# HYPE-EDIT-1: An Effective-Cost and Reliability Benchmark for Image Editing

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## Abstract

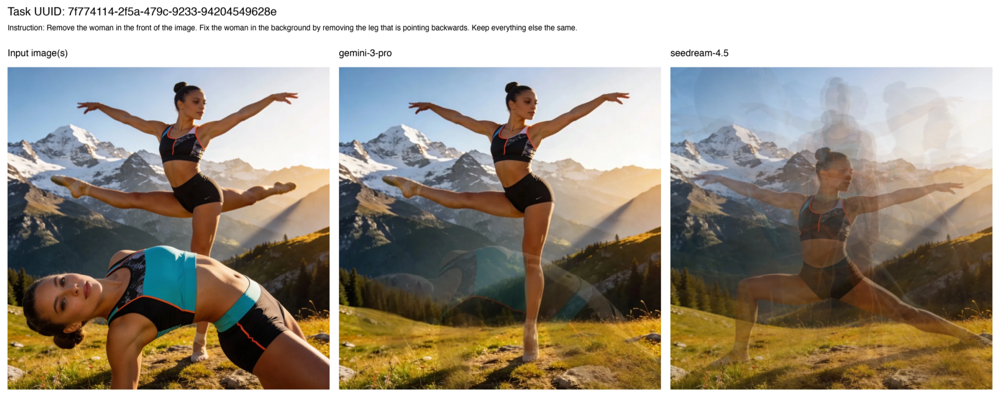
Public demos of image editing models are typically best-case samples; real workflows pay for retries and review time. We introduce HYPE-EDIT-1, a 100-task benchmark of reference-based marketing/design edits with binary pass/fail judging. For each task we generate 10 independent outputs to estimate per-attempt pass rate, pass@10, expected attempts under a retry cap, and an effective cost per successful edit that combines model price with human review time. We release 50 public tasks and maintain a 50-task held-out private split for server-side evaluation, plus a standardized JSON schema and tooling for VLM and human-based judging. Across the evaluated models, per-attempt pass rates span 34–83% and effective cost per success spans \$0.66–\$1.42. Models that have low per-image pricing are more expensive when you consider the total effective cost of retries and human reviews.

## 1 Introduction

Generative image editing models are increasingly used in product marketing, brand design, and creative production. In these settings, reliability matters as much as peak quality: a model that occasionally produces a perfect edit but frequently fails imposes significant time and cost overhead. Existing evaluations often emphasize best-case outputs, obscuring how many attempts are required to obtain a usable result. HYPE-EDIT-1 targets this gap by quantifying both reliability and effective cost on real-world editing tasks that require precise changes to reference images. Effective cost is important because current models are marketed around their cost per image, with models that are cheaper per image seen as 'more affordable'. This benchmark shows that once differences in the number of retries are accounted for, effective cost is not proportional to the per-image cost. For example, in our results a model priced at \$0.03/image still reaches about \$1.42 per successful edit once retries and review are accounted for, while a higher-priced model can be cheaper per success.

Figure 1 shows qualitative comparisons between Gemini 3 Pro Preview (Nano Banana Pro) and Seedream 4.5 on two public tasks. Each comparison image includes the input reference(s) on the left and a collage of 10 independent outputs per model (via the comparison image generator), highlighting differences in instruction adherence, consistency, and variation across retries.

HYPE-EDIT-1 is built around the notion that practical workflows demand consistency. For each task, the same prompt is executed repeatedly and scored independently, allowing us to estimate a success probability. These repeated trials underpin metrics that reflect the actual user experience of retrying a model until it succeeds.




(a) Task 7f774114 (public).


(b) Task 0dbb106f (public).

Figure 1: Qualitative comparisons between Gemini 3 Pro Preview (Nano Banana Pro) and Seedream 4.5. Each panel shows the input reference(s) alongside 10-sample collages for each model. The collage view makes it easy to see how repeated attempts at the same task can diverge, even for narrowly scoped edits such as remove or swap where minimal variation is expected. In practice, these collages often show partial instruction compliance or structure drift that would be hidden by selecting a single best output.

