TextTIGER: Text-based Intelligent Generation with Entity Prompt Refinement for Text-to-Image Generation

Anonymous authors
Paper under double-blind review

Abstract

When generating images from prompts that include specific entities, the model must retain as much entity-specific knowledge as possible. However, the number of entities is enormous, and new entities emerge; memorizing all of them completely is not realistic. To bridge this gap, our work proposes Text-based Intelligent Generation with Entity Prompt Refinement (TextTIGER). TextTIGER strengthens knowledge about entities that appear in the prompt by augmenting external information and then summarizes the expanded descriptions with large language models, preventing performance degradation that arises from excessively long inputs. To evaluate our method, we construct a new dataset consisting of captions, images, detailed descriptions, and lists of entities. Experiments with multiple image generation models show that TextTIGER improves image generation performance on widely used evaluation metrics compared with prompts that use captions alone. In addition, using Multimodal LLM (MLLM)-as-a-judge, which shows a strong correlation with human evaluation, we demonstrate that our method consistently achieves higher scores, which underscores its effectiveness. These results show that strengthening entity-related descriptions, summarizing them, and refining prompts to an appropriate length leads to substantial improvements in image generation performance. We will release the created dataset and code upon acceptance.

1 Introduction

Text-to-Image generation is a task that generates images from a given text (Zhang et al., 2023b; Croitoru et al., 2023) with a wide range of applications, including concept image creation and diagram generation (Zhang et al., 2023a). To generate images from textual information, image generation models such as Stable Diffusion (Rombach et al., 2022) adopt an architecture that combines a text encoder with a diffusion model (Ho et al., 2020). These models require carefully designed prompts to reflect the intended image content (Jeon et al., 2025; Lyu et al., 2024; Zhan et al., 2024; Zhang et al., 2023b).

In this process, the model should retain as much entity-specific knowledge as possible to generate images that meet user expectations. Such entities include proper nouns in the prompt, such as names of rivers, castles, and mountains (Seyler et al., 2018; Yamada et al., 2020; 2018; 2017; Gabrilovich et al., 2007).[1]

However, even large-scale image generation models cannot fully retain such knowledge or continuously acquire the latest information, as it demands substantial costs, i.e., the need to keep crawling for up-to-date information and to continuously train billion-scale models. Understanding entities correctly plays a crucial role in aligning with user intent in tasks such as an advertisement image generation task (Du et al., 2024; Mita et al., 2024). For example, as shown in Figure 1, when the prompt "Giant's Castle" is given, an image generation model may fail to interpret the entity correctly. Here, "Giant's Castle" refers to a mountain located in South Africa.[2] Moreover, simply appending externally retrieved information as a long context

[1] In our study, we define an entity as a named entity at the proper expression level, referring to a specific instance such as "Golden Gate Bridge" rather than an abstract concept such as "bridge" (Seyler et al., 2018; Huang et al., 2026).

[2] https://en.wikipedia.org/wiki/Giant%27s_Castle

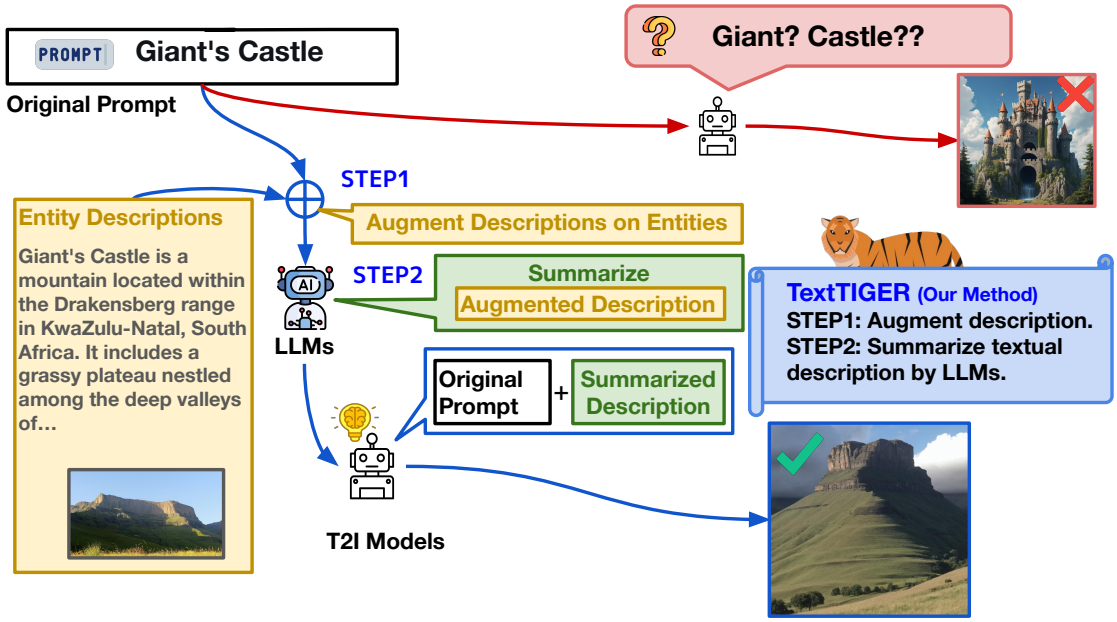

Figure 1: Overview of the proposed method. Our work (1) expands knowledge about entities and (2) summarizes the expanded descriptions to an appropriate length with LLMs, thereby improving the ability of image generation models to handle entities.

to the prompt does not enable effective and accurate processing, due to token length constraints such as a 512-token limit of text encoders (Tan et al., 2024; Zhang et al., 2024).

To address the limitation in entity understanding, we construct a new dataset consisting of image-caption pairs with annotated entity mentions that includes detailed descriptions for each entity, enabling systematic evaluation of how adding external knowledge about entities influences image generation quality. Based on this dataset, we propose a new method called Text-based Intelligent Generation with Entity Prompt Refinement (TextTIGER). Our method first retrieves entity-specific knowledge from external sources and expands the original prompt. For example, as shown in Figure 1, for the prompt "Giant's Castle," we retrieve additional context such as "Giant's Castle is a mountain located within the ...," which compensates for missing knowledge inside the model. Second, we leverage large language models (LLMs) (OpenAI et al., 2024; Singh et al., 2025; Yang et al., 2025; Grattafiori et al., 2024; Qwen et al., 2025) to summarize the retrieved descriptions concisely. This step preserves essential information while keeping the prompt within an appropriate token length. Finally, we generate images from these refined prompts, which mitigates both the model's knowledge limitations and the difficulty of processing long contexts.

Experiments with multiple image generation models together with LLMs on the constructed dataset show that our method substantially outperforms baseline approaches on widely used automatic evaluation metrics. While performance drops when we simply append descriptions, the performance improves when we summarize them, which supports the importance of concise descriptions of entities. Furthermore, evaluation results by Multimodal LLM (MLLM)-as-a-judge (Chen et al., 2024), which strongly correlate with human evaluation, indicate that images generated from prompts with entity description summary contain more entity-related content and exhibit greater faithfulness.

2 Related Work

Vision and Entity Knowledge In the Vision and Language (V&L) field, challenges in understanding visual and textual information often reveal the limited generalization ability of V&L models in generating text from images for applications such as newspapers (Lu et al., 2018; Liu et al., 2021), e-commerce (Ma

et al., 2022), fashion (Rostamzadeh et al., 2018), and artworks (Bai et al., 2021; Hayashi et al., 2024; Ozaki et al., 2025). Similarly, Kamigaito et al. (2023) show that the V&L model OFA (Wang et al., 2022) lacks sufficient entity knowledge in image generation tasks.

Several benchmarks also evaluate how well image generation models understand world knowledge (Chen et al., 2022; Zhao et al., 2025; Wu et al., 2025b; Niu et al., 2025). An extensive study by Chen et al. (2022) introduced "EntityDrawBench," a dataset covering 250 entities, and pointed out that image generation models lack knowledge about long-tail entities. Huang et al. (2026) introduced the "KITTEN" benchmark to evaluate knowledge-intensive generation and found that even the most advanced models often fail to generate entities with accurate visual details. In experiments across domains such as landmarks, plants, and animals, models including Stable Diffusion (Esser et al., 2024) and DALL-E 3 (Betker et al., 2023) produced images with substantial inaccuracies or missing critical features when asked to depict many real-world entities. These findings indicate that current diffusion models rely heavily on what they learn during training and lack robust factual grounding for many specific entities.

