Complex-Edit: CoT-Like Instruction Generation for Complexity-Controllable Image Editing Benchmark

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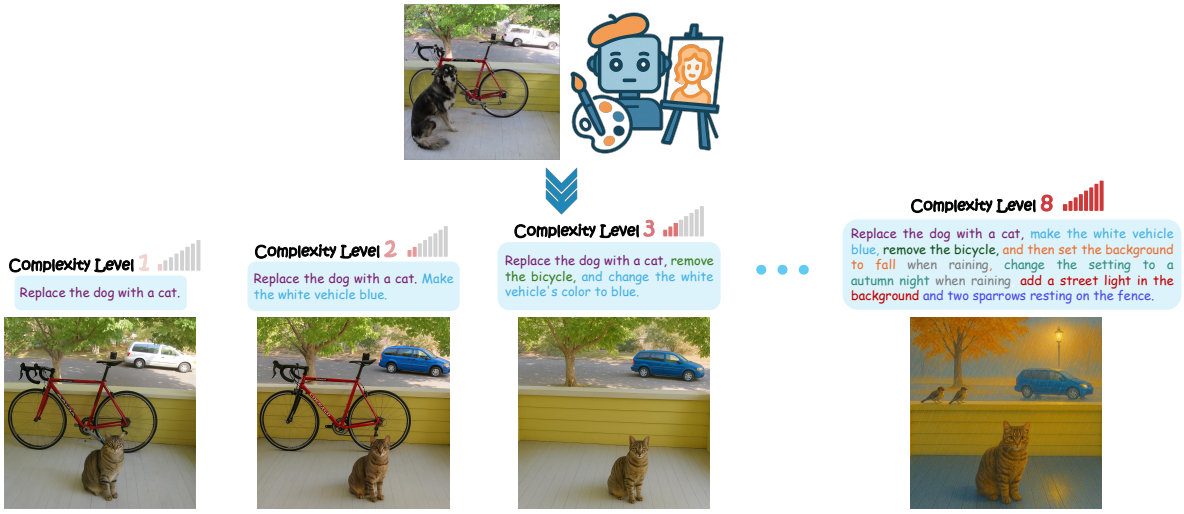


Figure 1: An illustration of our `Complex-Edit` Benchmark. This figure presents a structured progression of instruction complexity in image editing tasks, highlighting the transition from atomic edits to highly intricate transformations.

Abstract

We introduce `Complex-Edit`, a comprehensive benchmark designed to systematically evaluate instruction-based image editing models across instructions of varying complexity. To develop this benchmark, we harness GPT-4o to automatically collect a diverse set of editing instructions at scale. Our approach follows a well-structured "Chain-of-Edit" pipeline: we first generate individual atomic editing tasks independently and then integrate them to form cohesive, complex instructions. Additionally, we introduce a suite of metrics to assess various aspects of editing performance, along with a VLM-based auto-evaluation pipeline that supports large-scale assessments.

Our benchmark yields several notable insights: 1) Open-source models significantly underperform relative to proprietary, closed-source models, with the performance gap widening as instruction complexity increases; 2) Increased instructional complexity primarily impairs the models' ability to retain key elements from the input images; 3) Stronger models aren't necessarily more resilient towards higher complexity; 4) Decomposing a complex instruction into a sequence of atomic steps, executed in a step-by-step manner, substantially degrades performance across multiple metrics; 5) A straightforward Best-of-N selection strategy improves results for both direct editing and the step-by-step sequential approach; and 6) We observe a "curse of synthetic data": when synthetic data is involved in model training, the edited images from such models tend to appear increasingly synthetic as the complexity of the editing instructions rises — a phenomenon that intriguingly also manifests in the latest GPT-Image-1's outputs.

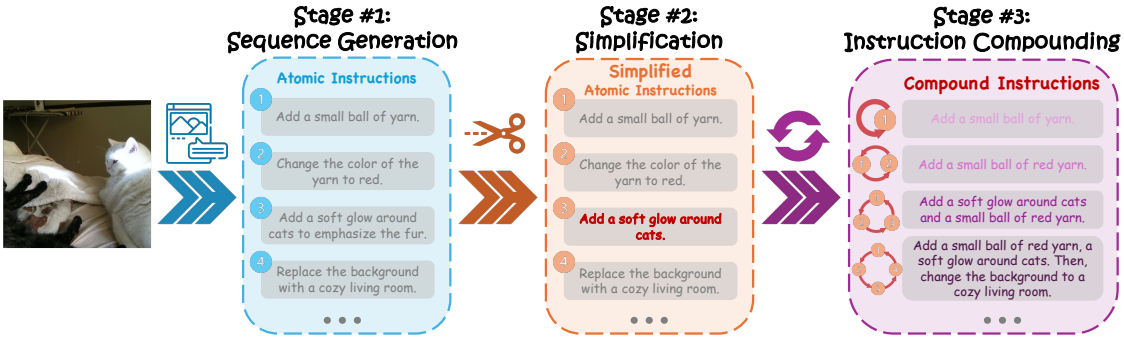


Figure 2: An overview of our data collection pipeline. The pipeline consists of three distinct stages: 1) **Stage #1 Sequence Generation**: for each image, a series of atomic instructions is produced; 2) **Stage #2 Simplification**: each fundamental instruction is refined to eliminate extraneous details, preserving only the essential description of the editing process; 3) **Stage #3 Instruction Compounding**: several atomic instructions are integrated into one comprehensive instruction.

1 Introduction

Since InstructPix2Pix (Brooks et al., 2023) introduced instruction-based image editing—where images are directly modified through textual commands—the field has witnessed remarkable progress. Noteworthy developments include enhancements in the quality of training images (Kawar et al., 2023; Zhang et al., 2024; Hui et al., 2025; Zhao et al., 2024; Wei et al., 2025; Baldridge et al., 2024), the evolution of model architectures from CNN-based to transformer-based diffusion models (Ma et al., 2024), the refinement of training methodologies (Simsar et al., 2024; Shi et al., 2024), and the on-going exploration of test-time scaling (Guo et al., 2025; Ma et al., 2025).

Despite these strides, much of the available training data and evaluation benchmarks rely on relatively simple editing instructions (Brooks et al., 2023; Zhang et al., 2023; 2024; Zhao et al., 2024; Yu et al., 2024; Wei et al., 2025; Sheynin et al., 2023; Ku et al., 2024b). Yet, real-world scenarios often demand the ability to handle instructions that vary considerably in complexity. For instance, while one user might simply request to "remove the car", another might need a more elaborate transformation, such as "replace the car with a blue bus featuring an iPhone advertisement on its side". The current lack of evaluation benchmarks capable of handling such diverse instruction complexities not only impedes our ability to rigorously assess existing editing models but also hampers the evaluation of emerging, more powerful systems (Guo et al., 2025; Ma et al., 2025).

To bridge this gap, we present a novel data generation pipeline that leverages advanced GPT models to create a diverse, scalable, and complexity-controllable evaluation dataset for image editing (see Fig. 2 for an illustration). Our approach follows a chain-of-thought-like (Wei et al., 2022) paradigm, unfolding in three key stages. First, in the *Sequence Generation* stage, an input image prompts GPT-4o to generate a series of simple instructions corresponding to predefined atomic operations (*e.g.*, "Add an Object", "Change the Object Color"), with each serving as an intermediate step toward a more complex editing task. Next, recognizing that these GPT-generated atomic instructions may contain superfluous/unnecessary details—such as added commentary on the operation's intention—we then move to a *Simplification* stage, where each instruction is trimmed to retain only its core editing intent. In this final *Instruction Compounding* stage, the simplified atomic instructions are merged into a single, coherent complex instruction (again, via GPT-4o), using the input image as contextual guidance. We name this new dataset `Complex-Edit`. Importantly, this structured process of creating `Complex-Edit` allows us to quantitatively control the editing instruction's complexity by simply adjusting the number of merged atomic instructions.

To evaluate performance on these complex instructions, we developed a comprehensive evaluation framework that measures three critical dimensions: (1) *Instruction Following*, which assesses whether the intended modifications are correctly applied; (2) *Identity Preservation*, which ensures that unspecified elements remain unchanged; and (3) *Perceptual Quality*, which evaluates the overall aesthetic quality and absence of artifacts. To support large-scale evaluations, we implement a vision language model (VLM)-based autograding system to quantify these dimensions. Our investigation further identifies important considerations in enhancing this

evaluation pipeline. For example, enabling chain-of-thought reasoning in VLM evaluations does not necessarily enhance evaluation quality—contrary to previous findings (Ku et al., 2024a; Hui et al., 2025)—while providing detailed rubrics and using direct numeric scoring (Xie et al., 2023; 2024; Zhou et al., 2024; Cui et al., 2024) consistently improves autograder performance.

Our extensive evaluation results reveal five key insights that were previously difficult to capture with existing benchmarks. First, open-source models significantly underperform compared to proprietary, closed-source models, with this disparity growing as editing complexity increases. Second, the increasing instruction complexity mainly affects editing models' identity preservation, while its impact on instruction following varies across models. Thirdly, more capable models do not reliably exhibit increased resilience to the negative effects of the higher instruction complexity. Fourth, unlike the benefits observed with chain-of-thought (CoT) reasoning in text generation, CoT-inspired sequential editing yields much worse results than directly executing complex instructions — we note this is because sequential editing significantly degrades outputs in instruction following, identity preservation, and perceptual quality. Fifth, simple techniques such as Best-of-N sampling improve direct editing outcomes across all three dimensions and, when applied to sequential editing, notably enhance identity preservation and perceptual quality. Lastly, our `Complex-Edit` reveals an emerging 'curse of synthetic data' — when training utilizes synthetic images, models tend to produce edited outputs with overly synthetic qualities under complex instructions, often resembling oil paintings or animations. More interestingly, this phenomenon is also observed with the latest GPT-Image-1, potentially suggesting that the incorporation of synthetic data may contribute to GPT-Image-1's advanced image generation capabilities.

We hope this newly developed benchmark, `Complex-Edit`, will not only deepen the understanding of instruction-based image editing models but also serve as a valuable framework for the rigorous evaluation of next-generation image editing systems, particularly those with test-time scalability.

2 Collection of `Complex-Edit`

As illustrated in Fig. 2, the collection of `Complex-Edit` is organized into three stages: 1) **Stage #1 Sequence Generation**: a sequence of atomic instructions are generated for each image; 2) **Stage #2 Simplification**: each atomic instruction is simplified to remove unnecessary information other than the description of the editing operation; 3) **Stage #3 Instruction Compounding**: multiple atomic instructions are combined into a single, complex instruction.

2.1 Sequence Generation

In this first stage, we define 24 distinct atomic operations that represent the most basic actions of image editing, which are grouped into 9 categories — *Object Manipulation and Transformation*, *Color and Tone Adjustments*, *Texture and Material Adjustments*, *Background and Environment, Lighting and Shadows*, *Text and Symbols*, *Composition and Cropping*, *Pose and Expression*, *Special Effects* — each of which captures a unique aspect of image editing, as shown in Fig. 3.

We provide detailed descriptions of each operation type in the Sec. A. These categorized atomic operation types and their descriptions, along with an input image, are fed into GPT-4o to generate a sequence of atomic instructions with a predetermined length. Each generated instruction is associated with one of the predefined atomic operations. We also record the atomic operation type for each instruction, with its distribution illustrated in Fig. 4. This metadata can facilitate the future development of specialized image editing models.