Figure 2 shows five example tasks from the benchmark, illustrating the diversity of editing instructions and task types.


(a) change: Add a handle to the mug. Keep everything else the same.


(b) remove: Remove all the artwork elements from the bag apart from its base color. Keep everything else the same.


(c) restructure: Swap the middle two drinks and their associated text below it. Keep everything else the same.


(d) enhance: Fix the product artwork in the first image [Image 1] by using the second image [Image 2] as the artwork reference. Change the artwork but keep everything else the same.


(e) change: Change the color of the vinyl inner circle from white to blue to exactly match the blue top of the perfume bottle. Keep everything else the same.

Figure 2: Example tasks from HYPE-EDIT-1 showing diverse editing instructions across different task types: change, remove, restructure, and enhance. Each panel shows the input reference image(s) with the instruction and task category.

## 2 Related Work

### 2.1 Instruction-following image editing models

Early image editing systems relied on domain-specific supervision, masks, or per-image optimization, which limited usability for open-ended edits. Conditional GAN editors such as Pix2Pix and CycleGAN enabled paired or unpaired translation but lacked open-ended instruction control (Isola et al., 2017; Zhu et al., 2017). Diffusion and inversion-based methods such as SDEdit (Meng et al., 2022), Null-Text Inversion (Mokady et al., 2023), and Prompt-to-Prompt (Hertz et al., 2022) made it possible to preserve input structure while changing semantics from text prompts, but often required masks or carefully tuned latent initializations. Blended Diffusion introduced localized edits with masking and CLIP guidance (Avrahami et al., 2022), while SINE explored single-image editing without explicit masks (SINE, 2023). InstructPix2Pix shifted the paradigm by training on synthetic instruction-image pairs, demonstrating that a single model can generalize to diverse edits without per-example optimization (Brooks et al., 2023). Imagic further showed that fine-tuning on a single input image enables non-rigid edits but at the cost of per-image optimization time (Kawar et al., 2023). Subsequent work introduced instruction-tuned models and curated datasets such as MagicBrush, which adds human-edited examples and multi-turn sessions (MagicBrush, 2023), and MGIE, which uses multimodal language models to refine editing instructions (Fu et al., 2024). These advances motivate benchmarks that test general instruction following while accounting for practical constraints like iteration cost and reliability.

Table 1: Comparison of HYPE-EDIT-1 with representative image editing benchmarks. Scales and attributes are reported from published descriptions where available.

| Benchmark | Scale | Edit scope | Evaluation | Repeats | Split |
|---|---|---|---|---|---|
| GIER | 6,179 images | local/global | GT outputs | No | Train/val/test |
| MagicBrush | 5,313 sessions | multi-turn | GT outputs | No | Train/val/test |
| TEdBench | 100 pairs | non-rigid | Human prefs | No | Test-only |
| EditVal | 648 tasks | 13 edit types | VLM metrics | No | Public + held-out |
| HATIE | 18,226 images | broad | Composite auto | No | Reported splits |
| I2EBench | 2,000 images | 16 dims | Learned judge | No | Public |
| SpotEdit | 500 samples | text+ref | GT + checks | No | Public |
| HYPE-EDIT-1 | 100 tasks | marketing edits | Human panel (majority) + VLM check | Yes (10x) | Public + private |

### 2.2 Datasets and benchmarks

Benchmarks for text-guided image editing have evolved from paired datasets with ground-truth targets to reference-free evaluation. GIER and MagicBrush provide paired edits and enable direct pixel or feature comparisons, but they cannot capture the one-to-many nature of creative edits (Shi et al., 2020; MagicBrush, 2023). TEdBench introduced a small, challenging test set for open-ended edits with human preference evaluation (Kawar et al., 2023). EditVal, HATIE, and I2EBench scale evaluation through VLM-based metrics that are calibrated against human judgments (Basu et al., 2023; Ryu et al., 2025; Li et al., 2024), while SpotEdit extends evaluation to multi-modal instructions with additional reference images and hallucination tests (Ghazanfari et al., 2025). Exemplar-guided datasets such as PaintByExample and DreamEdit highlight reference-image conditioning for editing (Yang et al., 2023; Li et al., 2023). Table 1 summarizes key differences between representative benchmarks and HYPE-EDIT-1.