Refinement of Image Generation Prompts Researchers have shown that prompt engineering effectively improves image generation (Jeon et al., 2025; Lyu et al., 2024; Zhan et al., 2024). Zhan et al. (2024) refine prompts by training a dedicated text encoder with image representations to generate desired images. Other work proposes generating images by training models with reinforcement learning (Ghasemi et al., 2025; Schulman et al., 2017; Rafailov et al., 2023) so that they produce optimized prompts (Hao et al., 2023). Methods that refine prompts with external knowledge also exist. Jeong et al. (2025) point out that models lack cultural understanding and refine prompts with models equipped with external knowledge to produce more appropriate output images. Image generation approaches based on Retrieval-Augmented Generation (Chen et al., 2022) also attempt prompt refinement with retrievers, e.g., for abstract prompts (Lyu et al., 2024) and for multiple objects (Yuan et al., 2025).

However, although these approaches leverage external knowledge or iterative refinement to improve prompt quality, they do not explicitly focus on supplementing entity-level knowledge. In particular, prior methods do not retrieve and inject structured, entity-specific factual descriptions to compensate for missing world knowledge in text-to-image models, overlooking the limitation of input length by the text encoder as well. Instead, they often use external information, such as cultural alignment or safety refinement, without explicitly addressing whether the model has sufficient factual grounding about individual named entities.

3 Dataset Construction for Entity-Aware Image Generation

To evaluate whether providing rich descriptive information for named entities improves image generation quality, we construct a new dataset. The existing dataset PopVQA (Haklay et al., 2025) provides large-scale image-caption pairs but does not include explicit entity-level information. As a result, its usefulness is limited in settings where models must understand specific named entities and correctly align them with visual content. In real-world applications, prompts often include proper nouns and named entities that presuppose background knowledge. Without access to such knowledge, even advanced image generation models may hallucinate incorrect visual content, miss distinctive attributes, or confuse entities.

To address this issue, we extend the original PopVQA by adding background descriptions for all named entities that appear in each caption. We extend these descriptions through the Wikipedia API.[3] Specifically, the metadata of PopVQA contains hyperlinks to Wikipedia pages corresponding to entities mentioned in the captions. We systematically follow these URLs and extract the introductory abstract of each page. These introductory paragraphs typically provide concise and informative summaries, including the definition, classification, origin, and notable characteristics of the entity. Such abstracts serve as natural and reliable sources of contextual knowledge, especially for uncommon, ambiguous, or culturally specific entities. For example, when given the caption "Liberty at sunset," the Wikipedia abstract provides supplementary information such as its location, height, appearance, and symbolic meaning. This knowledge often plays an important role in faithful image generation.

[3] https://www.mediawiki.org/wiki/API:Main_page

To ensure consistency and quality, we focus on the landmarks and paintings categories and retain only instances for which both the image and the linked Wikipedia page remain accessible at the time of dataset construction. Under these criteria, we extract 2,764 instances from the landmarks category and 2,245 instances from the paintings category, resulting in 5,009 valid instances in total. Each instance in our dataset consists of four elements: (1) the original image, (2) the corresponding caption, (3) the retrieved entity descriptions, and (4) the list of entities contained in those descriptions. The resulting new dataset enables controlled experimental analysis of how access to entity-specific background knowledge influences the behavior of text-to-image generation models. Details appear in Appendix C.5.

4 Proposed Method: TextTIGER

We propose a method that strengthens entity-specific knowledge by augmenting accurate descriptions of entities that appear in the prompt and then summarizing them to an appropriate length by LLMs, as shown in Figure 1. Our method effectively mitigates two major weaknesses of image generation models, i.e., (1) limited internal knowledge on entities, and (2) difficulty in handling long contexts. The proposed approach consists of the following 2 steps: STEP 1. augment entities with informative descriptions (§ 4.1), and STEP 2. summarize the descriptions with an LLM to the appropriate length (§ 4.2).

4.1 STEP 1: Augment Entities with Informative Descriptions

To enable image generation models to understand entities, we augment externally retrieved, information-rich descriptions to the entities that appear in the prompt. Specifically, we extract entities contained in the prompt and obtain corresponding descriptions to compensate for the model's limited internal knowledge.

4.2 STEP 2: Summarize the descriptions using LLMs

For the augmented entity-specific descriptions obtained in STEP 1, we use an LLM to generate summaries that preserve detailed entity information while keeping the length appropriate. Prior work (Juseon-Do et al., 2024) shows that explicitly specifying the input length and the desired number of output tokens helps LLMs manage length constraints effectively. From their motivation, we tokenize the augmented descriptions from STEP 1 using the tokenizer of the text encoder in the image generation model and explicitly provide the token count to the LLM, providing the detailed prompts in Appendix D.1. After this process, we concatenate the summarized entity-specific descriptions to the end of the original caption, forming a new prompt in the format "(caption + summarized description)" for image generation.

We refer to this as Text-based Intelligent Generation with Entity Prompt Refinement (TextTIGER).

5 Experimental Settings

5.1 Prompt Formats

To verify whether our proposed method, TextTIGER, properly improves entity-level image generation capability, we additionally compared 4 methods, as introduced in Table 1.

1. Cap-Only: This setting simply provides the caption that exists in the created dataset to image generation models, validating the baseline performance of image generation models.
2. Aug-Only: In this setting, we simply concatenate the entity descriptions to the caption, i.e., applying only the STEP 1 of our approach in § 4.1. We define this method to examine whether summarization is necessary.
3. RAG: STEP 1 of our proposed method, i.e., § 4.1, supplements missing knowledge about entities by retrieving external information, which closely relates to the Retrieval-Augmented Generation (RAG) (Lewis et al., 2020) method. However, prior work shows that entities are more challenging to handle than general knowledge (Shachar et al., 2025). To evaluate performance under a

Table 1: List of experimental settings and comparison methods in our study.

Method	Prompt for Image Generation
Cap-Only	The caption in the dataset.
Aug-Only	The caption + Augmented knowledge from Wikipedia.
RAG	The caption + Augmented knowledge retrieved from the datastore.
TextTIGER w/o Len	The caption + Summarized description generated by LLMs.
TextTIGER (Our proposed method)	The caption + Summarized description generated by LLMs with the explicit token length.

RAG-based framework, we compare a method that uses BM25 (Lù, 2024) as the retriever, since preliminary experiments show that BM25 achieves the best retrieval performance as demonstrated in Appendix C.2. As the datastore, we use PopVQA data and additionally collect 109,598 Wikipedia articles related to landmarks and 132,573 articles related to paintings. Our method takes the caption as input and concatenates the description retrieved from the datastore to evaluate whether RAG improves performance in this setting.

4. TextTIGER w/o Len: STEP 2 of our proposed method (§ 4.2) explicitly specifies the token length during summarization to generate prompts that suit image generation. To examine whether explicit token control improves prompt quality, we define a variant that performs summarization without specifying the token length. This comparison allows us to validate the effectiveness of STEP 2 and to examine whether we can apply prior findings (Juseon-Do et al., 2024) to prompt construction.

5.2 Summarization Models

To summarize to an appropriate length, we exploit LLMs with strong summarization capabilities, including Qwen2.5 (72B) (Qwen et al., 2025), Qwen3 (30B) (Yang et al., 2025), and Llama 3.3 (70B) (Grattafiori et al., 2024) for open models. As for proprietary models, we use GPT-4o (OpenAI et al., 2024) and GPT-5 (Singh et al., 2025) through API. Appendix C.1 provides detailed experimental settings.

5.3 Image Generation Models

To account for differences in text encoders, we use five image generation models. Specifically, we use Dreamlike 2.0 (defined as Dreamlike) (Art, 2023), which employs CLIP (Radford et al., 2021) as its text encoder, PixArt (Chen et al., 2023), which adopts T5 (Raffel et al., 2020), FLUX (Labs, 2024) and Stable Diffusion 3.5 (SD3.5) (Esser et al., 2024), both of which incorporate CLIP and T5, and Qwen-Image (defined as Qwen-Img) (Wu et al., 2025a), which uses Qwen (Bai et al., 2025) as its encoder. The maximum token lengths of the text encoders are 77 tokens for CLIP, 512 tokens for T5, and 4,096 tokens for Qwen-Image.

5.4 Evaluation Metrics

To measure how much entity-aware image generation improves, we adopt (1) automatic evaluation metrics, i.e., CLIPScore (Hessel et al., 2021), DINOScore (Oquab et al., 2024), and PickScore (Kirstain et al., 2023), and (2) Multimodal Large Language Models (MLLM)-as-a-judge (Chen et al., 2024) evaluated by Vision-Language Models (VLMs) (Qwen et al., 2025; Microsoft et al., 2025; Team et al., 2025).