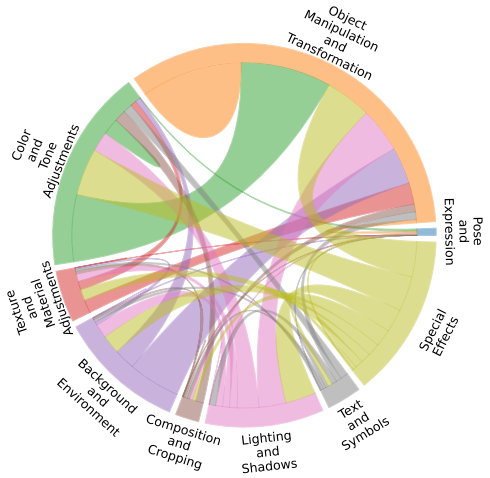


Figure 4: The distribution of atomic instructions among 9 operation categories. The arc thickness between two categories shows the number of adjacent instructions from these two categories.

2.2 Simplification

In practice, these GPT-generated instructions sometimes are unnecessarily rich in detail and may include extraneous commentary on the intentions of the editing operations, as shown in Fig. 2. Because our benchmark is designed to evaluate the performance of image-editing models on clear and concise instructions, we employ a dedicated simplification stage to eliminate any superfluous content. Specifically, each generated

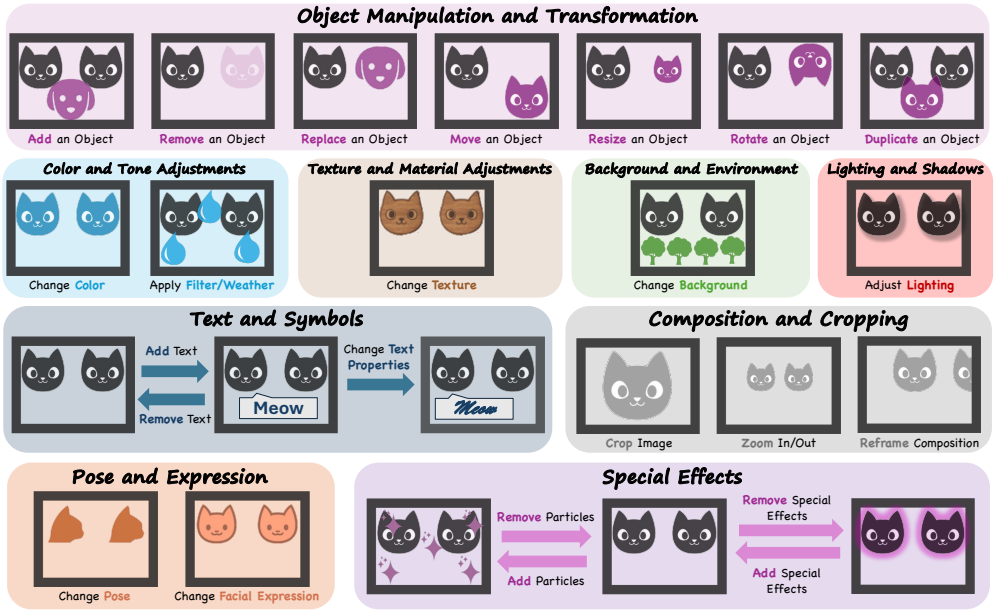


Figure 3: An illustration of 24 types of atomic editing operations in 9 categories.

atomic instruction is examined by GPT-4o to determine whether it requires further simplification; if so, GPT-4o outputs a simplified version adhering to the predefined response format, and the original instruction is replaced accordingly.

2.3 Instruction Compounding

Lastly, simplified atomic instructions are combined into compound instructions. Specifically, given a sequence of N atomic instructions, we progressively generate N compound instructions corresponding to different complexity levels: a compound instruction at complexity level C_i is formed by combining the first i atomic instructions in the sequence, with the simplest level (C_1) being identical to the first atomic instruction and the hardest level (C_N) integrating all N atomic instructions.

In implementation, rather than simply concatenating the instructions, atomic instructions are seamlessly integrated, which allows potential reordering or merging to produce to make the final outcome more natural and coherent. For example, in Fig. 2, rather than sequentially executing "add a ball of yarn" and "change the color of the yarn to red", the instructions are compounded into a single directive: "add a red ball of yarn".

2.4 Implementation Details

To ensure that GPT-4o fully understands our objectives, we carefully construct multiple few-shot examples for each of the three stages. Additionally, CoT reasoning (Wei et al., 2022) is enabled in both Stage #1 (Sequence Generation) and Stage #3 (Instruction Compounding) to enhance generation quality. Furthermore, to improve data diversity, we slightly increase the sampling temperature from 1.0 to 1.15 during Stage #1 (Sequence Generation). Although this adjustment promotes diversity, it also increases the likelihood of generating garbled text. To address this, we implement a rule-based filtration mechanism at each stage that detects and regenerates any flawed outputs.

3 Evaluation

Following prior works (Ku et al., 2024a; Hui et al., 2025), we employ VLM-based autograders to facilitate large-scale evaluation. However, we have observed that these frameworks do not fully capture the nuances of instruction-guided image editing. In response, we introduce several enhancements to address these limitations and improve the overall autograding framework.

3.1 Metric Design

Our evaluation framework focuses on two primary dimensions: 1) the alignment dimension—whether the output image reflects the changes specified by the editing instruction, and 2) the perceptual quality dimension—whether the output image looks aesthetically pleasing and is devoid of visual artifacts.

Figure 5: Examples of evaluation results for Instruction Following and Identity Preservation.

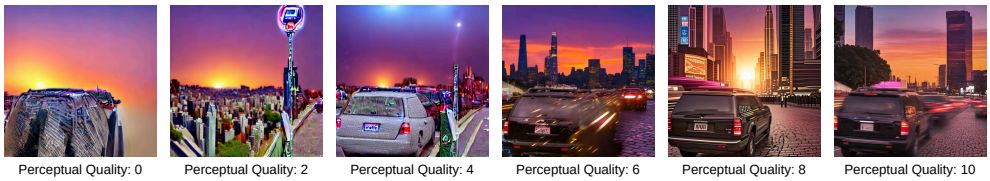


Figure 6: Examples of evaluation results for Perceptual Quality.

3.1.1 Alignment

Unlike HQ-Edit (Hui et al., 2025), which simply measures alignment as a single metric, we hereby decompose it into two complementary criteria: 1)**Instruction Following** (IF) measures whether the specified modifications are present in the output image; 2)**Identity Preservation** (IP) assesses whether elements of the input image that should remain unchanged are indeed preserved.

We would like to point out that these two criteria roughly correspond to the directional CLIP similarity (CLIP_{dir}) and image-wise CLIP similarity (CLIP_{img}) metrics used in earlier studies (Brooks et al., 2023; Zhang et al., 2023; 2024). When accessing IF and IP, we feed the VLM with a triplet containing {*input image*, *output image*, and *editing instruction*}. We provide a series of example results of IF and IP in Fig. 5.

3.1.2 Perceptual Quality

Beyond alignment, we also evaluate the overall visual quality of the generated images. Specifically, our **Perceptual Quality (PQ)** metric examines factors such as consistency in lighting and shadows, style coherence, and the seamless integration of elements. Because users may sometimes request bizarre or non-aesthetic edits, such as "add motion blur to these vehicles" or "enlarge the pet to match the height of the owner", one might argue that it is essential to include editing instructions when evaluating perceptual quality. However, as discussed in Sec. 4.1.4, our empirical results indicate that providing editing instructions to VLMs actually reduces the correlation between VLM and human evaluations. Consequently, for PQ evaluation, we only supply the VLM autograder with the edited image. Sample PQ results are provided in Fig. 6.

3.1.3 Overall Score

Lastly, we define the overall score, O, simply as the arithmetic mean of the three metrics to summarize performance: $O = \frac{IF+IP+PQ}{3}$.

3.2 Metric Calculation

3.2.1 Numeric Scoring v.s. Token Probability

In line with VIEScore and HQ-Edit, we instruct the VLM to assign a score between 0 and 10 for each metric. We refer to this method as **numeric scoring**. In addition, we explore another approach for metric computation: **token probalility**, which is widely used in test-time scaling and VLM post-training (Xie et al., 2023; 2024; Zhou et al., 2024; Cui et al., 2024). Specifically, rather than directly asking the VLM for a numerical score, we reformulate the evaluation as a binary classification task by posing a *yes-or-no question* to the VLM, *e.g.*, "Do the specified changes appear in the output image?". The score is then calculated as the normalized token probability for the affirmative response "Yes" using $\text{Prob}_{\text{Yes}}/(\text{Prob}_{\text{Yes}} + \text{Prob}_{\text{No}})$.

Table 1: Random sampling vs Discriminative sampling.

Deterministic	Correlation		
	IF	*IP*	*PQ*
	0.468	**0.530**	**0.234**
✓	0.461	0.507	0.215

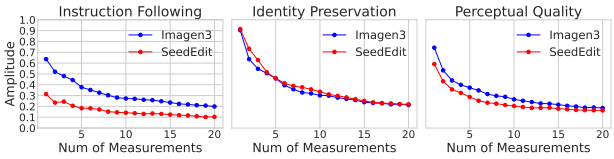
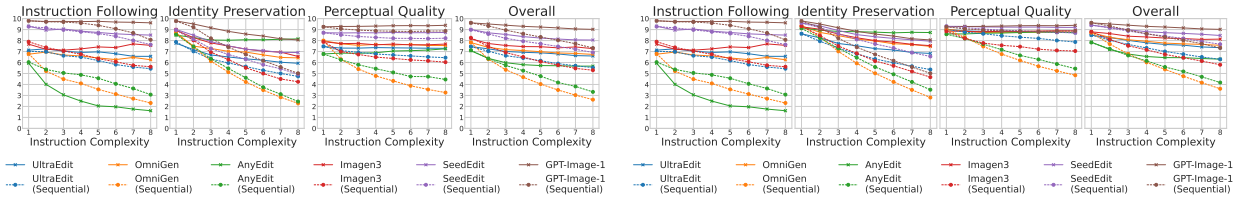


Figure 7: Relationship between per-sample variance and the number of measurements.

Table 2: Results from different scoring methods. We can observe that w/ COT and w/ Rubric are the best for IF and IP, and w/o COT and w/ rubric are the best for PQ.

Scoring Method	CoT	Rubric	Correlation		
			IF	*IP*	*PQ*
Token Prob			0.411	0.366	0.136
Token Prob	✓		0.447	0.460	0.158
Numeric			0.434	0.450	0.207
Numeric		✓	0.446	0.451	**0.234**
Numeric	✓	✓	**0.468**	**0.530**	0.208
			CLIP_{dir}	CLIP_{img}	
			0.182	0.523	



(a) Real input images. (b) Synthetic input images.

Figure 8: Evaluation results of direct and sequential editing. The instruction complexity level ranges from C_1 to C_8. This indicates that *IP* and *PQ* consistently dropped as the instruction complexity level grows, while it influence on *IF* varies among different models. Also, the performance gap between models is enhanced with increasing complexity.

