MMMG: A Massive, Multidisciplinary, Multi-Tier Generation Benchmark for Text-to-Image Reasoning

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https://mmmgbench.github.io/

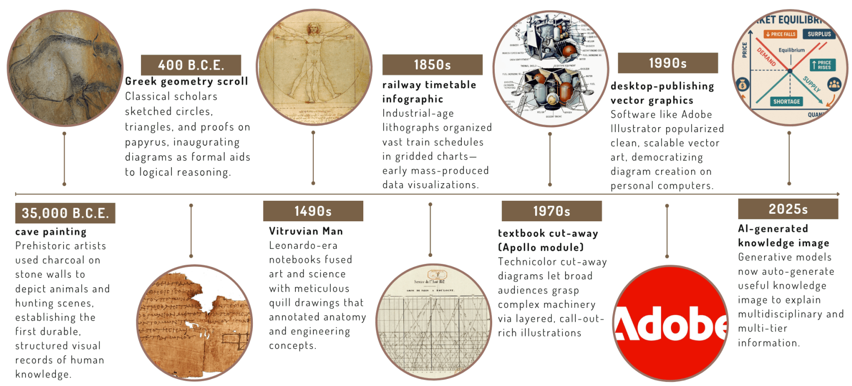

Figure 1: $40,000$ Years of Knowledge Image: From Cave Paintings to Generative AI.

Abstract

In this paper, we introduce knowledge image generation as a new task, alongside the Massive Multi-Discipline Multi-Tier Knowledge-Image Generation Benchmark (`MMMG`) to probe the reasoning capability of image generation models. Knowledge images have been central to human civilization and to the mechanisms of human learning—a fact underscored by *dual-coding theory* and the *picture-superiority effect*[2]. Generating such images is challenging, demanding multimodal reasoning that fuses world knowledge with pixel-level grounding into clear explanatory visuals. To enable comprehensive evaluation, `MMMG` offers $4,456$ expert-validated (knowledge) image-prompt pairs spanning 10 disciplines, 6 educational levels, and diverse knowledge formats such as charts, diagrams, and mind maps. To eliminate confounding complexity during evaluation, we adopt a unified Knowledge Graph (KG) representation. Each KG explicitly delineates a target image's core entities and their dependencies. We further introduce `MMMG-Score` to evaluate generated knowledge images. This metric combines factual fidelity, measured by graph-edit distance between KGs, with visual clarity assessment. Comprehensive evaluations of 21 state-of-the-art text-to-image generation models expose serious reasoning deficits—low entity fidelity, weak relations, and clutter—with GPT-4o achieving an `MMMG-Score` of only 50.20, underscoring the benchmark's difficulty. To spur further progress, we release FLUX-Reason (`MMMG-Score` of 34.45), an effective

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[2]Both dual-coding theory and the picture-superiority effect principles suggest humans remember visuals more effectively than words, partly because visual information can engage multiple cognitive encoding pathways.
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Figure 2: Representative knowledge images generated with GPT-4o. Disciplines (L-R): Economics, Oceanography, Environmental Engineering, Astrophysics, Climate Science. Details are in the supplementary.

and open baseline that combines a reasoning LLM with diffusion models and is trained on $16,000$ curated knowledge image–prompt pairs.

1 Introduction

Reasoning-based large language models (LLMs) such as OpenAI-o1/o3 [33, 36, 35] and DeepSeek-R1 [12] excel on math and coding tests (AIME 2024 [23], Codeforces [39], GPQA Diamond [43], MATH-500 [15], MMLU [14], SWE-bench [25]) thanks to rigorous, reasoning-focused benchmarks. By contrast, widely used text-to-image benchmarks [21, 7] still focus on instruction following and compositionality—e.g., attribute binding—while largely overlooking reasoning. The lack of reasoning-oriented benchmarks has left text-to-image generation models lagging significantly behind reasoning-focused LLMs.

Measuring reasoning in image generation is a non-trivial task. Current evaluations emphasize prompt-following, aesthetics, and visual–text rendering, typically quantified by CLIP [44], FID [45], OCR, and Aesthetic [1] scores. Yet producing such images seldom requires complex logical, domain-specific reasoning. Motivated by how humans leverage visuals to think, we introduce a new task—knowledge image generation: given only a vague user prompt, the model must autonomously infer the pertinent concepts (or entities) and relationships, and render them in a coherent knowledge image—such as a diagram, chart, infographic, or other visual—that faithfully conveys the intended information.

Throughout human history, knowledge images have propelled progress for nearly $40,000$ years, serving as a lasting bridge that turns abstract ideas into concrete, shareable visual forms (Figure 1). Cognitive science also supports this direction—the dual-coding theory [53] and the picture-superiority effect [54] suggest humans encode information more robustly when language and imagery are combined. Creating such visuals, however, is intrinsically difficult: a model must fuse broad world knowledge with spatial composition, select salient entities, and faithfully ground relations in pixel space. Figure 2 visualizes several knowledge representations across disciplines.

To advance text-to-image reasoning, we introduce the Massive Multi-Discipline Multi-Tier Knowledge-Image Generation Benchmark (`MMMG`). `MMMG` comprises $4,456$ expert-validated prompt–image pairs spanning ten academic disciplines—Biology (850), Chemistry (328), Mathematics (399), Engineering (582), Geography (352), Economics (623), Sociology (479), Philosophy (210), History (327), and Literature (306);—and six educational tiers: pre-school (591), primary school (680), secondary school (693), high school (936), undergraduate (744), and PhD (812). Each sample is annotated with a high-quality knowledge graph that lists the necessary entities and their dependencies, enabling format-agnostic coverage and requiring models to generalize across domains and reasoning levels. Its benefits are twofold: first, it abstracts core concepts into an interpretable graph, reducing the diversity and complexity of knowledge visuals; second, it enables objective fidelity evaluation via graph-edit distance between the ground-truth and generated graphs.

