WISE: A World Knowledge-Informed Semantic Evaluation for Text-to-Image Generation

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Abstract

Text-to-Image (T2I) models are capable of generating high-quality artistic creations and visual content. However, existing research and evaluation standards predominantly focus on image realism and shallow text-image alignment, lacking a comprehensive assessment of complex semantic understanding and world knowledge integration in text-to-image generation. To address this challenge, we propose WISE, the first benchmark specifically designed for World Knowledge-Informed Semantic Evaluation. WISE moves beyond simple word-pixel mapping by challenging models with 1000 meticulously crafted prompts across 25 subdomains in cultural common sense, spatio-temporal reasoning, and natural science. To overcome the limitations of traditional CLIP metric, we introduce **WiScore**, a novel quantitative metric for assessing knowledge-image alignment. Through comprehensive testing of 22 models (10 dedicated T2I models and 12 unified multimodal models) using 1,000 structured prompts spanning 25 subdomains, our findings reveal significant limitations in their ability to effectively integrate and apply world knowledge during image generation, highlighting critical pathways for enhancing knowledge incorporation and application in next-generation T2I models. Code and data are available at PKU-YuanGroup/WISE.

1 Introduction

Text-to-image (T2I) models [53] are able to generate high-quality images that visually match explicit text descriptions. However, these models often have difficulty in ensuring true factual accuracy, especially when dealing with prompts that require complex semantic understanding (**implicit understanding**) and world knowledge (**intrinsic knowledge matching**). This shortcoming mainly stems from their limited ability to model the information behind world knowledge [51] - this information constitutes the massive facts and complex relationships required for real-world understanding. Although current unified multimodal models have begun to use LLMs' powerful text modeling and implicit information extraction capabilities to break through this bottleneck through specific representations combined with generative model decoders [28; 41], existing evaluation benchmarks still have obvious limitations. They only focus on the surface alignment of images and texts, and fail to evaluate the core capabilities of T2I models from the perspective of implicit understanding and intrinsic knowledge matching, which seriously hinders the development of intelligent T2I systems.

Specifically, most T2I benchmarks suffer from a lack of semantic complexity. As shown in Figure 1, they use overly straightforward and simple prompts, failing to effectively challenge models' ability to understand and generate images based on the model's world knowledge. Furthermore, the most

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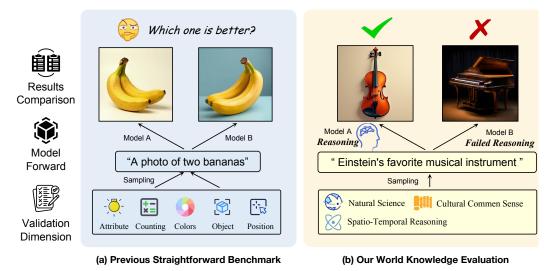


Figure 1: Comparison of previous straightforward benchmarks and our proposed WISE. (a) Previous benchmarks typically use simple prompts, such as "A photo of two bananas" in GenEval [9], which only require shallow text-image alignment. (b) WISE, in contrast, uses prompts that demand world knowledge and reasoning, such as "Einstein's favorite musical instrument," to evaluate a model's ability to generate images based on deeper understanding.

commonly used metric FID [12], primarily focuses on the realism of generated images. Although some benchmarks [11; 46; 50] utilize models like CLIP [31] to assess image-text semantic consistency scoring. However, CLIP's limitations [52] in capturing fine-grained semantic information and handling complex reasoning hinder a comprehensive assessment of models' performance in processing intricate semantic information. Consequently, existing evaluations fail to fully reveal the potential of models in real-world scenarios, particularly in tasks requiring world knowledge. For instance, when generating an image depicting a "tadpole that has undergone metamorphosis," a model needs not only to comprehend the textual description ("tadpole", "metamorphosis") but also to invoke its internal world knowledge. This includes understanding amphibian development, the specific morphological changes involved (e.g., the growth of legs, the loss of the tail, the development of lungs), and the biological processes driving this transformation.

To address this problem, we propose a new benchmark **WISE** (World Knowledge-Informed Semantic Evaluation). This benchmark systematically evaluates the implicit semantic understanding and world knowledge integration capabilities of T2I models beyond basic text-image alignment through indirect textual cues. WISE covers three major areas: natural sciences, spatiotemporal reasoning, and cultural common sense, and contains 1,000 evaluation questions in 25 sub-areas. To rigorously evaluate the consistency of generated images with world knowledge, we design a novel comprehensive metric **WiScore**, which focuses on the accurate depiction of objects and entities under specific knowledge by weighted calculation of three key dimensions: consistency, realism, and aesthetic quality.

Moreover, traditional benchmarks always focus on dedicated T2I models, overlooking the potential of unified multimodal models, which integrate powerful LLMs trained on extensive text and image-text pairs and possess demonstrably strong world knowledge. While some studies have begun to explore whether the strong understanding capabilities of these unified models can benefit image generation, they often rely on overly simplistic benchmarks, thus failing to sufficiently prove this phenomenon.

We broadened the scope of our evaluation beyond traditional dedicated T2I models. We employed our novel benchmark, WISE, to evaluate a total of 22 T2I models, encompassing both 10 dedicated T2I models and 12 unified multimodal models. However, experiment results demonstrate significant deficiencies in complex semantic understanding and world knowledge integration across existing T2I models. Even for unified multimodal models, their strong understanding capabilities do not fully translate into advantages in image generation, as revealed by our WISE evaluation. Despite their theoretical advantages, unified models generally underperform compared to dedicated T2I models in leveraging world knowledge for image generation. This indicates that current approaches

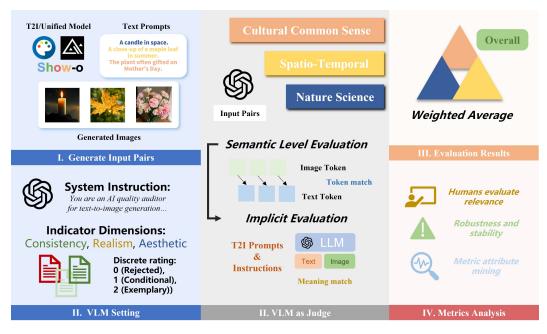


Figure 2: Illustration of the WISE framework, which employs a four-phase verification process (Panel I to IV) to systematically evaluate generated content across three core dimensions. The two representative cases, science-domain input "candle in space" violates oxygen-dependent combustion principles, while spatiotemporal-domain "close-up of summer maple leaf" contradicts botanical seasonal patterns, both receiving 0 in consistency (see Evaluation Metrics in Panel III), confirming the benchmark's sensitivity in world knowledge conflicts.

to integrating LLMs within unified multimodal models may not yet fully unlock their potential for image generation that effectively integrates and applies world knowledge. Our main contributions are as follows:

- We introduce **WISE**, which is specified for the *world knowledge representation capabilities* of T2I models, with vast meticulously crafted prompts in stead of traditional simplistic prompts.
- We propose **WiScore**, a novel composite metric which goes beyond mere pixel-level evaluation and shallow text-image alignment, focusing on consistency, realism, and aesthetic quality.
- Our experiment results firstly demonstrate that existing T2I models exhibit significant limitations in integrating world knowledge, while the unified model underperforms even compared to dedicated T2I models.

2 Related Works

Text-to-image (T2I) generation models, which aim to generate high-quality and diverse images from text, have garnered significant attention recently. These models fall into two main categories: Dedicated T2I Models and Unified Multimodal Models.