3.2.2 Detailed Rubric

In contrast to existing frameworks like VIEScore and HQ-Edit, we design comprehensive rubrics for each metric to guide the evaluation process and improve result interpretability. Detailed descriptions of these rubrics are provided in the Sec. B.1. In addition, we discuss the impact of these rubrics and different scoring approaches in Sec. 4.1.2.

3.3 Per-sample Variance

Previous evaluations of image-editing models using advanced proprietary VLMs, such as GPT-4o (Hurst et al., 2024) and Gemini (Team et al., 2023; 2024), have encountered issues with score stability, leading to score variations for individual samples across different runs. Although averaging over many samples generally mitigates these discrepancies at the dataset level, per-sample stability is crucial for test-time scaling, where accurate and consistent evaluation is required for each individual sample (Guo et al., 2025; Ma et al., 2025).

A straightforward approach to enhance stability utilizes multiple measurements to average the resultant scores, though this approach may considerably escalate computational costs. Alternatively, one can attempt to make VLM outputs more deterministic by using greedy random sampling techniques (*e.g.*, by setting the sampling probability mass to an extremely low value such as 1e-7). However, empirically, this deterministic approach slightly lower the correlation with human evaluations as shown in Tab. 1. Consequently, we adopted the first approach by default, utilizing the average score from 20 independent evaluations for each sample. Further discussion on reducing per-sample variance is included in Sec. 4.2.

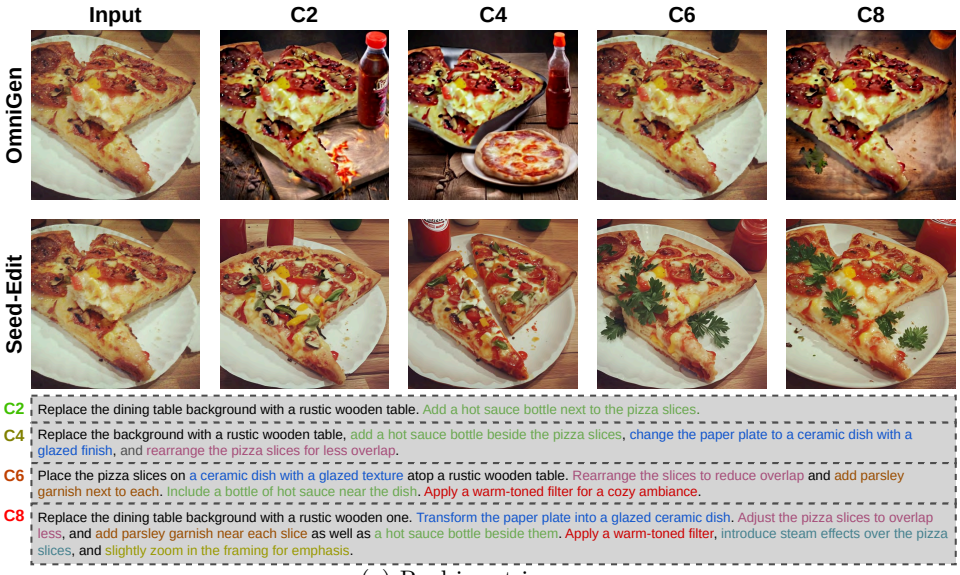
4 Meta-Evaluation for Metrics

In this section, we detail our meta-evaluation of the VLM-based auto-evaluation framework, focusing on design choices and their effectiveness in assessing image editing model outputs. We expect an effective auto-evaluation pipeline to satisfy two core criteria: 1) High correlation with human judgments, and 2) Low variance for ensuring reproducibility. Next, we first examine how various design decisions impact correlation with human evaluations (Sec. 4.1) and then describe our strategies for reducing per-sample variance (Sec. 4.2).

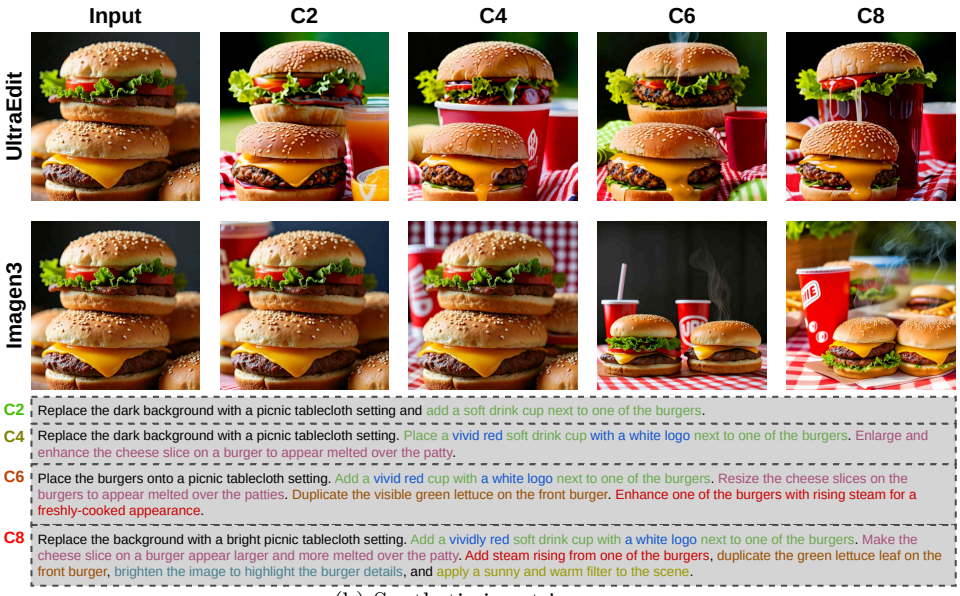
4.1 Correlation with Human Evaluation

4.1.1 Meta-Evaluation Settings

Meta-evaluation for instruction-based image editing metrics (Ku et al., 2024a; Hui et al., 2025) is typically performed by correlating human-assigned scores with metric values. However, we found that expecting human



(a) Real input images.



(b) Synthetic input images.

Figure 9: Outputs from open-source and proprietary models via direct editing. See results with more models in the Appendix Figs. 18 and 19.

raters to assign consistent numeric scores across diverse samples is challenging. Instead, for each input image and editing instruction, we present raters with a pair of output images and ask them to compare the outputs with respect to each metric. We then compute the correlation between these human comparisons and the differences in the corresponding metric scores. Additionally, we ask raters to choose their preferred output based on overall impression. This comparative approach allows us to align our metric aggregation with human intuition and to determine the best way to combine the three proposed metrics into a single score.

To ensure that our meta-evaluations generalize across varying levels of instruction complexity, we sampled 100 output images for each complexity level from C_1 (*i.e.*, the simplest level, just a single atomic instruction) to C_8 (*i.e.*, the hardest level, compounding from 8 atomic instructions) using both Imagen3 (Baldridge et al., 2024) and SeedEdit (Shi et al., 2024), resulting in 800 image pairs. Each pair was annotated independently by at least two human raters. We use GPT-4o as our VLM evaluator for the meta-evaluation study. Since

Table 3: Performance comparison between C_1 and C_8 on images. All models almost consistently underperform on all metrics when the complexity increases from C_1 to C_8.

Table 4: Real input images

Model	C_1				C_8				$C_8 - C_1$			
	IF	*IP*	*PQ*	*O*	*IF*	*IP*	*PQ*	*O*	Δ_{IF}	Δ_{IP}	Δ_{PQ}	Δ_O
UltraEdit	7.13	7.76	7.45	7.45	6.56	5.93	7.29	6.59	**-0.57**	**-1.82**	**-0.16**	**-0.85**
OmniGen	6.76	8.69	7.99	7.82	6.25	6.42	7.55	6.74	**-0.50**	**-2.27**	**-0.45**	**-1.07**
AnyEdit	5.94	8.50	6.78	7.07	1.61	**8.15**	7.25	5.67	**-4.33**	**-0.34**	**+0.47**	**-1.40**
Imagen3	7.67	8.93	7.90	8.17	7.56	6.55	7.68	7.27	**-0.11**	**-2.38**	**-0.22**	**-0.90**
SeedEdit	9.31	9.01	8.71	9.01	8.50	6.91	8.74	8.05	**-0.81**	**-2.10**	**+0.02**	**-0.96**
GPT-Image-1	**9.80**	**9.79**	**9.25**	**9.61**	**9.61**	8.06	**9.39**	**9.02**	**-0.18**	**-1.73**	**+0.14**	**-0.59**
Average	7.77	8.78	8.02	8.19	6.68	7.00	7.98	7.22	**-1.08**	**-1.77**	**-0.03**	**-0.96**

Table 5: Synthetic input image.

Model	C_1				C_8				$C_8 - C_1$			
	IF	*IP*	*PQ*	*O*	*IF*	*IP*	*PQ*	*O*	Δ_{IF}	Δ_{IP}	Δ_{PQ}	Δ_O
UltraEdit	7.82	8.61	9.02	8.48	6.51	6.83	8.72	7.35	**-1.30**	**-1.78**	**-0.30**	**-1.13**
OmniGen	7.80	9.34	9.05	8.73	6.49	7.47	8.74	7.57	**-1.31**	**-1.87**	**-0.31**	**-1.16**
AnyEdit	5.79	9.17	8.61	7.86	1.47	**8.73**	8.72	6.31	**-4.32**	**-0.44**	**+0.11**	**-1.55**
Imagen3	8.27	9.25	8.86	8.79	7.97	7.54	8.88	8.13	**-0.30**	**-1.72**	**+0.03**	**-0.66**
SeedEdit	9.33	9.60	9.29	9.41	8.25	7.94	9.20	8.46	**-1.08**	**-1.66**	**-0.10**	**-0.95**
GPT-Image-1	**9.82**	**9.79**	**9.55**	**9.72**	**9.42**	8.23	**9.58**	**9.08**	**-0.41**	**-1.56**	**+0.03**	**-0.64**
Average	8.14	9.29	9.06	8.83	6.69	7.79	8.97	7.82	**-1.45**	**-1.50**	**-0.09**	**-1.02**

the per-sample variance is yet to be discussed in Sec. 4.2, for now, we *naively* evaluate each sample 40 times and average the scores to reduce the per-sample variance.

4.1.2 Scoring Method and Rubric

As shown in Tab. 2, our experiments indicate that numeric scoring yields a higher correlation with human evaluation than token probability methods. Moreover, adding a detailed rubric to numeric scoring enhances this correlation consistently, highlighting the need for clear evaluation guidelines.

4.1.3 Chain-of-Thought

We additionally investigate the impact of CoT on our evaluation by adding an explicit instruction (*e.g.*, "explain your reasoning before answering the question") to encourage the VLM evaluator to articulate its reasoning prior to delivering the final score. The complete prompt for evaluation is provided in Appendix Sec. B.2. However, as shown in Tab. 2, our results indicate that CoT fails to enhance metric correlation consistently. In particular, CoT negatively affects the correlation for Perceptual Quality PQ when using numeric scoring. Consequently, we utilize numeric scoring with detailed rubrics and CoT only for Instruction Following IF and Identity Preservation IP, while CoT is disabled during Perceptual Quality PQ evaluation.

4.1.4 Instruction Input for Perceptual Quality

One might initially hypothesize that including the editing instructions alongside the output image could help the VLM discount aesthetically inferior modifications that are explicitly required by the instructions during Perceptual Quality PQ evaluation. However, our experiments reveal that providing the editing instructions significantly lowers the correlation with human evaluations from 0.234 to 0.046. Consequently, we exclude the editing instructions when evaluating Perceptual Quality PQ, ensuring that the VLM's assessments of image quality better align with human perception.