CLIPScore-T: We utilize CLIPScore (Hessel et al., 2021), which computes the cosine similarity between the hidden states produced by the text encoder and the image encoder of CLIP (Radford et al., 2021) trained with contrastive learning on image-text pairs, to measure how faithfully an image reflects a given sentence. We define this metric as CLIPScore-T and use it to measure the similarity between the generated image and the entity used for generation.

CLIPScore-I: Likewise, we compute the similarity between two different images using the hidden states produced by the image encoder of CLIP (Radford et al., 2021). Our work defines this metric as CLIPScore-I and uses it to measure the similarity between the reference image and the generated image.

Table 2: Results of experiments on the Landmarks category. We report CLIPScore-T and PickScore as evaluation metrics for text-to-image (Txt-Img) generation, and CLIPScore-I and DINOScore as evaluation metrics for image-to-image (Img-Img) generation.

T2I Model	Cap-Only	RAG		TextTIGER w/o Len					TextTIGER (Proposed Method)				
		Aug-Only	BM25	Qwen3	Qwen2.5	Llama3.3	GPT-4o	GPT-5	Qwen3	Qwen2.5	Llama3.3	GPT-4o	GPT-5
CLIPScore-T													
Dreamlike	23.978	20.939	20.743	20.351	20.237	20.604	20.216	20.288	24.672	24.870	**25.296**	24.846	24.829
PixArt	19.106	20.293	19.630	18.955	18.962	18.986	18.960	18.953	23.106	23.108	**23.244**	23.184	23.144
FLUX	21.454	20.572	20.292	19.945	19.407	19.457	19.290	19.289	23.675	23.793	**23.990**	23.686	23.669
SD3.5	23.882	21.432	21.258	20.571	20.753	20.840	20.799	20.746	25.032	25.397	**25.475**	25.371	25.329
Qwen-Img	22.417	17.472	17.706	20.094	19.922	19.886	19.953	19.913	24.338	24.340	24.235	**24.445**	24.414
CLIPScore-I													
Dreamlike	68.371	66.478	65.094	64.365	64.556	64.347	64.360	64.394	78.666	**79.073**	78.853	78.980	78.892
PixArt	59.679	68.515	66.432	62.484	62.729	62.338	62.590	62.593	75.864	76.252	75.435	**76.704**	76.639
FLUX	66.518	69.140	67.458	64.358	64.115	63.844	63.741	63.766	77.925	**78.433**	77.988	78.356	78.250
SD3.5	68.990	67.450	66.043	64.762	65.414	65.424	65.304	65.336	79.334	**79.939**	79.424	79.842	79.794
Qwen-Img	69.946	47.835	47.906	64.638	64.626	64.677	64.551	64.542	79.290	79.286	78.570	**79.672**	79.563
DINOScore													
Dreamlike	29.943	27.047	23.895	33.248	33.425	34.034	33.550	33.498	45.239	**45.557**	44.202	45.245	45.105
PixArt	19.033	34.843	29.151	34.862	35.119	34.682	35.100	35.036	45.938	**46.305**	43.949	45.927	45.869
FLUX	30.015	37.438	32.629	39.924	37.743	37.568	37.704	37.645	48.972	**50.335**	48.375	49.373	49.314
SD3.5	36.485	35.249	30.677	39.472	40.463	40.584	40.320	40.447	52.591	**53.636**	51.944	53.286	53.182
Qwen-Img	40.417	20.242	18.198	41.460	40.935	41.365	41.416	41.439	54.716	54.029	52.200	**54.739**	54.429
PickScore													
Dreamlike	20.556	19.092	19.934	18.517	18.556	18.517	18.584	18.586	24.756	24.784	24.743	24.821	**24.822**
PixArt	20.491	19.731	20.427	18.762	18.775	18.750	18.762	18.767	25.003	**25.018**	25.016	24.947	24.939
FLUX	20.837	19.838	20.604	19.014	18.914	18.939	18.942	18.934	**25.183**	25.165	25.132	25.166	25.169
SD3.5	20.532	19.137	19.962	18.550	18.588	18.593	18.602	18.602	24.703	**24.747**	24.658	24.731	24.729
Qwen-Img	20.614	17.891	18.792	18.801	18.485	18.676	18.505	18.506	**24.927**	24.621	24.592	24.618	24.615

DINOScore: We also compute image-image similarity using the DINO image encoder (Oquab et al., 2024), which they claim to outperform CLIP. As in CLIPScore-I, we measure the similarity between the reference image and the generated image. We define this similarity metric based on DINO as DINOScore.

PickScore: We adopt PickScore (Kirstain et al., 2023), which trains on human preference data and estimates the probability that an image aligns with a given textual instruction in a way humans prefer. PickScore builds on CLIP and, like CLIPScore-T, evaluates the similarity between text and image.

In our work, we use these four automatic metrics to evaluate whether image generation models improve their ability to generate entities accurately.

MLLM-as-a-judge: Huang et al. (2026) proposed "KITTEN," an evaluation framework based on Multimodal LLM (MLLM)-as-a-judge (Chen et al., 2024) for evaluating entity-level fidelity in generated images, and reported a high correlation with human evaluation, claiming that it serves as an effective substitute for manual assessment. In our study, we also adopt KITTEN to evaluate whether our proposed method, Text-TIGER, improves entity-aware image generation, and the detailed prompts are provided in Appendix D.2. Specifically, following KITTEN, we conduct an MLLM-as-a-judge evaluation from two perspectives: **Entity Alignment** and **Text Alignment**. **Entity Alignment** measures how accurately the generated image reflects the target entity, given a reference image that contains the entity, and VLMs rate this aspect on a 1–5 scale. **Text Alignment** measures how faithfully the generated image follows the input text prompt, and VLMs also rate this aspect on a 1–5 scale. As VLMs that serve as evaluators and support multiple image inputs, we use 3 models: Qwen 2.5 (Qwen et al., 2025), Phi 4 (Microsoft et al., 2025), and Gemma 3 (Team et al., 2025). In our work, to address the issue that VLMs do not sufficiently understand entities (Hayashi et al., 2024; Ozaki et al., 2025; Alonso et al., 2025), we insert a brief description of each entity into the evaluation prompt when applying MLLM-as-a-judge. Appendix C.1 provides the details of each model, and Appendix D.2 shows the specific prompts we use.

Table 3: Experimental results on the Paintings category. The interpretation is the same as in Table 2.

T2I Model	Cap-Only	RAG		TextTIGER w/o Len					TextTIGER (Proposed Method)				
		Aug-Only	BM25	Qwen3	Qwen2.5	Llama3.3	GPT-4o	GPT-5	Qwen3	Qwen2.5	Llama3.3	GPT-4o	GPT-5
CLIPScore-T													
Dreamlike	23.830	19.833	19.708	21.959	21.832	21.530	21.337	21.572	24.414	24.610	**24.712**	24.488	24.439
PixArt	21.459	20.557	19.931	21.379	21.205	21.107	20.753	20.757	23.810	23.874	**23.930**	23.659	23.696
FLUX	21.600	20.139	19.907	21.602	21.283	21.524	20.997	21.081	23.293	**23.563**	23.547	23.205	23.204
SD3.5	23.567	20.875	20.452	21.946	21.637	22.030	21.981	22.304	24.258	24.438	**24.599**	24.128	24.135
Qwen-Img	21.377	18.266	18.432	21.649	21.973	21.283	21.316	21.892	**24.205**	23.588	23.637	23.321	23.312
CLIPScore-I													
Dreamlike	55.861	58.167	57.851	56.194	56.654	56.309	55.951	55.933	**67.425**	66.476	66.972	65.772	65.737
PixArt	56.312	59.752	58.446	57.231	56.298	56.576	56.110	55.571	**66.714**	66.062	65.896	65.383	65.455
FLUX	53.715	57.519	57.144	56.769	56.937	56.914	56.424	57.004	**63.909**	62.955	62.841	62.008	61.950
SD3.5	56.427	57.525	57.789	58.186	57.514	57.680	58.191	57.424	**66.252**	65.555	65.769	64.524	64.471
Qwen-Img	56.199	49.763	51.657	56.156	56.092	56.729	55.215	56.049	**68.857**	67.618	66.910	67.120	67.151
DINOScore													
Dreamlike	30.673	27.454	26.636	32.047	34.949	36.700	34.040	32.965	**44.316**	42.476	43.615	41.010	40.732
PixArt	30.622	39.980	37.742	35.487	34.764	37.385	34.540	35.312	**44.037**	42.786	43.624	41.333	41.298
FLUX	24.118	32.084	30.600	36.908	**38.218**	36.275	36.390	36.412	33.839	33.459	34.046	31.523	31.335
SD3.5	30.465	32.520	32.224	38.880	39.296	39.074	37.479	38.324	39.366	38.307	**40.362**	35.848	35.845
Qwen-Img	33.026	24.967	26.042	39.765	39.409	40.556	38.342	39.335	**46.228**	46.167	45.632	45.072	45.345
PickScore													
Dreamlike	20.198	18.542	19.331	18.953	19.035	19.027	19.029	19.038	24.340	24.326	24.281	**24.367**	24.361
PixArt	20.678	19.278	19.906	19.351	19.326	19.375	19.283	19.249	24.733	**24.831**	24.767	24.812	24.811
FLUX	20.863	19.541	20.167	19.512	19.656	19.595	19.550	19.556	24.850	24.913	24.890	**24.921**	24.919
SD3.5	20.362	18.863	19.647	19.199	19.207	19.033	19.119	19.164	24.484	**24.508**	24.452	24.505	24.485
Qwen-Img	20.278	18.105	18.967	19.401	19.249	19.381	18.740	19.091	**24.582**	23.951	24.001	23.893	23.898

