AIGV-Assessor: Benchmarking and Evaluating the Perceptual Quality of Text-to-Video Generation with LMM

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Abstract

*The rapid advancement of large multimodal models (LMMs) has led to the rapid expansion of artificial intelligence generated videos (AIGVs), which highlights the pressing need for effective video quality assessment (VQA) models designed specifically for AIGVs. Current VQA models generally fall short in accurately assessing the perceptual quality of AIGVs due to the presence of unique distortions, such as unrealistic objects, unnatural movements, or inconsistent visual elements. To address this challenge, we first present **AIGVQA-DB**, a large-scale dataset comprising 36,576 AIGVs generated by 15 advanced text-to-video models using 1,048 diverse prompts. With these AIGVs, a systematic annotation pipeline including scoring and ranking processes is devised, which collects 370k expert ratings to date. Based on AIGVQA-DB, we further introduce **AIGV-Assessor**, a novel VQA model that leverages spatiotemporal features and LMM frameworks to capture the intricate quality attributes of AIGVs, thereby accurately predicting precise video quality scores and video pair preferences. Through comprehensive experiments on both AIGVQA-DB and existing AIGV databases, AIGV-Assessor demonstrates state-of-the-art performance, significantly surpassing existing scoring or evaluation methods in terms of multiple perceptual quality dimensions. The dataset and code are released at https://github.com/IntMeGroup/AIGV-Assessor.*

1. Introduction

Text-to-video generative models [12, 27, 44, 64, 73], including auto-regressive [23, 81] and diffusion-based [12, 27, 55] approaches, have experienced rapid advancements in recent years with the explosion of large multimodal models (LMMs). Given appropriate text prompts, these models can generate high-fidelity and semantically-aligned videos, commonly referred to as AI-generated videos (AIGVs), which have significantly facilitated the content creation in various domains, including entertainment, art, design, and advertising, *etc* [11, 13, 43]. Despite the significant progress, current AIGVs are still far from satisfactory. Unlike natural videos, which are usually affected by low-level distortions, such as noise, blur, low-light, *etc*, AIGVs generally suffer from degradations such as unrealistic objects, unnatural movements, inconsistent visual elements, and misalignment with text descriptions [25, 31, 43, 65, 79, 84, 85].

The unique distortions in AIGVs also bring challenges to the video evaluation. Traditional video quality assessment (VQA) methods [10, 18, 33, 35, 57, 70, 71] mainly focus on evaluating the quality of professionally-generated content (PGC) and user-generated content (UGC), thus struggling to address the specific distortions associated with AIGVs, such as spatial artifacts, temporal inconsistencies, and misalignment between generated content and text prompts. For evaluation of AIGVs, some metrics such as Inception Score (IS) [52] and Fréchet Video Distance (FVD) [61] have been widely used, which are computed over distributions of videos and may not reflect the human preference for an individual video. Moreover, these metrics mainly evaluate the fidelity of videos, while failing to assess the text-video correspondence. Vision-language pre-training models, such as CLIPScore [22], BLIPScore [37], and AestheticScore [53] are frequently employed to evaluate the alignment between generated videos and their text prompts. However, these models mainly consider the text-video alignment at the image level, while ignoring the dynamic diversity and motion consistency of visual elements that are crucial to the video-viewing experience.

In this paper, to facilitate the development of more comprehensive and precise metrics for evaluating AI-generated videos, we present **AIGVQA-DB**, a large-scale VQA dataset, including 36,576 AIGVs generated by 15 advanced text-to-video models using 1,048 diverse prompts. An

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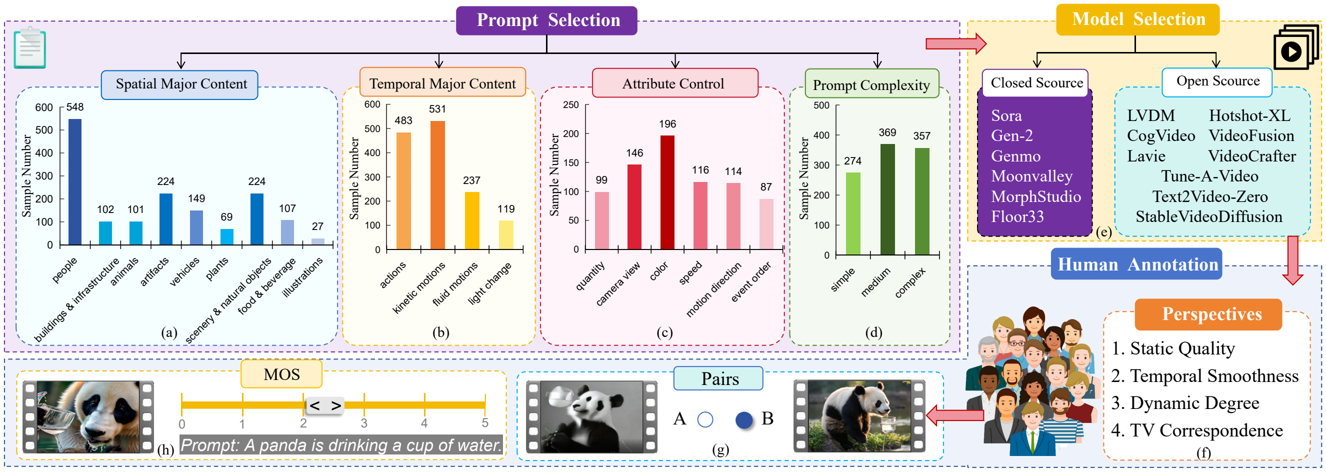


Figure 1. An overview of the AIGVQA-DB construction pipeline, illustrating the generation and the subjective evaluation procedures for the AIGVs in the database. (a) Prompt categorization according to the spatial major content. (b) Prompt categorization according to the temporal descriptions. (c) Prompt categorization according to the attribute control. (d) Prompt categorization according to the prompt complexity. (e) The 15 generative models used in the database. (f) Four visual quality evaluation perspectives, including static quality, temporal smoothness, dynamic degree, and text-video correspondence. (g) and (h) demonstrates the pair comparison and preference scoring processes, respectively.

overview of the dataset construction pipeline is shown in Figure 1. The prompts are collected from existing open-domain text-video datasets [7, 8, 38, 43, 68, 76] or manually-written, which can be categorized based on four orthogonal aspects respectively, as shown in Figure 1(a)-(d). Based on the AIGVs, we collect 370k expert ratings comprising both mean opinion scores (MOSs) and pair-wise comparisons, which are evaluated from four dimensions, including: (1) static quality, (2) temporal smoothness, (3) dynamic degree, and (4) text-video correspondence. Equipped with the dataset, we propose **AIGV-Assessor**, a large multimodal model-based (LMM-based) VQA method for AIGVs, which reformulates the quality regression task into an interactive question-and-answer (Q&A) framework and leverages the powerful multimodal representation capabilities of LMMs to provide accurate and robust quality assessments. AIGV-Assessor not only classifies videos into different quality levels through natural language output, but also generates precise quality scores through regression, thus enhancing the interpretability and usability of VQA results. Moreover, AIGV-Assessor also excels in pairwise video comparisons, enabling nuanced assessments that are closer to human preferences. Extensive experimental results demonstrate that AIGV-Assessor outperforms existing text-to-video scoring methods in terms of multiple dimensions relevant to human preference.