4.1.5 Different Averaging Formula for Overall Score

Previous studies (Ku et al., 2024a; Wei et al., 2025) advocate using the geometric mean to combine individual metrics to penalize low scores. In our case, switching from the geometric mean to the arithmetic mean resulted in a modest correlation increase from 0.334 to 0.386. Therefore, we compute the overall score as the arithmetic mean of the individual metrics.

4.1.6 Comparison with CLIP Scores

We further compare the correlation of Directional CLIP Score CLIP_{dir} and Image-wise CLIP Score CLIP_{img} with human evaluation, as these scores similarly assess aspects of Instruction Following IF and Identity Preservation IP. As reported in Tab. 2, these CLIP scores exhibit lower correlations with human evaluations compared to our metrics.

4.2 Per-Sample Variance

As discussed in Sec. 3.3, one way to reduce per-sample variance is to set the probability mass for sampling to an extremely small value, *e.g.*, 1e-7, thereby approximating the determinism of proprietary VLMs. However, as shown in Tab. 1, this approach slightly diminishes the correlation with human evaluations. Consequently, we disable deterministic sampling and instead perform multiple evaluations per sample, using the average score as the final metric.

To determine the required number of measurements per sample, we study the relationship between the number of measurements per sample and the variation in final scores across independent runs. Specifically, given K measurements for one sample, we compute average scores four times, each averaged from K distinct measurements, denoted as S_1, S_2, S_3, S_4. The variation for this sample is defined as $\frac{\max\{S_1,S_2,S_3,S_4\}-\min\{S_1,S_2,S_3,S_4\}}{2}$.

Table 6: Evaluation results with direct editing on real images with the instruction complexity at C_8.

Model	Prop. of Real Images	Realistic Style	IF	IP	PQ	O
UltraEdit	✓	★	6.56	5.93	7.29	6.59
OmniGen	✓✓✓	★★★★★	6.25	6.42	7.54	6.74
AnyEdit	✓✓✓	★★★★	1.60	**8.15**	7.25	5.67
SeedEdit	✓	★★	8.49	6.91	8.74	8.04
Imagen3	?	★	7.56	6.55	7.67	7.26
GPT-Image-1	?	★★	**9.61**	8.06	**9.39**	**9.02**

Fig. 7 shows that the variation amplitudes for all three metrics converge when $K = 20$. Therefore, we adopt 20 measurements per sample in all subsequent experiments.

5 Experiments

5.1 Experiment Setup

Dataset. Our `Complex-Edit` dataset comprises both realistic and synthetic images. Specifically, we select 531 deduplicated images from the EMU-Edit test set (Sheynin et al., 2024) to serve as our realistic image collection. In parallel, we use FLUX.1 (Labs, 2024) to generate an equivalent set of 531 synthetic images based on the captions associated with these real-world images, also sourced from EMU-Edit. Following Sec. 2, we create editing instructions with the complexity ranging from C_1 to C_8 for these images.

Models. Our experiments involve five advanced instruction-based image editing models: three open-source models (UltraEdit (Zhao et al., 2024), OmniGen (Xiao et al., 2024), AnyEdit (Yu et al., 2024)) and three proprietary models (Imagen3 (Baldridge et al., 2024), SeedEdit (Shi et al., 2024), GPT-Image-1 (OpenAI, 2025)). We evaluate each model on both realistic and synthetic images using editing instructions spanning complexity levels from C_1 to C_8. Note that, owing to usage policies for the proprietary models, results are reported on approximately 60% of the images for Imagen3, 95% for SeedEdit and 90% for GPT-Image-1. All the evaluation are performed by GPT-4o by default. In addition to GPT-4o, we also provide evaluation results by Gemini-2.5-Pro (Comanici et al., 2025) in Appendix Sec. C.

5.2 Effect of Increasing Complexity

Figure 10: A real image edited with a C_8 instruction. Outputs from certain models tend to lose the realistic style completely.

Fig. 8 illustrates the overall performance trends as instruction complexity increases. In general, higher complexity leads to a consistent decline in Identity Preservation across models, while Instruction Following and Perceptual Quality tend to fluctuate depending on the specific model. For instance, although AnyEdit exhibits a substantial drop in Instruction Following as complexity increases, its Perceptual Quality improves moderately. Additionally, proprietary models outperform open-source alternatives on both realistic and synthetic images, and the performance gap becomes more pronounced at higher complexity levels. Specifically, GPT-Image-1 significantly outperforms all other models at the hardest instruction complexity level C_8, particularly in terms of Instruction Following and Perceptual Quality.

Furthermore, both the GPT-4o's and Gemini-2.5-Pro's evaluation in Tab. 3 and Appendix Tab. 7 shows that open-source models' performance drops are not notably more severe than proprietary models other than GPT-Image-1. For example, when editing synthetic images, all open-source models have drops larger than 1 in Overall score while the Overall score's drop of Imagen3 and SeedEdit are 0.66 and 0.95 respectively, implying that stronger models may not be more resilient towards the negative impact of increased instruction complexity. Sample qualitative results are shown in Fig. 9.

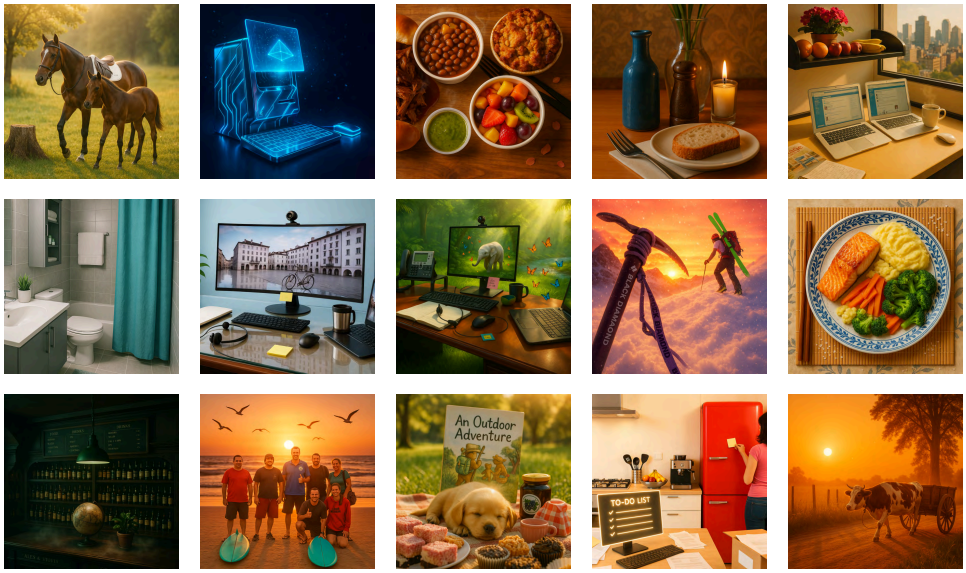
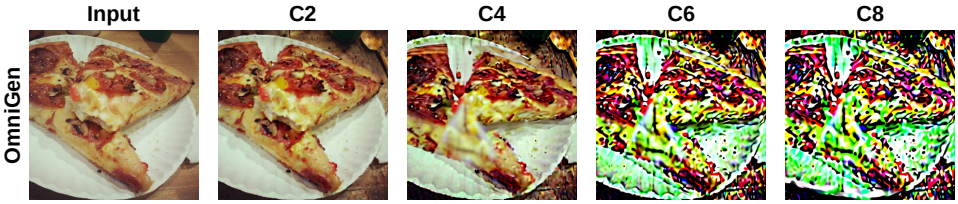
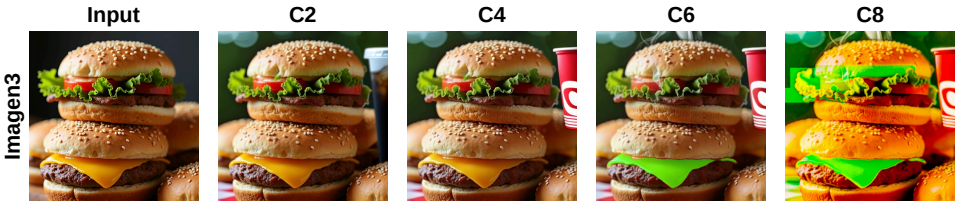


Figure 11: Real images edited with C_8 instructions by GPT-Image-1. Outputs from GPT-Image-1 severely lose the realistic style. See additional results in Appendix Fig. 23.



(a) Real input images.



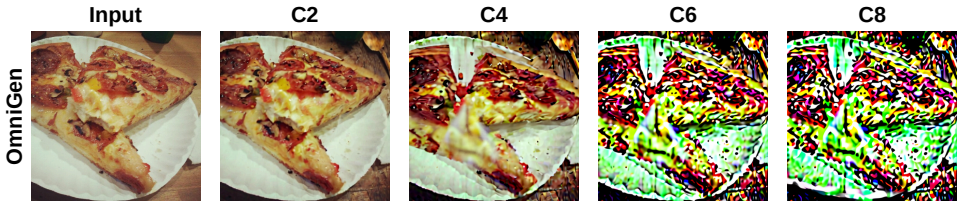
(b) Synthetic input images.

Figure 12: Qualitative results of sequential editing. The complexity level ranges from C_1 to C_8. It can be seen that IF and PQ are severely hurt by the growing instruction complexity. The instructions are the same ones in Fig. 9. Results with more models are shown in Appendix Figs. 20 and 21.

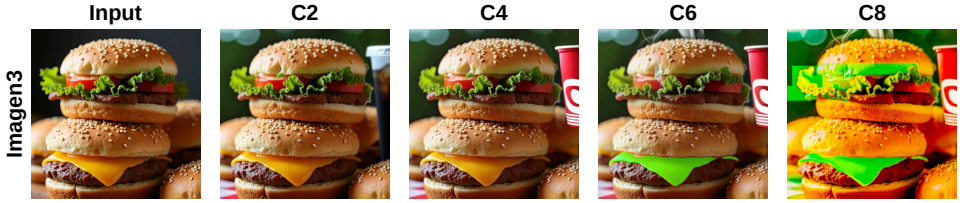
5.3 Curse of Synthetic data

Our qualitative analysis reveals an intriguing phenomenon: when applying extremely complex editing instructions (C_8) to real input images, the resulting outputs frequently lose their realistic appearance and adopt a distinctly synthetic aesthetic. Notably, UltraEdit is particularly susceptible to this effect compared to OmniGen and AnyEdit, as illustrated in Fig. 10. We attribute this trend to the composition of UltraEdit's training data, which contains a significantly higher proportion of synthetic images than the datasets used by OmniGen and AnyEdit (see Tab. 6). This observation aligns with the "curse of synthetic data" phenomenon discussed in (Gerstgrasser et al., 2024).

This phenomenon also extends to highly capable proprietary models, including SeedEdit, Imagen3, and even GPT-Image-1. Specifically, as illustrated in Fig. 11, the edited images produced by GPT-Image-1 completely lose their realistic style, even though its overall performance surpasses that of all other models evaluated. This observation may indicate that, although the training sources for Imagen3 and GPT-Image-1 are undisclosed,



(a) Real input images.



(b) Synthetic input images.