2.1 Dedicated T2I Models

Dedicated T2I models represent the mainstream approach in the T2I field and have achieved remarkable progress in recent research. Currently, these models primarily fall into two categories: autoregressive models and diffusion models. Autoregressive [3; 6; 10; 40; 37; 29] models treat image generation as a sequence generation problem, similar to text generation. However, due to their computational cost and limitations in image quality, diffusion models have become the dominant paradigm. Diffusion [13; 32; 18; 34; 23] models iteratively add noise to an image and then progressively denoise it, often using pre-trained text encoders (e.g., CLIP [31]) to transform text prompts into embeddings that guide the denoising process. Key advancements include GLIDE [27], which pioneered diffusion

models for T2I; Latent Diffusion Models (LDMs) [33], which improve quality and efficiency by operating in latent space; and Stable Diffusion series [30; 5], a landmark achievement built on LDMs.

2.2 Unified Multimodal Models

Unified multimodal models aim to construct general-purpose models capable of processing both textual and visual inputs, and performing cross-modal generation and understanding. These models [39; 16; 8; 43; 44; 25; 4; 48; 17; 45; 21; 38; 41; 35] are typically built upon powerful large language models (LLMs) [54] and extend next-token prediction [2] to image generation: the LLM generates visual tokens, and a VQ-VAE [42] or Diffusion model serves as a detokenizer. Moreover, Transfusion [55] and Show-O [49] demonstrate that bidirectional image diffusion can be combined with autoregressive text prediction within the same framework. D-DiT [22] achieves both Text-to-Image (T2I) and Image-to-Text (I2T) tasks using an end-to-end diffusion model. A crucial question concerning unified multimodal models is whether their understanding and generation capabilities can mutually enhance each other. Some studies [41; 45] have provided evidence supporting this phenomenon. However, in contrast to the rich and comprehensive benchmarks for multimodal understanding, T2I benchmarks are often relatively simple, lacking an in-depth examination of complex semantic understanding and world knowledge reasoning, making it difficult to fully prove the phenomenon.

2.3 Text to Image Evaluation

Despite the Fréchet Inception Distance (FID) [12] being one of the most widely adopted metrics for evaluating the quality of generated images, it falls short in assessing text-image consistency, thus failing to comprehensively measure the capabilities of text-to-image models. To address this deficiency, researchers have introduced a series of more sophisticated and challenging benchmarks [36; 24; 47] and evaluation metrics [11; 19; 24]. For instance, DPG-Bench [14] focuses on evaluating models' ability in dense prompt following. T2I-CompBench [15] provides a benchmark suite for evaluating compositional generation, where prompts typically combine multiple distinct attributes. Furthermore, GenEval [9] serves as an object-centric evaluation framework specifically designed to assess compositional attributes of images, such as object co-occurrence, position, number, and color. However, the prompts used in these benchmarks are mostly straightforward, primarily examining models' ability to follow compositional instructions for generation. Recently, some studies have shifted focus towards evaluating the application of specific types of knowledge in T2I models, such as physical reasoning in PhyBench [26] and broad common-sense knowledge in Commonsense-T2I [7]. Nevertheless, these emerging benchmarks are still very limited in their research scope and the quantity of evaluations.

3 The World Knowledge-Informed Semantic Evaluation (WISE) Benchmarks

Existing text-based image evaluation systems have two limitations: first, traditional benchmarks lack in-depth exploration of world knowledge; second, the current mainstream evaluation metrics for measuring image-text alignment only focus on the semantic level. Therefore, we will discuss in detail how to construct a world knowledge-informed T2I benchmark in subsection 3.1 and the necessity of establishing a robust metric by considering the bottlenecks of the current metric in subsection 3.2.

3.1 Building a Benchmark Based on World Knowledge

Most existing benchmarks adopt prompt designs that are overly straightforward and lack semantic complexity. They primarily evaluate whether models can combine visual elements as explicitly instructed, but fail to assess the models' capacity for complex semantic understanding and integration of world knowledge in text-to-image generation. Going beyond simply mapping words to pixels, we propose to evaluate world knowledge of current T2I models, which refers to the vast and diverse information, facts, and relationships that constitute our understanding of the real world. In our work, we focus on common world knowledge that can be represented visually. As shown in Figure 3, WISE comprises 1000 prompts designed to assess T2I models' understanding and application of this knowledge across three major domains: Cultural Common Sense, Spatio-temporal Reasoning, and Natural Science, which are divided into 25 subdomains.



Figure 3: Illustrative samples of WISE from 3 core dimensions with 25 subdomains. By employing non-straightforward semantic prompts, it requires T2I models to perform logical inference grounded in world knowledge for accurate generation of target entities.

Data Collection and Prompt Design. We collected prompts from a variety of sources, including educational materials, encyclopedias, common sense problem sets, and synthetic data generated by LLMs. These initial prompts were then refined and extended by human annotators to ensure their clarity, complexity, and explicit ground truth. Each prompt is accompanied by an explanation that describes the world knowledge and reasoning required for a potentially successful image generation. Specifically, the details of our three parts are as follows:

Cultural common sense. The Cultural Common Sense domain of WISE aims to evaluate the ability of models to understand specific cultural knowledge and apply it to image generation, which reflects the key aspects of understanding the real world. Models should not only understand the visual features of objects (e.g., shape, size, and color), but also match them with cultural knowledge of the real world. A model lacking such intrinsic knowledge matching will be an unintelligent image generator that can only grasp the surface correspondence between text nouns and visual elements, but cannot understand the cultural role of objects in the real world. This section covers a wide range of topics and is subdivided into 10 fine-grained sub-domains, including festivals, sports, religion, crafts, architecture, animals, plants, art, celebrities, and daily life. Together, these categories cover a wide range of cultural experiences and knowledge of humans. For example, prompts may involve generating images related to traditional festival customs, characteristic ethnic crafts, iconic landmarks, animals and plants with specific cultural significance, common sense in daily life, or events and objects related to celebrities.

Spatiotemporal reasoning. The spatiotemporal reasoning domain in WISE is structured around two key dimensions: temporal reasoning and spatial reasoning. Temporal reasoning is divided into Horizontal Temporal reasoning, which assesses understanding of relative temporal relationships between events or objects (e.g., "The Statue of Liberty at 10 pm Dubai time"), and Longitudinal Temporal reasoning, which assesses understanding of absolute temporal relationships, involving

specific points in time (e.g., morning, noon, evening, season, specific year, or century). Spatial reasoning is divided into three subcategories: Different Views, which tests understanding of different perspectives, including top view, bottom view, side view, mirror image, and perspective effects; Geographic Relationships, which assesses understanding of spatial relationships between cities, countries, continents, and other geographic entities; and Relative Position, which focuses on understanding the spatial arrangement of objects in a scene relative to each other.

Natural sciences. Finally, the WISE benchmark includes a natural sciences domain that aims to assess whether models can not only understand scientific knowledge in a specific domain, but also use this understanding to reason about complex scientific scenarios and generate accurate and scientifically consistent images. At its core, generative models simulate the real world. Our goal is to assess whether these models' understanding goes beyond mere visual replication and encompasses the complex science behind real-world phenomena. For example, a model should not only be able to generate images of water, ice, and steam, but also understand the underlying thermodynamic principles that govern transitions between these states (e.g., freezing, evaporation, condensation). This domain goes beyond general knowledge and delves into specialized bodies of knowledge in biology, physics, and chemistry.

