237	0.227	0.250
DreamBooth	0.253	0.249	0.246	0.246	0.231	0.235	0.235	0.239	0.281	0.270	0.229	0.240	0.229	0.257	0.252	0.255	0.236	0.224	0.246	0.245	0.245	0.239	0.269	0.280	0.262	0.274	0.249	0.249	0.262
Textual Inversion	0.227	0.220	0.210	0.212	0.204	0.198	0.212	0.206	0.240	0.251	0.204	0.217	0.200	0.209	0.212	0.222	0.219	0.181	0.217	0.211	0.209	0.205	0.230	0.254	0.233	0.261	0.226	0.248	0.242
λ-Eclipse	0.250	0.236	0.212	0.239	0.214	0.232	0.215	0.222	0.264	0.249	0.211	0.252	0.250	0.238	0.211	0.235	0.238	0.208	0.227	0.250	0.234	0.211	0.263	0.282	0.249	0.282	0.252	0.260	0.254
HiPer	0.245	0.252	0.224	0.243	0.218	0.226	0.230	0.227	0.293	0.265	0.212	0.235	0.232	0.247	0.243	0.259	0.235	0.193	0.244	0.234	0.243	0.234	0.274	0.281	0.265	0.289	0.252	0.264	0.258
NeTI	0.244	0.244	0.227	0.227	0.214	0.202	0.186	0.211	0.271	0.250	0.196	0.228	0.220	0.232	0.194	0.226	0.221	0.208	0.218	0.218	0.211	0.183	0.244	0.281	0.238	0.277	0.232	0.227	0.254

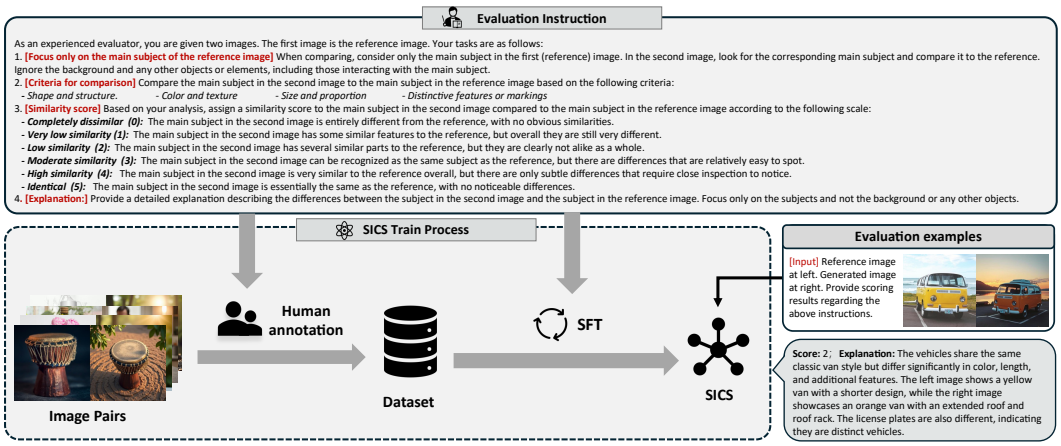


Figure 12: **The training process of SICS.** We constructed and annotated a dataset specifically tailored for subject consistency determination, and subsequently trained models using this dataset.

1. **Pearson Correlation Coefficient**
   - **Advantages:** Measures linear correlation between two continuous variables; simple to compute.
   - **Disadvantages:** Only suitable for linear relationships;sensitive to outliers; requires interval or ratio data; variables should be on the same scale.
   - **Applicability:** Use if both our metric and human scores are continuous and linearly related. If scales differ, standardize first.
2. **Spearman Rank Correlation Coefficient**
   - **Advantages:** Measures monotonic relationships; does not require linearity; robust to outliers; works with different scales and ordinal data.
   - **Disadvantages:** Only captures monotonic relationships; some information loss due to ranking.

Table 15: We evaluated the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **prompts with different scenarios**. Subject preservation, prompt following, and image quality are evaluated using SICS, CLIP-T, and HPSv2, respectively.