### 2.3 Model-based evaluation

With open-ended edits, learned metrics based on VLMs have become the standard alternative to pixel-level comparison. CLIP-based similarity scores, attribute classifiers, and composite metrics are commonly used to judge whether an edit satisfies the instruction while preserving unrelated content. EditVal, HATIE, and I2EBench each report correlations between automatic scores and human preferences, supporting the use of VLM judges at scale (Basu et al., 2023; Ryu et al., 2025; Li et al., 2024). HYPE-EDIT-1 follows this trend by providing a VLM judge example (Gemini 3 Flash (gemini-3-flash-preview)) and a human-judge web UI to support manual review.

### 2.4 Reliability and stochastic evaluation

Generative models are inherently stochastic, but most image editing benchmarks evaluate a single output per task. In other domains, pass@k-style metrics capture the probability of success over multiple attempts, reflecting how users iterate in practice (Chen et al., 2021). Image generation systems similarly rely on sampling and re-ranking, yet reliability metrics remain underreported. HYPE-EDIT-1 addresses this gap by evaluating each task over 10 independent attempts and reporting pass-at-10, expected attempts, and effective cost.

### 2.5 Workflow considerations and positioning

Creative workflows value iteration speed, predictability, and alignment with domain constraints such as marketing requirements or brand consistency. While prior benchmarks emphasize either scale or fine-grained edit categories, HYPE-EDIT-1 focuses on real-world marketing and design edits and explicitly measures reliability and effective cost. The benchmark is smaller than recent large-scale suites, but it provides repeated-trial evaluation, a public/private split to mitigate leakage, and both automated and human judging workflows, positioning it as a complementary, reliability-focused benchmark (Hartmann et al., 2024; Liu et al., 2023).

Table 2: HYPE-EDIT-1 dataset summary.

| Statistic | Value |
|---|---|
| Total tasks | 100 |
| Public tasks | 50 |
| Private tasks | 50 |
| Single-image tasks | 89 |
| Multi-image tasks | 11 |
| Task types (change/remove/restructure/enhance) | 50/21/17/12 |
| Resolution range (width x height) | 2048–5504 x 1728–5504 |
| Repeats per task | 10 |

## 3 Benchmark Design

### 3.1 Task construction

HYPE-EDIT-1 consists of curated, real-world image editing tasks drawn from marketing and design workflows. Each task includes one or two reference images and a concise instruction describing the desired edit. The tasks are not puzzle-like; instead, they require concrete modifications such as removing an object, adjusting the orientation of a product, or restructuring a layout.

### 3.2 Task types and scale

The benchmark contains 100 tasks split evenly between public and private sets. Task types include `change`, `remove`, `restructure`, and `enhance`. Most tasks use a single input image, while a smaller subset requires combining or transferring content from two images. Input image resolutions range from 2048 to 5504 pixels on the long edge.

### 3.3 Data schema and access

Tasks are stored as JSON entries with fields: `task_id`, `instruction`, `task_type`, `input_images`, and target `width` and `height`. Reference images are hosted at a stable CDN path keyed by the task identifier. The public split is released in the repository at `https://www.github.com/sourceful-official/hype-edit-1-benchmark`, while the private split is held for server-side evaluation to mitigate training contamination.

## 4 Evaluation Protocol

### 4.1 Repeated trials

For each model and task, HYPE-EDIT-1 generates $K = 10$ independent candidate outputs. This produces 1,000 outputs per model for the full benchmark. The repeated-trial setup allows the benchmark to estimate a per-task success probability rather than relying on a single example.