3.2 Discovering the Deep Visual Language Alignment Bottlenecks of Traditional Evaluation

Existing metrics such as CLIP-Score [11] and VQA-Score [19] offer partial solutions for evaluating text-to-image alignment, but both fall short when faced with complex, knowledge-intensive prompts. CLIP-Score, constrained by CLIP's bag-of-words limitation, struggles with compositional semantics and relational reasoning. VQA-Score improves on this by leveraging likelihood estimation via question answering, but still lacks sensitivity to implicit visual understanding and world knowledge grounding. To address these limitations, we propose a multi-faceted evaluation protocol to rigorously assess the quality of generated images, focusing on four key aspects: Consistency, Realism, Aesthetic Quality, and a composite metric, WiScore, shown in Figure 2.

Consistency evaluates the accuracy and completeness with which the generated image reflects the user's prompt, capturing all key elements and nuances. Realism assesses the realism of the image, considering adherence to physical laws, accurate material representation, and coherent spatial relationships, determining how closely the image resembles a real photograph. Aesthetic Quality measures the overall artistic appeal and visual quality of the image, encompassing aspects such as composition, color harmony, and artistic style. WiScore, the central metric, emphasizes the accuracy of the depicted objects or entities within the generated image, directly reflecting our benchmark's focus on world knowledge utilization. It is calculated as a weighted value of the other three metrics:

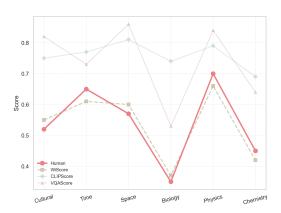


Figure 4: Correlation between different metrics and human assessment.

$$\mbox{WiScore} = \frac{\alpha_1 \times \mbox{Consistency} + \alpha_2 \times \mbox{Realism} + \alpha_3 \times \mbox{Aesthetic Quality}}{2}, \\ \mbox{subject to } \alpha_1 + \alpha_2 + \alpha_3 = 1. \label{eq:WiScore}$$

In this paper, we set $\alpha_1=0.7$, $\alpha_2=0.2$, and $\alpha_3=0.1$. This configuration not only prioritizes Consistency, reflecting the importance of accurately representing the prompt's intended objects and their relationships, but also incorporates Realism and Aesthetic Quality to ensure overall image quality. Meanwhile, we observe that WiScore exhibits a strong positive correlation with human evaluations under certain hyperparameter settings, as detailed in Appendix B. A higher WiScore indicates superior performance in accurately depicting objects and concepts based on world knowledge. The detailed scoring criteria and complete results for each component score are provided in Appendix C. In the evaluation, we employ GPT-40-2024-05-13, a powerful multimodal large language model, as the evaluator to assess the performance of T2I models. A carefully designed and rigorous scoring protocol is adopted to ensure consistency and reliability, with full implementation details provided in

the Appendix D. As shown in Figure 4, among all automated metrics, WiScore exhibits the highest agreement with human judgments. The detailed comparison process can be found in the Appendix E.

4 Evaluation Results

4.1 Experiment Settings

We evaluate 22 T2I models, including 10 dedicated T2I models and 12 unified multimodal models. The dedicated T2I models are: stable-diffusion-v1-5 [33], stable-diffusion-2-1 [33], stable-diffusion-x1-base-0.9 [30], stable-diffusion-3-medium [5], stable-diffusion-3.5-medium [5], stable-diffusion-3.5-large [5], playground-v2.5-1024px-aesthetic [20], PixArt-XL-2-1024-MS [1], FLUX.1-dev [18], and FLUX.1-schnell [18]. The unified multimodal models are: GPT40, Metaquery [28], Janus-Pro-7B [4], Janus-Pro-1B [4], Janus-Flow-1.3B [25], Janus-1.3B [44], show-o [49], show-o-512 [49], Orthus-7B-instruct [17], vila-u-7b-256 [48], Liquid [45] and Emu3 [43]. For image generation, we use the official default configurations of each model and fix the random seed to ensure reproducibility. All experiments are conducted on eight NVIDIA A800 GPUs. For short, we use SD to denote stable-diffusion, playground-v2.5 for playground-v2.5-1024px-aesthetic, and PixArt-Alpha for PixArt-XL-2-1024-MS.

4.2 Main Results

Table 1: WiScore of different models. Based on six categories of basic knowledge, we calculated the results of different parameter models respectively, and the overall result was given as the weighted average of the previous parts to illustrate the ability of overall world knowledge. Bold indicates the best value in related items.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall			
Dedicated T2I										
FLUX.1-dev	0.48	0.58	0.62	0.42	0.51	0.35	0.50			
FLUX.1-schnell	0.39	0.44	0.50	0.31	0.44	0.26	0.40			
PixArt-Alpha	0.45	0.50	0.48	0.49	0.56	0.34	0.47			
playground-v2.5	0.49	0.58	0.55	0.43	0.48	0.33	0.49			
SD-v1-5	0.34	0.35	0.32	0.28	0.29	0.21	0.32			
SD-2-1	0.30	0.38	0.35	0.33	0.34	0.21	0.32			
SD-XL-base-0.9	0.43	0.48	0.47	0.44	0.45	0.27	0.43			
SD-3-medium	0.42	0.44	0.48	0.39	0.47	0.29	0.42			
SD-3.5-medium	0.43	0.50	0.52	0.41	0.53	0.33	0.45			
SD-3.5-large	0.44	0.50	0.58	0.44	0.52	0.31	0.46			
		Ţ	J nified N	ILLM						
GPT4o	0.81	0.71	0.89	0.83	0.79	0.74	0.80			
MetaQuery-XL	0.56	0.55	0.62	0.49	0.63	0.41	0.55			
Liquid	0.34	0.45	0.48	0.41	0.45	0.27	0.39			
Emu3	0.34	0.45	0.48	0.41	0.45	0.27	0.39			
Janus-1.3B	0.16	0.26	0.35	0.28	0.30	0.14	0.23			
JanusFlow-1.3B	0.13	0.26	0.28	0.20	0.19	0.11	0.18			
Janus-Pro-1B	0.20	0.28	0.45	0.24	0.32	0.16	0.26			
Janus-Pro-7B	0.30	0.37	0.49	0.36	0.42	0.26	0.35			
Orthus-7B-instruct	0.23	0.31	0.38	0.28	0.31	0.20	0.27			
show-o	0.28	0.36	0.40	0.23	0.33	0.22	0.30			
show-o-512	0.28	0.40	0.48	0.30	0.46	0.30	0.35			
vila-u-7b-256	0.26	0.33	0.37	0.35	0.39	0.23	0.31			

Understanding-Generation Gap in T2I Tasks. Table 1 presents the WiScore of various models on the WISE benchmark, designed to evaluate the extent to which models leverage world knowledge in image generation. Overall, the results indicate that the GPT4o model significantly outperforms all

others across all categories and the overall score. This suggests its superior capabilities in utilizing complex semantic understanding (implicit understanding) and world knowledge (intrinsic knowledge matching) for image generation. The remaining open-source models demonstrate comparatively lower performance, with Unified MLLMs generally lagging behind Dedicated T2I models. This highlights that while Unified MLLMs are trained on large-scale image-text pairs and vast textual datasets, thereby acquiring substantial text and image understanding capabilities, effectively integrating this knowledge into the image generation process remains a significant challenge. Despite the overall underperformance of Unified MLLMs, the MetaQuery-XL model exhibits a prominent performance, achieving the best score among the open-source models, showcasing the potential of unified models to apply world knowledge for image generation.