Method	Subject Preservation					
	Background Change	**Variation in Subject Viewpoint or Size**	**Interaction with Other Entities**	**Attribute Change**	**Style Change**	**Imagination**
BLIP-Diffusion	0.204	0.207	0.201	0.182	0.189	0.195
IP-Adapter	0.233	0.230	0.224	0.177	0.203	0.209
MS-Diffusion	0.361	0.359	0.337	0.266	0.294	0.308
OminiControl	0.300	0.263	0.212	0.176	0.252	0.211
SSR-Encoder	0.206	0.201	0.200	0.166	0.171	0.188
UNO	**0.433**	**0.414**	**0.379**	**0.359**	**0.418**	**0.349**
Emu2	0.393	0.316	0.315	0.326	0.224	0.239
RealCustom++	0.386	0.384	0.353	0.297	0.314	0.310
OmniGen	0.238	0.167	0.159	0.125	0.155	0.133
Custom Diffusion	0.073	0.060	0.053	0.047	0.037	0.047
DreamBooth	0.180	0.157	0.138	0.139	0.128	0.144
Textual Inversion	0.121	0.102	0.104	0.109	0.074	0.098
λ-Eclipse	0.262	0.257	0.249	0.246	0.244	0.230
HiPer	0.148	0.130	0.127	0.116	0.106	0.125
NeTI	0.211	0.182	0.185	0.198	0.173	0.182
Aver.	0.250	0.229	0.216	0.195	0.199	0.198

Method	Prompt Following					
	Background Change	**Variation in Subject Viewpoint or Size**	**Interaction with Other Entities**	**Attribute Change**	**Style Change**	**Imagination**
BLIP-Diffusion	0.297	0.275	0.264	0.285	0.272	0.271
IP-Adapter	0.326	0.319	0.319	0.312	0.306	0.310
MS-Diffusion	0.342	**0.339**	**0.341**	0.324	**0.338**	0.341
OminiControl	0.338	0.334	0.337	**0.329**	0.326	**0.342**
SSR-Encoder	0.310	0.296	0.288	0.299	0.288	0.291
UNO	0.334	0.328	0.333	0.305	0.302	0.335
Emu2	0.308	0.305	0.297	0.295	0.313	0.308
RealCustom++	**0.343**	0.333	0.329	0.319	0.328	0.338
OmniGen	0.327	0.325	0.328	0.311	0.315	0.327
Custom Diffusion	0.326	0.317	0.320	0.328	0.325	0.323
DreamBooth	0.326	0.318	0.319	0.319	0.323	0.320
Textual Inversion	0.303	0.299	0.300	0.296	0.298	0.296
λ-Eclipse	0.302	0.292	0.289	0.285	0.286	0.299
HiPer	0.325	0.323	0.315	0.318	0.318	0.311
NeTI	0.309	0.305	0.301	0.296	0.295	0.297
Aver.	0.321	0.314	0.312	0.308	0.309	0.314

Method	Image Quality					
	Background Change	**Variation in Subject Viewpoint or Size**	**Interaction with Other Entities**	**Attribute Change**	**Style Change**	**Imagination**
BLIP-Diffusion	0.234	0.220	0.199	0.235	0.239	0.214
IP-Adapter	0.269	0.263	0.258	0.272	0.276	0.259
MS-Diffusion	0.291	0.292	0.292	0.287	0.300	0.301
OminiControl	0.285	0.283	0.290	**0.293**	0.294	0.296
SSR-Encoder	0.256	0.246	0.231	0.256	0.256	0.238
UNO	0.282	0.281	0.283	0.268	0.275	0.276
Emu2	0.262	0.260	0.249	0.252	0.268	0.270
RealCustom++	**0.300**	**0.298**	**0.295**	0.284	**0.301**	**0.307**
OmniGen	0.263	0.259	0.271	0.257	0.260	0.282
Custom Diffusion	0.245	0.236	0.237	0.248	0.231	0.240
DreamBooth	0.252	0.242	0.239	0.250	0.246	0.243
Textual Inversion	0.228	0.222	0.222	0.230	0.225	0.221
λ-Eclipse	0.247	0.242	0.233	0.241	0.249	0.242
HiPer	0.250	0.247	0.241	0.255	0.247	0.240
NeTI	0.239	0.231	0.230	0.240	0.236	0.230
Aver.	0.260	0.255	0.251	0.258	0.260	0.257

- **Applicability:** Highly suitable for our scenario, especially when metrics have different scales or are not linearly related.

