702 APPENDIX 703

A DETAILED EVALUATION RESULTS ON EXISTING HALLUCINATION BENCHMARKS

We provide the detailed evaluation results of open-source LVLMs on existing hallucination benchmarks in Table 6. Additionally, the complete evaluation results of Table 2 and Table 3 are presented in Table 7 and Table 8, respectively.

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Table 6: Evaluation results of open-source LVLMs on existing hallucination benchmarks. * represents the evaluation metric used in our quality measurement. Acc denotes the accuracy, A-Score and R-Score denotes the accuracy and relevancy hallucination score in GAVIE. The top-2 results are bolded and <u>underlined</u>, respectively.

716	Model	POPE	AMBER-d	HallusionBench	AMBER-g	OpenCHIAR	MMHal	GAV	/IE
717	hidder	$\mathbf{Acc}\uparrow^*$	Acc↑*	$\mathbf{Acc}\uparrow^*$	$\mathbf{CHAIR}{\downarrow}^*$	$\mathbf{OCH} \downarrow^*$	Score↑*	A-Score↑*	R-Score [↑]
718	BLIP2-OPT-3B	0.607	0.584	0.425	0.035	0.431	2.042	6.487	6.230
	BLIP2-OPT-7B	0.602	0.571	0.425	0.037	0.376	2.552	6.974	6.592
719	BLIP2-Flan-T5-XL	0.771	0.768	0.589	0.033	0.258	3.125	6.277	5.411
720	InstructBLIP-Flan-T5-XL	0.821	0.780	0.547	0.071	0.487	3.177	7.265	6.614
120	InstructBLIP-Flan-T5-XXL	0.807	0.802	0.535	0.151	0.525	3.552	7.285	6.879
721	InstructBLIP-Vicuna-13B	0.832	0.801	0.506	0.190	0.510	3.531	7.272	6.757
700	InstructBLIP-Vicuna-7B	0.831	0.753	0.480	0.085	0.470	3.635	7.250	6.740
122	InternLM-XComposer-VL-7B	0.818	0.777	0.552	0.109	0.470	3.156	6.647	5.807
723	LLaVa-1.5-13B	0.827	0.801	0.525	0.067	0.486	3.688	7.657	7.400
120	LLaVa-1.5-7B	0.815	0.744	0.532	0.075	0.496	3.823	7.670	7.404
724	MiniGPT4-LLaMa-2	0.548	0.461	0.445	0.186	0.546	3.292	7.369	7.121
705	MiniGPT4-Vicuna-13B	0.553	0.605	0.396	0.162	0.547	3.552	6.966	6.641
720	MiniGPT4-Vicuna-7B	0.548	0.622	0.450	0.170	0.558	3.177	6.925	6.693
726	MiniGPT-v2	0.794	0.702	0.489	0.153	0.497	3.281	7.593	7.299
	MiniGPT-v2-Grounding	-	-	-	0.096	0.463	-	-	-
727	MiniGPT-v2-VQA	0.807	0.724	0.507	-	-	2.833	6.114	5.379
728	Otter	0.661	0.595	0.434	0.102	0.493	3.042	7.191	6.944
120	Qwen-VL	0.791	0.761	0.574	0.026	0.243	3.333	6.038	5.231
729	Shikra-7B	0.798	0.803	0.382	0.089	0.489	2.688	7.282	7.030
730	Shikra-7B-VQA	0.830	0.781	0.505	-	-	2.958	6.513	5.856

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Table 7: Evaluation results on POPE, AMBER-d and HallusionBench under original test and parallel
test. Yes(%) denotes the proportion of responses answering "*yes*" to the given question. -p denotes
the results under parallel test.