### 4.2 Pass or fail judging

Each output is judged against the task instruction by a panel of five human raters who vote PASS or FAIL without seeing which model produced the image; the majority vote determines the final label. We also run a visual-language model (VLM) judge for alignment using a deterministic scoring prompt and a fixed threshold for PASS/FAIL. The VLM judge (Gemini 3 Flash (gemini-3-flash-preview)) is used as a check and agrees with the human majority in roughly 80% of cases. The VLM is more critical and often fails on subtle changes that remain acceptable to human reviewers. The repository includes a Gemini 3 Flash (gemini-3-flash-preview) judge example and a human-judge web UI.

### 4.3 Reliability and effective cost

Let $y_{t,k} \in \{0,1\}$ denote whether the $k$-th attempt on task $t$ is successful. With $T$ tasks and $K$ repeats, overall reliability is

$$R = \frac{1}{TK} \sum_{t=1}^{T} \sum_{k=1}^{K} y_{t,k}. \tag{1}$$

We report Pass Rate (P@1) as the probability of success on the first attempt and Pass@10 (P@10) as the probability of at least one success across the 10 attempts.

We report expected attempts and effective cost using the same retry-cap model implemented in our internal analysis script; the equations here allow reproduction.

### 4.4 Cost model

The benchmark cost model combines (1) the model's per-candidate generation cost, (2) an estimated human review cost per candidate, and (3) the expected number of attempts required for a task. For model $m$, the per-attempt cost is

$$C_{attempt} = C_{model}(m) + C_{review}. \tag{2}$$

We estimate review cost with a default hourly rate of \$50 and 20 seconds of inspection time per image,

$$C_{review} = (50/3600) \cdot 20 \approx 0.278. \tag{3}$$

For each task $t$, we estimate a pass rate $p_t$ from the full $K = 10$ candidates and compute the expected number of attempts with a maximum retry budget $A = 4$ (reflecting a practical user retry limit). The expected attempts and success probability under this cap are

$$E_t = \begin{cases} \frac{1-(1-p_t)^A}{p_t} & \text{if } p_t > 0, \\ A & \text{if } p_t = 0, \end{cases} \qquad S_t = 1 - (1 - p_t)^A. \tag{4}$$

We then aggregate across tasks to compute pass@4 and effective cost per success using the retry-cap model:

$$p@4 = \frac{1}{T} \sum_t S_t, \quad E = \frac{1}{T} \sum_t E_t. \tag{5}$$

$$C_{eff} = \frac{E \cdot C_{attempt}}{p@4}. \tag{6}$$

Table 3 lists the per-candidate model costs used in our analysis, which serve as the inputs to $C_{model}(m)$.

### 4.5 Image models

We evaluate a mix of current flagship and preview image models used for instruction-following edits. Model identifiers match the benchmark configuration.

- gemini-3-pro-preview: Gemini 3 Pro Preview (Nano Banana Pro), released November 2025 by Google; 2K resolution outputs.
- seedream-4.5: ByteDance Seedream 4.5 flagship image model; 2K resolution outputs.
- seedream-4.0: ByteDance's previous flagship image model.

Table 3: Per-candidate model costs used in our analysis (USD).

| Model | Cost per candidate ($) |
|---|---|
| gemini-3-pro-preview | 0.134 |
| seedream-4.5 | 0.04 |
| seedream-4.0 | 0.03 |
| gpt-image-1.5 | 0.17 |
| flux-2-max | 0.10 |
| riverflow-2-b1 | 0.15 |
| qwen-image-edit-2511 | 0.03 |

- gpt-image-1.5: OpenAI's flagship image model; 1K-1.5K resolution and limited aspect ratios.
- flux-2-max: Black Forest Labs flagship image model; 2K outputs and additional reasoning support.
- riverflow-2-b1: Sourceful Riverflow 2 (Beta) pre-release model targeted for Q1 2026.
- qwen-image-edit-2511: Alibaba's latest flagship Qwen Image Edit model, released December 2025; 2K image resolution.

### 4.6 Hype Gap

We report the Hype Gap (Best-of-10 Uplift) as the difference, in percentage points, between pass@10 and pass@1. Let $p$@1 be the success rate on the first attempt and $p$@10 be the probability of achieving at least one success within 10 attempts. Then

$$\text{HypeGap} = p@10 - p@1. \tag{7}$$

Lower Hype Gap indicates consistent performance between a model's typical outputs and its best-of-10 results, while a larger Hype Gap implies that strong edits are possible but less reliable in practical use.