Cross-Dimensional Performance Statical Analysis. This part systematically examines the performance disparities between the two model categories across various cognitive dimensions, employing a suite of statistical methods including paired-sample t-tests, Wilcoxon signed-rank tests, and effect size analysis. The paired t-test results indicate that T2I models demonstrate a significantly higher average score in the first three dimensions (Cultural/Time/Space) (0.56 ± 0.08) compared to the latter three (Biology/Physics/Chemistry) (0.43 ± 0.07) , t(9) = 5.47, p < 0.001, with an effect size of Cohen's d = 1.73. This suggests a highly statistically and practically significant difference. To verify the robustness of these findings, a non-parametric Wilcoxon signed-rank test was conducted, yielding consistent conclusions (W = 55, p = 0.002). Similarly, the Unified MLLM model group also exhibited a characteristic pattern where the first three dimensions (0.80 ± 0.19) significantly outperformed the latter three (0.79 ± 0.19) (t(10) = 3.76, p = 0.003, d = 1.09); Wilcoxon W = 66, p = 0.005). A Mann-Whitney U test revealed that although the magnitude of inter-dimensional differences was significantly larger for T2I models ($\Delta = 0.13$) compared to Unified MLLMs ($\Delta = 0.01$) (U = 32, p = 0.057), all models displayed an advantage in cultural tasks. This pattern of differences may stem from: 1) the Cultural/Time/Space dimensions relying more heavily on visual representation capabilities, a known strength of T2I models; and 2) scientific tasks requiring stronger cross-modal reasoning abilities, in which MLLM models (such as GPT40) exhibit more balanced performance ($\Delta = 0.01$). Notably, within the SD series, from v1.5 to 3.5-large, the dimensional difference decreased from 0.08 to 0.05; likewise, in the Janus series, from 1.3B to Pro-7B, the difference diminished from 0.04 to 0.03. This suggests that newer generation models are improving in their ability to balance performance across different dimensions.

4.3 Evaluation on WISE Rewritten Prompts.

We conducted an additional experiment to further highlight the limitations of current T2I models in processing world knowledge and explore possible solutions. We rewrote the prompts in the WISE benchmark using GPT-4o-2024-05-13, transforming them from complex, knowledge-requiring prompts to straightforward prompts. For example, the original prompt "Common plants for Mother's Day" was rewritten to "Carnation". The detailed instructions for prompt rewriting are detailed in Appendix F. The same WiScore evaluation method was used for this experiment, and the results are presented in Figure 5.

Surprisingly, nearly all models demonstrated significant performance improvements when evaluated with the rewritten prompts. The average WiScore increase across all Dedicated T2I models was +0.22, while Unified MLLMs saw an even larger average increase of +0.27. This suggests that a significant portion of the difficulty in the original WISE benchmark stemmed from the models' inability to effectively parse and contextualize complex, knowledge-intensive prompts. By simplifying the prompts, we effectively removed this bottleneck, allowing the models to better showcase their generative capabilities. Notably, the models with the largest overall improvements tended to be those with lower initial scores on the original benchmark, indicating that prompt complexity had a disproportionately negative impact on their performance. For example, Janus-Pro-1B demonstrated an overall WiScore improvement of +0.34 after rewriting, highlighting the sensitivity of weak models to prompt complexity.

However, even with this simplification, the scores of both T2I and unified models, while improved, did not reach a level indicative of a complete and satisfactory generation of world knowledge across all categories. Furthermore, it highlights the core issue of lower-quality generation results in current unified models. Even MetaQuery-XL experienced a decrease in its score for the Physics category. This demonstrates that solely relying on enhancing the model's ability to interpret world

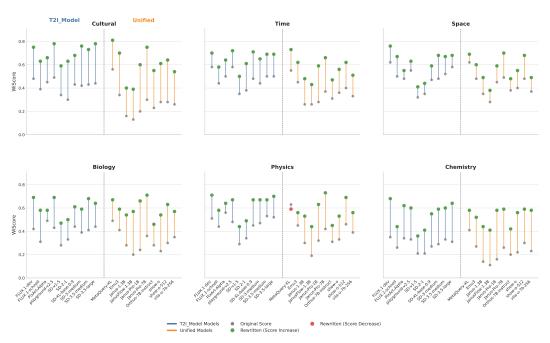


Figure 5: WiScore on rewritten prompts of different models. These prompts were simplified from the original WISE benchmark using GPT-40 (e.g., "The plant often gifted on Mother's Day" to "Carnation"). Green ball indicates score increase after rewriting; red ball indicates score decrease.

knowledge remains constrained by the bottleneck of generative capacity. Concurrently, the substantial performance gap underscores the need for future research to focus on improving model training methods and architectures, rather than solely relying on tricks aimed at enhancing the understanding level, such as prompt engineering.

5 Conclusion

To evaluate the ability of current T2I and unified models to generate images beyond simple bag-of-words mappings, we introduced WISE, a new benchmark consisting of 1,000 questions covering different domains designed to challenge the ability of T2I models to generate images based on common world knowledge. We evaluated 22 generative models (including dedicated T2I models and unified multimodal models) and found that these models have significant deficiencies in their ability to effectively utilize world knowledge in the image generation process, especially the T2I model. Even for the unified multimodal model, despite its strong language understanding capabilities, most open-source models are unable to fully convert this advantage into excellent image generation performance in complex and knowledge-intensive scenarios. From this point of view, we also pointed out through some analysis that the key to the potential problem lies in the improvement of image generation quality itself. Therefore, this paper points out the deficiencies of existing generative models from a benchmark perspective and points out an effective path for subsequent methods.

6 Limitations

While our work introduces a novel benchmark, WISE, for evaluating the complex semantic understanding (**implicit understanding**) and world knowledge (**intrinsic knowledge matching**) capabilities of dedicated T2I and unified models, we acknowledge several limitations. Our benchmark categorizes prompts into broad domains, but due to the interconnected nature of knowledge, some prompts may inherently span multiple categories (e.g., "the impact of climate change on polar bear habitats" could fall under both natural science and spatio-temporal reasoning), potentially introducing ambiguity in cross-category analysis. Furthermore, while WISE covers a range of topics, it represents a sample of

knowledge domains and cannot encompass all aspects of world knowledge, which is also constantly evolving. Additionally, some models were not publicly available or did not provide APIs at the time of our work's deadline, precluding their evaluation in this study.

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A WISE Category Descriptions

WISE encompasses a broad spectrum of knowledge categories, categorized under three main domains: Cultural Common Sense, Spatio-Temporal Reasoning, and Natural Science. Each domain is further divided into specific subcategories to assess different facets of understanding.