Figure 13: Qualitative results of sequential editing. The complexity level ranges from C_1 to C_8. It can be seen that IF and PQ are severely hurt by the growing instruction complexity. The instructions are the same ones in Fig. 9. Results with more models are shown in Appendix Figs. 20 and 21.

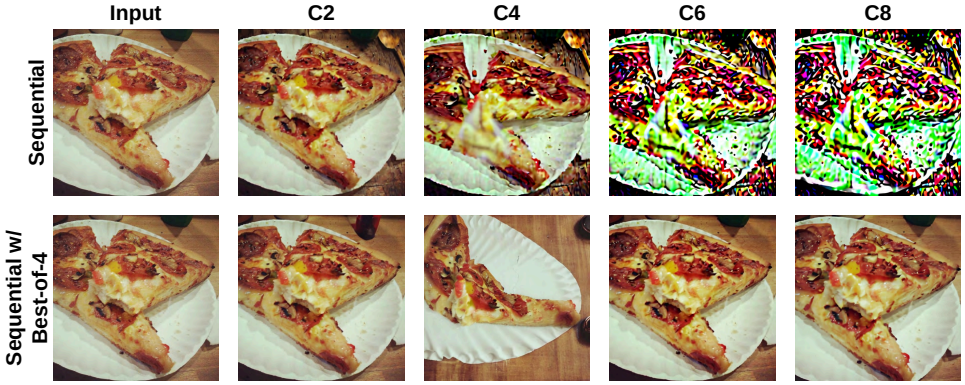


Figure 14: Qualitative results of sequential editing with and without Best-of-4 with OmniGen on real input images. The complexity level is at C_8. This shows that sequential editing can benefit a lot from Best-of-N in terms of IF and PQ. The instructions are the same ones in Fig. 9a. Qualitative results with more models are shown in Appendix Fig. 22.

these models likely incorporate synthetic data into their training sets, which in turn contributes to their impressive performance as well as the emergence of a distinctly synthetic aesthetic.

5.4 Test-Time Scaling Approaches

5.4.1 CoT-like Sequential Editing

Our data pipeline composes complex instructions by combining sequences of atomic editing operations, suggesting that sequential application of these atomic steps should be equivalent to executing the complex instruction directly. Moreover, this way of decomposing a complex task and then sequentially executing it has been proven effective in both language generation (Wei et al., 2022) and text-to-image generation (Guo et al., 2025).

Formally, given an input image x, a complex instruction T at complexity level C_i, and a corresponding sequence of atomic instructions $t_1, \ldots, t_i$, we define the outputs for direct and sequential editing as follows: $y_{\text{direct}} = f(x, T)$, and $y_{\text{sequence}} = f^i(x, \{t_1, \ldots, t_i\}) = f(f(f(\ldots f(x, t_1) \ldots, t_{i-1}), t_i))$.

We evaluate sequential editing on both real and synthetic images. Our results (summarized in Fig. 8 and illustrated qualitatively in Fig. 13) reveal that sequential editing yields a steady decline in performance across all three metrics, with accumulating visual artifacts and distortions—even for strong proprietary models such as Imagen3, SeedEdit and GPT-Image-1. Notably, AnyEdit demonstrates improved Instruction Following

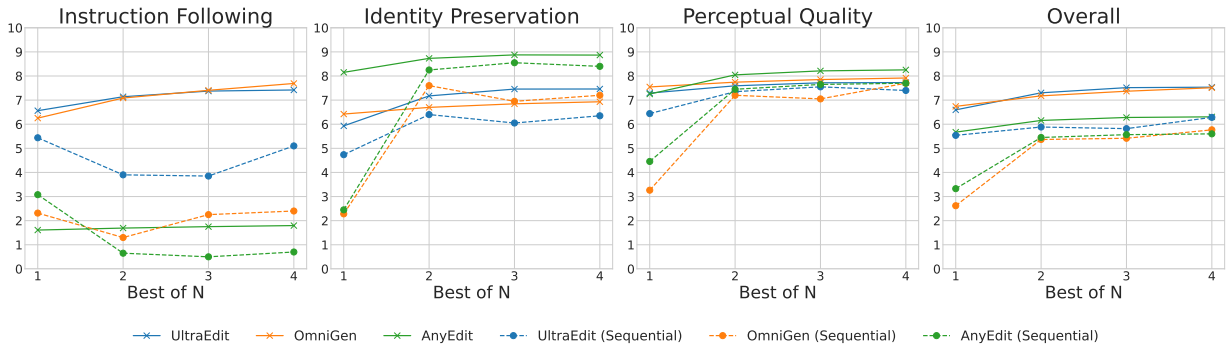


Figure 15: Direct and Sequential Editing results w/ Best-of-N of open-source models on real input images. The complexity level is at C_8. This shows that Best-of-N can improve IF and PQ, especially for sequential editing. However, sequential editing with Best-of-N can still barely surpass direct editing without Best-of-N.

with sequential editing compared to direct editing, although this improvement is offset by a reduction in Identity Preservation.

5.4.2 Best-of-N

We also experiment with Best-of-N, which is another simple test-time-scaling method commonly used for text-to-image generation (Guo et al., 2025; Ma et al., 2025). For direct editing, we generate N candidate outputs for each input image and select the one with the highest overall score O. For sequential editing, we generate N candidates at each step and choose the candidate with the highest overall score O to proceed to the next editing operation. When evaluating an intermediate candidate at the i-th step during sequential editing, instead of considering it as the output of a single-step edit produced with the predecessor output and an atomic instruction, *e.g.* $f(y_{i-1}, t_i)$ with $y_{i-1} = f^{i-1}(x, \{t_1, \ldots, t_{i-1}\})$, we evaluate it as the output from the original input image with a compound instruction T_i. This compound instruction T_i has C_i complexity and encompasses all the atomic instructions up to the i-th step: $\{t_1, \ldots, t_i\}$. The rationale here is that the intermediate result should best represent the cumulative effects of all preceding atomic steps on the original image, ensuring the final output best reflects all atomic steps and consequently the final compound instruction.

Our evaluations with open-source models on real-life images (see Fig. 15) indicate that increasing N gradually improves direct editing performance across all metrics. For sequential editing, even a Best-of-N strategy with $N = 2$ produces significant gains in Identity Preservation and Perceptual Quality; however, the improvement in Instruction Following is less consistent. Qualitative comparisons are provided in Fig. 14.

6 Related Works

Instruction-Based Image Editing InstructPix2Pix (Brooks et al., 2023) introduced instruction-based image editing, where images are modified through text instructions, improving user interaction. This required a large dataset created using fine-tuned GPT-3 (Achiam et al., 2023) and the Prompt-to-Prompt (Hertz et al., 2022) Diffusion Model, but editing was limited by these models' quality. Research explored new methods: MagicBrush (Kawar et al., 2023) used curated annotations, HQ-Edit (Hui et al., 2025) utilized advanced language models with text-to-image systems for better datasets, MGIE (Fu et al., 2023) and SmartEdit (Huang et al., 2024) applied multilevel language learning for more precise edits, and UltraEdit (Zhao et al., 2024) used advanced masking for detailed manipulation. OmniGen (Xiao et al., 2024) expanded model architecture and data with a Transformer framework for processing text and visuals and inferring edits. UIP2P (Simsar et al., 2024) introduced cyclic editing for unsupervised image editing without paired training images. These methods have significantly advanced instruction-based image editing.

7 Conclusion

In this work, we introduced `Complex-Edit`, a comprehensive benchmark designed to systematically evaluate instruction-based image editing models across varying levels of instruction complexity. Through extensive experiments, `Complex-Edit` enable us to uncover multiple key insights regarding the limitations and capabilities of current models. We hope this benchmark will drive future advancements in developing more powerful instruction-based image editing models, especially those with test-time scaling ability.

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A Atomic Editing Operations

Here we present the descriptions for all the 24 atomic operation types. These operation types are also fed to GPT-4o during Stage #1 (Sequence Generation) of our data pipeline, as discussed in Sec. 2.1.

- **Object Manipulation and Transformation**
  - *Add an Object*: Insert a new element into the image.
  - *Remove an Object*: Eliminate an existing element from the image.
  - *Replace an Object*: Swap one element with another.
  - *Move an Object*: Change the position of an existing element within the image.
  - *Resize an Object*: Adjust the size of an existing element.
  - *Rotate an Object*: Rotate an element to a specified angle.
  - *Duplicate an Object*: Create a copy of an existing element.
- **Color and Tone Adjustments**
  - *Change Color*: Replace the color of an element with a specified color.
  - *Apply Filter/Weather*: Add a color filter or weather effect to the entire image or specific parts.
- **Texture and Material Adjustments**
  - *Change Texture*: Apply a texture to an element (e.g., change from metal to wood).
- **Background and Environment**
  - *Change Background*: Replace the background with a different scene or color.
- **Lighting and Shadows**
  - *Adjust Lighting*: Change the overall lighting or lighting of specific elements.
- **Text and Symbols**
  - *Add Text*: Insert text into the image.
  - *Remove Text*: Eliminate existing text from the image.
  - *Change Text Properties*: Modify font, color, size, or position of existing text.
- **Pose and Expression**
  - *Change Pose*: Modify the stance or posture of a person or object.
  - *Change Facial Expression*: Alter the facial expression of a character.
- **Composition and Cropping**
  - *Crop Image*: Adjust the framing of the image by removing outer areas.
  - *Reframe Composition*: Change the focus or arrangement of elements within the image.
  - *Zoom In/Out*: Adjust the zoom level to focus on specific elements or show a broader view.
- **Special Effects**
  - *Add Special Effects*: Introduce effects like glow, motion blur, or lens flare.
  - *Remove Special Effects*: Eliminate existing special effects from the image.
  - *Add Particles*: Insert particles like dust.
  - *Remove Particles*: Remove existing particles from the image.

B Prompts for Evaluation

B.1 Rubrics

In the rubric for each metric we propose, we specify the detailed textual description for every score from 0 to 10, and most scores have a textual example to reduce ambiguity. All the rubrics for evaluation in are listed in Fig. 16.

Rubric for Instruction Following.

* 10 (Perfect Instruction Following): All the required changes occur in the output image.
* 9 (Near Perfect Instruction Following with negligible deviations): Almost all instructed changes are present but negligible deviations exist (e.g., a tiny color variation such as the cat in the image is now black but the ears are grey).
* 7-8 (Strong Instruction Following with minor deviations): Most required changes are applied accurately. Minor deviations exist but do not substantially alter the intended modification (e.g., a car is changed to blue as instructed, but the reflection on its surface still contains a red tint).
* 5-6 (Moderate Instruction Following with noticeable deviations): The output reflects an attempt to follow instructions but with moderate errors (e.g., adding a required element but with incorrect attributes like color or shape).
* 3-4 (Weak Instruction Following with major deviations): Most required modifications are missing, incorrect, or only vaguely implemented. Significant elements from the instruction are misrepresented (e.g., when instructed to add a hat, a small, barely visible accessory is added to the head, but it does not resemble a proper hat).
* 1-2 (Minimal Instruction Following with severe deviations): A vague attempt is made, but the required modifications are either incorrect or so minimal that they do not fulfill the instruction (e.g., the instruction asks to remove a person from the image, but they are still visible, just slightly blurred or faded instead of being properly erased.).
* 0 (Complete failed Instruction Following): The output image is entirely unrelated to the instruction.