## 5 Benchmark Usage

The code repository, including task files and tooling, is available at `https://www.github.com/sourceful-official/hype-edit-1-benchmark`. The benchmark release includes the public task set, a Gemini 3 Flash (gemini-3-flash-preview) judge example implementation, and a human-judge web UI. The code is licensed under the MIT license; the tasks and reference imagery are licensed under CC BY 4.0 and were created by Sourceful, which grants the rights to use these assets under that license. We define a standard directory layout keyed by dataset, model name, and task identifier to support consistent reporting and longitudinal tracking of reliability improvements over time.

## 6 Results and Discussion

HYPE-EDIT-1 is designed as a living benchmark. The latest model evaluations are reported alongside the benchmark release and are updated as new models appear. Because the benchmark emphasizes repeated trials and cost-adjusted metrics, it is well suited to analyze trade-offs between high-cost, high-reliability models and lower-cost models that require more retries.

### 6.1 Combined Dataset Results

Table 4 summarizes the combined split, while Figure 3 visualizes pass rates, pass-at-10 reliability, expected attempts, effective cost, and hype gap. The gap between pass rate and pass@10 illustrates how strongly "best-of" sampling can inflate perceived performance.

Table 4: Combined split results summary (human majority labels; VLM judge used only as a check).

| Model | Pass Rate (%) | Pass@4 (%) | Expected Attempts | Effective Cost ($) |
|---|---|---|---|---|
| riverflow-2-b1 | 82.7 | 90.5 | 1.40 | 0.66 |
| gemini-3-pro-preview | 63.8 | 79.9 | 1.85 | 0.95 |
| gpt-image-1.5 | 61.2 | 70.3 | 2.04 | 1.30 |
| flux-2-max | 45.7 | 63.8 | 2.38 | 1.41 |
| qwen-image-edit-2511 | 45.4 | 57.4 | 2.48 | 1.33 |
| seedream-4.0 | 35.6 | 57.4 | 2.64 | 1.42 |
| seedream-4.5 | 34.4 | 59.9 | 2.63 | 1.39 |

### 6.2 Public Dataset Results

Figure 4 reports the public split performance across reliability, cost, and hype gap metrics.

### 6.3 Private Dataset Results

Figure 5 reports the private split performance across reliability, cost, and hype gap metrics.

## 7 Future Work

HYPE-EDIT-1 is intended as a first reliability-focused benchmark for reference-based marketing/design edits. We plan a larger follow-on release that expands both scale and evaluation robustness. Key directions include:

- Scale and coverage: expand task count, increase the diversity of marketing constraints (layout, typography, product packshots, brand compliance), and broaden multi-image edits.
- Judging robustness: evaluate with multiple independent VLM judges and release a larger human-labeled subset to measure judge correlation and bias; additionally, report judge disagreement rates and borderline-case analysis.
- Richer reporting: provide breakdowns by task type and difficulty, and add confidence intervals via bootstrap resampling across tasks.
- Operational sensitivity: report effective-cost sensitivity to review time, labor rate, and retry-cap budgets, and explore alternative user workflows such as selecting the best-of-N candidates.

## 8 Limitations

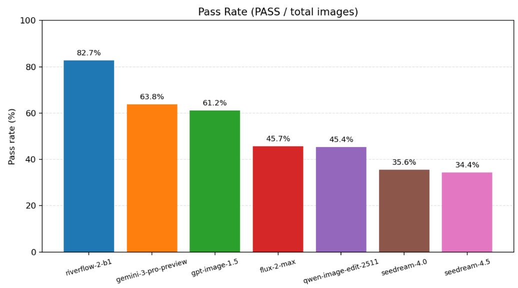
HYPE-EDIT-1 focuses on marketing and design edits, so its task distribution does not cover every possible editing scenario. The repeated-trial protocol assumes that attempts are independent, which may not perfectly model real-world conditions. Automated judging checks depend on the reliability of the judge model and may introduce bias in borderline cases, which is why we rely on human majority labels and use the VLM as a secondary check.