3. **Kendall Rank Correlation Coefficient**

Table 16: We evaluated the performance of various methods on DSH-Bench dataset, specifically analyzing their effectiveness across **images with different difficulty levels**. Subject preservation, prompt following, and image quality are evaluated using SICS, CLIP-T, and HPSv2, respectively.

Method	Subject Preservation			Prompt Following			Image Quality		
	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Medium	Hard
BLIP-Diffusion	0.221	0.209	0.190	0.284	0.278	0.273	0.198	0.227	0.232
IP-Adapter	0.266	0.233	0.206	0.316	0.315	0.316	0.236	0.270	0.278
MS-Diffusion	0.410	0.362	0.312	**0.340**	**0.339**	**0.335**	0.278	0.297	0.299
OminiControl	0.294	0.256	0.242	0.337	0.336	0.331	0.278	0.292	0.294
SSR-Encoder	0.234	0.212	0.174	0.299	0.295	0.294	0.220	0.251	0.257
UNO	**0.469**	**0.405**	**0.383**	0.326	0.325	0.319	0.261	0.281	0.283
Emu2	0.349	0.346	0.332	0.308	0.306	0.301	0.239	0.263	0.268
RealCustom++	0.448	0.379	0.331	0.334	0.333	0.329	**0.281**	**0.300**	**0.303**
OmniGen	0.224	0.188	0.170	0.321	0.324	0.321	0.249	0.267	0.272
Custom Diffusion	0.067	0.061	0.060	0.323	0.324	0.322	0.234	0.241	0.241
DreamBooth	0.184	0.163	0.139	0.323	0.322	0.319	0.232	0.248	0.249
Textual Inversion	0.092	0.112	0.115	0.295	0.300	0.299	0.206	0.226	0.233
λ-Eclipse	0.286	0.260	0.235	0.302	0.293	0.286	0.228	0.244	0.248
HiPer	0.139	0.145	0.122	0.323	0.319	0.315	0.230	0.251	0.251
NeTI	0.203	0.189	0.190	0.303	0.302	0.298	0.214	0.237	0.242
Aver.	0.259	0.235	0.213	0.316	0.314	0.311	0.239	0.260	0.263

Table 17: **Experiment hyperparameters on DSH-Bench.** LR: learning rate, Steps: training steps, GS: guidance scale

Method	T2I Model	Batch Size	LR	Train Steps	GS	Infer Steps	Additional parameter
BLIP-Diffusion	SD v1.5	N/A	N/A	N/A	7.5	25	N/A
IP-Adapter	SDXL	N/A	N/A	N/A	7.5	30	ip_adapter_scale: 0.5
MS-Diffusion	SDXL	N/A	N/A	N/A	7.5	30	scale: 0.6
OminiControl	FLUX.1-schnell	N/A	N/A	N/A	3.5	10	condition_scale: 1
SSR-Encoder	SD v1.5	N/A	N/A	N/A	7.5	30	λ : 0.5
UNO	FLUX.1-dev	N/A	N/A	N/A	4	25	N/A
Emu2	SDXL	N/A	N/A	N/A	3.0	50	N/A
RealCustom++	SDXL	N/A	N/A	N/A	7.5	25	N/A
OmniGen	SDXL	N/A	N/A	N/A	2.5	50	img_guidance_scale: 1.8
λ-Eclipse	SDXL	N/A	N/A	N/A	7.5	50	N/A
Textual Inversion	SD v1.5	4	5e-4	3000	7.5	50	N/A
DreamBooth	SD v1.5	1	2.5e-6	250	7.5	50	N/A
Custom Diffusion	SD v1.4	2	1e-5	250	6.0	100	N/A
HiPer	SD v1.4	1	5e-3	1500	7.5	50	N/A
NeTI	SD v1.4	2	1e-3	250	7.5	50	N/A

- **Advantages:** Also measures monotonic relationships; robust to outliers; suitable for rank/ordinal data.
- **Disadvantages:** More computationally intensive than Spearman; only captures monotonic relationships.
- **Applicability:** Also highly suitable, especially for smaller datasets or when we want a more robust rank-based measure.