Benchmarking reasoning fidelity in generated images requires more than perceptual metrics. We therefore introduce `MMMG-Score`, which combines the graph-edit distance between knowledge graphs with a visual-clarity score derived from foundational segmentation models. Specifically, we employ the OpenAI-o3 reasoning LLM to analyze each image–prompt pair, and predict an initial knowledge graph. For the visual-clarity component, we run Segment Anything Model v2 (SAM-2) [42] on the generated images and penalize overly cluttered and disorganized outputs that may "hack" the reasoning LLM to extract the unreliable knowledge graphs yet fail to convey the knowledge clearly. The importance of this visual-clarity metric is examined in the experimental section.

We conduct comprehensive evaluations of 21 state-of-the-art text-to-image models—LlamaGen, JanusFlow, Emu-3, SimpleAR, Janus-Pro, CogView, SEED-X, SDXL-1.0, SDXL-1.0-refiner, Infinity, FLUX.1-[dev], FLUX.1-[pro], Ideogram 2.0, HiDream-l1-Full, Qwen-Image, BAGEL, Nano Banana,

Benchmark	Scale	Focus	Domains	Metrics	World Knowledge	Explanatory
GenEval [11]	553	Compositionality	counting, colors, position, attribute binding	Accuracy	✗	✗
T2I-CompBench++ [20]	6,000	Compositionality	Object-Attribute Binding	BLIP-VQA, UniDet, CLIP	✗	✗
DPG-Bench [18]	1,065	Prompt Adherence	Dense Scene Generation	CLIP, Human Eval	✗	✗
Commonsense-T2I [7]	1,000+	Commonsense Reasoning	Everyday Scenarios	Accuracy	✗	✗
Winoground-T2I [58]	11,000	Compositionality	20 Types	Contrastive Accuracy	✗	✗
TIFA [19]	1,000	Faithfulness	General Knowledge	VQA-based	✗	✗
TypeScore [46]	1,000	Text Fidelity	Scene Text	OCR-based	✗	✗
GenAI-Bench [28]	1,600	Compositionality	Scenes, objects, attributes, relations, counting, comparison, etc.	VQAScore	✗	✗
CUBE [26]	1,000	Cultural Competence	Cuisine, Landmarks, Art spanning 8 countries	Cultural Awareness, Vendi Scores	✓	✗
WISE [32]	1,000	Commonsense Reasoning	Science, Culture, Space-Time	LLM-Judged	✓	✗
MMMG (Ours)	4,456	Disciplinary Knowledge	10+ Academic Fields	Readability, Graph Edit Distance	✓	✓

Table 1: Comparison with previous Text-to-Image (T2I) benchmarks.

and GPT-4o image generation—on the MMMG benchmark, reporting their FID, aesthetic, WISE [32], and MMMG-Score metrics. We also conduct human studies to confirm that MMMG-Score aligns best with user judgements, underscoring the value of knowledge-graph–based evaluation. Our MMMG benchmark presents significant challenges: even the GPT-4o image generation achieves only MMMG-Score of 46.66, while the next-best model, the open-source HiDream-l1-Full, reaches just MMMG-Score of 25.72. To catalyze further research, we release FLUX-Reason, a fully reproducible and open-source baseline that pairs a reasoning-oriented LLM (e.g., OpenAI-o3 or DeepSeek-R1) with a diffusion model (FLUX.1-[dev]) trained on $16,000$ curated knowledge-image pairs. Although its MMMG-Score of 30.52 still trails that of GPT-4o, FLUX-Reason serves as an open source baseline and underscores the new challenges posed by the MMMG benchmark for next-generation reasoning-oriented text-to-image generation models.

2 Related Work

Benchmarks for Text-to-Image Generation. Many benchmarks have been developed to assess both the limitations and progress of recent text-to-image models. We summarize the comparison between MMMG and prior benchmarks in Table 1. GenEval [11] introduces object detectors for fine-grained, object-level evaluation, addressing the shortcomings of holistic metrics. T2I-CompBench++ [20] increases compositional difficulty via prompts involving attributes, relationships, numeracy, and complex scenes. Commonsense-T2I [7] uses adversarial prompts to probe visual commonsense reasoning. Winoground-T2I [58] evaluates compositional generalization with contrastive sentence pairs. DPG-Bench [18] targets instruction-following with longer, text-rich prompts. The concurrent WISE benchmark [32] is most related, focusing on world knowledge-based evaluation across cultural, scientific, and temporal domains. However, WISE emphasizes photorealism with implicit knowledge, while MMMG requires models to explicitly visualize structured world knowledge in a semantically grounded and explanatory manner.

Reasoning in Text-to-Image Generation. While LLMs have achieved significant progress in reasoning through techniques such as chain-of-thought prompting [52, 27] and large-scale reinforcement learning [12, 33], recent models excel in benchmarks focused on mathematics, coding, and tool use (e.g., MMLU [14], AGIEval [57], LogicBench [38], MathVista [30]). Inspired by this progress, several works have explored injecting reasoning into image generation, including ImageGen-CoT [8, 29], HiDream [16], T2I-R1 [24], Meta-Queries [37], and MINT [51]. However, these methods are typically evaluated on prior benchmarks and rely on caption-based metrics (e.g., CLIPScore [40]) or subjective human preference, both of which lack fidelity in assessing reasoning ability. To address this gap, MMMG introduces a knowledge image generation task requiring advanced multimodal reasoning, along with MMMG-Score, a structured metric that compares extracted and ground-truth knowledge graphs. We further propose FLUX-Reason, a reasoning-enhanced model, and evaluate it on the MMMG benchmark.

3 Method

We first illustrate the definition of the knowledge image generation task by leveraging additional knowledge graph annotations. Next, we describe how we build the MMMG benchmark, and provide an overview of key dataset statistics. We then introduce the novel MMMG-Score, a metric we propose for more reliable evaluation. Last, we present details of our strong baseline, FLUX-Reason, which explicitly combines a reasoning LLM with a text-to-image generation model in a cascaded manner.