## 9 Broader Impact

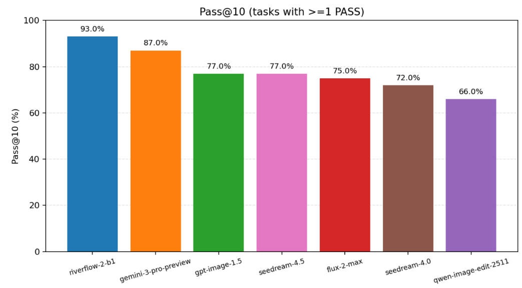
Reliable editing benchmarks can improve transparency in model evaluation and help users understand the operational cost of deploying image models. However, broad access to high-quality editing capabilities can be misused for deceptive content or brand impersonation. Responsible deployment should pair improved reliability metrics with safeguards and watermarking where appropriate.

## 10 Conclusion

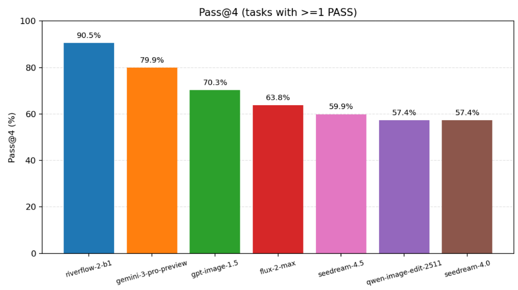
HYPE-EDIT-1 introduces a benchmark that measures both reliability and effective cost for image editing models using repeated trials on real-world tasks. The benchmark provides open tooling, a public dataset, and a private evaluation split to enable consistent, reproducible comparisons. We hope this benchmark drives model improvements that matter in practical workflows, not just curated examples.



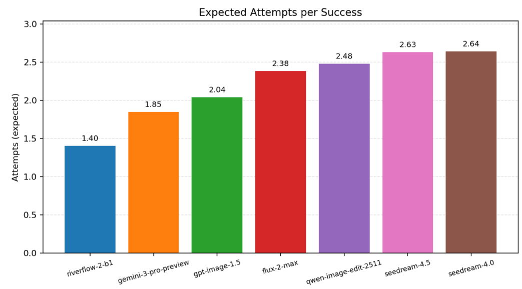

(a) Pass rate (combined).



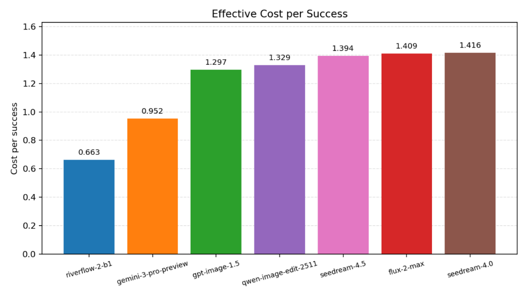

(b) Pass at 10 (combined).



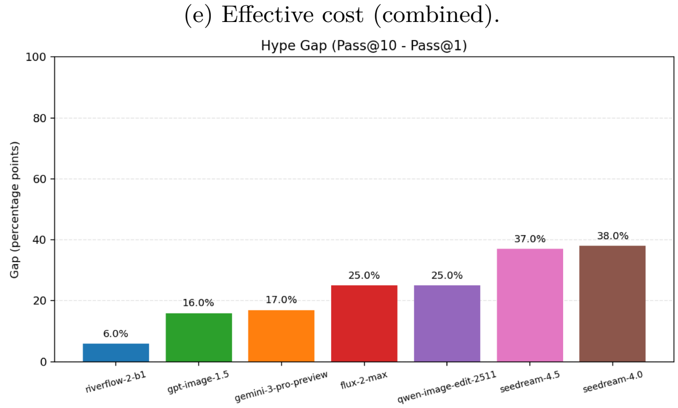

(c) Pass at 4 (combined).




(d) Expected attempts (combined).