4. **Krippendorff's Alpha**
   - **Advantages:** Handles multiple raters and various data types (nominal, ordinal, interval, ratio); can handle missing data.
   - **Disadvantages:** Mainly used for inter-rater reliability, not for correlation; does not indicate the direction of association; computationally complex.
   - **Applicability:** Not suitable for our scenario, as it is designed to measure agreement among multiple raters.

Consequently, we choose *Kendall's τ value* and *Spearman correlation coefficient value*.

E.3 Details of Prompt Generation

We present below a comparative analysis of prompts generated by three state-of-the-art vision-language models: GPT-4o, Gemini 2.5 Pro, and Claude. The specific instruction used to generate the

prompts can be found in Figure 5. A qualitative evaluation of these prompts reveals no significant or discernible differences in their content or structure. Given the comparable performance across the models, we selected GPT-4o for all prompt generation tasks in this study. Moreover, the results generated by GPT-4o include slightly more complex and diverse descriptions of the environment, which makes the model's generation and application more intricate and challenging. This choice also aligns with the methodology established in the Dreambench++, ensuring methodological consistency with prior work. The example is as follows:

Background Change

1. **Gemini 2.5 Pro:** A single african drum resting on the red earth of the African savanna at sunset.
2. **Claude:** An african drum standing on a sandy beach with waves in the background
3. **GPT-4o:** A single african drum placed on a sandy beach with gentle waves in the background under a clear sky.
4. **Gemini 2.5 Pro:** An african drum placed on a clean, white studio background.
5. **Claude:** An african drum placed in a lush green rainforest clearing.
6. **GPT-4o:** An african drum positioned on a wooden table inside a cozy rustic cabin with warm lighting and wooden walls.

Variation in Subject Viewpoint or Size

1. **Gemini 2.5 Pro:** A low-angle shot of an african drum sitting on a wooden stage, illuminated by a single, warm spotlight from above, with dust motes dancing in the light.
2. **Claude:** A low-angle shot of an african drum on a stage, with spotlights creating dramatic shadows.
3. **GPT-4o:** An african drum viewed from a high-angle perspective, placed on a grassy hilltop overlooking a distant mountain range with scattered wildflowers around it.
4. **Gemini 2.5 Pro:** Bird's-eye view of an african drum next to a crackling campfire at dusk, with the flickering firelight casting long, dancing shadows on the ground.
5. **Claude:** A bird's-eye view of an african drum in the center of a circular stone pattern in a park.
6. **GPT-4o:** A close-up shot of an african drum resting on a cobblestone pathway in a small village, with faint rays of sunlight filtering through nearby trees and a soft shadow cast beneath it.

Interaction with Other Entities

1. **Gemini 2.5 Pro:** A close-up shot of a musician's hands, blurred with motion, striking the surface of an african drum, with beads of sweat flying off the drumhead.
2. **Claude:** An african drum being played by multiple hands in a crowded marketplace, with motion blur on the hands.
3. **GPT-4o:** An african drum being played by a young boy surrounded by a group of people dancing in a circle under the moonlight at an outdoor festival, motion blurs capturing the dynamic movements of the dancers.
4. **Gemini 2.5 Pro:** A group of children in a circle, their joyful faces illuminated by the sun, all reaching out to play a large african drum together.
5. **Claude:** An african drum partially submerged in a clear lake, with its reflection visible on the water's surface
6. **GPT-4o:** An african drum partially obscured by tall reeds in a dense wetland, with a heron standing nearby and its reflection visible in the water below.

Attribute Change

1. **Gemini 2.5 Pro:** An african drum carved entirely from shimmering, translucent crystal, with glowing runes etched onto its surface.

2. **Claude:** An african drum made entirely of clear, shimmering crystal.
3. **GPT-4o:** An african drum painted entirely in vibrant rainbow colors and decorated with intricate tribal patterns.
4. **Gemini 2.5 Pro:** A futuristic, metallic african drum with a holographic drumhead that displays vibrant sound visualizations with every beat.
5. **Claude:** An african drum with a top made of stained glass, creating colorful patterns when light shines through.
6. **GPT-4o:** An african drum crafted from polished metal instead of wood, with a reflective surface that mirrors its surroundings.