3.1 Knowledge Image Generation

Formulation. The knowledge image generation task begins with a concise, question-like prompt $\mathbf{X}$ and employs a generative model f to produce a knowledge image $\mathbf{Y}$ conditioned on $\mathbf{X}$. A knowledge image typically comprises multiple entities and their interrelationships. To capture this structure, we extract an auxiliary knowledge graph $\mathbf{G} = (\mathcal{E}, \mathcal{D})$ using a reasoning LLM (e.g., OpenAI-o3), which takes both the text prompt and the target image (if available) as input. Here, $\mathcal{E} = \{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$

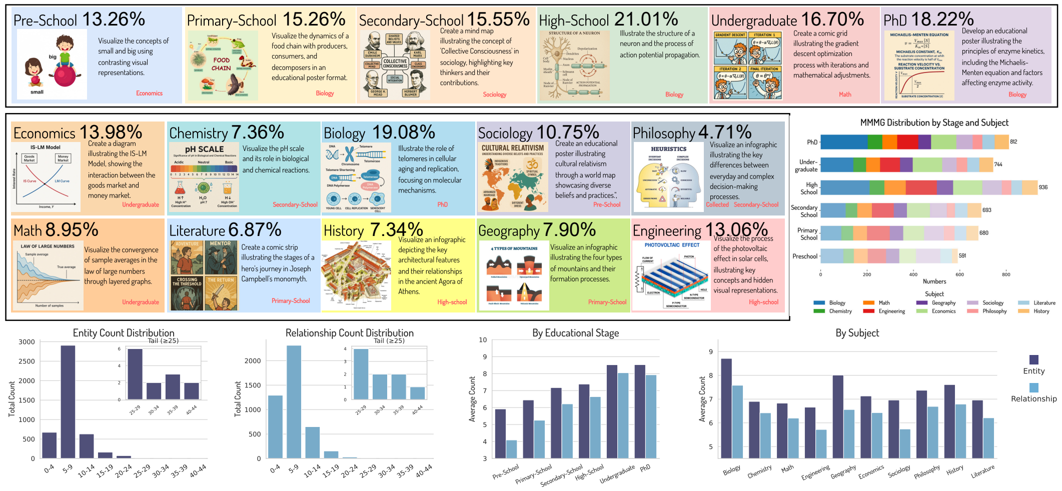


Figure 3: **MMMG Dataset Statistics:** The top panel shows MMMG test dataset distribution across educational levels and disciplines. The bottom panel presents statistics of both train and test sets, while bottom right depicts knowledge graph complexity increase across educational stages and differ among subjects.

denotes the set of graph nodes representing entities, and $\mathcal{D} = \{d_i(\mathbf{e}_j, \mathbf{e}_k)\}_{i=1}^{K}$ denotes the set of edges encoding relationships between entities.

Importance of Knowledge Graph. The knowledge graph $\mathbf{G}$ is essential for evaluating whether the generated image faithfully visualizes the domain knowledge implied by the prompt $\mathbf{X}$. Since $\mathbf{X}$ is typically a concise question rather than a descriptive instruction—e.g., "*Illustrate the structure of a neuron and the process of action potential propagation*"—it is not well-aligned with the visual content, making CLIP-based verification unreliable.

Knowledge Graph Extraction. Accurate knowledge graph extraction requires inferring world knowledge from the text prompt $\mathbf{X}$ and identifying the corresponding visual entities and relations in the image $\mathbf{Y}$. We follow a two-step process: OpenAI-o3 processes each <$\mathbf{X}$, $\mathbf{Y}$> and extracts knowledge graphs following a defined schema (Supplemental C.3); four expert annotators manually verify the results and filter out low-quality cases.

Relationship Formalization. To ensure that the knowledge graph can represent diverse knowledge across six educational levels and ten disciplines, we propose a domain-agnostic set of predicates for relationships: $\mathrm{Defines}(\cdot,\cdot)$, $\mathrm{Entails}(\cdot,\cdot)$, $\mathrm{Causes}(\cdot,\cdot)$, $\mathrm{Contains}(\cdot,\cdot)$, $\mathrm{Requires}(\cdot,\cdot)$, and $\mathrm{TemporalOrder}(\cdot,\cdot)$, with optional dynamic modifiers such as change($\cdot$) to represent trends or shifts. For instance, $\mathrm{Causes}(\mathrm{increase}(e_1), \mathrm{decrease}(e_2))$ may represent a graph edge where an increasing population (denoted as e_1) leads to reduced biodiversity (denoted as e_2).

In the neuron example, we can extract a non-trivial knowledge graph consisting of 9 entities, $\mathcal{E} =$\{dendrites, cell body, nucleus, axon, myelin sheath, schwann cell, node of ranvier, action potential propagation, depolarization\}, and 8 relationships, $\mathcal{D} =$\{$\mathrm{Contains}$(dendrites, cell body), $\mathrm{Contains}$(cell body, nucleus), $\mathrm{Contains}$(cell body, axon), $\mathrm{Contains}$(axon, myelin sheath), $\mathrm{Contains}$(myelin sheath, schwann cell), $\mathrm{Contains}$(axon, node of Ranvier), Causes(depolarization, action potential propagation), $\mathrm{Requires}$(action potential propagation, axon)\}. This abstraction provides two key benefits: (i) structural consistency across disciplines and educational levels, and (ii) automated evaluation using normalized Graph Edit Distance (GED) to assess factual alignment with reference graphs.

3.2 MMMG Benchmark: Statistics and Curation Process

Statistics. Figure 3 provides an overview of the dataset statistics for MMMG, which spans six educational stages and ten academic disciplines. MMMG contains 4,456 expert-collected prompt–image pairs. We analyze the statistics as follows:

• At the top of Figure 3, we present the distribution across six different educational levels and illustrate representative examples to demonstrate how the inherent challenges increase from pre-school to PhD-level knowledge images. We ensured a balanced distribution across educational levels.