6 Results and Discussions

Tables 2 and 3 present the results of the automatic evaluation metrics as described in § 5.4. In general, focusing on the Landmarks category in Table 2, TextTIGER achieves the best performance across the metrics, as indicated by the **bold** scores in the table, showing that augmenting entity-specific content and summarizing it to an appropriate length effectively improves entity-aware image generation.

In contrast, the Aug-Only setting shows little improvement over Cap-Only, indicating that simply appending additional knowledge does not lead to better performance. Moreover, when we compare TextTIGER w/o Len with the TextTIGER, TextTIGER consistently performs better, supporting the importance of explicitly controlling the summary length to construct prompts that better suit image generation models. We observe the same trend in the Paintings category shown in Table 3, and these consistent improvements across both domains demonstrate the generalization ability of our method.

6.1 Does TextTIGER Perform Effectively?

We showed that TextTIGER shows clear improvements when we compare the baseline. Taking a closer look at the result, for CLIPScore-T, PixArt improves from 21.459 to 23.930 with summaries generated by Llama 3.3, and Qwen-Img improves from 21.377 to 24.205 with summaries generated by Qwen 3. For DINOScore, Qwen-Img improves from 30.465 under Cap-Only to 46.228 when we use the optimized prompt summarized by Qwen 3.

Next, we examine whether simply expanding entity knowledge enables image generation models to understand entities. When we compare RAG setting with TextTIGER, TextTIGER consistently achieves better overall performance. For example, in CLIPScore-I, FLUX achieves 57.525 under the RAG-style expansion, whereas LLM-based summarization raises the score up to 68.857, yielding an improvement of more than 10 points. Across other automatic evaluation metrics, TextTIGER also outperforms Cap-Only, which demonstrates that TextTIGER effectively enhances entity-aware image generation.

Table 4: Token length statistics ($\text{mean}_{\pm\text{std}}$). **Bold** indicates the results of TextTIGER.

Model	Landmarks			Paintings		
	Aug-Only	w/o Len	TextTIGER	Aug-Only	w/o Len	TextTIGER
Qwen3	$733.2_{\pm 408.1}$	$190.2_{\pm 18.1}$	$\mathbf{75.4}_{\pm 15.1}$	$467.5_{\pm 384.0}$	$186.3_{\pm 24.2}$	$\mathbf{74.8}_{\pm 20.1}$
Llama 3.3	$707.5_{\pm 393.9}$	$96.9_{\pm 22.8}$	$\mathbf{33.9}_{\pm 9.0}$	$454.9_{\pm 373.7}$	$88.8_{\pm 27.9}$	$\mathbf{31.1}_{\pm 9.1}$
Qwen 2.5	$733.2_{\pm 408.1}$	$103.9_{\pm 20.4}$	$\mathbf{40.1}_{\pm 7.5}$	$467.5_{\pm 384.0}$	$100.5_{\pm 23.4}$	$\mathbf{39.2}_{\pm 8.9}$
GPT-4o/5	$693.6_{\pm 387.3}$	$105.2_{\pm 14.1}$	$\mathbf{45.9}_{\pm 5.5}$	$446.0_{\pm 368.3}$	$112.4_{\pm 20.2}$	$\mathbf{45.4}_{\pm 5.7}$

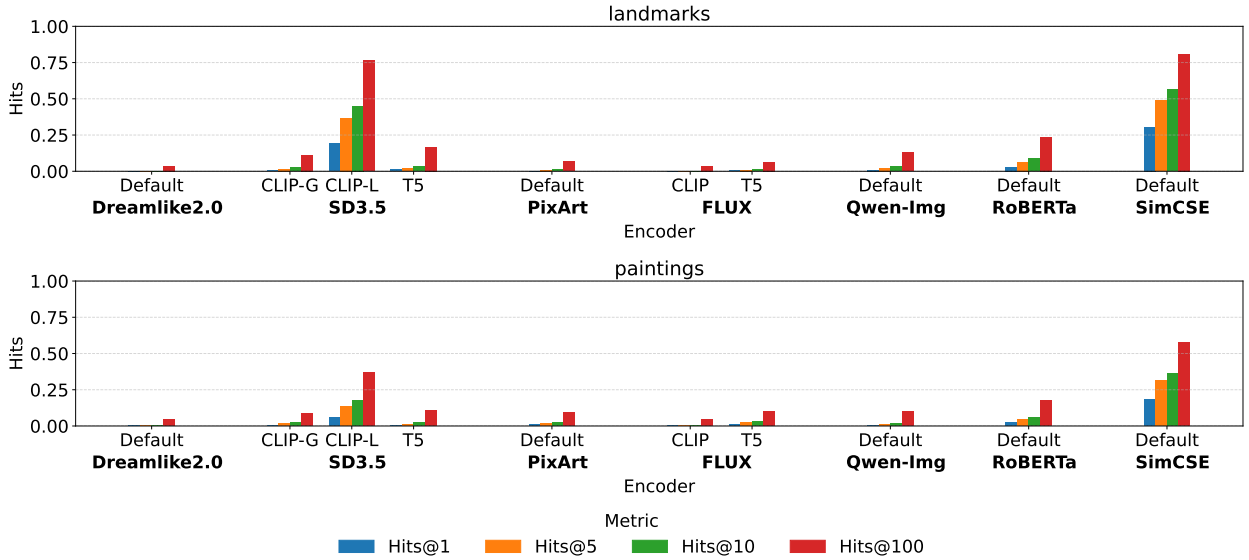

Figure 2: Visualization of how well the text encoders of image generation models understand entities. We examine whether each model can retrieve the correct description when given an entity as input.

We also analyze whether explicit length control during summarization is necessary. When we compare TextTIGER w/o Len with TextTIGER, the TextTIGER consistently achieves better performance. Moreover, TextTIGER w/o Len performs at a level comparable to Cap-Only, which highlights that instructing LLMs to summarize without explicit token-length control can even degrade performance. In contrast, TextTIGER improves performance, proving that image generation models remain highly sensitive to token length, yet can substantially benefit when the refined prompt fits within an appropriate input length.

Table 4 reports the measured prompt token lengths for three knowledge expansion methods: Aug-Only, TextTIGER w/o Len, and TextTIGER. We compute the token counts using the tokenizer of each summarization model. For the proprietary GPT-4o/5 models, we use the `tiktoken` library (`https://github.com/openai/tiktoken`). The results in the table further confirm that explicitly controlling the token length during summarization, as proposed by Juseon-Do et al. (2024), improves the performance.