736	Model	P	OPE	РО	PE-p	AM	BER-d	AMB	ER-d-p	Hallusi	onBench	Hallusi	onBench-p
737	mouti	Acc ↑	Yes(%)	$Acc \uparrow$	Yes(%)	$Acc \uparrow$	Yes(%)	Acc ↑	Yes(%)	$Acc \uparrow$	Yes(%)	Acc ↑	Yes(%)
151	Ground Truth	-	0.333	-	0.667	-	0.5	-	0.5	-	0.429	-	0.571
738	BLIP2-OPT-3B	0.584	0.608	0.385	0.303	0.605	0.691	0.465	0.183	0.425	0.821	0.521	0.611
700	BLIP2-OPT-7B	0.571	0.711	0.390	0.545	0.602	0.760	0.405	0.300	0.425	0.857	0.509	0.666
739	BLIP2-Flan-T5-XL	0.768	0.299	0.698	0.847	0.771	0.326	0.754	0.691	0.589	0.209	0.525	0.476
740	InstructBLIP-Flan-T5-XL	0.780	0.383	0.728	0.785	0.821	0.439	0.812	0.596	0.547	0.408	0.571	0.550
140	InstructBLIP-Flan-T5-XXL	0.802	0.417	0.751	0.799	0.807	0.430	0.795	0.651	0.535	0.537	0.590	0.716
741	InstructBLIP-Vicuna-13B	0.801	0.345	0.355	0.039	0.833	0.460	0.499	0.012	0.506	0.704	0.474	0.352
740	InstructBLIP-Vicuna-7B	0.753	0.409	0.371	0.344	0.831	0.479	0.368	0.499	0.480	0.704	0.538	0.690
742	InternLM-XComposer-VL-7B	0.777	0.341	0.736	0.551	0.818	0.520	0.773	0.553	0.552	0.465	0.491	0.441
743	LLaVa-1.5-13B	0.801	0.380	0.704	0.738	0.827	0.439	0.802	0.581	0.525	0.604	0.543	0.516
740	LLaVa-1.5-7B	0.744	0.364	0.527	0.534	0.815	0.478	0.569	0.439	0.532	0.593	0.488	0.458
744	MiniGPT4-LLaMa-2	0.461	0.783	0.538	0.706	0.548	0.883	0.463	0.818	0.445	0.709	0.479	0.538
745	MiniGPT4-Vicuna-13B	0.605	0.344	0.425	0.357	0.553	0.538	0.465	0.521	0.396	0.699	0.400	0.510
745	MiniGPT4-Vicuna-7B	0.622	0.251	0.398	0.217	0.548	0.202	0.497	0.184	0.450	0.340	0.424	0.294
7/6	MiniGPT-v2	0.702	0.389	0.387	0.368	0.794	0.475	0.386	0.345	0.489	0.596	0.513	0.494
740	MiniGPT-v2-VQA	0.724	0.360	0.397	0.370	0.807	0.448	0.366	0.371	0.507	0.605	0.508	0.539
747	Otter	0.595	0.715	0.438	0.756	0.661	0.759	0.461	0.804	0.434	0.856	0.527	0.804
	Qwen-VL	0.761	0.193	0.440	0.220	0.791	0.325	0.500	0.021	0.574	0.409	0.453	0.258
748	Shikra-7B	0.803	0.216	0.376	0.253	0.798	0.384	0.401	0.191	0.382	0.633	0.363	0.376
749	Shikra-7B-VQA	0.781	0.373	0.503	0.483	0.830	0.439	0.564	0.329	0.505	0.622	0.480	0.459

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B CONSTRUCTION OF PARALLEL-FORMS BENCHMARKS

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We construct the parallel-forms benchmarks by generating equivalent prompts for different tasks.
 In detail, yes-or-no questions are rewritten into negative forms with opposite ground truth answers.
 Multiple-choice questions are reconstructed with randomly shuffled options. Prompts for image

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757	Table 8: Evaluation results on AMBER-g and OpenCHAIR under original test and parallel test. Avg
758	Len denotes the average length of model responses, i.e., the average number of wordsp denotes the
759	results under parallel test.

Model	AMBER-g AMBER-g-p OpenCHAIR Op		Open					
	$\mathbf{CHAIR}\downarrow$	Avg Len	$\mathbf{CHAIR}\downarrow$	Avg Len	$\mathbf{OCH} \downarrow$	Avg Len	$\mathbf{OCH} \downarrow$	
LIP2-OPT-3B	0.035	10.25	0.065	24.74	0.431	60.86	0.456	
IP2-OPT-7B	0.037	9.66	0.096	18.37	0.376	21.85	0.395	
IP2-Flan-T5-XL	0.033	9.11	0.041	10.57	0.258	11.01	0.265	
tructBLIP-Flan-T5-XL	0.071	72.42	0.040	10.57	0.487	104.46	0.272	
structBLIP-Flan-T5-XXL	0.151	104.66	0.037	10.37	0.525	103.07	0.261	
structBLIP-Vicuna-13B	0.190	106.98	0.033	11.47	0.510	100.18	0.271	
structBLIP-Vicuna-7B	0.085	80.53	0.031	10.66	0.470	93.04	0.265	
ternLM-XComposer-VL-7H	B 0.109	56.44	0.044	22.53	0.470	64.33	0.433	
LaVa-1.5-13B	0.067	74.46	0.071	72.18	0.486	86.04	0.478	
LaVa-1.5-7B	0.075	74.82	0.075	70.60	0.496	86.12	0.489	
liniGPT4-LLaMa-2	0.186	58.99	0.180	54.53	0.546	62.73	0.551	
iniGPT4-Vicuna-13B	0.162	95.15	0.162	91.06	0.547	96.35	0.555	
1iniGPT4-Vicuna-7B	0.170	64.15	0.177	58.37	0.558	81.68	0.568	
liniGPT-v2	0.153	83.09	0.133	74.02	0.497	76.32	0.494	
/iniGPT-v2-Grounding	0.096	26.04	0.091	25.48	0.463	25.44	0.463	
Otter	0.102	47.15	0.128	63.46	0.493	55.94	0.506	
Jwen-VL	0.026	10.23	0.017	6.21	0.243	9.64	0.241	
hikra-7B	0.089	73.78	0.087	71.97	0.489	79.85	0.448	
Q: Is there a dog	in the image?	11	Q:	Is there no c	log in the i	mage?		
GT: Yes.			Ŭ ĜĨ	No.				
			\neg					
Multip O: How many d	le-choice Ques	stion mage?	0.	Mult What is the	iple-choice	Question	image?	
(A) One. (B)	Two. (C) Thre	ee. (D) Four	. Q .	(A) Four. (B) Two. (C) One. (D) Three.				
GT: (A)			GI	Г: (C)				
			\neg $-$					
Im	age Captionin	g		Iı	nage Capt	ioning		
Q: Describe the	mage.		Q:	Provide a de	escription of	of the image		
Fi	ee-form VQA		\neg	1	Free-form	VQA		
Q: What is the w	eather like in t	he image?	Q:	How to des	cribe the w	eather in the	e image?	
Figure	6: Example	s of paral	lel-forms	prompts i	for differ	ent tasks	•	