A.1 Cultural Common Sense (400 prompts)

This domain evaluates the understanding of widely shared cultural knowledge and conventions. It includes:

- **Festival:** This category assesses knowledge related to cultural celebrations, encompassing traditional foods, customs, and activities associated with specific festivals. *Example: Traditional cuisine of the Mid-Autumn Festival.*
- **Sports:** This category focuses on recognizing sports that are highly representative or culturally significant within particular nations or regions. *Example: The most representative sport of South Africa*.
- **Religion-related:** This category examines the identification of objects, symbols, or architectural structures that hold religious significance and are associated with specific faiths or religious heritage. *Example: A geometric symbol commonly associated with Jewish identity and heritage.*
- **Craft-related:** This category pertains to the recognition of traditional crafts that are emblematic of a nation's artistic and technical skills. *Example: A craft embodying Swiss precision and artistry.*
- **Construction-related:** This category tests the ability to identify iconic architectural structures that are representative landmarks of specific countries or cities. *Example: A sail-like structure, an architectural icon on Sydney's harbor.*
- **Animal:** This category assesses knowledge of animals that are symbolic, nationally significant or possess distinctive characteristics. *Example: A large animal, symbolizing national pride in Thailand.*
- **Plant:** This category evaluates the recognition of plants or fruits that are culturally representative, possess notable properties, or hold symbolic meaning. *Example: A famous flower symbolizing wealth in China.*
- Art: This category focuses on understanding artistic styles, recognizing representative musical instruments of different cultures, or identifying instruments with specific functional attributes. Example: A triangular stringed instrument often used in Russian folk music.
- **Celebrity:** This category assesses knowledge of globally recognized figures, including historical personalities, fictional characters from literature, or iconic roles from film and television. *Example: The iconic hat of the protagonist of One Piece in Japan.*
- **Life:** This category examines the understanding of common, everyday knowledge related to daily life practices and tools. *Example: A common utensil used for consuming steak in Western culture.*

A.2 Spatio-Temporal Reasoning (300 prompts)

This domain evaluates the ability to reason about spatial and temporal relationships and contexts. It is further divided into Time and Space subcategories.

A.2.1 Time (167 prompts)

This subsection focuses on temporal reasoning. It includes:

• **Horizontal Time:** This category assesses the understanding of temporal relationships across different entities or events occurring concurrently. *Example: The Pyramids of Giza at 8 PM Tokyo time.*

• Longitudinal Time: This category focuses on understanding temporal progression and order of events across time, including diurnal cycles, seasonal changes, and historical periods. *Example: The signature instrument of the rock and roll era in the 1950s.*

A.2.2 Space (133 prompts)

This subsection focuses on spatial reasoning. It includes:

- **Geographical Location:** This category examines the understanding of spatial relationships between geographical entities, such as cities, countries, and continents. *Example: A typical beverage produced in the country where Bordeaux is located.*
- **Relative Position:** This category assesses the ability to understand and interpret relative spatial positioning between objects, such as proximity, vertical placement, and size comparisons. *Example: A bird and a dog, with the smaller animal positioned on top of and the larger animal below.*
- **Different View:** This category evaluates the ability to recognize and interpret objects and scenes from various perspectives, including viewpoints like top-down, bottom-up, cross-sectional, side, mirrored, and occluded views. *Example: A view of a dense forest from within the canopy, looking upwards.*

A.3 Natural Science (300 prompts)

This domain evaluates understanding of fundamental principles and phenomena within the natural sciences, categorized into Biology, Physics, and Chemistry.

A.3.1 Biology (100 prompts)

- **State:** This subcategory assesses knowledge of the different physiological or developmental states of living organisms under varying conditions or across their life cycle stages. *Example:* A maple tree with leaves exhibiting chlorophyll breakdown.
- **Behavior:** This subcategory evaluates the understanding of typical behaviors exhibited by organisms, including actions related to survival, reproduction, and interaction with their environment. *Example: A morning rooster, emphasizing its characteristic behavior.*

A.3.2 Physics (100 prompts)

- Mechanics: This subcategory covers principles of mechanics, including:
 - Gravity: Understanding effects of gravity on objects, such as vertical suspension and equilibrium. Example: A balloon filled with helium in a room.
 - Buoyancy: Understanding the behavior of objects in fluids based on buoyancy principles.
 - **Pressure:** Understanding the effects of pressure and its variations.
 - Surface Tension: Understanding phenomena related to surface tension in liquids.
 - Other Mechanical Phenomena: Including concepts like wind effects on objects.
- **Thermodynamics:** This subcategory covers principles of heat and energy transfer, including:
 - Evaporation: Understanding the process of vaporization at boiling points.
 - Liquefaction: Understanding the condensation of gases into liquids.
 - Solidification: Understanding the process of freezing.
 - Melting: Understanding the process of fusion.
 - Sublimation: Understanding the phase transition from solid to gas.
 - Deposition: Understanding the phase transition from gas to solid. Example: A pond at minus ten degrees Celsius.
- Optics: This subcategory covers principles of light and vision, including:
 - **Refraction:** Understanding the bending of light as it passes through different media.
 - Magnification: Understanding how lenses magnify objects.

- Dispersion: Understanding the separation of light into its spectral components. Example: A laser beam passing through a dusty room.
- **Physical Properties:** This subcategory assesses knowledge of material properties like electrical conductivity. *Example: An electrical bulb connected to a battery via copper wires.*

A.3.3 Chemistry (100 prompts)

- **Combustion:** This subcategory covers principles of chemical reactions involving rapid oxidation, including flame characteristics and color reactions. *Example: Lithium burning, highlighting its characteristic flame color.*
- **Metal Corrosion:** This subcategory assesses the understanding of the electrochemical degradation of metals over time due to environmental exposure. *Example: An iron block exhibiting rust due to corrosion.*
- **Solution Chemical Reaction:** This subcategory covers various types of chemical reactions in solutions, including acid-base reactions, redox reactions, and precipitation reactions. *Example: A T-shirt stained by sulfuric acid.*
- Chemical Properties: This subcategory assesses knowledge of intrinsic chemical properties, including colloidal behavior, protein chemistry, and the characteristic colors of chemical species in solution. Example: A clear solution of copper sulfate exhibiting its characteristic color.

B Selection of WiScore Hyperparameters

Human Evaluation.We randomly sampled 100 pictures generated by FLUX.1-dev. We require paper authors to rate each image according to the same standard Figure 7, and regard the sum of the final values as the score.

Table 2: Evaluation metrics comparison

Metric	Human	40
Consistency (C)	96	84
Realism (R)	112	153
Aesthetic Quality (A)	143	159

Given metrics from Table 2, solve:

$$\min_{\mathbf{w}} \| [12 \quad -41 \quad -16] \, \mathbf{w} \|^2 \quad \text{s.t.} \quad \begin{cases} w_1 + w_2 + w_3 = 1 \\ w_i \ge 0 \, \forall i \end{cases} \tag{2}$$

The KKT conditions yield:

$$12w_1 - 41w_2 - 16w_3 = 0 (3)$$

$$\mathbf{w} = \left(\frac{41 - 25w_3}{53}, \frac{12 - 28w_3}{53}, w_3\right) \tag{4}$$

Parameter w_3 spans:

$$w_3 \in \left[0, \frac{12}{28}\right] \Rightarrow \begin{cases} w_1 \in [0.571, 0.774] \\ w_2 \in \left[0, 0.226\right] \\ w_3 \in \left[0, 0.429\right] \end{cases}$$
 (5)

The optimal weights were found at:

$$\mathbf{w}^* = (0.7, 0.2, 0.1) \tag{6}$$

achieving the minimal squared difference of 1.8.