(a) Instruction Following.

Rubric for Identity Preservation.

* 10 (Perfect Identity Preservation): All key elements that should remain unchanged are completely preserved and indistinguishable from the input (e.g., a person's face, expression, and proportions remain completely unchanged except for the required edits).
* 9 (Near Perfect Identity Preservation with negligible distortion): Key elements that should remain unchanged are preserved with negligible distortion (e.g., A person's face is identical except for a tiny, imperceptible variation in hair texture).
* 7-8 (Strong Identity Preservation with minor distortion): Small details of the key elements may have changed, but they do not significantly disrupt the overall identity (e.g., a pet's fur pattern remains mostly accurate, but a minor detail like a stripe or spot is different).
* 5-6 (Moderate Identity Preservation with noticeable distortion): Most of the key elements remain recognizable but with noticeable distortions (e.g., the instruction asks to change a car's color, but the car's shape or size is modified along with the color).
* 3-4 (Weak Identity Preservation with major distortion): Key elements maintain a general resemblance but noticeable changes are present (e.g., the instruction asks to brighten the sky, but additional buildings in the background appear or disappear).
* 1-2 (Minimal Identity Preservation with severe distortion): Most key elements are significantly altered or replaced. The key elements in the output retain only minor aspects of the original, but major features are incorrect (e.g., a person's face is still a human face, but it no longer resembles the original person at all).
* 0 (Complete failed Identity Preservation): All key elements that should remain unchanged are altered, distorted, or missing.

(b) Identity Preservation.

Rubric for Perceptual Quality.

* 10 (Perfect Perceptual Quality): The image appears flawlessly natural, and all objects are seamlessly integrated into the environment with consistent lighting and shadows. There is no visual artifact at all.
* 9 (Near Perfect Perceptual Quality with negligible incoherence): The image is very close to perfect, but a tiny, almost imperceptible inconsistency exists. Seamless integration, but one might notice an extremely subtle flaw. (e.g., a person added to a group photo blends in perfectly, but upon close examination, their shadow is slightly softer than others.)
* 7-8 (Strong Perceptual Quality with minor incoherence): Minor incoherence and artifacts are present but they do not significantly detract from the overall harmony. (e.g., a sunset scene where the added reflections on water are slightly off in intensity, but the image still looks highly realistic.)
* 5-6 (Moderate Perceptual Quality with noticeable incoherence): There is noticeable visual artifacts affecting the image's harmony. Lighting and shadows may be misaligned or inconsistent. (e.g., an animal is distorted in size or shape, making it appear out of place in the scene.)
* 3-4 (Weak Perceptual Quality with major incoherence): Disharmonious elements are prominent, greatly disturbing the visual harmony. (e.g., an animal's shape or a person's face is greatly distorted, only showing some resemblance of the animal species or a human face.)
* 1-2 (Minimal Perceptual Quality with severe incoherence): The whole scene is distorted, making it difficult to recognize the objects or subjects in the image.
* 0 (Complete failed Perceptual Quality): The image is completely random and makes no sense at all.

(c) Perceptual Quality.

Figure 16: Rubrics for evaluating Instruction Following, Identity Preservation and Perceptual Quality.

B.2 System Prompts

The system prompts that we use for evaluation are provided in Fig. 17.

System Prompt for Instruction Following and Identity Preservation.

You are required to evaluate the result of an instruction-based image editing model.
Given an input image, an output image and a text instruction, you are required to access the output image based on whether the changes made to the input image align with the text instruction.

You are required to give two integer scores in [0, 10] based on the following criteria:
1. Instruction Following: whether the required changes occur in the output image, regardless of whether unnecessary changes are also made. 10 means that all the changes required by the instruction occur in the output image, 0 means that no changes required by the instruction occur in the output image.
2. Identity Preservation: whether elements that should not be changed stay the same in the output image, regardless of whether required changes occur. 10 means that no unnecessary changes occur in the output image, 0 means that all elements in the input image that should be kept the same are changed in the output image.

Here is the detailed rubric for Instruction Following:
`<INSTRUCTION_FOLLOWING_RUBRIC>`

Here is the detailed rubric for Identity Preservation:
`<IDENTITY_PRESERVATION_RUBRIC>`

Note that these two scores should be graded independently, and a low score for one criterion should not affect the score for the other criterion. For example, an output image that is identical to the input image should have an Instruction Following score of 0, but an Identity Preservation score of 10. Also, an output image that has no relevance with the input image should have an Identity Preservation score of 0 unless the instruction specifically orders the model to create a whole different image, but it should not affect the Instruction Following score as long as changes required by the instruction occur in the output.

If the instruction contains several atomic operations, evaluate the Instruction Following for each atomic operation separately and then average the scores as the assessment for Instruction Following.

Explain your reasoning before answering the question.

(a) Instruction Following and Identity Preservation.

System Prompt for Perceptual Quality.

You are required to evaluate a model-generated image.
Given an output, you are required to access the output image's "Perceptual Quality".

You are required to give one integer score in [0, 10] with 0 indicating extreme disharmony characterized by numerous conflicting or clashing elements, and 10 indicating perfect harmony with all components blending effortlessly.

These are the criteria:
1. Consistency in lighting and shadows: The light source and corresponding shadows are consistent across various elements, with no discrepancies in direction or intensity.
2. Element cohesion: Every item in the image should logically fit within the scene's context, without appearing misplaced or extraneous.
3. Integration and edge smoothness: Objects should blend seamlessly into their surroundings, with edges that do not appear artificially inserted or poorly integrated.
4. Aesthetic uniformity and visual flow: The image should not only be aesthetically pleasing but also facilitate a natural visual journey, without abrupt interruptions caused by disharmonious elements.

Here is the detailed rubric for scoring:
`<PERCEPTUAL_QUALITY_RUBRIC>`

(b) Perceptual Quality.

Figure 17: System prompt for evaluating Instruction Following, Identity Preservation and Perceptual Quality.

C Additional Quantitative Results

C.1 Evaluation by Gemini-2.5-Pro of C_1 and C_8 complexities

Here we present the comparison between evaluation results of direct editing with C_1 and C_8 instructions, in supplement to the results from GPT-4o evaluation shown in Tab. 3. We only measured once for each sample with Gemini-2.5-Pro due to cost limitation. As we report average scores across the test set, the variance of each score is expected to be < 0.01, sufficient for reliability.

The observations based on Tab. 7 remain consistent as ones discussed in Sec. 5.2, that at the highest instruction complexity level C_8, GPT-Image-1 excels over all other models in Instruction Following and Perceptual Quality; and performance drops in open-source models are comparable to proprietary ones, except for GPT-Image-1.

Table 7: Performance comparison between C_1 and C_8 on images. All models almost consistently underperform on all metrics when the complexity increases from C_1 to C_8. Evaluated by Gemini-2.5-Pro.

Table 8: Real input images

Model	C_1				C_8				$C_8 - C_1$			
	IF	*IP*	*PQ*	*O*	*IF*	*IP*	*PQ*	*O*	Δ_{IF}	Δ_{IP}	Δ_{PQ}	Δ_O
UltraEdit	6.63	5.26	5.94	5.94	5.25	3.37	4.98	4.53	**-1.38**	**-1.89**	**-0.96**	**-1.41**
OmniGen	6.43	7.44	6.82	6.90	5.17	4.35	5.47	5.00	**-1.26**	**-3.09**	**-1.35**	**-1.90**
AnyEdit	5.26	7.31	5.50	6.02	1.01	7.81	6.51	5.11	**-4.25**	**+0.51**	**+1.01**	**-0.91**
Imagen3	7.25	**8.32**	7.71	7.76	6.70	4.65	6.53	5.96	**-0.55**	**-3.67**	**-1.18**	**-1.80**
SeedEdit	9.17	6.29	7.96	7.81	7.67	3.83	7.69	6.40	**-1.50**	**-2.46**	**-0.27**	**-1.41**
GPT-Image-1	**9.78**	8.06	**9.10**	**8.98**	**9.45**	**5.04**	**9.25**	**7.92**	**-0.33**	**-3.01**	**+0.15**	**-1.06**
Average	7.42	7.11	7.17	7.24	5.88	4.84	6.74	5.82	**-1.54**	**-2.27**	**-0.43**	**-1.42**

Table 9: Synthetic input image.

Model	C_1				C_8				$C_8 - C_1$			
	IF	*IP*	*PQ*	*O*	*IF*	*IP*	*PQ*	*O*	Δ_{IF}	Δ_{IP}	Δ_{PQ}	Δ_O
UltraEdit	7.31	6.82	8.50	7.55	4.97	4.70	7.69	5.79	**-2.34**	**-2.12**	**-0.81**	**-1.76**
OmniGen	7.46	8.68	8.52	8.22	5.15	6.19	7.68	6.34	**-2.31**	**-2.48**	**-0.84**	**-1.88**
AnyEdit	5.31	8.68	7.98	7.32	0.78	**8.83**	8.33	5.98	**-4.53**	**+0.15**	**+0.35**	**-1.34**
Imagen3	7.64	8.43	8.49	8.19	7.11	6.54	8.37	7.34	**-0.53**	**-1.90**	**-0.12**	**-0.85**
SeedEdit	9.05	8.36	8.96	8.79	6.97	6.86	8.63	7.49	**-2.08**	**-1.50**	**-0.33**	**-1.30**
GPT-Image-1	**9.69**	**8.68**	**9.40**	**9.26**	**9.09**	6.17	**9.54**	**8.27**	**-0.60**	**-2.52**	**+0.15**	**-0.99**
Average	7.74	8.27	8.64	8.22	5.68	6.55	8.37	6.87	**-2.07**	**-1.73**	**-0.27**	**-1.35**

D Additional Qualitative Results

Here we present more comprehensive qualitative results.

D.1 Direct Editing

Additional qualitative results of direct editing with more models are shown in Figs. 18 and 19, indicating that the gap between open-source and proprietary models expands with increasing complexity of the instruction. Also, Identity Preservation and Perceptual Quality continue to drop as instruction complexity increases, while the effect on Instruction Following varies from model to model. One can refer to the discussion in Sec. 5.2 for more detailed insights.

D.2 Sequential Editing

We illustrate additional qualitative results of sequential editing with more models in Figs. 20 and 21, showing that all three aspects, particularly Identity Preservation and Perceptual Quality, consistently degrade, as visual artifacts and distortions accumulate with an increase in the number of intermediate steps. Even advanced proprietary models, *i.e.* Imagen3 and SeedEdit, demonstrate limitations in maintaining the identity of key elements and the overall quality of output images. More in-depth discussions are given in Sec. 5.4.1.

D.3 Best-of-N

Additional qualitative results of sequential editing combined with Best-of-4 with more open-source models are shown in Fig. 22. It can been noticed that the Identity Preservation and Perceptual Quality of sequential editing's results can be substantially improved with Best-of-4. A more comprehensive analysis of this topic is provided in Sec. 5.4.2.

The Identity Preservation and Perceptual Quality of sequential editing improve significantly with Best-of-4, as analyzed in detail in Sec. 5.4.2.

D.4 Direct Editing with GPT-Image-1

We provide more qualitative results with GPT-Image-1 via direct editing real-life images in Fig. 23. These results imply that while GPT-Image-1 is capable of generating edited images of exceptional quality, output images with very complex instructions prune to lose the realistic feeling in the original images. This may imply a lack of real-life images in GPT-Image-1's training data. See Sec. 5.3 for a more in-depth analysis.