Style Change

1. **Gemini 2.5 Pro:** A cubist painting of an african drum, deconstructed into geometric shapes and shown from multiple perspectives simultaneously.
2. **Claude:** An african drum rendered in the style of Vincent van Gogh's 'Starry Night', with swirling brushstrokes and vibrant colors.
3. **GPT-4o:** An african drum depicted in the Cubist art style, with fragmented geometric shapes and abstract distortions.
4. **Gemini 2.5 Pro:** An african drum depicted in the style of Japanese Ukiyo-e woodblock print, with flat colors, bold outlines, and a serene composition.
5. **Claude:** A cubist interpretation of an african drum, broken down into geometric shapes and multiple perspectives.
6. **GPT-4o:** An african drum illustrated in watercolor art, blending soft pastel tones with fluid brushstrokes, surrounded by splashes of color in the background.

Imagination

1. **Gemini 2.5 Pro:** A fleet of miniature african drums floating through a cosmic nebula, propelled by rhythmic sound waves that ripple through the stardust.
2. **Claude:** An african drum as a spaceship, with tiny alien creatures using it to explore the galaxy.
3. **GPT-4o:** An african drum floating in mid-air, surrounded by glowing orbs of light that pulse rhythmically as if responding to the drum's silent beat.
4. **Gemini 2.5 Pro:** In an enchanted forest, an ancient african drum is covered in moss and glowing mushrooms; when played, it causes the surrounding trees to grow and bloom instantly.
5. **Claude:** An african drum transformed into a living creature, with eyes and limbs, dancing in a magical forest.
6. **GPT-4o:** An african drum transformed into a magical portal, with swirling galaxies and stars emerging from its open top.

E.4 Details of Human Annotation

E.4.1 Annotation Verification Guidelines For Subject Difficulty Level Classification

Task Objective

- Verify the difficulty label assigned by the model (Easy / Medium / Hard) for the "subject detail preservation" when an image is used as a reference image.
- Subject: the primary, most prominent object or semantic entity in the image

Label Definitions (must align strictly)

- **Easy**: Low surface complexity, homogeneous texture, near-uniform color/material; virtually no high-frequency details. Examples: smooth, solid-colored ceramic mug; smooth sphere; plain object without text/markings.
- **Medium**: Contains discernible high-frequency features while maintaining globally simple, coherent structure; local details are present but not overwhelmingly dense. Examples: cylindrical container with readable text/logo; simple shapes with a few clear markings/scales/brand labels.
- **Hard**: Non-uniform texture distribution with multi-scale geometric/details; dense, fine-grained features across regions that materially affect the subject's appearance. Examples: book cover with fine calligraphy and intricate patterns; woven/engraved/ornamented materials; many lines of small text with layout hierarchy.

Step-by-Step Decision Process

1. **Identify the subject**
   - Select the single most salient object (by size, focus sharpness, centrality, semantic importance).
   - Multiple visible parts forming one entity (e.g., front and back of one book) count as one subject.
2. **Assess scale and detail density**
   - High-frequency details: small text, granular textures, dense lines/patterns, fine edges, repetitive microstructures.
   - Multi-scale: presence of large contours plus mid/small-scale text/patterns that meaningfully define appearance.
3. **Evaluate texture uniformity and surface complexity**
   - Uniform materials (solid/near-solid color, smooth, gradual highlights) $\rightarrow$ tends to *Easy*.
   - Simple shape with a few clear elements (e.g., a single line of text, logo) $\rightarrow$ tends to *Medium*.
   - Complex surface patterns with non-uniform textures across regions, multiple areas with distinct details $\rightarrow$ often *Hard*.
4. **Evaluate readable elements**
   - More numerous/smaller/denser text, more font variations, and deeper layout hierarchy increase difficulty.
   - A single large word or single big logo alone does not imply *Hard*; typically *Medium*.
5. **Shape and geometry**
   - Basic primitives (sphere/cylinder/cube) without details $\rightarrow$ *Easy*.
   - Basic primitives with a few marks/engraved lines $\rightarrow$ *Medium*.
   - Irregular shapes, folds/pleats, filigree, cutouts, elaborate ornaments $\rightarrow$ often *Hard*, depending on detail density.
6. **Lighting and material cues (auxiliary only)**
   - Specular highlights or reflections alone do not equal high-frequency detail. If the surface lacks true microstructure/patterns, it can still be *Easy*.
   - Genuine material textures (wood grain, fabric weave, leather grain, brushed metal) may raise difficulty to *Medium/Hard* based on density and multi-scale complexity.
7. **Context and occlusion (consider only if they affect visible details)**
   - Complex backgrounds do not increase subject difficulty unless inseparable from or part of the subject surface.