The main contributions of this paper are summarized as follows:

- We construct AIGVQA-DB, a large-scale dataset comprising 36,576 AI-generated videos annotated with MOS scores and pairwise comparisons. Compared with existing benchmarks, AIGVQA-DB provides a more comprehensive assessment of the capabilities of text-to-video models from multiple perspectives.

Table 1. An overview of popular text-to-video (T2V) and image-to-video (I2V) generation models. † Representative variable.

Model	Year	Mode	Resolution	Frames	Open
CogVideo [23]	22.05	T2V	480×480	32	✓
Make-a-Video [55]	22.09	T2V	256×256	16	✓
LVDM [21]	22.11	T2V	256×256	16	✓
Tune-A-Video [73]	22.12	T2V	512×512	8	✓
VideoFusion [44]	23.03	T2V	128×128	16	✓
Text2Video-Zero [27]	23.03	T2V	512×512	8	✓
ModelScope [64]	23.03	T2V	256×256	16	✓
Lavie [67]	23.09	T2V	512×320	16	✓
VideoCrafter [12]	23.10	T2V, I2V	1024×576	16	✓
Hotshot-XL [1]	23.10	T2V	672×384	8	✓
StableVideoDiffusion [9]	23.11	I2V	576×1024	14	✓
AnimateDiff [20]	23.12	T2V, I2V	384×256	20	✓
Floor33 [2]	23.08	T2V,I2V	1024×640	16	–
Genmo [3]	23.10	T2V, I2V	2048×1536	60	–
Gen-2 [4]	23.12	T2V, I2V	1408×768	96	–
MoonValley [5]	24.01	T2V, I2V	1184×672	200†	–
MorphStudio [6]	24.01	T2V, I2V	1920×1080	72	–
Sora [7]	24.02	T2V, I2V	1920×1080	600†	–

- Based on AIGVQA-DB, we evaluate and benchmark 15 representative text-to-video models, and reveal their strengths and weaknesses from four crucial preference dimensions, *i.e.,* static quality, temporal smoothness, dynamic degree, and text-to-video correspondence.
- We present a novel LMM-based VQA model for AIGVs, termed AIGV-Assessor, which integrates both spatial and temporal visual features as well as prompt features into a LMM to give quality levels, predict quality scores, and conduct quality comparisions.
- Thorough analysis of our AIGV-Assessor is provided and extensive experiments on our proposed AIGVQA-DB and other AIGV quality assessment datasets have shown the effectiveness and applicability of AIGV-Assessor.

2. Related Work

2.1. Text-to-video Generation

Recent advancements in text-to-video generative models have substantially broadened video creation and modifica-

Table 2. Summary of existing text-to-image and text-to-video evaluation datasets.

Dataset Types	Name	Numbers	Prompts	Models	Annotators	Dimensions	MOSs / Pairs	Annotation
AIGIQA	AGIQA-3k [34]	2,982	180	6	21	2	5,964	MOS
	AIGCIQA2023 [63]	2,400	100	6	28	3	7,200	MOS
	RichHF-18k [39]	17,760	17,760	3	3	4	71,040	MOS
	HPS [75]	98,807	25,205	1	2,659	1	25,205	Pairs
	Pick-a-Pic [29]	-	37,523	3	4,375	1	584,247	Pairs
AIGVQA	MQT [15]	1,005	201	5	24	2	2,010	MOS
	EvalCrafter [42]	2,500	700	5	7	4	1,024	MOS
	FETV [43]	2,476	619	4	3	3	7,428	MOS
	LGVQ [84]	2,808	468	6	20	3	8,424	MOS
	T2VQA-DB [31]	10,000	1,000	9	27	1	10,000	MOS
	GAIA [13]	9,180	510	18	54	3	27,540	MOS
	AIGVQA-DB (Ours)	**36,576**	**1,048**	**15**	**120**	**4**	**122,304**	**MOS and Pairs**

tion possibilities. As shown in Table 1, these models exhibit distinct characteristics and capacities, including modes, resolution, and total frames. CogVideo [23] is an early text-to-video (T2V) model capable of generating short videos based on CogView2 [16]. Make-a-video [55] adds effective spatial-temporal modules on a diffusion-based text-to-image (T2I) model (*i.e.*, DALLE-2 [50]). VideoFusion [44] also leverages the DALLE-2 and presents a decomposed diffusion process. LVDM [21], Text2Video-Zero [27], Tune-A-Video [73], and ModelScope [64] are models that inherit the success of Stable Diffusion (SD) [51] for video generation. Lavie [67] extends the original transformer block in SD to a spatio-temporal transformer. Hotshot-XL [1] introduces personalized video generation. Beyond these laboratory-driven advancements, the video generation landscape has also been enriched by a series of commercial products. Notable among them are Floor33 [2], Gen-2 [4], Genmo [3], MoonValley [5], MorphStudio [6], and Sora [7], which have gained substantial attention in both academia and industry, demonstrating the widespread application potential of AI-assisted video creation.