6.2 Do Encoders Understand Entities?

Our work showed that supplementing entity information with external knowledge improves image generation performance. We now ask how well the text encoders of image generation models internally represent entities themselves. To answer this question, we adopt a knowledge probing framework (Kalo & Fichtel, 2022; Wiland et al., 2024; Petroni et al., 2019; Youssef et al., 2023; Jinno et al., 2026). Our work constructs an entity retrieval task using the hidden states produced by each text encoder and evaluates performance with Hits@k ($k \in \{1, 5, 10, 100\}$ in our work). Specifically, we input a description of each entity and use its embedding representation to retrieve the corresponding gold entity from a datastore. For the datastore, we take the

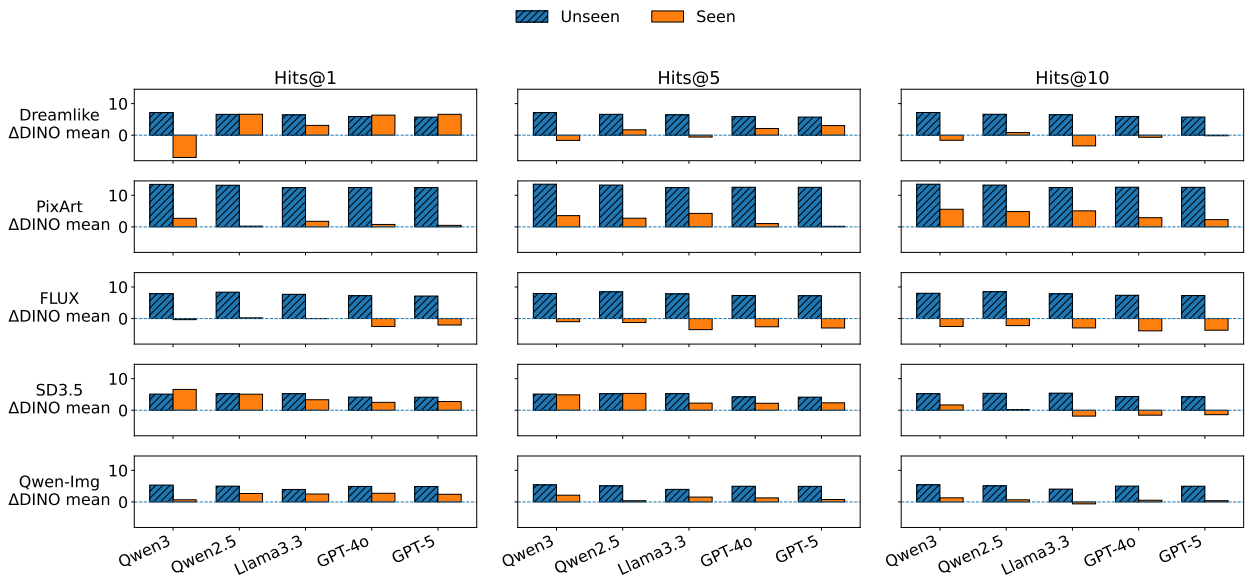

Figure 3: Visualization of whether our proposed method, TextTIGER, effectively handles unseen entities. The y-axis shows the difference in DINOScore between Cap-Only and TextTIGER. The blue bins represent the subset of previously unseen entities, and the orange bins represent the subset of seen entities.

5,009 descriptions constructed in § 3 and rewrite them into ambiguous expressions using GPT-5 so that they do not directly contain the gold entity names, guaranteeing semantic entity understanding evaluation.

Figure 2 presents the results. For the Landmarks category (top row), the default encoders of Dreamlike, PixArt, FLUX, and Qwen-Img achieve almost zero Hits@1 and Hits@5, and even Hits@100 remains extremely low. When we use CLIP-G and CLIP-L text encoders in SD3.5, performance improves to some extent. However, even then, Hits@100 stays around 0.7, and accuracy at smaller k remains low. This observation is the same trend in the Paintings category (bottom row). The text encoders of image generation models fail to reliably identify the correct entity from ambiguous descriptions. In contrast, the sentence embedding models introduced for comparison, SimCSE (Gao et al., 2021) and RoBERTa (Liu et al., 2019), achieve much higher performance. In Landmarks, SimCSE exceeds 0.8 in Hits@100 and clearly outperforms image generation encoders in Hits@10 and Hits@5 as well. We observe the same pattern in Paintings, where SimCSE consistently shows strong retrieval performance, highlighting the difference between text encoders trained for NLP tasks and those used in image generation models. These findings suggest that although text encoders in image generation models suffice for image conditioning, they struggle with knowledge-intensive reasoning that requires uniquely identifying entities from ambiguous descriptions. In other words, their internal entity knowledge remains limited, supporting our motivation that supplementing entity knowledge with external information effectively addresses this limitation.

6.3 Do Descriptions Support Unseen Entities?

To verify whether our augmented approach, as introduced in § 4.1, truly benefits "unseen" entities, we split entities into two groups based on the retrieval results in § 6.2 under the Cap-Only setting, i.e., "seen" (Hits=1) and "unseen" (Hits=0). We then computed the difference in DINOScore as introduced in § 5.4 between Cap-Only and TextTIGER as ΔDINO and analyzed how the effect varies depending on whether the entity was known or unknown. Figure 3 presents the results. [4] The most notable observation is that for Hits=0, namely cases where the text encoder failed to correctly identify the entity (blue bars), ΔDINO consistently shows positive values across many models. In particular, PixArt and FLUX exhibit

[4]Among the automatic evaluation metrics, we base our analysis on DINOScore in our study.We choose DINOScore because it shows the widest score range in Tables 2 and 3, which facilitates clearer analysis.

Table 5: Results of the MLLM-as-a-judge-based KITTEN text alignment evaluation (Txt-Img). C denotes the Cap-Only (Baseline) method. Q3, Q25, L3, G4, and G5 represent image generation results using summaries produced by Qwen3, Qwen2.5, Llama3.3, GPT-4o, and GPT-5, respectively.

T2I Model	Evaluator																	
	Gemma3						Qwen2.5 VL						Phi4					
	C	Q3	Q25	L3	G4	G5	C	Q3	Q25	L3	G4	G5	C	Q3	Q25	L3	G4	G5
Dreamlike	3.38	4.40	4.39	4.42	4.38	4.39	2.62	3.63	3.64	3.64	3.65	3.64	2.59	3.55	3.57	3.57	3.59	3.58
PixArt	3.11	4.48	4.49	4.50	4.46	4.48	2.51	3.72	3.73	3.74	3.72	3.72	2.52	3.70	3.75	3.78	3.74	3.75
FLUX	3.24	4.38	4.40	4.39	4.35	4.36	2.37	3.61	3.62	3.61	3.60	3.59	2.58	3.63	3.67	3.65	3.63	3.64
SD 3.5	3.44	4.44	4.46	4.45	4.43	4.42	2.57	3.71	3.72	3.69	3.71	3.71	2.54	3.66	3.69	3.69	3.67	3.66
Qwen-Img	3.43	4.47	4.33	4.30	4.28	4.28	2.53	3.70	3.59	3.52	3.57	3.57	2.65	3.56	3.25	3.24	3.24	3.23

Table 6: Results of the KITTEN entity alignment evaluation (Img-Img). See Table 5 for details.

T2I Model	Evaluator																	
	Gemma3						Qwen2.5 VL						Phi4					
	C	Q3	Q25	L3	G4	G5	C	Q3	Q25	L3	G4	G5	C	Q3	Q25	L3	G4	G5
Dreamlike	2.44	3.47	3.50	3.47	3.47	3.47	1.43	2.47	2.48	2.45	2.43	2.45	2.03	3.09	3.11	3.07	3.07	3.06
PixArt	2.22	3.62	3.64	3.60	3.61	3.61	1.18	2.64	2.69	2.64	2.63	2.62	1.73	3.22	3.27	3.27	3.21	3.23
FLUX	2.35	3.54	3.58	3.53	3.55	3.56	1.28	2.53	2.60	2.50	2.51	2.53	2.05	3.15	3.23	3.17	3.14	3.13
SD3.5	2.59	3.64	3.68	3.64	3.66	3.65	1.67	2.76	2.85	2.79	2.81	2.81	2.28	3.30	3.35	3.33	3.28	3.29
Qwen-Img	2.60	3.71	3.62	3.54	3.63	3.63	1.62	2.78	2.71	2.59	2.70	2.70	2.34	3.27	3.14	3.07	3.11	3.10

large positive improvements for Hits@1, Hits@5, and Hits@10, indicating that adding external descriptions markedly improves visual alignment when the model lacks sufficient internal entity knowledge. This finding demonstrates that even when the model does not internally encode adequate entity knowledge, structured external information can improve generation quality.

In contrast, for Hits=1, where the encoder already retrieved the correct entity (orange bars), ΔDINO does not consistently remain positive. Depending on the model and the value of k, the improvement becomes small or slightly negative. For example, FLUX shows negative differences in some Hits=1 cases, suggesting that when the model already encodes the entity to some extent, additional descriptions do not necessarily provide further benefits and may even introduce redundancy. We observe similar patterns in SD3.5 and Qwen-Img. While unknown entities consistently benefit from augmentation, the effect on known entities depends on the model, indicating that external descriptions mainly compensate for missing internal representations rather than further strengthening already encoded knowledge.