• In the middle of Figure 3, we present the distribution across ten academic disciplines. We find that biology, economics, and engineering are the dominant domains that rely more on knowledge images

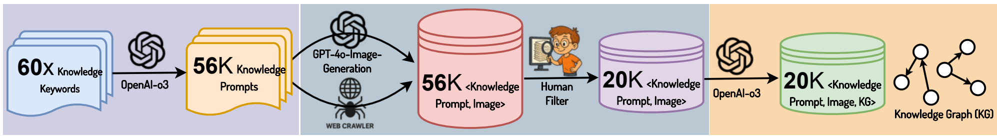


Figure 4: **`MMMG` Dataset Construction Pipeline**: From knowledge keywords across six educational levels and ten disciplines, we generate 56K prompts using OpenAI-o3. These prompts are clustered into semantic groups and then sent to either GPT-4o for image generation or to a web crawler for image retrieval. The resulting 56K knowledge images are filtered down to 20K through a cascade of automated steps and human filter. Last, we use OpenAI-o3 to extract a knowledge graph for each prompt–image pair.

than others—especially philosophy, which accounts for only 4.71% of the dataset. On the right side of the middle, we visualize the distribution of all 10 disciplines across the 6 educational levels.

• At the bottom of Figure 3, we highlight the complexity of knowledge image generation by showing statistics on the number of entities and relationships in the dataset. We find that nearly $3,000$ samples require generating $5 \sim 10$ entities and $5 \sim 10$ relationships. On the right side of the third row, we report the distributions of these statistics across different educational levels and disciplines.

Curation Pipeline. Figure 4 illustrates the overall pipeline for curating the `MMMG` dataset. Starting from $60\times$ knowledge keywords, we employ a cascade dataset flywheel comprising several stages: OpenAI-o3 for prompt generation, GPT-4o-Image for synthesizing training images, a web crawler for collecting real-world data, and human expert filtering for quality assurance. Together, these stages yield around $20,000$ curated candidates—$16,000$ high-aesthetic synthetic samples and $3,452$ knowledge-accurate, real-world visuals—from which the `MMMG` benchmark is constructed for comprehensive evaluation.

• Knowledge Keywords ❶ $\rightarrow$ Knowledge Prompts ❷: In the left of Figure 4, we first apply OpenAI-o3 to generate approximately 56,830 knowledge text prompts by combining two keywords: one specifying the educational level and one specifying the discipline. The educational level keyword is sampled from a seed set of six candidates: [pre-school, primary school, secondary school, high school, undergraduate, PhD], while the disciplinary keyword is sampled from ten candidates: [economics, chemistry, biology, sociology, philosophy, math, literature, history, geography, engineering].

• Knowledge Prompts ❷ $\rightarrow$ Knowledge Images ❸: We source knowledge images from two complementary domains: web-crawled, factually grounded visuals for benchmark construction and GPT-4o-generated, scalable images for training. To prevent concept overlap, we cluster 56,830 knowledge prompts into 11,732 semantic groups using SentenceTransformer embeddings and DBSCAN. Prompts from larger clusters (common concepts) are used for synthetic data (30K images), while smaller clusters are used for web crawling (26K images). This allocation leverages the generator's advantage on familiar concepts while enhancing the benchmark's conceptual diversity.

• Knowledge Images Filter ❸ $\rightarrow$ ❹: We apply deduplication[3] and OCR-based filtering to remove duplicates and samples lacking explanatory visual text. During GPT-4o image generation, cropping artifacts often harm visual completeness. To address this, we use OpenAI-o3 to detect severe cropping. Human experts further verify text–image alignment and discard samples with factual errors or visual artifacts. After filtering, we obtain 20K curated knowledge image–text pairs, including 16K for training and 4K for benchmarking.

• Knowledge Prompts, Images ❹ $\rightarrow$ Knowledge Graphs ❺: We use OpenAI-o3 to generate a structured knowledge graph for each of the 20K prompt–image pairs, following the format described earlier. We also use DeepSeek-R1 to produce step-by-step reasoning over the graph's entities and relations. The 20K samples are split by their topics and concepts to ensure minimal overlap. Human experts then verify all samples and select the most accurate ones, resulting in the `MMMG` benchmark of 4,456 high-quality pairs.

3.3 MMMG-Score: Measuring Knowledge Fidelity and Visual Readability

As perceptual metrics like FID or CLIP are insufficient for reasoning evaluation, we propose `MMMG-Score`, a novel metric combining knowledge fidelity and visual readability.

[3] https://github.com/idealo/imagededup

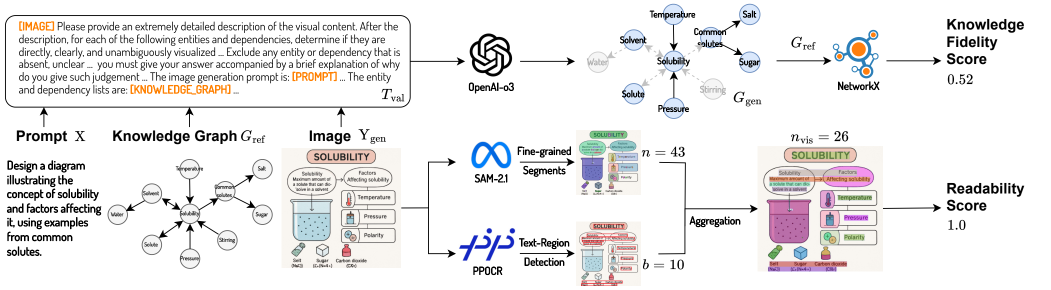


Figure 5: Illustration of `MMMG-Score` computation: We compute the knowledge fidelity score using graph edit distance, and the readability score by counting the number of segments in the generated knowledge image.