2.2. Text-to-video Evaluation

The establishment of the AI-generated image quality assessment (AIGIQA) dataset is relatively well-developed, including both mean opinion scores (MOSs) for absolute quality evaluations, and pairwise comparisons for relative quality judgments. Recent developments in text-to-video generation models have also spurred the creation of various AI-generated video quality assessment (AIGVQA) datasets, addressing different aspects of the T2V generation challenge, as shown in Table 2. MQT [15] consists of 1,005 videos generated by 5 models using 201 prompts. EvalCrafter [42] and FETV [43] extend the scale of the videos, prompts, and evaluation dimensions. LGVQ [84] increases the number of annotators, providing more reliable MOSs. T2VQA-DB [31] consists of 10,000 videos from 1,000 prompts representing a significant improvement in scale. GAIA [13] collects 9,180 videos focusing on action quality assessment in AIGVs, but falls short in addressing the consistency between the generated visuals and their textual prompts. Most existing VQA datasets predominantly rely on MOS, an absolute scoring method, which suffers from the same drawback: absolute scores alone may cause ambiguity and overlook subtle quality differences. In contrast, our AIGVQA-DB includes both MOSs and pairwise comparisons, addressing the limitations of current works by providing fine-grained preference feedbacks.

3. Database Construction and Analysis

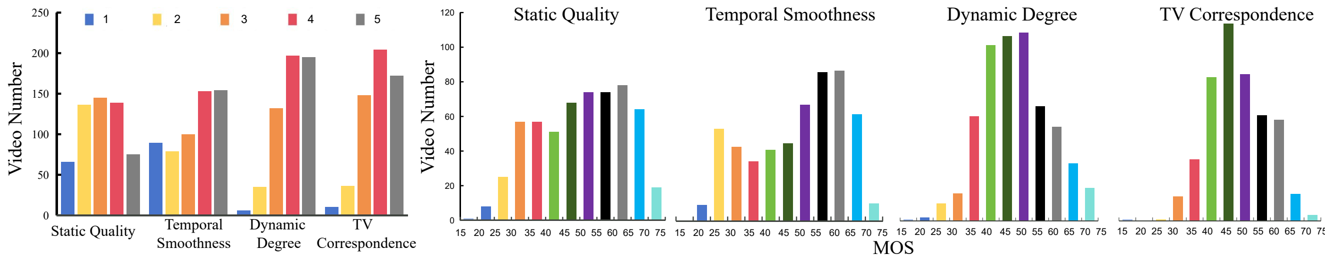
3.1. Data Collection

Prompt Scources and Categorization. Prompts of the AIGVQA-DB are primarily sourced from existing open-domain text-video pair datasets, including InternVid [68], MSRVTT [76], WebVid [8], TGIF [38], FETV [43] and Sora website [7]. We also manually craft prompts describing highly unusual scenarios to test the generalization ability of the generation models. As shown in Figure 1(a)-(d), we follow the categorization principles from FETV [43] to organize each prompt based on the "spatial major content", "temporal major content", "attribute control", and "prompt complexity".

Text-to-Video Generation. We utilize 15 latest text-to-video generative models to create AI-generated videos as shown in Figure 1(e). We leverage open-source website APIs and code with default weights for these models to produce AIGVs. For the construction of the MOS subset, we collect 48 videos from the Sora Website [7], along with their corresponding text prompts. Using these prompts, we generate additional videos using 11 different generative models. This process results in a total of 576 videos (12 generative models $\times$ 48 prompts). In addition to the MOS subset, we construct the pair-comparison subset using 1,000 diverse prompts, and 12 generative models including 8 open-sourced and 4 close-sourced are employed for text-to-video generation. Specifically, for each prompt, we generate four distinct videos for each open-source generative model and one video for each closed-source generative model. This process yields a total of 36,000 videos. More details of the database can be found in the *supplementary material*.

3.2. Subjective Experiment Setup and Procedure

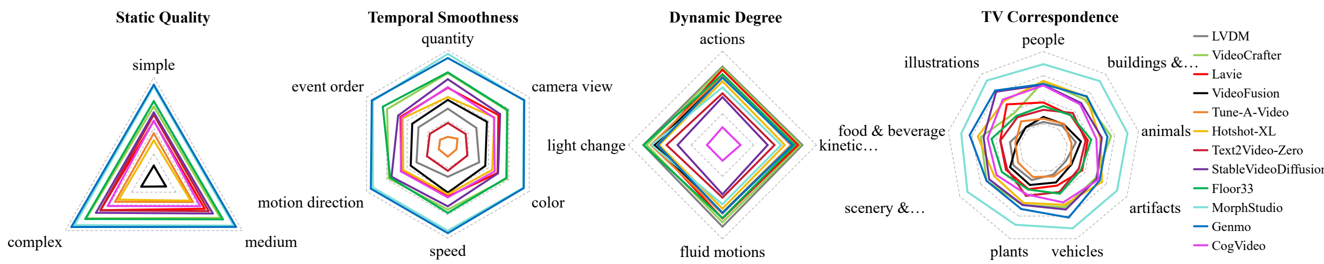
Due to the unique and unnatural characteristics of AI-generated videos and the varying target video spaces dictated by different text prompts, relying solely on a single score, such as "quality", to represent human visual preferences is insufficient. In this paper, we propose to measure



(a) Distribution of Raw Scores

(b) Distribution of Mean Opinion Scores (MOSs)

Figure 2. Video score distribution from the four perspectives including static quality, temporal smoothness, dynamic degree, and t2v correspondence. (a) Distribution of raw scores. (b) Distribution of Mean Opinion Scores (MOSs)



(a) (b) (c) (d)

Figure 3. Comparison of averaged win rates of different generation models across different categories. (a) Results across prompt complexity. (b) Results across attribute control. (c) Results across temporal major contents. (d) Results across spatial major contents.

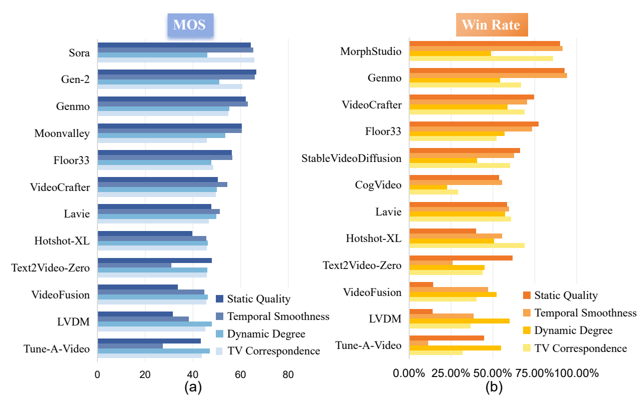


Figure 4. (a) Comparison of text-to-video generation models regarding the MOS in terms of four dimensions sorted bottom-up by their averaged MOS. (b) Comparison of text-to-video generation models regarding the win rate in terms of four dimensions sorted bottom-up by their averaged win rate.