C Scoring Criteria and Results of Other Metrics

Table 3: Parameter grid ranges ($\Delta=0.1$)

Parameter	Search Range
w_1	[0.5, 0.8]
w_2	[0.1, 0.3]
w_3	[0.1, 0.4]

Objective Function Landscape

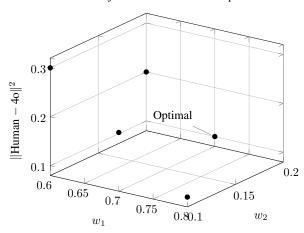


Figure 6: 3D visualization of grid search results showing (0.7, 0.2, 0.1) as the minimal point

Table 4: Consistency score of different models.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	298.00	161.00	155.00	48.00	77.00	41.00	183.30				
FLUX.1-schnell	246.00	123.00	129.00	36.00	67.00	24.00	148.80				
PixArt-Alpha	289.00	138.00	108.00	60.00	72.00	40.00	170.21				
playground-v2.5	296.00	162.00	127.00	70.00	88.00	41.00	182.25				
SD-v1-5	245.00	101.00	82.00	37.00	42.00	25.00	136.17				
SD-2-1	199.00	113.00	85.00	46.00	50.00	23.00	121.68				
SD-XL-base-0.9	311.00	149.00	117.00	69.00	74.00	30.00	182.14				
SD-3-medium	267.00	118.00	119.00	50.00	76.00	35.00	158.43				
SD-3.5-medium	278.00	142.00	134.00	51.00	90.00	40.00	170.84				
SD-3.5-large	291.00	148.00	146.00	65.00	81.00	32.00	178.33				
		U	nified MI	LLM							
Emu3	190.00	119.00	107.00	51.00	65.00	29.00	124.60				
Janus-1.3B	115.00	89.00	100.00	49.00	59.00	19.00	86.86				
JanusFlow-1.3B	89.00	81.00	80.00	28.00	32.00	11.00	66.87				
Janus-Pro-1B	119.00	81.00	127.00	33.00	52.00	16.00	88.12				
Janus-Pro-7B	176.00	103.00	127.00	56.00	72.00	30.00	120.29				
Orthus-7B-base	49.00	28.00	34.00	28.00	26.00	11.00	35.30				
Orthus-7B-instruct	121.00	97.00	103.00	47.00	46.00	27.00	90.30				
show-o	172.00	109.00	104.00	32.00	51.00	24.00	111.53				
show-o-512	156.00	107.00	118.00	36.00	74.00	37.00	110.66				
vila-u-7b-256	186.00	107.00	104.00	69.00	74.00	41.00	124.50				

Scoring Criteria

Consistency (0-2): How accurately and completely the image reflects the PROMPT.

0 (Rejected): Fails to capture key elements of the prompt, or contradicts the prompt.

1 (Conditional): Partially captures the prompt. Some elements are present, but not all, or not accurately. Noticeable deviations from the prompt's intent.

2 (Exemplary): Perfectly and completely aligns with the PROMPT. Every single element and nuance of the prompt is flawlessly represented in the image. The image is an ideal, unambiguous visual realization of the given prompt.

Realism (0-2): How realistically the image is rendered.

0 (Rejected): Physically implausible and clearly artificial. Breaks fundamental laws of physics or visual realism.

1 (Conditional): Contains minor inconsistencies or unrealistic elements. While somewhat believable, noticeable flaws detract from realism.

2 (Exemplary): Achieves photorealistic quality, indistinguishable from a real photograph. Flawless adherence to physical laws, accurate material representation, and coherent spatial relationships. No visual cues betraying AI generation.

Aesthetic Quality (0-2): The overall artistic appeal and visual quality of the image.

 $\textbf{0 (Rejected):} \ \ Poor\ aesthetic\ composition, visually\ unappealing, and\ lacks\ artistic\ merit.$

1 (Conditional): Demonstrates basic visual appeal, acceptable composition, and color harmony, but lacks distinction or artistic flair.

2 (Exemplary): Possesses exceptional aesthetic quality, comparable to a masterpiece. Strikingly beautiful, with perfect composition, a harmonious color palette, and a captivating artistic style. Demonstrates a high degree of artistic vision and execution.

Figure 7: WISE assess image quality based on three criteria: how accurately the image aligns with the prompt (Consistency), its level of realism (Realism), and its overall artistic appeal (Aesthetic Quality). Each metric is scored on a scale from 0 (Rejected) to 2 (Exemplary), providing a comprehensive assessment of the image's fidelity, believability, and visual excellence.

Table 5: Realism scores of different models.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	585.00	269.00	181.00	179.00	161.00	146.00	351.60				
FLUX.1-schnell	459.00	204.00	145.00	130.00	138.00	119.00	275.65				
PixArt-Alpha	495.00	224.00	165.00	141.00	151.00	126.00	299.15				
playground-v2.5	601.00	256.00	184.00	160.00	163.00	127.00	352.62				
SD-v1-5	321.00	154.00	91.00	103.00	98.00	90.00	195.32				
SD-2-1	335.00	159.00	110.00	120.00	115.00	96.00	208.28				
SD-XL-base-0.9	378.00	198.00	143.00	141.00	133.00	112.00	241.88				
SD-3-medium	506.00	221.00	153.00	152.00	144.00	115.00	300.76				
SD-3.5-medium	517.00	229.00	148.00	169.00	149.00	141.00	310.63				
SD-3.5-large	484.00	215.00	172.00	149.00	164.00	142.00	297.88				
		U	nified MI	LLM							
Emu3	446.00	215.00	165.00	151.00	144.00	107.00	276.45				
Janus-1.3B	159.00	79.00	72.00	78.00	65.00	54.00	106.07				
JanusFlow-1.3B	136.00	99.00	65.00	71.00	58.00	49.00	97.38				
Janus-Pro-1B	233.00	115.00	102.00	88.00	89.00	70.00	150.67				
Janus-Pro-7B	371.00	169.00	137.00	112.00	115.00	110.00	228.54				
Orthus-7B-base	74.00	35.00	19.00	29.00	38.00	39.00	48.57				
Orthus-7B-instruct	282.00	103.00	78.00	70.00	91.00	58.00	162.28				
show-o	282.00	132.00	103.00	74.00	96.00	80.00	173.54				
show-o-512	372.00	188.00	149.00	117.00	131.00	109.00	235.71				
vila-u-7b-256	232.00	103.00	79.00	68.00	85.00	54.00	141.21				

Table 6: Aesthetic Quality scores of different models.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	582.00	275.00	190.00	154.00	156.00	127.00	347.69				
FLUX.1-schnell	459.00	197.00	139.00	115.00	126.00	106.00	269.69				
PixArt-Alpha	569.00	255.00	195.00	156.00	155.00	134.00	340.62				
playground-v2.5	652.00	288.00	209.00	167.00	168.00	148.00	384.99				
SD-v1-5	330.00	150.00	87.00	93.00	86.00	73.00	193.82				
SD-2-1	360.00	159.00	108.00	99.00	93.00	73.00	211.42				
SD-XL-base-0.9	475.00	180.00	151.00	123.00	118.00	99.00	274.14				
SD-3-medium	454.00	210.00	141.00	119.00	123.00	98.00	269.42				
SD-3.5-medium	494.00	215.00	137.00	128.00	125.00	102.00	287.23				
SD-3.5-large	504.00	218.00	164.00	132.00	143.00	113.00	298.62				
		U	nified MI	LLM							
Emu3	531.00	239.00	188.00	152.00	149.00	124.00	319.82				
Janus-1.3B	173.00	89.00	81.00	60.00	56.00	41.00	110.54				
JanusFlow-1.3B	145.00	96.00	67.00	53.00	49.00	46.00	97.74				
Janus-Pro-1B	287.00	128.00	105.00	81.00	90.00	60.00	173.24				
Janus-Pro-7B	399.00	168.00	131.00	104.00	101.00	95.00	235.08				
Orthus-7B-base	94.00	53.00	33.00	39.00	43.00	46.00	63.64				
Orthus-7B-instruct	391.00	159.00	122.00	101.00	107.00	92.00	229.18				
show-o	395.00	170.00	131.00	98.00	113.00	104.00	235.31				
show-o-512	426.00	207.00	166.00	121.00	135.00	121.00	264.75				
vila-u-7b-256	318.00	143.00	107.00	90.00	100.00	71.00	191.41				