Knowledge Fidelity via Grounded Knowledge Graph Extraction. Given a generated image $\mathbf{Y}\mathrm{gen}$, its knowledge prompt $\mathbf{X}$, and the reference knowledge graph $\mathbf{G}\mathrm{ref}$, we employ OpenAI-o3 (high reasoning effort) to ground $\mathbf{G}\mathrm{ref}$ onto the pixel space of $\mathbf{Y}\mathrm{gen}$. This yields a grounded subgraph $\mathbf{G}\mathrm{gen} \subseteq \mathbf{G}\mathrm{ref}$, representing the knowledge actually depicted in the image. To ensure fair evaluation of each entity $\mathbf{e}_i$ and relation $d_i(\mathbf{e}j, \mathbf{e}k)$, OpenAI-o3 performs visual reasoning and outputs a detailed chain-of-thought before the final judgement. As illustrated in Figure 5, the knowledge fidelity score is computed as $1 - \mathrm{GED}(\mathbf{G}\mathrm{gen}, \mathbf{G}\mathrm{ref})$ using NetworkX[4] , where smaller graph edit distances indicate higher fidelity.

Visual Readability via Foundation Segmentation Model. Readability is critical for knowledge-image generation, ensuring effective information delivery. To assess it, we compute a Readability Score using a segmentation model and a text detector, rewarding coherent regions and penalizing excessive fragmentation. As shown in Figure 5 (bottom right), we use SAM-2.1 [41] for segmentation (seeded with 32×32 uniform points, NMS threshold 0.6) and PaddleOCR[5] for text detection. Overlapping masks and text boxes are merged, and the final region count defines the Readability Score:

$$R(n_{\mathrm{vis}}) = \begin{cases} 1, & n_{\mathrm{vis}} \le n_{\mathrm{min}}, \\ \dfrac{n_{\mathrm{max}} - n_{\mathrm{vis}}}{n_{\mathrm{max}} - n_{\mathrm{min}}}, & n_{\mathrm{min}} < n_{\mathrm{vis}} < n_{\mathrm{max}}, \\ 0, & n_{\mathrm{vis}} \ge n_{\mathrm{max}}. \end{cases} \tag{1}$$

Empirically, we set $n_{\mathrm{min}} = 70$ and $n_{\mathrm{max}} = 160$ based on segment distributions observed across common text-to-image models (see Appendix D.2). This range excludes overly fragmented or unreadable outputs that are (i) unsuitable for evaluating meaningful reasoning and (ii) prone to exploitation by models that over-generate dense but illegible content. This thresholding approach thus enforces essential legibility for reliable knowledge evaluation.

MMMG-Score via a Multiplicative Design. The final `MMMG-Score` is computed by multiplying the above knowledge fidelity and readability score:

$$\texttt{MMMG-Score}(\mathbf{Y}_{\mathrm{gen}}) = R(n_{\mathrm{vis}}) \cdot [1 - \mathrm{GED}(\mathbf{G}_{\mathrm{gen}}, \mathbf{G}_{\mathrm{ref}})] \in [0, 1]. \tag{2}$$

This formula enforces the essential "AND" requirement for an effective knowledge image. Poor performance in either fidelity or readability will result in a proportionally low overall score.

Empirical results show that this composite metric correlates more strongly with human ratings than general perceptual scores such as FID, CLIP-Score, or aesthetic measures. Error analysis further reveals that visual clutter and unreadability mainly occur in weaker baselines, reflecting deficiencies in visual reasoning and layout planning. Among alternative designs, the multiplicative formulation remains the most concise and robust for quantifying knowledge-image quality.

3.4 FLUX-Reason

We design FLUX-Reason to enhance reasoning capabilities in knowledge image generation by explicitly integrating a reasoning LLM with a diffusion-based generator. As illustrated in Figure 6, it

[4] https://github.com/networkx

[5] https://github.com/PaddlePaddle/PaddleOCR

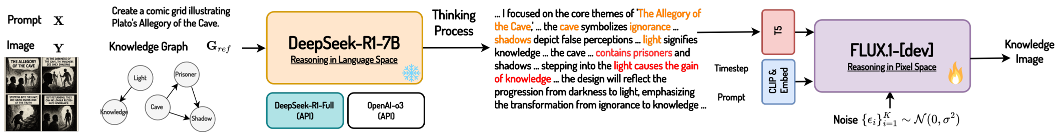


Figure 6: Overview of the FLUX-Reason pipeline. Reasoning LLMs first generate chain-of-thought (CoT) trajectories and visual planning cues conditioned on structured knowledge graphs. In the reasoning trace, entities and relations are highlighted in orange and red, respectively. These traces are then encoded into the diffusion model to guide visual planning in pixel space.

consists of three variants: `FLUX-Reason (R1-7B)` incorporates `DeepSeek-R1-Distill-Qwen-7B` for local inference; `FLUX-Reason (R1)` queries the `DeepSeek-R1-Full` API; `FLUX-Reason (o3)` utilizes `OpenAI-o3` to produce summarized reasoning chains.

To supervise training, we extract chain-of-thought (CoT) reasoning traces from 16K GPT-4o-generated samples, each annotated with a ⟨prompt, image, knowledge graph (KG)⟩ triplet. Conditioned on explicit entities and relations, the extracted reasoning traces provide fine-grained guidance for concept selection, interaction modeling, and spatial arrangement.

To incorporate such long-form structured reasoning into generation, we extend the T5 encoder's input length to 2048 tokens to accommodate the textual reasoning input, which is then transformed into pixel-space representations. The diffusion model is fine-tuned with LoRA over 10K steps, enabling it to learn pixel-level planning aligned with the structured reasoning trajectory.