the human visual preferences of AIGVs from four perspectives. **Static quality** assesses the clarity, sharpness, color accuracy, and overall aesthetic appeal of the frames when viewed as standalone images. **Temporal smoothness** evaluates the temporal coherence of video frames and the absence of temporal artifacts such as flickering or jittering. **Dynamic degree** evaluates the extent to which the video incorporates large motions and dynamic scenes, which contributes to the overall liveliness and engagement measurement of the content. **Text-video (TV) correspondence** assesses how accurately the video content reflects the details, themes, and actions described in the prompt, ensuring that the generated video effectively translates the text input into a visual narrative. Each of these four visual perception perspectives is related but distinct, offering a comprehensive evaluation for AIGVs. To evaluate the quality of the videos in the AIGVQA-DB, we conduct subjective experiments adhering to the guidelines outlined in ITU-R BT.500-14 [17, 54]. For the MOS annotation type, we use a 1-5 Likert-scale judgment to score the videos. For the pairs annotation type, participants are presented with pairs of videos and asked to choose the one they prefer, providing a direct comparison method for evaluating relative video quality. The videos are displayed using an interface designed with Python Tkinter, as illustrated in Figure 1(g)-(h). A total of 120 graduate students participate in the experiment.

3.3. Subjective Data Processing

In order to obtain the MOS for an AIGV, we linearly scale the raw ratings to the range $[0, 100]$ as follows:

$$z_{ij} = \frac{r_{ij} - \mu_{ij}}{\sigma_i}, \quad z'_{ij} = \frac{100(z_{ij} + 3)}{6},$$

$$\mu_i = \frac{1}{N_i} \sum_{j=1}^{N_i} r_{ij}, \quad \sigma_i = \sqrt{\frac{1}{N_i - 1} \sum_{j=1}^{N_i} (r_{ij} - \mu_{ij})^2}$$

where r_{ij} is the raw ratings given by the i-th subject to the j-th video. N_i is the number of videos judged by subject i. Next, the MOS of the video j is computed by averaging the rescaled z-scores as follows:

$$MOS_j = \frac{1}{M} \sum_{i=1}^{M} z'_{ij}$$

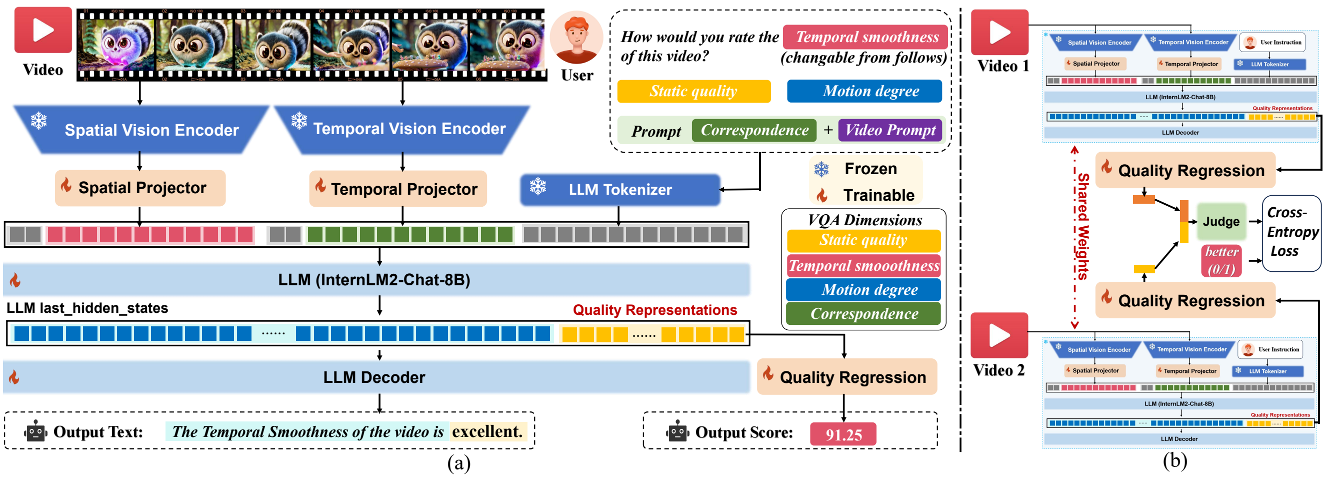


Figure 5. The framework of AIGV-Assessor: (a) AIGV-Assessor takes AI-generated video frames as input and outputs both text-based quality levels and numerical quality scores. The system begins with the extraction of spatiotemporal features using two vision encoders, which are then passed through spatial and temporal projection modules to generate aligned visual tokens into language space. The LLM decoder produces text-based feedback describing the video quality level for four evaluation dimensions, respectively. Simultaneously, the last-hidden-states from the LLM are used to perform quality regression that outputs final quality scores in terms of four dimensions. (b) AIGV-Assessor is fine-tuned on pairwise comparison, further allowing the model to output the evaluation comparison between two videos.

where MOS_j indicates the MOS for the j-th AIGV, M is the number of subjects, and z'_{ij} are the rescaled z-scores.

For the pairs annotation type, given a text prompt p_i, and 12 video generation models labeled $\{A, B, C, ..., L\}$, we generate videos using each model, forming a group of videos $G_{i,j} = \{V_{i,A,j}, V_{i,B,j}, V_{i,C,j}, ..., V_{i,L,j}\}$. For each prompt p_i, we generate four different videos randomly for each of the eight open-source generative models and one video for each of the four closed-source generative models, resulting in a group of 36 videos $\{G_{i,A,1}, G_{i,A,2}, G_{i,A,3}, G_{i,A,4}, G_{i,B,1}, ...G_{i,L,1}\}$. For each group, we create all possible pairwise combinations, resulting in C_{36}^2 pairs: (V_{A1}, V_{B1}), (V_{A1}, V_{B2}), (V_{A1}, V_{B3}), (V_{A1}, V_{B4}), (V_{A1}, V_{C1}), ... , (V_{K1}, V_{L1}). In the AIGVQA-DB construction pipeline, a prompt suite of 1000 prompts results in 630,000 ($1000 \times C_{36}^2$) pairwise video comparisons. From this extensive dataset, we randomly sample 30,000 pairs for evaluation from four perspectives. Each pair is judged by three annotators, and the final decision of the better video in each pair is determined by the majority vote. Finally, we obtain a total of 46,080 reliable score ratings (20 annotators $\times$ 4 perspectives $\times$ 576 videos) and 360,000 pair ratings (3 annotators $\times$ 4 perspectives $\times$ 30,000 pairs).