6.4 Results of the MLLM-as-a-judge

The results of MLLM-as-a-judge shown in Tables 6 and 5 demonstrate that introducing external knowledge clearly improves the entity-related capabilities of image generation models in our study. When we look at entity alignment (Img-Img), compared with Cap-Only, all settings that incorporate external knowledge through summaries generated by Qwen3, Qwen2.5, Llama3.3, GPT-4o, and GPT-5 consistently achieve higher scores across all image generation models. For example, under the Gemma3 evaluator, Dreamlike improves from 2.44 in Cap-Only to approximately 3.47. PixArt increases from 2.22 to above 3.6, and SD3.5 rises from 2.59 to the high 3.6 range. We observe similar trends with Qwen2.5 VL and Phi4 as evaluators. Models that remain in the low 1–2 range under Cap-Only consistently improve to around 2.5–3.3 after adding external knowledge, indicating that generated images reflect entity-specific characteristics more accurately when compared with reference images. The externally augmented entity descriptions contribute directly to improved visual alignment.

Table 7: Actual images generated by SD 3.5 alongside the reference images and their evaluation scores. The scores are reported in the order of {DINO / Gemma3 / Qwen2.5 / Phi4}.

Pattern	Landmarks		Paintings	
	Białowieża Forest	**Po-i-Kalyan**	**Sacred conversation**	**Solly Madonna**
Ref. Img				
Cap-Only				
	3.12 / 2 / 2/ 1	2.07 / 1 / 1 / 1	3.25 / 1 / 1 / 1	3.18 / 2 / 1 / 1
Proposed Method (TextTIGER)				
Qwen3				
	85.12 / 4 / 4 / 3	80.25 / 4 / 5 / 3	85.75 / 4 / 4 / 3	84.50 / 4 / 4 / 4
Llama3.3				
	90.21 / 4 / 4 / 4	82.23 / 4 / 5 / 3	78.234 / 4 / 4 / 3	52.12 / 1 / 2 / 2

We observe similar improvements in text alignment (Txt-Img). With the Gemma3 evaluator, Dreamlike increases from 3.38 under Cap-Only to around 4.4, and PixArt improves from 3.11 to approximately 4.48. FLUX and SD3.5 also gain nearly one full point compared with Cap-Only. These gains indicate that prompts enriched with external knowledge strengthen the consistency between textual instructions and generated images. Under Qwen2.5 VL and Phi4 evaluators, Cap-Only remains around 2.3–2.6, whereas knowledge-augmented settings rise to approximately 3.6–3.7, showing that models reflect entity information in the prompt more faithfully after augmentation. Importantly, these improvements do not depend on a specific image generation model or evaluator. Dreamlike, PixArt, FLUX, SD3.5, and Qwen-Img all outperform Cap-Only in both entity alignment and text alignment. These consistent gains suggest that augmenting entity descriptions with external knowledge systematically compensates for internal knowledge gaps.

6.5 Qualitative Analysis of Generated Images

Our work further verifies that the tendency aligns with the actual visual outputs by examining the generated images shown in Tables 7 and 8. Table 7 compares images generated by SD 3.5. For the Landmarks examples "Białowieża Forest" and "Po-i-Kalyan," and the Paintings examples "Sacred conversation"and "Solly Madonna," Cap-Only produces images that clearly diverge from the reference images. For instance, in "Białowieża Forest," the model generates a generic forest scene, but it fails to reflect distinctive contextual or symbolic elements. The DINO score remains as low as 3.12. In contrast, TextTIGER with Qwen3 summarization raises the score to 85.12, and with Llama3.3 to 90.21. The generated images visually exhibit a closer match to the atmosphere and composition of the reference forest scene. A similar pattern appears in "Po-i-Kalyan." Cap-Only achieves only 2.07, whereas TextTIGER improves the score to around 80. The generated image reproduces characteristic architectural elements such as domes and minarets, and this visual improvement corresponds directly to the large gains in automatic evaluation. In the Paintings

Table 8: Actual generated images produced using summaries by Qwen3, along with the corresponding reference images and their evaluation scores. See Table 7 for details.

Pattern	Landmarks		Paintings	
	Ca' Vendramin Calergi	**Palazzo Grassi**	**Freedom from Want**	**Palazzo Dario**
Ref. Img				
Cap-Only (by FLUX)				
	1.03 / 1 / 1/ 1	57.23 / 4 / 3 / 4	3.03 / 1 / 1 / 1	40.23 / 2 / 2 / 3
Proposed Method (TextTIGER)				
Dreamlike				
	56.23 / 4 / 4 / 4	60.45 / 4 / 3 / 3	75.93 / 3 / 3 / 3	60.23 / 4 / 4 / 4
SD3.5				
	60.06 / 3 / 4 / 4	75.75 / 3 / 3 / 4	60.23 / 4 / 4 / 4	60.22 / 4 / 3 / 5

category, "Sacred conversation" and "Solly Madonna" show abstract or distorted outputs under Cap-Only. After applying TextTIGER, the images clearly depict structured religious compositions with coherent figure arrangements. Both DINO and MLLM-based scores (Gemma3, Qwen2.5, Phi4) rise to around 4, matching the visible improvements. Table 8 presents additional examples using Qwen3 summarization. For "Ca' Vendramin Calergi," Cap-Only with FLUX yields a near failure case with a score of 1.03. After applying TextTIGER, the score increases to 56.23 with Dreamlike, 60.06 with SD3.5, and 89.13 with Qwen-Img. Visually, Cap-Only produces an incorrect portrait-like image, which indicates entity misidentification. TextTIGER instead generates a Venetian palace façade that matches the target entity. The increase in automatic metrics aligns with improved entity recognition. "Freedom from Want" exhibits the same pattern. Cap-Only scores 3.03 and fails to depict the intended scene. TextTIGER raises the score to the 60–75 range and successfully reconstructs the iconic family dining composition. DINO and MLLM-based evaluations, many around 4 points, match the visual improvements.

7 Conclusion

We addressed the limitations of current text-to-image generation models in handling entity-specific knowledge, which is essential for producing user-intended outputs. To validate this problem, we introduced a novel dataset that enriches image–caption pairs with entity annotations and detailed descriptions. Leveraging this dataset, we proposed TextTIGER, a method that augments prompts with external information and uses LLMs to summarize the information, ensuring the inclusion of essential knowledge while keeping the prompt within a length suitable for image generation models. Our experiments demonstrated that TextTIGER consistently outperforms baseline approaches across both automatic metrics MLLM-as-a-judge. These results confirm that entity-aware prompt refinement is a promising direction for improving reliability.

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A Future Work

This study leaves several directions for future work.

First, we acknowledge the absence of human evaluation. In our work, we demonstrated that our method improves image generation performance using KITTEN, an entity-based evaluation framework shown to have a strong correlation with human judgment in evaluating whether generated images contain the intended entities. Through this framework, we verified that our approach enhances entity-level controllability in image generation. However, a direct human evaluation remains an important complementary validation. Conducting large-scale human studies, particularly for image generation tasks, incurs substantial financial and logistical costs. Due to budget constraints beyond the scope of this project, we were unable to perform such evaluations. Thus, we leave comprehensive human evaluation as an important direction for future work.

Second, regarding the choice of image generation models, we evaluated our method on 5 open models but did not include proprietary models such as GPT-Image. [5] While we demonstrated that our approach is effective across different text encoder settings, it is in principle applicable to API-based commercial models as well. However, since such models require per-generation API costs, conducting large-scale controlled experiments would necessitate substantial additional costs. For this reason, extending the evaluation to proprietary models is also left for future work.

Finally, further investigation into summarization evaluation is possible. Our results indicate that improved summarization quality leads to better image generation performance. Although automatic summarization metrics such as ROUGE (Lin, 2004) could be employed for additional analysis, higher ROUGE scores do not necessarily correspond to prompts that are optimal for image generation. Because our objective is to improve generation performance rather than maximize textual overlap with reference summaries, we did not include ROUGE-based evaluation in this study. Exploring the relationship between conventional summarization metrics and downstream image generation quality remains an interesting direction for future research.

B Ethical Considerations

The data used in our study were created using links that were valid as of December 2025. However, because the images and articles referenced by these links depend on Wikipedia, they may be subject to edits by other users. Thus, the reproducibility of the data cannot be fully guaranteed. The code and dataset used in our work will be made publicly available upon acceptance.

C Appendix

C.1 Detailed Model Settings

Table 9 shows lists of detailed model names used in our experiment.

[5] `https://developers.openai.com/api/docs/guides/image-generation/`

Table 9: Detailed models' name and their citations.