captioning and free-form VQA are rephrased into synonymous expressions. Examples of the parallelforms equivalent prompts are shown in Figure 6.

C DETAILS OF HUMAN EVALUATION

As mentioned in Section 3.2, we randomly select 100 image-instruction pairs from each hallucination benchmark and manually review the responses of all models. The human evaluation is carried out by human evaluators specializing in NLP. The evaluation for one benchmark takes about 3 hours to complete on average. We provide instructions for the human evaluators as follows:

"Given the instruction and the image, please determine whether the response provided by a Large
Vision-Language Model (LVLM) contains any hallucination. Hallucination here refers to the situation that the response is inconsistent with the input image."

EXAMPLES OF EXISTING HALLUCINATION BENCHMARK EVALUATION D

We provide an evaluation example for each existing hallucination benchmark in Figure 7, 9, 10, 11, 12, 13.

Ε **EXAMPLES OF FILTERED LOW-QUALITY IMAGE-INSTRUCTION PAIRS**

In the construction of HQH, we manually review and remove the low-quality samples in all candidate image-instruction pairs. The examples of filtered data are illustrated in Figure 14, 15.

COMPARISON OF BENCHMARK SIZES FOR OPEN-ENDED TASKS F

Table 9 presents a comparison of the sizes of HQH and existing open-ended benchmarks, where HQH stands as the largest.

	Benchmark	Size (Number of Samples)
Table 9:	Comparison of	Benchmark Sizes for Open-Ended Tasks

	» (- (- (p »)
AMBER-g	1004
OpenCHAIR	2000
MMHal	96
GAVIE	1000
HQH (Ours)	4000

MORE EVALUATION RESULTS ON HQH G

We conduct a more extensive evaluation of several other open-source LVLMs on HQH. The results are presented in Table 10, showing that some of these models perform exceptionally well, particularly GLM-4V and Qwen2-VL.

Table 10: More extensive evaluation results of open-source LVLMs on HQH.

Model	Hallucination Rate \downarrow									
nouci	Attribute	Action	Counting	Environment	Comparison	Relation	OCR	Existence	Overall	
InterVL2	0.253	0.332	0.446	0.328	0.394	0.454	0.400	0.644	0.406	
LLaVa-OneVision	0.134	0.348	0.168	0.204	0.390	0.436	0.252	0.366	0.287	
Qwen2-VL	0.134	0.080	0.150	0.230	0.176	0.228	0.220	0.344	0.195	
GLM-4V	0.098	0.068	0.158	0.100	0.162	0.306	0.154	0.286	0.167	
InternLM-XComposer2-VL	0.118	0.110	0.174	0.120	0.251	0.350	0.226	0.528	0.235	
MiniCPM-Llama2-v2.5	0.138	0.126	0.198	0.250	0.238	0.316	0.210	0.646	0.265	
mPLUG-Owl2	0.268	0.296	0.432	0.332	0.455	0.554	0.504	0.598	0.430	
Phi-3-Vision	0.162	0.134	0.218	0.172	0.315	0.378	0.222	0.384	0.248	
Yi-VL	0.258	0.382	0.482	0.438	0.531	0.528	0.570	0.670	0.482	

DISCUSSION ON POTENTIAL DATA LEAKAGE Η

To assess the potential risk of data leakage, we apply the Multimodal Leakage (ML) metric (Chen et al., 2024), which is designed to quantify the extent of data leakage in multimodal benchmarks. Specifically, ML calculates the difference in scores between an LVLM without visual inputs and its LLM base (without multimodal training) under the given benchmark. Higher ML value indicates more potential data leakage, as it suggests that the model performance without visual input surpasses that of its unimodal base, likely due to exposure to evaluation samples during multimodal training. Conversely, an ML value close to 0 indicates no data leakage.