3.4. AIGV Analysis from Four Perspectives

As shown in Figure 2, the videos in the AIGVQA-DB cover a wide range of perceptual quality. We further analyze the win rates of various generation models across categories in Figure 3, revealing the strengths and weaknesses of each T2V model. As shown in Figure 3(a), the performances of T2V models rank uniform for different prompt complexity items in terms of static quality, which manifests current T2V model rank consistently for different prompts, likely due to shared architectures like diffusion-based systems, with common strengths and limitations in handling complex prompts. As shown in Figure 3(b), in terms of attribute control, StableVideoDiffusion [9] excels in managing quantity over event order, as it first generates static images before animating them, preserving the original event sequence. As shown in Figure 3(d), in terms of spatial content, most videos featuring "plants" and "people" show poor T2V correspondence. More comparison and analysis can be found in the *supplementary material.* We also launch comparisons among text-to-video generation models regarding the MOS and pairwise win rates shown in Figure 4. Notably, models such as LVDM [21] demonstrate exceptional performance in handling dynamic content, but exhibit relatively lower performance in temporal smoothness. Sora [7] and MorphStudio [6] perform well in static quality and temporal smoothness while lagging in dynamic degree. Additionally, closed-source models exhibit much better performance compared to open-source models.

4. Proposed Method

4.1. Model Structure

Spatial and Temporal Vision Encoder. As shown in Figure 5(a), the model leverages two different types of encoders to capture the spatial and temporal characteristics of the video: (1) 2D Encoder: A pre-trained 2D vision transformer (InternViT [69]) is used to process individual video frames. (2) 3D Encoder: A 3D network, *i.e.,* SlowFast [19], is employed to extract temporal features by processing sequences of video frames.

Spatiotemporal Projection Module. Once the spatial and temporal features are extracted, they are projected into a

Table 3. Performance comparisons of the state-of-the-art quality evaluation methods on the AIGVQA-DB from four perspectives. The best performance results are marked in **RED** and the second-best performance results are marked in **BLUE**.

Dimension	Static Quality				Temporal Smoothness				Dynamic Degree				TV Correspondence			
Methods / Metrics	Pair Acc	SRCC	PLCC	KRCC	Pair Acc	SRCC	PLCC	KRCC	Pair Acc	SRCC	PLCC	KRCC	Pair Acc	SRCC	PLCC	KRCC
NIQE [49]	54.32%	0.0867	0.1626	0.0615	52.67%	0.0641	0.1152	0.0451	45.64%	0.1765	0.2448	0.1194	46.99%	0.1771	0.2231	0.1193
QAC [80]	49.96%	0.1022	0.1363	0.0680	54.90%	0.1633	0.2039	0.1105	54.72%	0.0448	0.0427	0.0295	54.48%	0.0303	0.0197	0.2233
BRISQUE [48]	59.98%	0.2909	0.2443	0.1969	55.67%	0.2325	0.1569	0.1553	44.60%	0.1351	0.0959	0.0893	51.02%	0.1294	0.1017	0.0869
BPRI [46]	52.28%	0.2181	0.1723	0.1398	47.26%	0.1766	0.0880	0.1138	46.83%	0.1956	0.1688	0.1329	49.13%	0.1569	0.1548	0.1052
HOSA [77]	61.54%	0.2420	0.2106	0.1643	57.31%	0.2311	0.1757	0.1559	44.97%	0.0755	0.0449	0.0496	52.23%	0.1645	0.1324	0.1097
BMPRI [47]	53.71%	0.1690	0.1481	0.1075	49.31%	0.1434	0.0844	0.0894	45.07%	0.1153	0.0925	0.0777	48.43%	0.1567	0.1500	0.1041
V-Dynamic [25]	51.34%	0.0768	0.0792	0.0494	31.91%	0.3713	0.4871	0.2557	53.11%	0.1466	0.0253	0.0988	46.96%	0.0405	0.0576	0.0223
V-Smoothness [25]	61.63%	0.6748	0.4506	0.4590	76.59%	0.8526	0.8313	0.6533	47.63%	0.2446	0.2328	0.1580	61.28%	0.3188	0.3073	0.2214
CLIPScore [22]	47.09%	0.0731	0.0816	0.0473	46.33%	0.0423	0.0334	0.0271	52.99%	0.0675	0.0835	0.0439	55.62%	0.1519	0.1731	0.1014
BLIPScore [37]	53.24%	0.0492	0.0421	0.0330	53.07%	0.0659	0.0487	0.0437	53.03%	0.1786	0.1904	0.1205	61.53%	0.1813	0.1896	0.1219
AestheticScore [53]	70.24%	0.6713	0.6959	0.4784	54.82%	0.5154	0.4946	0.3484	52.96%	0.2295	0.2322	0.1527	59.64%	0.2381	0.2440	0.1602
ImageReward [78]	56.69%	0.2606	0.2646	0.1749	54.09%	0.2382	0.2305	0.1600	53.90%	0.1840	0.1836	0.1237	63.97%	0.2311	0.2450	0.1568
UMTScore [43]	48.93%	0.0168	0.0199	0.0117	49.93%	0.0302	0.0370	0.0207	52.69%	0.0168	0.0198	0.0117	53.82%	0.0172	0.0065	0.0108
Video-LLaVA [40]	50.90%	0.0384	0.0513	0.0297	50.36%	0.0431	0.0281	0.0347	50.34%	0.1561	0.1436	0.1176	50.54%	0.1364	0.1051	0.1009
Video-ChatGPT [45]	51.20%	0.1242	0.1587	0.0940	50.16%	0.0580	0.0533	0.0453	50.47%	0.0724	0.0436	0.0563	50.07%	0.0357	0.0124	0.0274
LLaVA-NeXT [36]	52.85%	0.1239	0.1625	0.0954	52.41%	0.4021	0.3722	0.3052	51.84%	0.1767	0.1655	0.1328	59.20%	0.4116	0.3428	0.3261
VideoLLaMA2 [14]	52.73%	0.2643	0.3271	0.1928	52.27%	0.3608	0.2450	0.2696	50.78%	0.1900	0.1561	0.1379	54.25%	0.1656	0.1633	0.1210
Qwen2-VL [66]	56.50%	0.4922	0.5291	0.3838	49.12%	0.1681	0.4219	0.1233	52.08%	0.1122	0.1335	0.0849	53.30%	0.3111	0.2775	0.2306
HyperIQA [56]	68.30%	0.7931	0.8093	0.5969	54.65%	0.7426	0.6630	0.5407	53.32%	0.2103	0.2100	0.1384	57.54%	0.6226	0.6250	0.4432
MUSIQ [26]	66.46%	0.7880	0.8044	0.5773	55.16%	0.7199	0.6920	0.5034	52.85%	0.5206	0.4846	0.3521	58.46%	0.4125	0.4093	0.2844
LIQE [83]	63.86%	0.8776	0.8691	0.7008	55.84%	0.7935	0.7720	0.6084	49.02%	0.5303	0.5840	0.3837	55.10%	0.3862	0.3639	0.2640
VSFA [35]	46.43%	0.3365	0.3421	0.2268	50.95%	0.3317	0.3273	0.2202	51.46%	0.1201	0.1362	0.0815	48.07%	0.1024	0.1064	0.0666
BVQA [33]	29.98%	0.4594	0.4701	0.3268	37.65%	0.3704	0.3819	0.2507	**55.08%**	0.4594	0.4701	0.3268	42.32%	0.3720	0.3978	0.2559
simpleVQA [57]	68.12%	0.8355	0.6438	0.8489	54.14%	0.7082	0.7008	0.4978	53.08%	0.4671	0.3160	**0.3994**	58.20%	0.4643	0.5440	0.3163
FAST-VQA [70]	70.64%	0.8738	0.8644	0.6860	**62.93%**	0.9036	0.9134	0.7166	54.34%	0.5603	**0.5703**	0.3895	**65.05%**	**0.6875**	**0.6704**	**0.4978**
DOVER [71]	**72.92%**	**0.8907**	**0.8895**	**0.7004**	58.83%	**0.9063**	**0.9195**	**0.7187**	53.16%	0.5549	0.5489	0.3800	62.35%	0.6783	0.6802	0.4969
Q-Align [72]	71.86%	0.8516	0.8383	0.6641	57.95%	0.8116	0.7025	0.6195	53.71%	**0.5655**	0.5012	0.3950	62.91%	0.5542	0.5647	0.3870
AIGV-Assessor (Ours)	**79.83%**	**0.9162**	**0.9190**	**0.7576**	**76.60%**	**0.9232**	**0.9216**	**0.8038**	**60.30%**	**0.6093**	**0.6082**	**0.4435**	**70.32%**	**0.7500**	**0.7697**	**0.5591**
Improvement	+ 6.9%	+2.7%	+3.0%	+ 5.7%	13.7%	+1.7%	+0.2%	+8.5%	+5.2%	+4.4%	+3.8%	+ 4.4%	+5.3%	+6.3%	+9.9%	+6.13%