Decision Boundaries and Edge Cases

- *Easy vs. Medium*: Are there local details that must be faithfully reproduced to recognize the subject (e.g., small text, scales, granular texture)? If present and more than minimal, lean *Medium*.

- *Medium vs. Hard*: Are there multi-scale, regionally distributed complex details (e.g., title + subtitle + fine print over a textured background; or patterns + filigree + material grain) that jointly define appearance? If yes, lean *Hard*.
- **Text cases**:
  - Single large brand word: *Medium*.
  - Multiple lines of small text, varied font sizes, complex hierarchy: *Hard*.
- **Texture cases**:
  - Uniform matte/gloss: *Easy*.
  - Discernible but sparse texture (e.g., coarse weave with large spacing): *Medium*.
  - Fine, dense, non-uniform texture (e.g., fine weave, leather grain, wood grain overprinted with graphics): *Hard*.
- **Shape cases**:
  - Smooth ceramic mug (no pattern): *Easy*.
  - Measuring cup with a few scales/digits: *Medium*.
  - Book cover with fine calligraphy plus intricate patterns/material grain: *Hard*.

Operational Protocol and Output Format For each image, output:

1. **Difficulty verification**: choose *Easy / Medium / Hard / Uncertain*.
2. **Consistency with model label**: *Consistent / Inconsistent*.

Quality Control and Consistency

- Reduce borderline oscillation. If on the boundary, use majority voting over three axes: high-frequency detail density, texture uniformity, multi-scale complexity.
- If image quality is too low (blur/low resolution) to assess detail density, mark *Uncertain* and state the reason.
- Do not score based on aesthetics or unrelated factors (exposure, colorfulness), unless they impair detail discernibility.

E.4.2 Annotation Verification Guidelines For Prompt Generation

This guidelines defines the validation criteria for human annotators to assess whether prompts generated by a large model, based on an image subject, comply with task standards and formatting requirements. Please verify each item strictly and record any non-compliance with brief explanations in the annotation tool.

1. Overall Objective Annotators should determine whether the model-generated prompts, given the clearly defined subject `subject_name` (provided by the task input or uniquely identifiable from the image), meet the following:

1. Content centers on the subject and matches the semantic requirements of the corresponding category (background change, variation in subject viewpoint or size, interaction with other entities, attribute changes, style changes, imagination).
2. Quantity and structure meet the required counts.
3. Language is clear, unambiguous, and executable as image-generation prompts.
4. No prohibited or unsafe content (e.g., safety, ethics, copyright issues). Mark as non-compliant if present.

2. Input and Output Specifications (Strict)

- Input: an image (with a subject) and the model's JSON output.
- The model output must be valid JSON with the following six top-level fields (names must match exactly):

  - "background change": list with 2 items
  - "variation in subject viewpoint or size": list with 2 items
  - "interaction with other entities": list with 2 items
  - "attribute changes": list with 2 items
  - "style changes": list with 2 items
  - "imagination": list with 2 items
- Each list element is an natural-language prompt (preferably a complete sentence) and must explicitly include the subject name: `subject_name`.
- JSON must be machine-parseable: paired quotes, correct commas and brackets, and no comments or trailing commas.

3. Category Definitions and Decision Criteria Read each prompt and decide whether it satisfies the semantic requirements of its assigned category. If not, label it "Non-compliant – Category Error."