Model	Params.	HuggingFace / OpenAI API Name	Citation
Summarization Models			
Qwen3	30B	Qwen/Qwen3-30B-A3B-Instruct-2507	Yang et al. (2025)
Llama 3.3	70B	meta-llama/Llama-3.3-70B-Instruct	Grattafiori et al. (2024)
Qwen2.5	72B	Qwen/Qwen2.5-72B-Instruct	Qwen et al. (2025)
GPT-4o	–	gpt-4o-mini-2024-07-18	OpenAI et al. (2024)
GPT-5	–	gpt-5-nano-2025-08-07	Singh et al. (2025)
Image Generation Models			
Dreamlike	–	dreamlike-art/dreamlike-photoreal-2.0	Art (2023)
PixArt	–	PixArt-alpha/PixArt-XL-2-1024-MS	Chen et al. (2023)
FLUX	12B	black-forest-labs/FLUX.1-dev	Labs (2024)
SD3.5	–	stabilityai/stable-diffusion-3.5-large	Esser et al. (2024)
Qwen-Img	–	Qwen/Qwen-Image	Wu et al. (2025a)
MLLM-as-a-judge Models			
Gemma 3	4B	google/gemma-3-4b-it	Team et al. (2025)
Phi 4	6B	microsoft/Phi-4-multimodal-instruct	Microsoft et al. (2025)
Qwen 2.5-VL	7B	Qwen/Qwen2.5-VL-7B-Instruct	Bai et al. (2025)
Retriever Models and Embedding Models			
BGE	0.1B	BAAI/bge-base-en-v1.5	Xiao et al. (2024)
Contriever	0.1B	facebook/contriever	Lei et al. (2023)
E5	0.1B	intfloat/e5-base	Wang et al. (2024)
RoBERTa	0.1B	FacebookAI/roberta-base	Liu et al. (2019)
SimCSE	0.1B	princeton-nlp/sup-simcse-roberta-large	Gao et al. (2021)

Summarization Task All experiments were conducted using the Transformers library (Wolf et al., 2020) with the random seed fixed at 42 for reproducibility. Qwen2.5 / 3, and Llama3.3 were quantized to 4-bit precision using the bitsandbytes library (Dettmers et al., 2022).

Image Generation Task All experiments were carried out using the diffusers library (von Platen et al., 2022). The image resolution was fixed at 512 × 512 pixels. The guidance scale was set to 4.5, the number of inference steps to 30, and the random seed to 42.

C.2 Difference in Retriever Performance

Table 10 presents the difference in retriever performance. Preliminary experiments compared both sparse and dense retrievers to determine the most suitable retrieval method for our RAG-based setting. As shown in Table 10, BM25 achieved the highest accuracy (31.99%), slightly outperforming dense retrievers such as BGE, Contriever, and E5.

Although the performance differences are relatively small, BM25 consistently yielded the best results among the candidates. Based on this observation, we selected BM25 as the retriever for the experiments reported in the main paper.

Table 10: Comparison of retriever accuracy (%).

Retriever	Correct (%)
Sparse retriever	
BM25	**31.99**
Dense retriever	
BGE	31.58
Contriever	31.36
E5	31.65

C.3 Can a RAG Approach Serve as a Substitute?

The results in Tables 2 and 3 show that a naive RAG approach (Aug-Only, BM25) cannot sufficiently substitute our method.

For example, in the Landmarks category, CLIPScore-T for Dreamlike drops from 23.978 under Cap-Only to 20.939 with Aug-Only and 20.743 with BM25. Rather than improving performance, RAG degrades it. We observe similar trends for PixArt, FLUX, and Qwen-Img, where RAG fails to consistently outperform Cap-Only. In the Paintings category, RAG occasionally produces small improvements for certain metrics. However, it does not match the consistent and substantial gains achieved by TextTIGER, suggesting that simply retrieving and appending external documents increases noise and redundancy, which prevents the model from effectively leveraging critical entity information. Image generation models face constraints in input token length and attention allocation. Thus, directly injecting unstructured retrieval outputs does not necessarily work well.

Although RAG provides a general framework for leveraging external knowledge, it does not replace our entity-focused summarization and structured knowledge injection. Challenges such as retrieval accuracy, summarization quality, and noise reduction remain unresolved, leaving further performance improvements through RAG-style approaches for future work.

C.4 Does the Choice of Text Encoder Affect Performance?

The results in Tables 2 and 3 indicate that the choice of text encoder influences baseline performance to some extent. However, the effect of TextTIGER consistently appears across encoder types. First, we examine Dreamlike and SD3.5, which use CLIP as the text encoder. When we move from Cap-Only to TextTIGER, all evaluation metrics improve substantially. For instance, in Landmarks, CLIPScore-T for Dreamlike increases from 23.978 to a maximum of 25.296, and for SD3.5 from 23.882 to 25.475. We observe similar gains in CLIPScore-I, DINOScore, and PickScore, indicating that external knowledge injection strongly enhances entity understanding even for CLIP-based encoders.

Next, we analyze PixArt, which uses the T5 encoder. Under Cap-Only, their scores remain comparable to or slightly lower than CLIP-based models. However, applying TextTIGER consistently improves performance. In Landmarks, CLIPScore-T for PixArt rises from 19.106 to 23.244, and DINOScore and PickScore show similar improvements. Our result observes the same pattern in Paintings, indicating that entity-specific knowledge augmentation benefits T5-based encoders as well. Therefore, the primary driver of performance gains lies in external knowledge injection rather than in any specific encoder architecture.

Table 11: Hits@K results across categories. Best results per column are in bold.

Model	Encoder	Landmarks				Paintings			
		Hits@1	Hits@5	Hits@10	Hits@100	Hits@1	Hits@5	Hits@10	Hits@100
Dreamlike2.0	CLIP	0.000	0.002	0.004	0.036	0.000	0.002	0.004	0.045
SD3.5	CLIP-G	0.007	0.016	0.025	0.111	0.002	0.014	0.022	0.084
SD3.5	CLIP-L	0.190	0.367	0.451	0.765	0.060	0.131	0.175	0.369
SD3.5	T5	0.012	0.021	0.032	0.167	0.003	0.012	0.022	0.104
PixArt	T5	0.004	0.009	0.012	0.068	0.011	0.019	0.023	0.095
FLUX	CLIP	0.000	0.002	0.004	0.036	0.000	0.002	0.004	0.045
FLUX	T5	0.005	0.008	0.012	0.066	0.011	0.022	0.029	0.100
Qwen-Img	Qwen (LLM)	0.009	0.024	0.034	0.130	0.004	0.009	0.017	0.103
RoBERTa	BERT	0.029	0.064	0.089	0.238	0.025	0.042	0.059	0.178
SimCSE	BERT	**0.306**	**0.489**	**0.563**	**0.809**	**0.181**	**0.314**	**0.362**	**0.579**

C.5 Examples of Our Created Dataset

Tables 12 and 13 show examples of our created dataset.

Table 12: An example of the created dataset in Paintings category.

Entity	Description	Ref. Image
Queen Victoria	Victoria was Queen of the United Kingdom of Great Britain and Ireland from 20 June 1837 until her death in 1901. Her reign of 63 years and 216 days, which was longer than those of any of her predecessors, constituted the Victorian era, a period of industrial, political, scientific, and military change within the United Kingdom marked by a great expansion of the British Empire. In 1876, the British parliament voted to grant her the additional title of Empress of India.	
British Empire	The British Empire comprised the dominions, colonies, protectorates, mandates, and other territories ruled or administered by the United Kingdom and its predecessor states. It began with the overseas possessions and trading posts established by England in the late 16th and early 17th centuries, and colonisation attempts by Scotland during the 17th century. At its height in the 19th and early 20th centuries, it became the largest empire in history and, for a century, was the foremost global power. By 1913, the British Empire held sway over 412 million people, 23 percent of the world population at the time, and by 1920, it covered 35.5 million km2 (13.7 million sq mi), 24 per cent of the Earth's total land area. As a result, its constitutional, legal, linguistic, and cultural legacy is widespread. At the peak of its power, it was described as "the empire on which the sun never sets", as the sun was always shining on at least one of its territories.	
Great Britain	Great Britain is an island in the North Atlantic Ocean off the north-west coast of continental Europe, consisting of the countries England, Scotland and Wales. With an area of 209,331 km2 (80,823 sq mi), it is the largest of the British Isles, the largest European island, and the ninth-largest island in the world. It is dominated by a maritime climate with narrow temperature differences between seasons. The island of Ireland, with an area 40 per cent that of Great Britain, is to the west – these islands, along with over 1,000 smaller surrounding islands and named substantial rocks, comprise the British Isles archipelago.	
United Kingdom of Great Britain and Ireland	The United Kingdom of Great Britain and Ireland was established by the Acts of Union in 1801 that united the Kingdom of Great Britain and the Kingdom of Ireland into one sovereign state. It continued in this form until 1927, when it evolved into the United Kingdom of Great Britain and Northern Ireland, after the Irish Free State gained a degree of independence in 1922.	
Victorian era	In the history of the United Kingdom and the British Empire, the Victorian era was the reign of Queen Victoria, from 20 June 1837 until her death on 22 January 1901, although slightly different definitions are sometimes used. The era followed the Georgian era and preceded the Edwardian era, and its later half overlaps with the first part of the Belle Époque era of continental Europe.	