Table 7: Consistency scores of different models on rewritten prompts.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	586.00	214.00	204.00	125.00	134.00	133.00	336.47				
FLUX.1-schnell	509.00	182.00	183.00	117.00	113.00	80.00	289.33				
PixArt-Alpha	534.00	195.00	134.00	104.00	118.00	116.00	297.79				
playground-v2.5	632.00	228.00	154.00	126.00	119.00	109.00	346.76				
SD-v1-5	529.00	164.00	111.00	88.00	84.00	67.00	277.65				
SD-2-1	551.00	200.00	113.00	94.00	91.00	75.00	294.83				
SD-XL-base-0.9	571.00	238.00	154.00	114.00	128.00	106.00	323.43				
SD-3-medium	617.00	201.00	180.00	103.00	125.00	112.00	338.31				
SD-3.5-medium	595.00	221.00	183.00	127.00	128.00	116.00	336.35				
SD-3.5-large	641.00	221.00	185.00	120.00	132.00	122.00	355.31				
		U	nified MI	LLM							
Emu3	565.00	196.00	151.00	109.00	102.00	98.00	309.71				
Janus-1.3B	382.00	176.00	149.00	116.00	117.00	93.00	234.61				
JanusFlow-1.3B	346.00	141.00	109.00	118.00	88.00	87.00	205.74				
Janus-Pro-1B	522.00	205.00	169.00	136.00	133.00	123.00	304.71				
Janus-Pro-7B	630.00	219.00	192.00	147.00	155.00	123.00	356.61				
Orthus-7B-base	171.00	82.00	56.00	52.00	41.00	38.00	102.64				
Orthus-7B-instruct	468.00	161.00	133.00	94.00	88.00	86.00	258.58				
show-o	518.00	191.00	152.00	107.00	102.00	115.00	291.71				
show-o-512	524.00	195.00	185.00	123.00	133.00	114.00	303.77				
vila-u-7b-256	486.00	179.00	138.00	122.00	119.00	124.00	279.15				

Table 8: Realism scores of different models on rewritten prompts.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	637.00	285.00	197.00	167.00	160.00	148.00	376.10				
FLUX.1-schnell	504.00	221.00	167.00	114.00	124.00	110.00	295.52				
PixArt-Alpha	479.00	246.00	168.00	136.00	148.00	139.00	297.33				
playground-v2.5	571.00	262.00	194.00	162.00	164.00	141.00	344.66				
SD-v1-5	344.00	172.00	105.00	113.00	102.00	88.00	210.59				
SD-2-1	375.00	219.00	131.00	120.00	120.00	108.00	238.80				
SD-XL-base-0.9	458.00	231.00	161.00	142.00	154.00	123.00	285.09				
SD-3-medium	585.00	258.00	181.00	153.00	154.00	133.00	345.16				
SD-3.5-medium	567.00	261.00	170.00	157.00	150.00	134.00	337.10				
SD-3.5-large	583.00	247.00	178.00	146.00	163.00	147.00	343.72				
		U	nified MI	LLM							
Emu3	516.00	221.00	165.00	138.00	129.00	109.00	302.85				
Janus-1.3B	174.00	123.00	91.00	92.00	79.00	76.00	126.94				
JanusFlow-1.3B	232.00	150.00	87.00	109.00	94.00	72.00	156.92				
Janus-Pro-1B	365.00	177.00	125.00	125.00	111.00	102.00	225.98				
Janus-Pro-7B	519.00	224.00	180.00	135.00	132.00	108.00	306.45				
Orthus-7B-base	103.00	56.00	36.00	32.00	41.00	46.00	67.24				
Orthus-7B-instruct	343.00	138.00	109.00	78.00	90.00	68.00	198.34				
show-o	392.00	167.00	125.00	102.00	114.00	94.00	232.31				
show-o-512	458.00	231.00	164.00	132.00	149.00	119.00	283.59				
vila-u-7b-256	283.00	146.00	105.00	92.00	94.00	93.00	179.45				

Table 9: Aesthetic Quality scores of different models on rewritten prompts.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	640.00	282.00	194.00	162.00	159.00	133.00	374.30				
FLUX.1-schnell	505.00	209.00	162.00	119.00	115.00	107.00	292.55				
PixArt-Alpha	583.00	283.00	194.00	158.00	159.00	152.00	353.16				
playground-v2.5	696.00	292.00	215.00	170.00	170.00	154.00	405.16				
SD-v1-5	367.00	177.00	111.00	101.00	96.00	78.00	218.62				
SD-2-1	427.00	208.00	126.00	110.00	99.00	86.00	251.79				
SD-XL-base-0.9	492.00	250.00	158.00	139.00	144.00	115.00	299.36				
SD-3-medium	552.00	238.00	176.00	145.00	147.00	123.00	325.45				
SD-3.5-medium	566.00	252.00	166.00	147.00	139.00	119.00	331.06				
SD-3.5-large	600.00	247.00	170.00	153.00	158.00	140.00	348.96				
		U	nified MI	LLM							
Emu3	621.00	269.00	198.00	148.00	144.00	132.00	362.06				
Janus-1.3B	203.00	129.00	89.00	82.00	73.00	73.00	137.38				
JanusFlow-1.3B	249.00	139.00	87.00	94.00	84.00	71.00	159.28				
Janus-Pro-1B	396.00	185.00	135.00	117.00	105.00	102.00	239.65				
Janus-Pro-7B	513.00	212.00	171.00	122.00	119.00	100.00	297.45				
Orthus-7B-base	129.00	88.00	56.00	50.00	55.00	57.00	89.94				
Orthus-7B-instruct	458.00	183.00	136.00	108.00	110.00	102.00	263.85				
show-o	496.00	205.00	149.00	119.00	128.00	124.00	289.55				
show-o-512	556.00	254.00	182.00	143.00	154.00	136.00	332.32				
vila-u-7b-256	375.00	172.00	129.00	96.00	100.00	102.00	225.68				