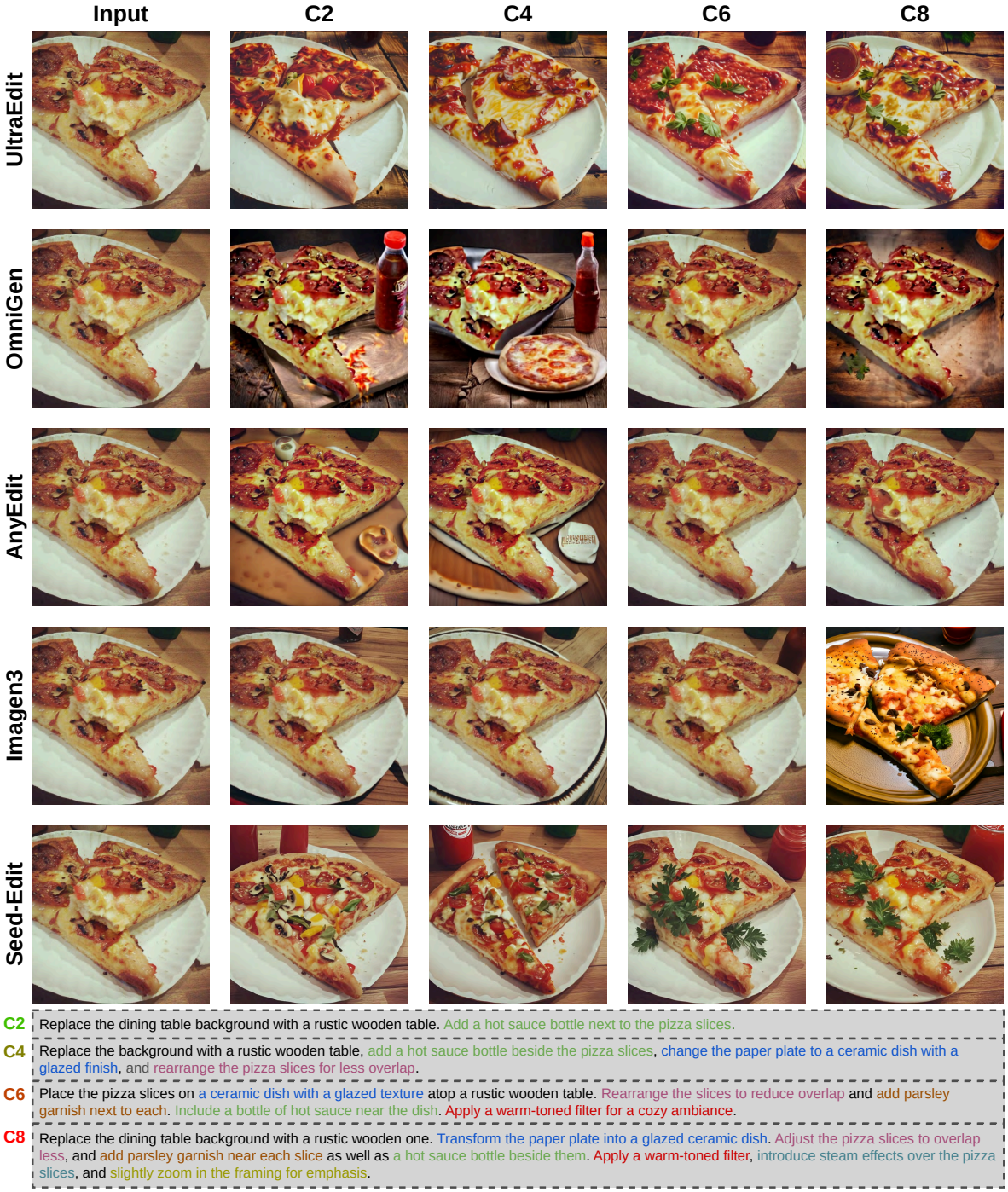


Figure 18: Additional qualitative results with direct editing on real-life images. As instruction complexity increases, the gap between open-source and proprietary models widens, and both Identity Preservation and Perceptual Quality decline, with variable effects on Instruction Following across models. See Sec. 5.2 for more details.

C2 Replace the dark background with a picnic tablecloth setting and add a soft drink cup next to one of the burgers.

C4 Replace the dark background with a picnic tablecloth setting. Place a vivid red soft drink cup with a white logo next to one of the burgers. Enlarge and enhance the cheese slice on a burger to appear melted over the patty.

C6 Place the burgers onto a picnic tablecloth setting. Add a vivid red cup with a white logo next to one of the burgers. Resize the cheese slices on the burgers to appear melted over the patties. Duplicate the visible green lettuce on the front burger. Enhance one of the burgers with rising steam for a freshly-cooked appearance.

C8 Replace the background with a bright picnic tablecloth setting. Add a vividly red soft drink cup with a white logo next to one of the burgers. Make the cheese slice on a burger appear larger and more melted over the patty. Add steam rising from one of the burgers, duplicate the green lettuce leaf on the front burger, brighten the image to highlight the burger details, and apply a sunny and warm filter to the scene.

Figure 19: Additional qualitative results with direct editing on synthetic images. As instruction complexity increases, the gap between open-source and proprietary models widens, and both Identity Preservation and Perceptual Quality decline, with variable effects on Instruction Following across models. See Sec. 5.2 for more details.

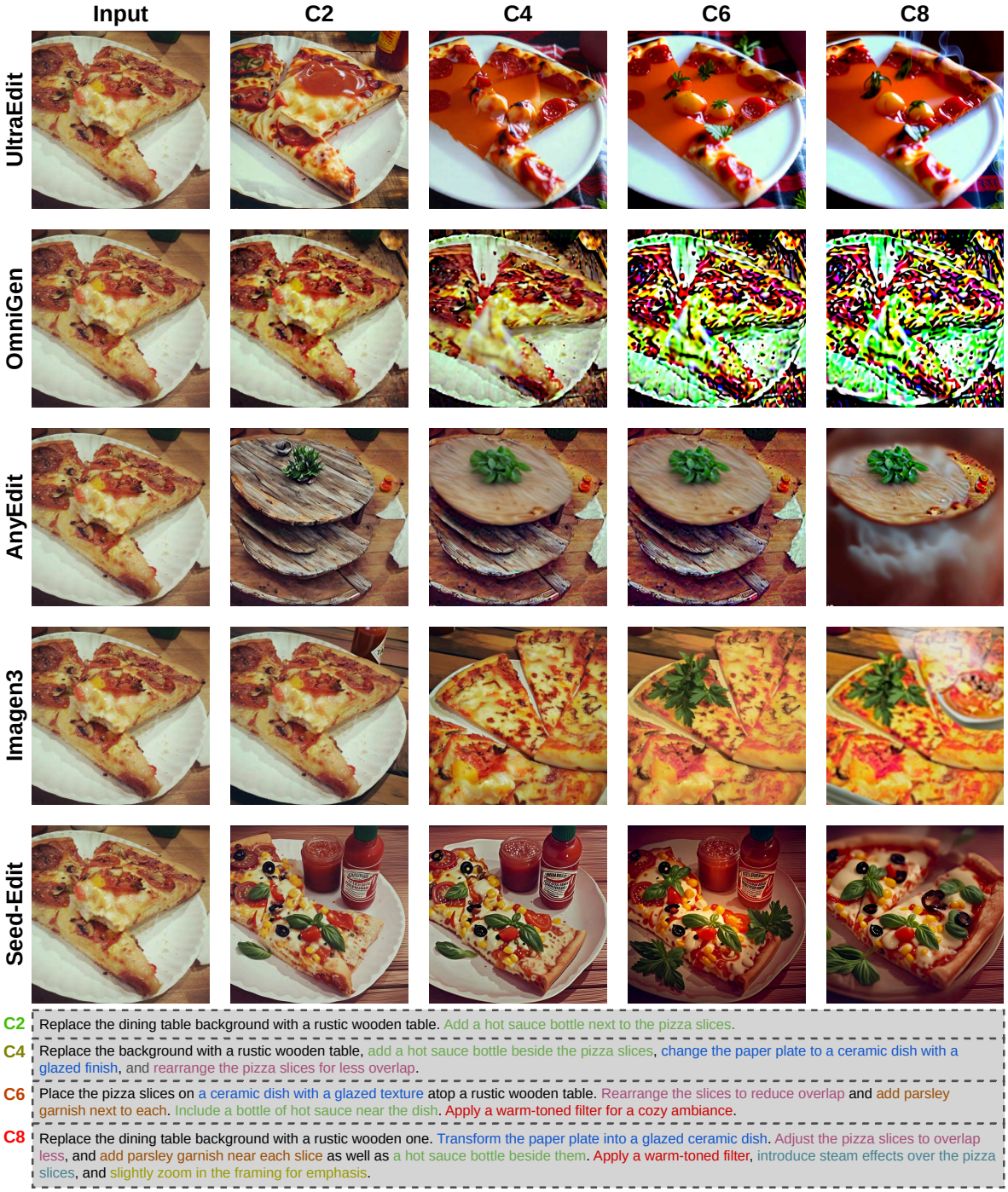
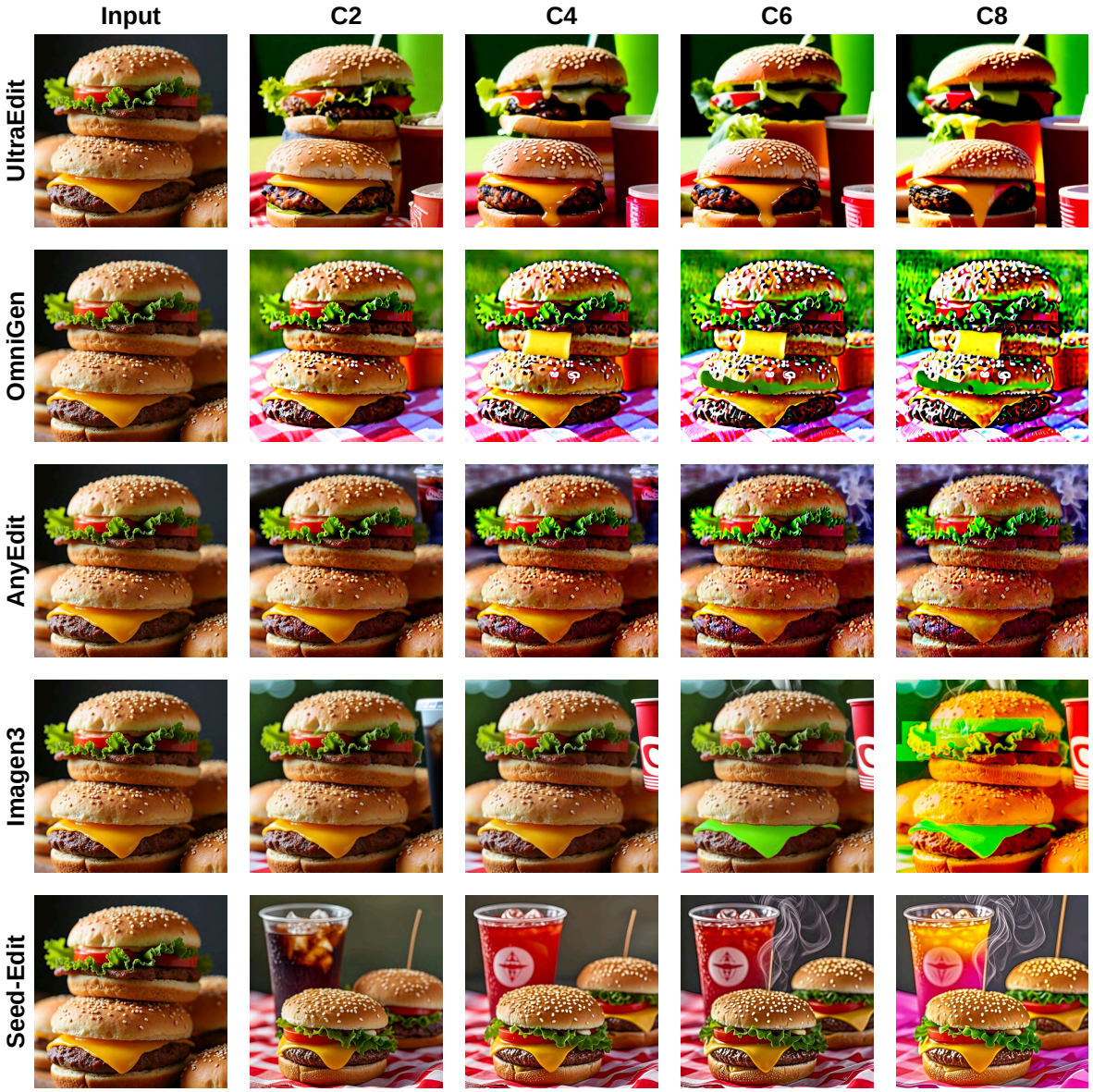