shared feature space for alignment with text-based queries. This is done through two projection modules that map the spatial and temporal visual features respectively into the language space. The mapped visual tokens are aligned with text tokens, enabling the model to query the video content in a multimodal fashion.

Feature Fusion and Quality Regression. We apply LLM (InternVL2-8B [69]) to combine the visual tokens and user-provided quality prompts to perform the following tasks: (1) Quality level descriptions: the model generates a descriptive quality level evaluation of the input video, such as "The static quality of the video is (bad, poor, fair, good, excellent)." This initial categorization provides a preliminary classification of the video's quality, which is beneficial for subsequent quality regression tasks. By obtaining a rough quality level, the model can more accurately predict numerical scores in later evaluations. (2) Regression score output: the model uses the final hidden states from the LLM to perform a regression task, outputting numerical quality scores for the video from four different dimensions.

4.2. Training and Fine-tuning Strategy

The training process of AIGV-Assessor follows a three-stage approach to ensure high-quality video assessment with quality level prediction, individual quality scoring, and pairwise preference comparison capabilities. This process includes: (1) training the spatial and temporal projectors to align visual and language features, (2) fine-tuning the vision encoder and LLM with LoRA [24], and training the quality regression module to generate accurate quality scores, (3) incorporating pairwise comparison training using the pair-comparison subset with a pairwise loss function for robust video quality comparison.

Spatiotemporal Projector Training. The first stage focuses on training the spatial and temporal projectors to extract meaningful spatiotemporal visual features and map them into the language space. Through this process, the LLM is able to produce the quality level descriptions *i.e.,* bad, poor, fair, good, excellent.

Quality Regression Fine-tuning. Once the model can generate coherent descriptions of video quality level, the second stage focuses on fine-tuning the quality regression module. The goal here is to enable the model to output stable and precise numerical quality scores (MOS-like predictions). The quality regression model takes the last-hidden-state features from LLM as input and generates quality scores from four perspectives. The training objective uses an L1 loss function to minimize the difference between the predicted quality score and the groundtruth MOS.

Pairwise Comparison Fine-tuning. The third stage mainly focuses on integrating the pairwise comparison into the training pipeline. As shown in Figure 5(b), two input video pairs share network weights within the same batch. We design a judge network inspired by LPIPS [82] to determine which video performs better. This network leverages

Table 4. Performance comparisons on LGVQ [84] and FETV [43].

Aspects	Methods	LGVQ			FETV		
		SRCC	PLCC	KRCC	SRCC	PLCC	KRCC
Spatial	MUSIQ [26]	0.669	0.682	0.491	0.722	0.758	0.613
	StairIQA [59]	0.701	0.737	0.521	0.806	0.812	0.643
	CLIP-IQA [62]	0.684	0.709	0.502	0.741	0.767	0.619
	LIQE [83]	0.721	0.752	0.538	0.765	0.799	0.635
	UGVQ [84]	**0.759**	**0.795**	**0.567**	**0.841**	**0.841**	**0.685**
	AIGV-Assessor (Ours)	**0.803**	**0.819**	**0.617**	**0.853**	**0.856**	**0.699**
	Improvement	+ 4.4%	+2.4%	+5.0%	+1.2%	+1.5%	+1.4%
Temporal	VSFA [35]	0.841	0.857	0.643	0.839	0.859	0.705
	SimpleVQA [57]	0.857	0.867	0.659	0.852	0.862	0.726
	FastVQA [70]	0.849	0.843	0.647	0.842	0.847	0.714
	DOVER [71]	0.867	0.878	0.672	0.868	0.881	0.731
	UGVQ [84]	**0.893**	**0.907**	**0.703**	**0.897**	**0.907**	**0.753**
	AIGV-Assessor (Ours)	**0.900**	**0.920**	**0.717**	**0.936**	**0.940**	**0.815**
	Improvement	+0.7%	+1.3%	+1.4%	+3.9%	+3.3%	+6.2%
Alignment	CLIPScore [22]	0.446	0.453	0.301	0.607	0.633	0.498
	BLIPScore [37]	0.455	0.464	0.319	0.616	0.645	0.505
	ImageReward [78]	0.498	0.499	0.344	0.657	0.687	0.519
	PickScore [28]	0.501	0.515	0.353	0.669	0.708	0.533
	HPSv2 [74]	0.504	0.511	0.357	0.686	0.703	0.540
	UGVQ [84]	**0.551**	**0.555**	**0.394**	**0.734**	**0.737**	**0.572**
	AIGV-Assessor (Ours)	**0.577**	**0.578**	**0.411**	**0.753**	**0.746**	**0.585**
	Improvement	+2.6%	+2.3%	+1.7%	+1.9%	+0.9%	+1.3%