(1) BACKGROUND CHANGE (2 ITEMS)

- Requirement: Only change the background environment or setting; the subject's default attributes remain unchanged (color/material/shape/appearance unchanged). No interactions or complex effects.
- Acceptable: Simple location/time/weather descriptions (e.g., in a park," by the sea," "at sunset").
- Prohibited: Large viewpoint changes (e.g., bird's-eye view, low-angle close-up), strongly stylized lighting techniques, obstruction/reflection/motion effects, interactions, or attribute changes (e.g., color/material swaps).

(2) VARIATION IN SUBJECT VIEWPOINT OR SIZE (2 ITEMS)

- Requirement: Moderate adjustments to subject location, perspective, and lighting are allowed; add non-interactive environmental elements (buildings, roads, trees, etc.).
- Must include more than lighting changes: at least one clear change in perspective/composition/scene elements.
- Prohibited: Interactions with other animals/people; obstruction, reflection, motion effects; changes to inherent subject attributes.

(3) INTERACTION WITH OTHER ENTITIES (2 ITEMS)

- Requirement: Include one or more of the following:
  - Interactions between the subject and other animals/people or multi-subject interactions.
  - Visual effects such as obstruction, reflection, motion blur/trails.
- May combine perspective, lighting, and environmental changes.
- Prohibited: Changing the subject's inherent attributes (color/shape/material/appearance); if attributes change, it belongs in "attribute changes."

(4) ATTRIBUTE CHANGES (2 ITEMS)

- Requirement: Change the subject's own attributes (color, shape, material, components' appearance, patterns, structural details).
- Changes should focus on the subject itself, not merely environment or lighting.
- Prohibited: Purely stylistic changes (e.g., in the style of Impressionism") belong in style changes"; scene/interaction-only changes belong in background change/variation in subject viewpoint or size/interaction with other entities.

(5) STYLE CHANGES (2 ITEMS)

- Requirement: Change the overall artistic style (art movements, media, periods, processes, rendering methods).
- Example dimensions: Impressionism, Cubism, Baroque, Minimalism, cyberpunk, watercolor, oil painting, pixel art, low-poly, woodcut/printmaking, cel shading, photorealism, etc.
- Prohibited: Only changing inherent subject attributes (belongs in attribute changes"); only changing perspective/interaction/obstruction (belongs in other categories).
- Copyright and sensitivity: Avoid using identifiable living/modern specific artist names or protected signature styles. If present, mark Non-compliant – Copyright/Style."

(6) IMAGINATION (2 ITEMS)

- Requirement: Construct unrealistic or fantastical scenarios (science fiction, fantasy, surrealism), allowing violations of physical laws or common sense.
- Must still center on the subject and include the subject name.
- Prohibited: Vague fantasies unrelated to the subject; avoid illegal, harmful, or clearly unsafe content.

4. Common Compliance Requirements

SUBJECT CONSISTENCY

- Every prompt must contain the literal string `subject_name` (e.g., the subject is {subject_name}" or subject_name standing..."). If missing or misspelled, mark Non-compliant – Subject Missing/Error."
- Content must revolve around the subject, with a clear role and visibility. If the subject is ignored or replaced, mark Non-compliant – Subject Irrelevant."

SEMANTIC CLARITY AND NON-CONTRADICTION

- No contradictory descriptions (e.g., midnight with strong sunlight," underwater and on a desert" simultaneously).
- Do not include elements exceeding the category scope (e.g., complex interactions/effects in background change/variation in subject viewpoint or size; attribute/style changes in background change/variation in subject viewpoint or size/interaction with other entities).
- In attribute changes," do not let style terms be the primary change; conversely, in style changes," avoid attribute edits as the main point.

DIVERSITY AND NON-REPETITION

- Prompts within the same field should have substantive differences (location/viewpoint/elements/interaction types/attribute or style dimensions).
- Avoid mere synonym swaps or repeating the same composition.

SAFETY AND ETHICS

- No violent harm, hate, explicit adult content, illegal activity, or instructions for dangerous behavior.
- For people, avoid identifiable personal or sensitive information.
- Avoid generating protected brand logos or named-artist signature styles. Prefer generic style descriptors.