Figure 20: Additional qualitative results with sequential editing on real-life images. Identity Preservation and Perceptual Quality, degrade as visual artifacts and distortions increase with more intermediate steps. Even advanced proprietary models, *i.e.* Imagen3 and SeedEdit, struggle to maintain element identity and quality in output images. More in-depth analysis is in Sec. 5.4.1.



C2 Replace the dark background with a picnic tablecloth setting and add a soft drink cup next to one of the burgers.

C4 Replace the dark background with a picnic tablecloth setting. Place a vivid red soft drink cup with a white logo next to one of the burgers. Enlarge and enhance the cheese slice on a burger to appear melted over the patty.

C6 Place the burgers onto a picnic tablecloth setting. Add a vivid red cup with a white logo next to one of the burgers. Resize the cheese slices on the burgers to appear melted over the patties. Duplicate the visible green lettuce on the front burger. Enhance one of the burgers with rising steam for a freshly-cooked appearance.

C8 Replace the background with a bright picnic tablecloth setting. Add a vividly red soft drink cup with a white logo next to one of the burgers. Make the cheese slice on a burger appear larger and more melted over the patty. Add steam rising from one of the burgers, duplicate the green lettuce leaf on the front burger, brighten the image to highlight the burger details, and apply a sunny and warm filter to the scene.

Figure 21: Additional qualitative results with sequential editing on synthetic images. Identity Preservation and Perceptual Quality, degrade as visual artifacts and distortions increase with more intermediate steps. Even advanced proprietary models, *i.e.* Imagen3 and SeedEdit, struggle to maintain element identity and quality in output images. More in-depth analysis is in Sec. 5.4.1.

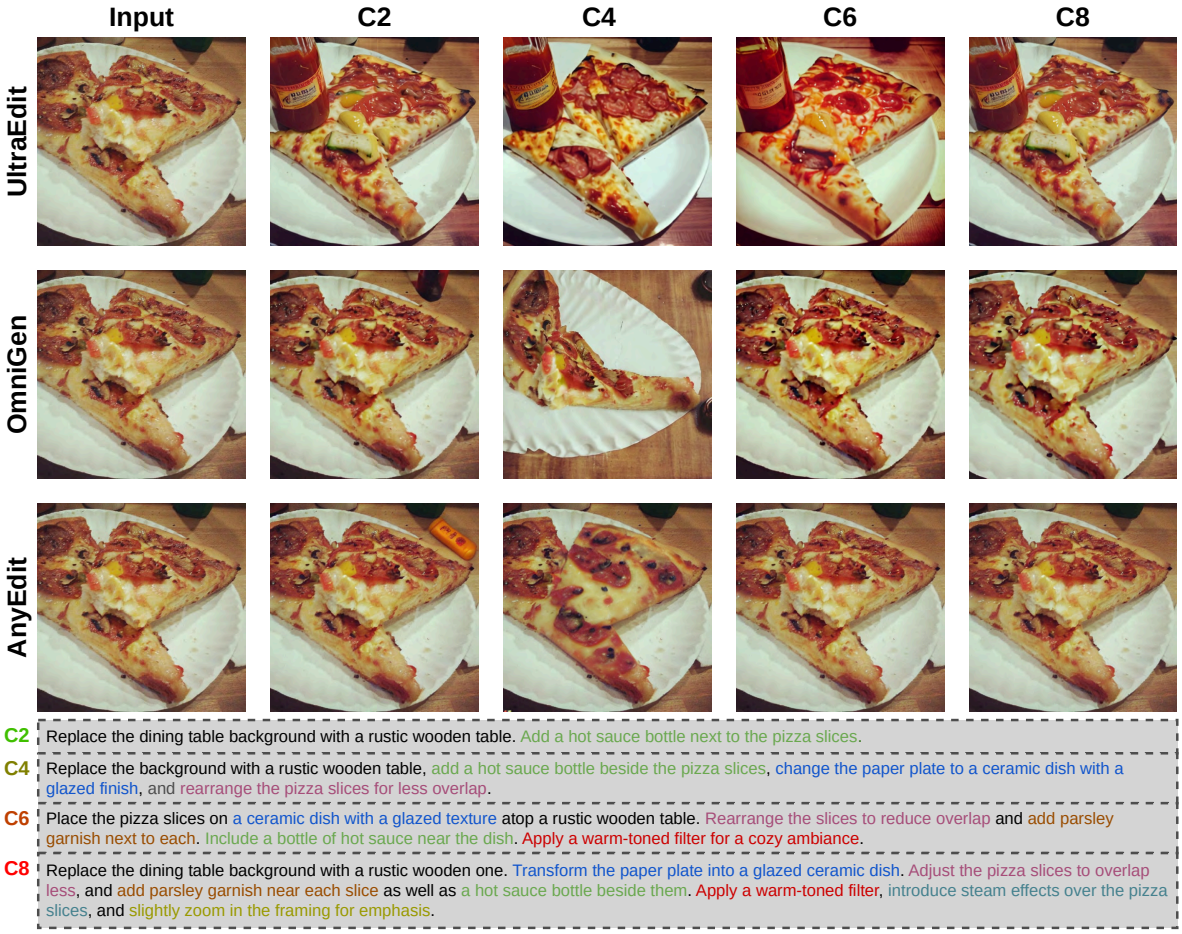


Figure 22: Qualitative results with sequential editing with Best-of-4 on real-life images. Identity Preservation and Perceptual Quality of sequential editing improve significantly with Best-of-4. Refer to Sec. 5.4.2 for more detailed discussions.

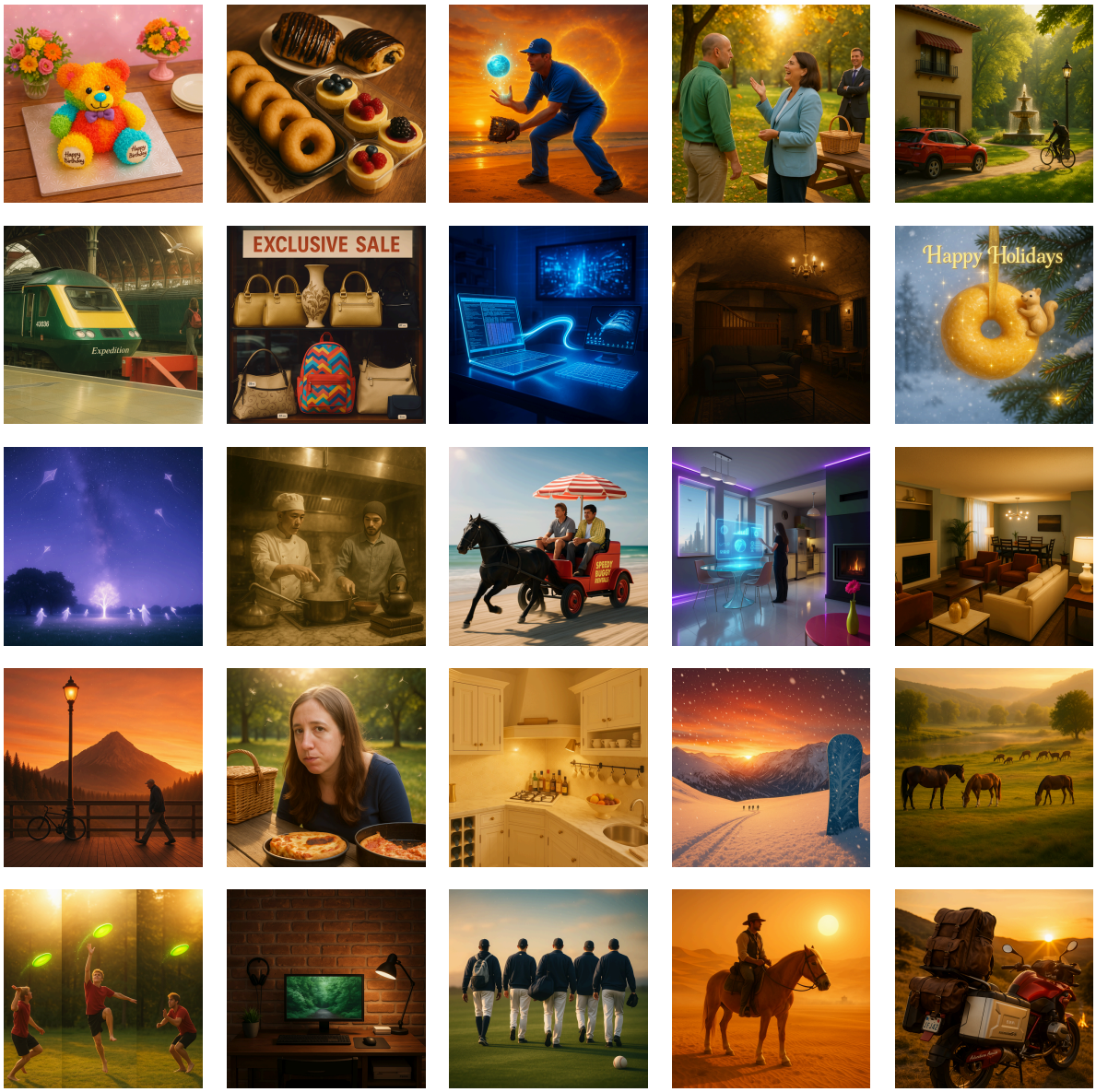


Figure 23: More real-life images edited with C_8 instructions by GPT-Image-1. Outputs from GPT-Image-1 severely lose the realistic style. Refer to Sec. 5.3 for a detailed discussion.