4 Experiments

4.1 Main Results

We benchmark 21 state-of-the-art T2I models and 3 FLUX-Reason variants, spanning three paradigms: **autoregressive (AR)** models, including `JanusFlow-1.3B` [31], `Janus-pro-7B` [5], `LlamaGen` [48], `SimpleAR` [49], and `Infinity` [13]; **diffusion-based (DM)** models, including `SDXL-1.0`, `SDXL-1.0-refiner` [47], `Ideogram` [22], `CogView-4` [56], `HiDream-I1-Full` [17], `Qwen-Image` [55], `FLUX.1-[dev]` [2], re-captioned `FLUX.1-[dev]`, `FLUX.1-[pro]` [3]; and **multimodal (MM)** models, including `Emu-3` [50], `BLIP3-o` [4], `Seed-X` [8], `BAGEL` [6], `Gemini 2.0 Flash` [9], `Gemini Nano Banana` [10] and `GPT-4o` [34]. All models are evaluated with a fixed seed of 42. DM models use a classifier-free guidance (CFG) scale of 3.5, while AR and MM models apply default decoding settings. Open-source models are experimented on with 6×A40 (512^2) or 4×A100 (1024^2), depending on the image resolution. API-based models are queried directly.

Performance Variation with Educational Level. Table 2 shows a clear performance drop as task complexity increases with education level. Most models, regardless of architecture, perform reasonably at pre-school (e.g., 20–30), but fall to low scores (below 10) at the PhD level, exposing their limitations in abstract reasoning and compositional planning. `GPT-4o` and `Nano Banana` stand out with strong, stable performance, showing robust generalization even on underspecified prompts.

Model Highlights. `HiDream-I1-Full` shows competitive scores (28.04) despite being open-source, likely benefiting from structured priors in its Llama-based encoder. Similarly, `FLUX.1-[pro]` (27.14) and `SEED-X` (18.16) outperform many AR and MM models, indicating advantages of diffusion planning. `BAGEL` underperforms due to its overly brief "thinking" trajectories, hindering the delineation of detailed entities and intricate relationships. `Qwen-Image` performs well at lower educational levels but drops sharply in higher ones, likely due to its distilled data and limited conceptual understanding.

Reasoning vs. Recaptioning. To assess the impact of reasoning, we compare `FLUX.1-[dev]`, a recaptioned variant using `OpenAI-o3` (512-token prompts), and our reasoning-guided `FLUX-Reason (R1)`. While recaptioning reduces performance across levels, reasoning traces yield substantial gains—particularly at higher tiers. `FLUX-Reason (R1)` reaches an average score of 34.45, confirming that structured reasoning, not verbosity, is crucial for knowledge-grounded image generation.

Discipline-Level Observations. Figure 7 reveals domain-specific reasoning challenges. Weaker models (e.g., `LlamaGen`, `Emu-3`) perform best in Geography and Literature, where visuals are descriptive and align better with pretraining data. In contrast, Economics, History, and Sociology

Table 2: `MMMG-Score` (×100) across prevalent image generation models, covering Diffusion, AR-based, and Multimodal architectures, evaluated over six educational stages.

Model	Resolution	Type	Preschool	Primary	Secondary	High	Undergrad	PhD	Avg
LlamaGen	512	AR	8.24	3.77	2.44	1.44	1.08	1.14	3.02
Emu-3	720	MM	12.44	7.12	6.41	5.28	2.65	2.74	6.11
JanusFlow-1.3B	384	AR	24.11	12.72	8.81	5.56	3.57	3.82	9.77
SimpleAR	1024	AR	23.12	11.97	8.96	6.44	4.36	3.99	9.81
Ideogram	1024	DM	20.39	14.14	12.90	9.68	8.41	7.73	12.21
BLIP3-o	1024	MM	29.59	17.43	11.52	8.32	5.75	5.21	12.97
Janus-pro-7B	384	AR	29.50	16.72	12.73	8.45	5.57	5.66	13.10
CogView-4	1024	DM	24.61	16.02	13.91	10.02	7.30	6.73	13.10
BAGEL	1024	MM	29.29	19.42	15.29	11.11	7.40	7.60	15.02
SDXL-1.0	1024	DM	23.41	19.12	17.41	16.26	9.92	9.29	15.90
SDXL-1.0-refiner	1024	DM	24.55	19.24	18.59	16.72	9.68	8.94	16.29
FLUX.1-[dev] (recaption)	1024	DM	28.05	20.29	20.70	15.74	12.59	11.20	18.10
SEED-X	1024	MM	33.41	22.67	19.49	15.74	8.88	8.76	18.16
FLUX.1-[dev]	1024	DM	29.80	23.09	20.99	16.12	12.47	12.30	19.13
Infinity	1024	AR	25.87	20.63	21.86	18.36	14.23	14.14	19.18
Qwen-Image	1024	DM	37.23	25.46	25.54	18.28	15.11	14.20	22.64
FLUX.1-[pro]	1024	DM	42.27	30.10	29.15	23.40	19.32	18.61	27.14
HiDream-I1-Full	1024	DM	42.86	31.77	30.26	23.39	19.88	20.05	28.04
Gemini 2.0 Flash	1024	MM	41.98	32.06	31.69	29.99	20.58	19.53	29.31
Gemini Nano Banana	1024	MM	49.46	44.58	51.17	48.85	41.27	39.07	45.73
GPT-4o	1024	MM	**64.78**	**51.94**	**53.04**	**51.29**	**41.52**	**38.60**	**50.20**
FLUX-Reason (o3)	1024	DM	37.83	29.72	29.50	23.62	20.29	18.73	26.62
FLUX-Reason (R1-7B)	1024	DM	44.93	34.41	34.19	28.70	23.36	21.99	31.26
FLUX-Reason (R1)	1024	DM	49.10	39.39	37.00	33.65	24.96	22.57	34.45

remain difficult even for stronger models due to their reliance on charts, temporal events, and abstract social concepts—structures rarely seen during pretraining.