Table 13: An example of the created dataset in Landmarks category.

Entity	Description	Ref. Image
Taj Mahal	The Taj Mahal is an ivory-white marble mausoleum on the right bank of the river Yamuna in Agra, Uttar Pradesh, India. It was commissioned in 1631 by the fifth Mughal emperor, Shah Jahan, to house the tomb of his beloved wife, Mumtaz Mahal; it also houses the tomb of Shah Jahan himself. The tomb is the centrepiece of a 17-hectare (42-acre) complex, which includes a mosque and a guest house, and is set in formal gardens bounded on three sides by a crenellated wall.	
Agra	Agra is a city on the banks of the Yamuna river in the Indian state of Uttar Pradesh, about 230 kilometres (140 mi) south-east of the national capital Delhi and 330 km west of the state capital Lucknow. It is also the part of Braj region. With a population of roughly 1.6 million, Agra is the fourth-most populous city in Uttar Pradesh and twenty-third most populous city in India.	
India	India, officially the Republic of India, is a country in South Asia. It is the seventh-largest country by area; the most populous country since 2023; and, since its independence in 1947, the world's most populous democracy. Bounded by the Indian Ocean on the south, the Arabian Sea on the southwest, and the Bay of Bengal on the southeast, it shares land borders with Pakistan to the west; China, Nepal, and Bhutan to the north; and Bangladesh and Myanmar to the east. In the Indian Ocean, India is near Sri Lanka and the Maldives; its Andaman and Nicobar Islands share a maritime border with Myanmar, Thailand, and Indonesia.	
Marble	Marble is a metamorphic rock consisting of carbonate minerals (most commonly calcite (CaCO3) or dolomite (CaMg(CO3)2) that have recrystallized under the influence of heat and pressure. It has a crystalline texture, and is typically not foliated (layered), although there are exceptions.	
Mausoleum	A mausoleum is an external free-standing building or standalone structure constructed as a monument enclosing the burial chamber of a deceased person or people. A mausoleum without the person's remains is called a cenotaph. A mausoleum may be considered a type of tomb, or the tomb may be considered to be within the mausoleum.	
Mosque	A mosque, also called a masjid, is a place of worship for Muslims. The term usually refers to a covered building, but can be any place where Islamic prayers are performed; such as an outdoor courtyard.	
Mumtaz Mahal	Mumtaz Mahal was the empress consort of Mughal Empire from 1628 to 1631 as the chief consort of the fifth Mughal emperor, Shah Jahan. The Taj Mahal in Agra, often cited as one of the Wonders of the World, was commissioned by her husband to act as her tomb.	

D Prompts

We list the prompts used during experiments below.

D.1 Prompts for Summarization Task

Prompt for Summarization (TextTIGER)

You must generate **ONLY ONE THING**:
a single English prompt for an image-generation model.
Do NOT output explanations, comments, apologies, thoughts, or any other text.

HARD OUTPUT FORMAT CONSTRAINT
You MUST output **ONLY** the following block EXACTLY in this format:

<SummaryStart>
English prompt for the image generator, within 70 tokens, nothing else
<SummaryEnd>

- No additional text before or after the tags.
- No reasoning steps.
- No markdown.
- No prefaces or suffixes.
- No self-talk.
- No comments.
- No variable placeholders.

TASK (STRICT)
Create the **optimal** English prompt for generating an iconic image of **`{title}`**.

Use only information logically inferable from the summary below.
Assume the image-generation model does NOT know what "`{title}`" is.

REQUIREMENTS
- Length: ** 70 tokens**
- Include **all concrete visual details** required for correct generation:
- environment (sea, mountains, city, interior, etc.)
- physical structure, shapes
- materials, colors
- atmosphere, lighting
- perspective or composition
- style (only if described or inferable)
- measurements (height/width) if included in the summary
- Do NOT include:
- citations
- mentions of "summary," "tokens," or the instructions
- analysis or meta text
- any text outside <SummaryStart> ··· <SummaryEnd>
- Generate
- ONLY prompt
- ONLY in English
- ONLY 1 sentence

REFERENCE SUMMARY
Below is the summary of `{abstract_tokens}` tokens.
Use ONLY the information contained in it.

— SUMMARY BELOW —
`{abstract}`
— END SUMMARY —

Now output ONLY the required block:

<SummaryStart>
...
<SummaryEnd>

<SummaryStart>

Prompt for Summarization (TextTIGER w/o Len)

You must generate **ONLY ONE THING**:
a single English prompt for an image-generation model.
Do NOT output explanations, comments, apologies, thoughts, or any other text.

HARD OUTPUT FORMAT CONSTRAINT
You MUST output **ONLY** the following block EXACTLY in this format:

<SummaryStart>
English prompt for the image generator, nothing else
<SummaryEnd>

- No additional text before or after the tags.
- No reasoning steps.
- No markdown.
- No prefaces or suffixes.
- No self-talk.
- No comments.
- No variable placeholders.

TASK (STRICT)
Create the **optimal** English prompt for generating an iconic image of ***{title}***.

Use only information logically inferable from the summary below.
Assume the image-generation model does NOT know what "{title}" is.

REQUIREMENTS
- Include **all concrete visual details** required for correct generation:
- environment (sea, mountains, city, interior, etc.)
- physical structure, shapes
- materials, colors
- atmosphere, lighting
- perspective or composition
- style (only if described or inferable)
- measurements (height/width) if included in the summary
- Do NOT include:
- citations
- mentions of "summary" or the instructions
- analysis or meta text
- any text outside <SummaryStart> ··· <SummaryEnd>
- Generate
- ONLY prompt
- ONLY in English

— SUMMARY BELOW —
{abstract}
— END SUMMARY —

Now output ONLY the required block:

<SummaryStart>
...
<SummaryEnd>

<SummaryStart>

D.2 Prompts for MLLM-as-a-judge (KITTEN)

Prompt for Entity Alignment

In this task, you will be provided with a Prompt, Reference Images, and a Generated Image. Your job is to assess the factual accuracy of the generated image with respect to the prompt and the reference images. The goal is to ensure that the entity described in the prompt is factually correct and accurately represented.

First, evaluate how faithfully the generated image represents the reference entity.
Consider whether the key features and overall appearance of the reference entity are accurately depicted.
Question 1: How faithfully does the generated image represent the entity mentioned in the prompt?

Candidate Answers:
1 (Not faithful at all): The generated image does not represent the reference entity at all.
There are no discernible visual similarities to the reference entity.
2 (Barely faithful): The generated image faintly represents the reference entity, with significant effort needed to see any resemblance.
Minor visual elements may be present, but crucial features or characteristics are missing or significantly misrepresented.
3 (Somewhat faithful): The generated image somewhat represents the reference entity, but it's not prominent. There is a clear visual connection in terms of composition, style, or some key elements, but there are noticeable differences, omissions, or misinterpretations.
4 (Mostly faithful): The generated image mostly represents the reference entity and clearly presents it. The generated image draws strong visual inspiration with a strong connection in terms of overall composition, style, key elements, and/or subject matter, despite some variations in details.
5 (Completely faithful): The generated image fully represents the reference entity accurately.
It captures all key elements, composition, and style in a way that is almost identical to the reference entity.

Answer in the exact format below:
Question 1:
Answer: [1-5]
Reason: [Provide a clear explanation for your answer]

Prompt for Prompt Alignment

In this task, you will be provided with a Prompt and a Generated Image.

Evaluate how well the generated image captures all aspects described in the prompt.
Focus on background elements, contextual details, materials, styles, and other visual features.

Question 2: How well does the generated image depict the details described in the prompt?

Candidate Answers:
1 (Not at all): None of the described elements are present in the image.
2 (Slightly): A few minor elements are present, but most are missing or inaccurate.
3 (Moderately): Some elements are present and somewhat accurate, but others are missing or misrepresented.
4 (Mostly): Most of the described elements are clearly and accurately depicted.
5 (Completely): All relevant aspects of the prompt are thoroughly and accurately represented.

Answer in the exact format below:
Question 2:
Answer: [1-5]
Reason: [Provide a clear explanation for your answer]