E.4.3 Annotation Guidelines For Labeling of the SICS Training Datasets

For detailed annotation guidelines, please refer to the Appendix E.2.

E.4.4 Annotator Recruitment, Training, and Consensus Protocol

We provide the following elaboration on annotator requirements and the specifics of our annotation pipeline:

1. All annotators involved in this work possess extensive experience in domain-relevant annotation. They have previously participated in similar tasks and have a thorough understanding of subject-driven text-to-image (T2I) generation.
2. All annotators hold a bachelor's degree or higher and are between 25 and 30 years old, ensuring the capability to accurately comprehend and implement the annotation guidelines.
3. We provided human annotators with sufficient training to ensure full understanding of the subject-driven T2I task and to promote unbiased, accurate evaluations. Detailed annotation guidelines are provided (see Figure 5 and Figure 12), and we conducted meetings with all annotators to comprehensively align and explain the rules.
4. To ensure consensus on annotation standards, we conducted a calibration process. Annotators first labeled a small pilot dataset; we then reviewed discrepant cases and provided targeted feedback and additional training. This iterative process was repeated until all annotators demonstrated high consistency in their understanding of the differentiation criteria for each annotation task.
5. During the formal annotation phase, each sample was independently labeled by five annotators. To construct a high-confidence training dataset, we applied a consensus-based filtering criterion, retaining only samples for which at least four annotators (i.e., $\geq 80\%$) assigned identical labels.

F More Generation Examples

Figure 13 shows the generation examples of different methods across different difficulty levels. Figure 14 shows the generation examples of different methods across different prompt scenarios. The blue block highlights encoder-based methods, and the green block highlights fine-tuning-based methods.

G Large Language Model Usage Statement

In this work, we leverage large language models to assist human annotators during data labeling and to generate prompts. Detailed procedures are provided in the Appendix E.3, Appendix E.4, Section 2.1.1 and Section 2.1.3. We also employed large language models to aid in manuscript preparation.

H Limitations

DSH-Bench addresses the limitations of current subject-driven T2I generation benchmarks by providing a comprehensive and diverse dataset with 459 subject images and 5,508 prompts, covering categories such as person, mammal, clothing, and so on. However, the benchmark is constrained to 459 subject images. Increasing the number of test samples could enhance the credibility and complexity of the evaluation. Additionally, we did not conduct a cross-analysis between subject difficulty and prompt scenario. Despite meticulous manual reviews, some unintentional annotation errors may still be present.

Figure 13: **Examples of images generated by all methods on different subjects difficulty level.**

Figure 14: **Examples of images generated by all methods on different prompt scenarios.**

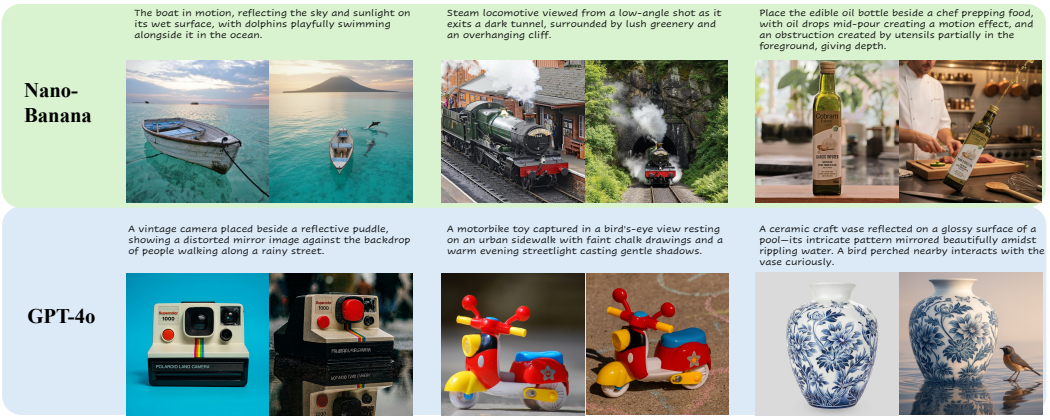


Figure 15: **Examples of badcases generated by GPT-4o and Nano-Banana on hard examples**