learned features and evaluates the perceptual differences between the two videos, allowing more reliable quality assessments in video pair comparison.

Loss Function. In the first stage, the spatial and temporal projectors are trained to align visual and language features using language loss. The second stage refines the vision encoder, LLM, and quality regression module's scoring ability with an L1 loss. The third stage incorporates pairwise comparison training with cross-entropy loss to improve the model's performance on relative quality evaluation.

5. Experiments

5.1. Experiment Settings

Evaluation Datasets and Metrics. Our proposed method is validated on five AIGVQA datasets: AIGVQA-DB, LGVQ [84], FETV [43], T2VQA [31], and GAIA [13]. To evaluate the correlation between the predicted scores and the ground-truth MOSs, we utilize three evaluation criteria: Spearman Rank Correlation Coefficient (SRCC), Pearson Linear Correlation Coefficient (PLCC), and Kendall's Rank Correlation Coefficient (KRCC). For pair comparison, we adopt the comparison accuracy as the metric.

Reference Algorithms. To assess the performance of our proposed method, we select state-of-the-art evaluation metrics for comparison, which can be classified into five groups: (1) Handcrafted-based I/VQA models, including: NIQE [49], BRISQUE [48], QAC [80], BMPRI [47], HOSA [77], BPRI [46], HIGRADE [32], *etc.* (2) Action-related evaluation models, including: V-Dynamic [25], V-Smoothness [25] which are proposed in VBench [25]. (3) Vision-language pre-training models, including: CLIPScore [22], BLIPScore [37], AestheticScore [53], ImageReward [78], and UMTScore [43]. (4) LLM-based models, including: Video-LLaVA [40], Video-ChatGPT [45], LLaVA-NeXT [36], VideoLLaMA2 [14], and Qwen2-VL [66]. (5) Deep learning-based I/VQA models, including: HyperIQA [56], MUSIQ [26], LIQE [83], VSFA [35], BVQA [33], SimpleVQA [58], FAST-VQA [70], DOVER [71], and Q-Align [72].

Table 5. Performance comparisons on T2VQA-DB [31].

Aspects	Methods	T2VQA-DB			Sora Testing		
		SRCC	PLCC	KRCC	SRCC	PLCC	KRCC
zero-shot	CLIPScore [22]	0.1047	0.1277	0.0702	0.2116	0.1538	0.1406
	BLIPScore [37]	0.1659	0.1860	0.1112	0.2116	0.1038	0.1515
	ImageReward [78]	0.1875	0.2121	0.1266	0.0992	0.0415	0.0748
	UMTScore [43]	0.0676	0.0721	0.0453	0.2594	0.0840	0.1680
finetuned	SimpleVQA [57]	0.6275	0.6388	0.4466	0.0340	0.2344	0.0237
	BVQA [37]	0.7390	0.7486	0.5487	0.4235	0.2489	0.2635
	FAST-VQA [70]	0.7173	0.7295	0.5303	0.4301	0.2369	0.2939
	DOVER [71]	0.7609	0.7693	0.5704	0.4421	0.2689	0.2757
	T2VQA [31]	**0.7965**	**0.8066**	**0.6058**	**0.6485**	**0.3124**	**0.4874**
	AIGV-Assessor (Ours)	**0.8131**	**0.8222**	**0.6364**	**0.6612**	**0.3318**	**0.5075**
	Improvement	+ 1.7%	+1.6%	+3.1%	+1.3%	+1.9%	+2.0%

Table 6. Performance comparisons on GAIA [13].

Dimension	Subject		Completeness		Interaction	
Methods / Metrics	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
V-Smoothness [25]	0.2402	0.1913	0.1474	0.1625	0.1741	0.1693
V-Dynamic [25]	0.1285	0.0831	0.0903	0.0682	0.1141	0.0758
Action-Score [42]	0.2023	0.1823	0.2867	0.2623	0.2689	0.2432
Flow-Score [42]	0.1471	0.1541	0.0816	0.1273	0.1041	0.1309
CLIPScore [22]	0.3398	0.3330	0.3944	0.3871	0.3875	0.3821
BLIPScore [37]	0.3453	0.3386	0.4174	0.4082	0.4044	0.3994
LLaVAScore [41]	0.3484	0.3436	0.4189	0.4133	0.4077	0.4025
TLVQM [30]	0.5037	0.5137	0.4127	0.4158	0.4079	0.4093
VIDEVAL [60]	0.5237	0.5446	0.4283	0.4375	0.4121	0.4234
VSFA [35]	0.5594	0.5762	0.4940	0.5017	0.4709	0.4811
BVQA [37]	0.5702	0.5888	0.4876	0.4946	0.4761	0.4825
SimpleVQA [58]	0.5920	0.5974	0.4981	0.5078	0.4843	0.4971
FAST-VQA [70]	0.6015	0.6092	0.5157	0.5215	0.5154	0.5216
DOVER [71]	**0.6173**	**0.6301**	**0.5198**	**0.5323**	**0.5164**	**0.5278**
AIGV-Assessor (Ours)	**0.6842**	**0.6897**	**0.6635**	**0.6694**	**0.6329**	**0.6340**
Improvement	+6.7%	+6.0%	+14.4%	+13.7%	+11.65%	+10.6%

Training Settings. Traditional handcrafted models are directly evaluated on the corresponding databases, and the average score of all frames is calculated. For vision-language pre-training and LLM-based models, we load the pre-trained weights for inference. CLIPscore [22], BLIPscore [37], and other vision-language pre-training models are calculated directly as the average cosine similarity between text and each video frame. SimpleVQA [58], BVQA [33], FAST-VQA [70], DOVER [71], and Q-Align [72] are fine-tuned on every test dataset. For deep learning-based IQA and VQA models, all experiments for each method are retrained on each dimension using the same training and testing split as the previous literature at a ratio of 4:1. All results are averaged after ten random splits.