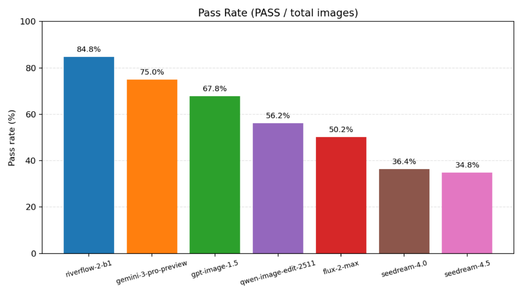



(e) Effective cost (combined).

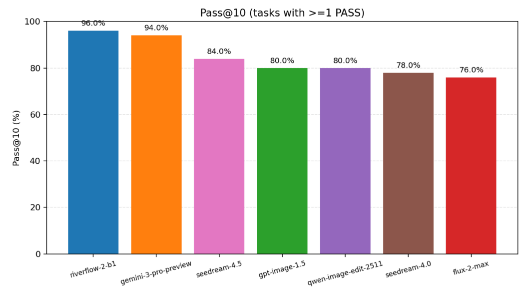



(f) Hype gap (combined).

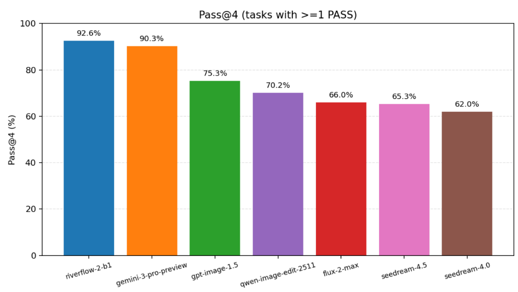
Figure 3: Combined split summary charts (human majority labels; VLM judge used only as a check).



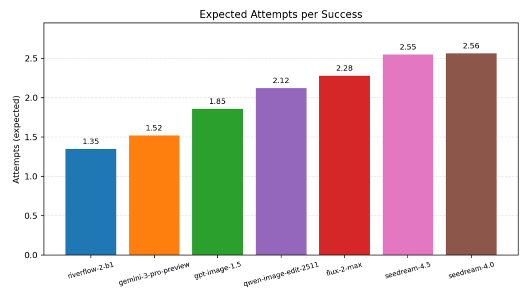

(a) Pass rate (public).



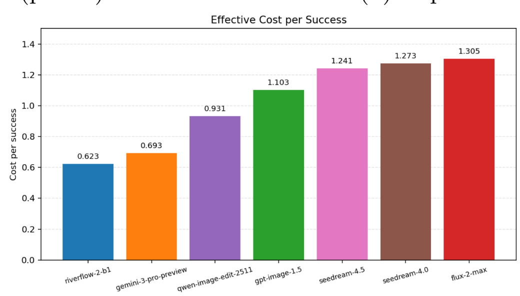

(b) Pass at 10 (public).



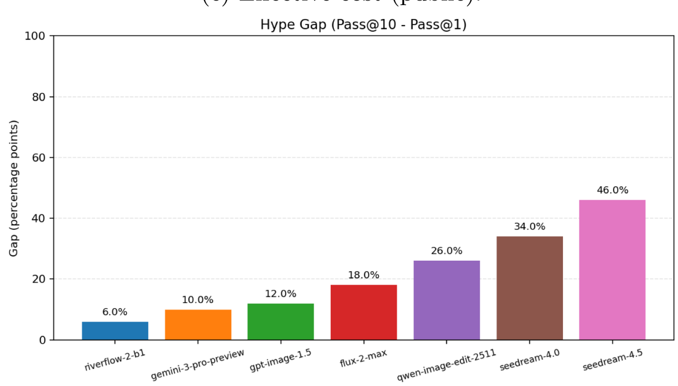

(c) Pass at 4 (public).




(d) Expected attempts (public).

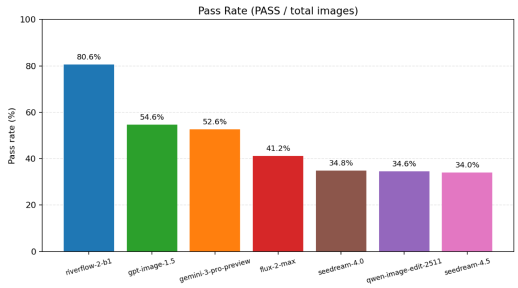



(e) Effective cost (public).