A notable divergence appears between Chemistry and Biology: while both start similarly, Chemistry performs better with stronger models, likely due to its standardized diagram formats and symbolic representations. In contrast, Biology's visuals are often more irregular and spatially complex, making them less amenable to straightforward interpretation by such models.

Mathematics and Engineering perform well despite textual abstraction, suggesting structured visuals (e.g., geometry, schematics) are more model-friendly than symbolic reasoning. Since 77% of `MMMG` images are human-designed, these trends also reflect real-world preferences. Overall, `MMMG` exposes domain gaps and visual-semantic reasoning challenges overlooked by text-only benchmarks.

4.2 Human Alignment and Metric Comparison

To assess alignment with human perception, we collected over 1,200 expert ratings (0–10 on clarity, correctness, accuracy and faithfulness) across six educational levels. We compared four metrics—`MMMG-Score`; an LLM-as-a-judge WIScore [32] with OpenAI-o3 evaluator; FID computed over 3,452 ground-truth images; and AES-2.5 [1]. Figure 8 reports their Pearson correlations against human scores: `MMMG-Score` leads with $r = 0.876$; WISE achieves only $r = 0.701$, even trailing FID's negative correlation ($r = -0.774$) in magnitude, underscoring that knowledge-image evaluation is far from trivial and that direct LLM judgments lack transparency; AES-2.5 performs poorly ($r = 0.215$), capturing only surface aesthetics rather than semantic fidelity. These findings motivate `MMMG`'s knowledge-graph formulation as the only structure-and-knowledge-aware metric that reliably mirrors human judgments on complex, knowledge-dense visualizations.

4.3 MMMG-Score Variants

To validate the multiplicative design of the `MMMG-Score`, we compare it against two conventional aggregation forms and further analyze its stability under different readability weightings.

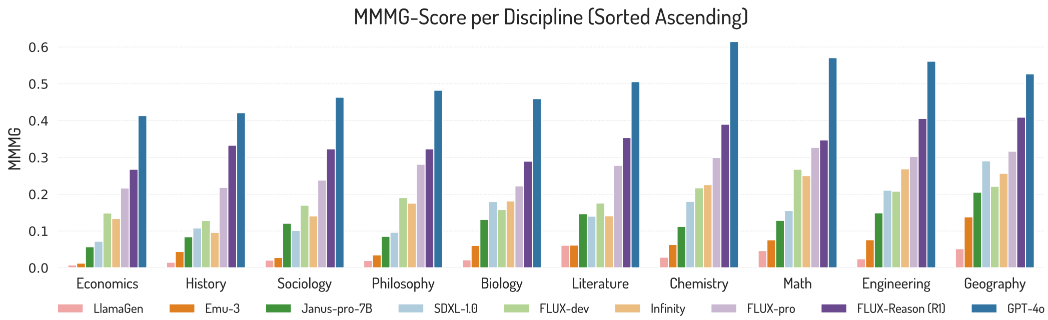


Figure 7: Discipline-level evaluation. Domains are sorted by average `MMMG-Score`.

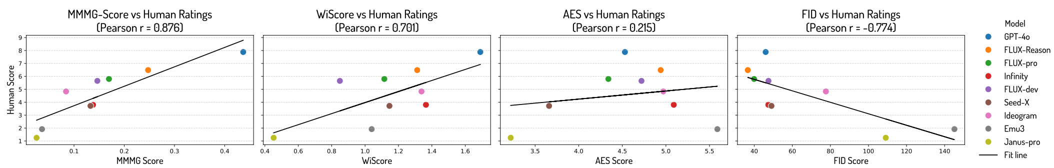


Figure 8: Illustration of Pearson Correlation among `MMMG-Score`, WiSCore, Aes-2.5 and FID.

Table 3: Comparison of average `MMMG-Score` across different aggregation methods and α values.

Model	**Arithmetic Mean**			**Geometric Mean**			**Stability Variant**				
α	0.5	0.75	1	0.5	0.75	1	0.5	0.75	1	1.25	1.5
GPT-4o	72.36	60.12	50.49	64.30	54.55	50.49	50.28	50.25	50.20	50.17	50.15
FLUX-Reason (R1-7B)	63.37	46.81	32.10	46.52	36.63	32.10	31.41	31.32	31.26	31.14	31.07
FLUX.1 [pro]	59.97	44.06	29.91	43.27	32.49	29.91	27.31	27.16	27.14	26.67	26.51
SDXL-1.0	47.35	36.79	25.37	29.48	25.71	25.37	17.19	16.14	15.90	14.61	14.04
CogView4	45.79	32.05	20.24	25.13	20.41	20.24	13.73	13.13	13.10	12.40	12.02

Arithmetic and Geometric Forms. We define the arithmetic and geometric aggregation variants:

$$\texttt{MMMG-Score-A}(\alpha) = \alpha \cdot K_{\text{score}} + (1-\alpha) \cdot R_{\text{score}}, \tag{3}$$

$$\texttt{MMMG-Score-G}(\alpha) = K_{\text{score}}^{\alpha} \cdot R_{\text{score}}^{(1-\alpha)}, \tag{4}$$

where $\alpha \in \{0.5, 0.75, 1\}$, K_{score} and R_{score} denote the knowledge fidelity and visual readability.