5.2. Results and Analysis

Table 3 presents the pairwise win rates and the score prediction correlation between predicted results and human ground truths. The results indicate that handcrafted-based methods consistently underperform across all four evalu-

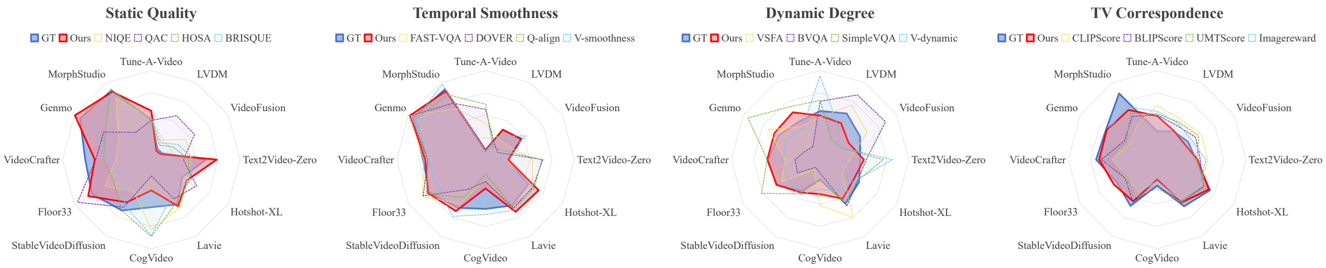


Figure 6. Comparison of win rates of different generation models across four dimensions evaluated by different VQA methods, demonstrating our AIGV-Assessor has better win-rate evaluation ability aligned with Ground Truth (GT).

Table 7. Ablation study of the proposed AIGV-Assessor method.

	Feature & Strategy				Static Quality			Temporal Smoothness			Dynamic Degree			T2V Correspondence		
No.	spatial	temporal	quality level	LoRA finetuning	SRCC	PLCC	KRCC	SRCC	PLCC	KRCC	SRCC	PLCC	KRCC	SRCC	PLCC	KRCC
(1)	✔		✔		0.864	0.866	0.726	0.870	0.868	0.727	0.556	0.572	0.432	0.616	0.620	0.492
(2)	✔			✔	0.874	0.876	0.723	0.875	0.876	0.736	0.558	0.573	0.431	0.723	0.734	0.533
(3)	✔		✔	✔	0.887	0.884	0.722	0.881	0.883	0.706	0.562	0.575	0.433	0.739	0.758	0.544
(4)	✔	✔	✔		0.887	0.888	0.753	0.917	0.910	0.796	0.569	0.536	0.438	0.688	0.673	0.557
(5)	✔	✔		✔	0.905	0.908	0.754	0.919	0.917	0.799	0.589	0.587	0.441	0.742	0.763	0.549
(6)	✔	✔	✔	✔	**0.916**	**0.919**	**0.758**	**0.923**	**0.922**	**0.804**	**0.609**	**0.608**	**0.444**	**0.750**	**0.770**	**0.559**

ation perspectives. Vision-language pre-training methods such as CLIPscore [22] and BLIPscore [37] demonstrate moderate performance but are still surpassed by more specialized and fine-tuned VQA models. Specifically, deep learning-based models like FAST-VQA [70] and DOVER [71] achieve more competitive performances after fine-tuning. However, they are still far away from satisfactory. Notably, most VQA models perform better on quality evaluation than on text-video correspondence, as they lack text prompts input used in video generation, making it challenging to extract relation features from the AI-generated videos, which inevitably leads to the performance drop. Finally, the performance exploration of recent LMMs on our database shows that current LMMs are able to produce meaningful evaluations, which can motivate future works to further explore the use of LMMs for AIGV assessment.

The proposed AIGV-Assessor achieves the best performance compared to the competitors for both MOS prediction and pair ranking tasks in terms of all four dimensions. To further validate the effectiveness and generalizability of our proposed model, we also evaluate it on four other AIGVQA datasets [13, 31, 43, 84]. From Tables 4-6, we observe that AIGV-Assessor consistently achieves the best performance across these datasets. As shown in Figure 6, AIGV-Assessor achieves the highest overlap in area with Ground Truth (GT), indicating that AIGV-Assessor can reliably perform T2V model benchmarking, outperforming other assessment models in discerning quality differences in AI-generated videos.

5.3. Ablation Study

We conduct ablation experiments to verify the effectiveness of the main components in our AIGV-Assessor method, including the spatial feature, the temporal feature, the quality level, and the LoRA finetuning strategy. Additionally, we assess how each feature contributes to the performance across different quality dimensions. The results of these experiments are summarized in Table 7. Experiments (1), (2), and (3) validate the effectiveness of the quality regression module and the LoRA finetuning strategy, confirming that fine-tuning and quality regression significantly enhance model performance over only regressing the generated text outputs from the LLM. The addition of temporal features, as seen in Experiments (4), (5), and (6), significantly improves model performance. Experiment (6), which integrates all components, yields the best overall performance, showing that the combination of spatial and temporal features, quality level prediction, and LoRA finetuning provides the most robust and accurate AIGV assessment.

6. Conclusion

In this paper, we study the human visual preference evaluation problem for AIGVs. We first construct AIGVQA-DB, which includes 36,576 videos generated based on 1048 various text-prompts, with the MOSs and pair comparisons evaluated from four perspectives. Our detailed manual evaluations reflect different aspects of human visual preferences on AIGVs and reveal critical insights into the strengths and weaknesses of various text-to-video models. Based on the database, we evaluate the performance of state-of-the-art quality evaluation models and establish a new benchmark, revealing their limitations in measuring the perceptual preference of AIGVs. Finally, we propose AIGV-Assessor, a novel VQA model that leverages the capabilities of LMMs to give quality levels, predict quality scores, and compare preferences from four dimensions. Extensive experiments demonstrate that AIGV-Assessor achieves state-of-the-art performance on both AIGVQA-DB and other AIGVQA benchmarks, validating its robustness in understanding and evaluating the AI-generated videos.

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