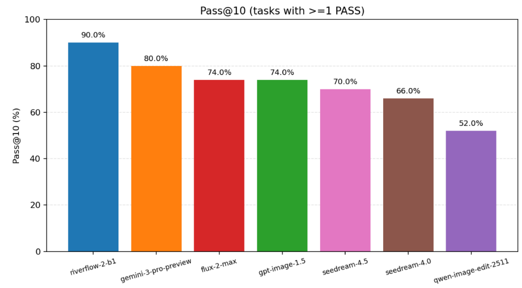



(f) Hype gap (public).

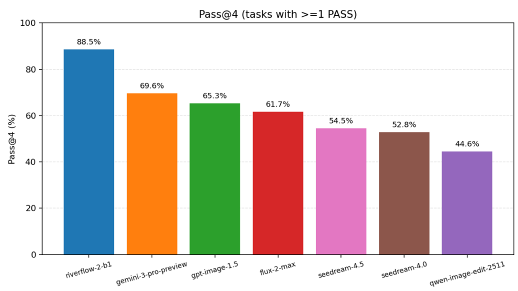
Figure 4: Public split summary charts (human majority labels).



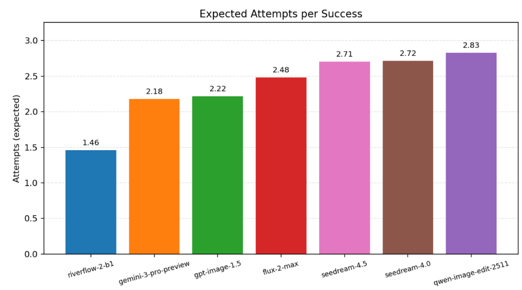

(a) Pass rate (private).



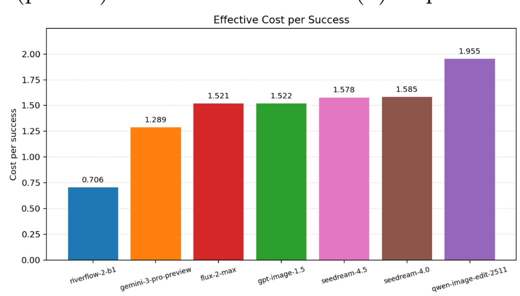

(b) Pass at 10 (private).



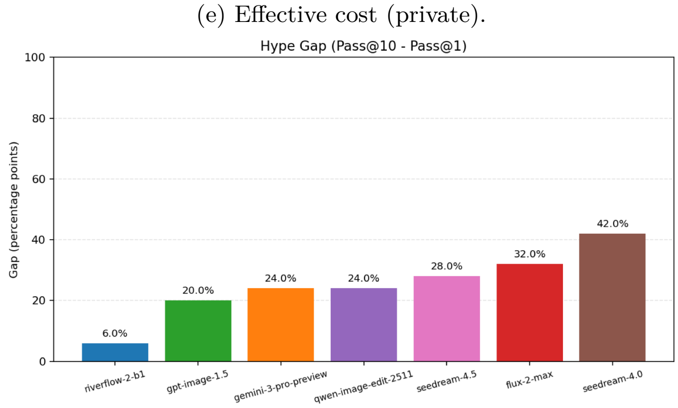

(c) Pass at 4 (private).




(d) Expected attempts (private).




(e) Effective cost (private).




(f) Hype gap (private).

Figure 5: Private split summary charts (human majority labels).

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# A Reproducibility Checklist

- Code and task files are available at `https://www.github.com/sourceful-official/hype-edit-1-benchmark`.
- Code is licensed under MIT; tasks and reference imagery are licensed under CC BY 4.0.
- Public tasks are provided in `public.json`.
- A Gemini 3 Flash (gemini-3-flash-preview) judge example implementation is included.
- A human-judge web UI is included for manual evaluation.