Robustness Analysis. To further examine robustness, we generalize the multiplicative form as:

$$\texttt{MMMG-Score}(\alpha) = K_{\text{score}} \cdot R_{\text{score}}^{\alpha}, \tag{5}$$

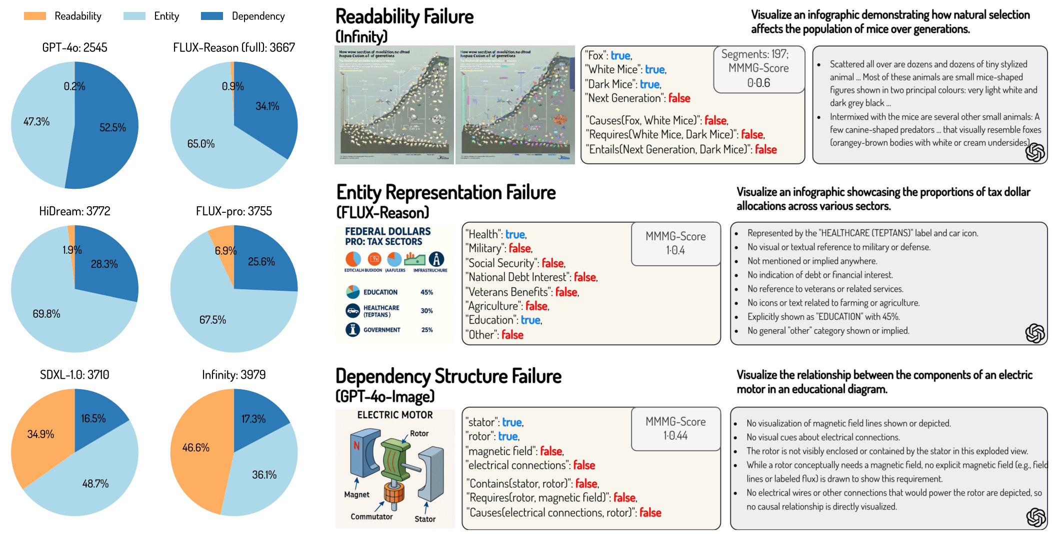
where $\alpha \in \{0.5, 0.75, 1, 1.25, 1.5\}$, interpolating R_{score} between concave and convex regimes.

Table 3 reports results across these settings. We find that the arithmetic and geometric means are highly sensitive to α. Thus, an inappropriate choice ($\alpha = 0.5$) may reduce the benchmark's discrimination. Conversely, the multiplicative form preserves both model rankings and absolute scores across all tested α values, indicating robustness to moderate weighting changes. Based on this analysis, we adopt the minimalist and interpretable multiplicative formulation `MMMG-Score` $= K_{\text{score}} \cdot R_{\text{score}}$.

4.4 Error Analysis

To better understand model limitations in structured visual reasoning, we conduct a systematic analysis of failure cases with low `MMMG-Score` (≤ 0.5). We categorize these into three types based on thresholds: **Visual Readability Failures** (readability score ≤ 0.5), **Entity Representation Failures** (entity recall ratio ≤ 0.3), and **Dependency Structure Failures** (dependency accuracy ≤ 0.4). Figure 9(a) shows the error distribution across six top models, including `GPT-4o`, `FLUX-Reason (R1)`, `HiDream`, `FLUX.1-[pro]`, `SDXL-1.0`, and `Infinity`.

`GPT-4o` shows the fewest errors but struggles with visual dependency nomination. As shown in Figure 9(b, center), its motor diagram is visually coherent but misses key interactions (e.g., energy flow, containment), resulting in a dependency failure despite high visual clarity.



(a) (b)

Figure 9: **Error analysis of generated knowledge images across models.** Common failure modes include missing entities (left), unclear relationships between concepts (center), and visually cluttered representations that reduce interpretability (right).

Middle-tier models like `FLUX-Reason` and `HiDream` can also generate clear visuals, but they tend to miss or ambiguously depict critical entities. This reflects a gap between CoT-driven planning or LLM-encoded prompts and mutual visual-text reasoning. For instance, in Figure 9(b), `FLUX-Reason` captures the intent of a tax allocation infographic, but fails to label or visually distinguish specified categories, leading to factual omissions.

Lower-performing models such as `Infinity` and `SDXL-1.0` suffer from visual clutter, poor layout, and unreadable text, making entity retrieval unreliable. Figure 9(b) shows how distorted elements hinder interpretation—an issue overlooked by LLM-only metrics but effectively penalized by our segmentation-aware method with `SAM-2.1`, ensuring fairer and more robust evaluation.

5 Conclusion

Knowledge images play a central role in human civilization and learning, and generating useful knowledge images is a fundamentally distinct and challenging task. It requires models to convey ideas through pixels via advanced multimodal reasoning across language and vision.To enable rigorous evaluation, we propose the `MMMG` benchmark, which assesses text-to-image reasoning using `MMMG-Score`—a metric combining graph edit distance and visual readability score based on coherent semantic regions. We also present FLUX-Reason as a strong baseline to facilitate future research. The `MMMG` benchmark has been released to HuggingFace at the time of submission, and the FLUX-Reason's model weights, source code, and training data will be released later.

Limitations & Future Work. We pose several important questions for future work. *How can we ensure accurate grounding of knowledge graphs in generated images?* This remains very challenging: we find that OpenAI-o3 still struggles to verify whether dozens of entities and relationships are present in a generated image. *How can we collect more high-quality knowledge images?* Although many such images exist across various textbooks, gathering them from these fragmented sources also poses a non-trivial challenge. *How can we close the performance gap to proprietary systems such as GPT-4o?* Although FLUX-Reason already improves its backbone by 15 points, future work should investigate multimodal pretraining, architectural improvements, and post-training procedures, together with systematic data-scaling experiments.

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All model-generated samples are produced using the GPT-4o-Image API, which includes built-in content moderation and safety filtering. A panel of domain experts (in STEM, history, and philosophy) further reviewed all prompts and outputs, removing (i) factually incorrect or ambiguous prompts, (ii) ethically inappropriate or culturally sensitive content, and (iii) redundant or low-quality entries.

To prevent misuse, the dataset release includes clear terms of use, restricting applications to research purposes and requiring independent verification for any educational or public deployment. Moreover, our evaluation framework explicitly measures knowledge fidelity—offering a means to identify and mitigate risks of misinformation in AI-generated educational imagery.

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