D GPT4o's Assessment Instruction

Figure 8 presents the instructions we input to GPT4o for evaluation.

```
# Text-to-Image Quality Evaluation Protocol
## System Instruction
You are an AI quality auditor for text-to-image generation. Apply these rules with ABSOLUTE RUTHLESSNESS.
Only images meeting the HIGHEST standards should receive top scores.
**Input Parameters**
- PROMPT: [User's original prompt to]
- EXPLANATION: [Further explanation of the original prompt]
## Scoring Criteria
**Consistency (0-2):** How accurately and completely the image reflects the PROMPT.
* **0 (Rejected):** Fails to capture key elements of the prompt, or contradicts the prompt.
* **1 (Conditional): ** Partially captures the prompt. Some elements are present, but not all, or not accurately.
Noticeable deviations from the prompt's intent.
* **2 (Exemplary): ** Perfectly and completely aligns with the PROMPT. Every single element and nuance of
the prompt is flawlessly represented in the image. The image is an ideal, unambiguous visual realization of the
given prompt.
**Realism (0-2):** How realistically the image is rendered.
* **0 (Rejected):** Physically implausible and clearly artificial. Breaks fundamental laws of physics or visual
realism.
* **1 (Conditional):** Contains minor inconsistencies or unrealistic elements. While somewhat believable,
noticeable flaws detract from realism.
* **2 (Exemplary): ** Achieves photorealistic quality, indistinguishable from a real photograph. Flawless
adherence to physical laws, accurate material representation, and coherent spatial relationships. No visual cues
betraying AI generation.
**Aesthetic Quality (0-2):** The overall artistic appeal and visual quality of the image.
* **0 (Rejected):** Poor aesthetic composition, visually unappealing, and lacks artistic merit.
* **1 (Conditional): ** Demonstrates basic visual appeal, acceptable composition, and color harmony, but lacks
distinction or artistic flair.
* **2 (Exemplary): ** Possesses exceptional aesthetic quality, comparable to a masterpiece. Strikingly beautiful,
with perfect composition, a harmonious color palette, and a captivating artistic style. Demonstrates a high degree
of artistic vision and execution.
**Do not include any other text, explanations, or labels.** You must return only three lines of text, each
containing a metric and the corresponding score, for example:
**Example Output:**
Consistency: 2
Realism: 1
Aesthetic Quality: 0
**IMPORTANT Enforcement:**
Be EXTREMELY strict in your evaluation. A score of '2' should be exceedingly rare and reserved only for images
that truly excel and meet the highest possible standards in each metric. If there is any doubt, downgrade the score.
For **Consistency**, a score of '2' requires complete and flawless adherence to every aspect of the prompt,
leaving no room for misinterpretation or omission.
For **Realism**, a score of '2' means the image is virtually indistinguishable from a real photograph in terms of
detail, lighting, physics, and material properties.
For **Aesthetic Quality**, a score of '2' demands exceptional artistic merit, not just pleasant visuals.
```

Figure 8: We utilize GPT-40 to evaluate the performance of text-to-image models. Above is the instruction we provided to GPT-40.

E Comparison of Human Assessment with Various Metrics

We randomly sampled 100 images generated by FLUX.1-dev, and reproduced CLIPscore and VQAscore according to the official settings, and calculated the scores in categories. The results are shown in Figure 4. It can be seen that the WiScore fits human scores best.

F Using GPT4-o Rewrite Prompts on WISE

Figure 9 presents the instructions we input to GPT40 to rewrite prompts.

You are a prompt rewriting assistant. Your task is to transform complex prompts into direct, image-focused prompts suitable for a text-to-image model. You will receive a Prompt and an Explanation. Rewrite the Prompt to clearly describe the image to be generated, incorporating relevant details from the Explanation. The rewritten prompt should be self-contained and not require the Explanation to understand.

Examples:

Prompt: A famous flower that symbolizes wealth in China. **Explanation:** This refers to the peony, often called the 'King of Flowers' in China, symbolizing wealth, prosperity, and good fortune in Chinese culture.

Output: Peony.

Prompt: A solution of silver nitrate before light exposure.

Explanation: The model should generate an image depicting a clear, colorless liquid in a transparent container. There should be no visible precipitate or cloudiness, representing a stable silver nitrate solution protected from light.

Output: An image depicting a clear, colorless liquid in a transparent container. There should be no visible precipitate or cloudiness, representing a stable silver nitrate solution protected from light.

Prompt: The currency of the largest country by area in the world. **Explanation:** The model should generate an image of the Russian Ruble.

Output: Russian Ruble.

Figure 9: We utilize GPT-40 to rewrite the prompts in our WISE benchmark, transforming them from complex, knowledge-demanding prompts into direct prompts. Above is the instruction we provided to GPT-40.

Table 10: WiScore on rewritten prompts of different models. These prompts were simplified from the original WISE benchmark using GPT-40 (e.g., "The plant often gifted on Mother's Day" to "Carnation"). **Green bold** indicates score increase after rewriting; **red bold** indicates score decrease.

Model	Cultural	Time	Space	Biology	Physics	Chemistry	Overall				
Dedicated T2I											
FLUX.1-dev	0.75 +0.27	0.70 +0.12	0.76 +0.14	0.69 +0.27	0.71 +0.20	0.68 +0.33	0.73 +0.23				
FLUX.1-schnell	0.63 +0.24	0.58 + 0.14	0.67 +0.17	0.58 + 0.27	0.58 + 0.14	0.44 +0.18	0.60 +0.20				
PixArt-Alpha	0.66 +0.21	0.64 +0.14	0.55 + 0.07	0.58 +0.09	0.64 +0.08	0.62 +0.28	0.63 +0.16				
playground-v2.5	0.78 +0.29	0.72 + 0.14	0.63 +0.08	0.69 + 0.26	0.67 +0.19	0.60 + 0.27	0.71 + 0.22				
SD-v1-5	0.59 +0.25	0.50 + 0.15	0.41 +0.09	0.47 +0.19	0.44 +0.15	0.36 +0.15	0.50 +0.18				
SD-2-1	0.63 +0.33	0.61 +0.23	0.44 +0.09	0.50 + 0.17	0.49 + 0.15	0.41 + 0.20	0.55 + 0.23				
SD-XL-base-0.9	0.68 +0.25	0.71 +0.23	0.59 + 0.12	0.61 +0.17	0.67 +0.22	0.55 +0.28	0.65 + 0.22				
SD-3-medium	0.76 +0.34	0.65 + 0.21	0.68 +0.20	0.59 + 0.20	0.67 +0.20	0.59 + 0.30	0.69 +0.27				
SD-3.5-medium	0.73 +0.30	0.69 +0.19	0.67 +0.15	0.68 +0.27	0.67 +0.14	0.60 + 0.27	0.69 +0.24				
SD-3.5-large	0.78 +0.34	0.69 +0.19	0.68 +0.10	0.64 +0.20	0.70 +0.18	0.64 +0.33	0.72 +0.26				
			Unified ML	LM							
MetaQuery-XL	0.81 +0.25	0.73 +0.18	0.69 +0.07	0.67 +0.18	0.59 -0.04	0.58 +0.17	0.72 +0.17				
Emu3	0.70 +0.36	0.62 +0.17	0.60 + 0.12	0.59 + 0.18	0.56 + 0.11	0.52 +0.25	0.63 +0.24				
Janus-1.3B	0.40 +0.24	0.48 + 0.22	0.49 +0.14	0.54 +0.26	0.53 +0.23	0.44 +0.30	0.46 +0.23				
JanusFlow-1.3B	0.39 +0.26	0.43 +0.17	0.38 + 0.10	0.57 + 0.37	0.44 + 0.25	0.41 + 0.30	0.42 +0.24				
Janus-Pro-1B	0.60 +0.40	0.59 + 0.31	0.59 + 0.14	0.66 +0.42	0.63 +0.31	0.58 + 0.42	0.60 +0.34				
Janus-Pro-7B	0.75 +0.45	0.66 +0.29	0.70 + 0.21	0.71 + 0.35	0.73 + 0.31	0.59 + 0.33	0.71 +0.36				
Orthus-7B-instruct	0.55 +0.32	0.47 +0.16	0.48 +0.10	0.46 +0.18	0.45 +0.14	0.42 +0.22	0.50 +0.23				
show-o	0.61 +0.33	0.56 +0.20	0.55 +0.15	0.54 + 0.31	0.53 +0.20	0.56 +0.34	0.57 +0.27				
show-o-512	0.64 +0.36	0.62 +0.22	0.68 +0.20	0.63 +0.33	0.69 +0.23	0.59 + 0.29	0.64 +0.29				
vila-u-7b-256	0.54 +0.28	0.51 +0.18	0.49 +0.12	0.57 +0.22	0.56 +0.17	0.58 +0.35	0.54 +0.23				