We calculate ML for the top-performing models on our HQH benchmark, as shown in Table 11. For comparison, we include ML of other benchmarks as reported by Chen et al. (2024). The results show

that HQH achieves lower average ML across models compared to other benchmarks, demonstrating that HQH has minimal data leakage.

Additionally, our HQH is relatively challenging, as most models perform poorly, which further supports that our benchmark effectively differentiates models and avoids inflating performance due to potential data leakage.

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Table 11: Multimodal Leakage↓ (%) of LVLMs on HQH and other benchmarks. For closed-source models, we compare the results of GPT-4V and Gemini-Vision-Pro as reported by Chen et al. (2024).

Model	HQH	SEEDBench	MMBench	ScienceQA
LLaVA-1.5-13b	1.0	10.7	9.8	7.0
LLaVA-1.5-7b	0.8	4.9	9.2	5.2
Qwen-VL	2.3	11.9	0.3	4.0
Gemini-1.5-Pro	1.5	0.0	0.0	0.0
GPT-40	0.7	18.3	5.4	3.9
Average	0.5	5.4	3.8	1.7

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I DISCUSSION ON HQH EVALUATION

In our HQH evaluation, we provide GPT with textual image information based on annotations from Visual Genome, asking GPT to extract key information from the comprehensive textual descriptions and assess whether the model's responses align with the information. In this section, we discuss several potential issues that may arise during the evaluation process.

I.1 POTENTIAL ANNOTATION NOISE

Although the annotations from Visual Genome are generated by Amazon Mechanical Turk (AMT)
 workers following strict guidelines and are generally of high quality, as human-generated data, they
 may still contain minor textual noise, such as non-alphabetic characters, stopwords, or occasional
 spelling errors.

To mitigate this issue, we manually review all image-instruction pairs, removing samples affected by noise, such as those with incorrect ground truth answers. Additionally, our evaluation criteria define "non-hallucination" based on the semantic similarity between the LVLM response and the ground truth annotation, ensuring that minor textual noise does not affect GPT's judgment.

901 I.2 POTENTIAL MISSING-ANNOTATION SCENARIOS

In our evaluation, there may exist missing-annotation scenarios where the response captures facts not included in the annotations. However, their impact on the overall evaluation results is minimal. On one hand, our questions are designed to focus on specific aspects, such as the attributes of a particular object, rather than broad image captioning tasks, which constrains the model's responses and reduces the likelihood of overly divergent answers. On the other hand, the image information we utilize is highly comprehensive, covering nearly all major objects within the images.

In our validity measurement, we compare human evaluation based on visual images with HQH
 evaluation conducted by GPT using textual annotations. The results show a strong correlation,
 indicating that the potential issues mentioned above are minimal and have limited impact on the
 overall evaluation results.

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J EXAMPLES OF HQH EVALUATION

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We present two examples of GPT-assisted evaluation in HQH, as shown in Figure 16, 17. Note that
 we do not provide ground truth in the evaluation of existence hallucination as the image details are informative enough.

918 K DATASET DOCUMENTATION

920 We provide additional information on the introduced HQH benchmark in this section.

Motivation. HQH is a high-quality hallucination benchmark for LVLMs built on Visual Genome dataset. It is created to evaluate the performance of LVLMs across different types of hallucination, highlighting their shortcomings. By providing a comprehensive and detailed assessment, HQH aims to advance the development of more accurate and reliable LVLMs.

Composition. HQH utilizes images and annotations from Visual Genome, consisting of 4000 image instruction pairs. These pairs are evenly distributed across 8 hallucination types, with 500 pairs for
 each type.

Usage and Distribution. HQH is released at https://github.com/HQHBench/HQHBench.
 The data is saved in JSON format, and the evaluation code is also provided. All experiments are conducted on 4 × RTX 3090 GPUs.

License. Following Visual Genome, HQH is under CC BY 4.0 license, ensuring that we obtain consent to use and curate the data.

935 Ethical concerns. HQH is constructed based on the existing publicly available dataset Visual 936 Genome, which does not contain any personally identifiable information or offensive content.



1023 1024 Figure 8: An example of AMBER-d evaluation. Hallucination is marked in red. The model response mentions a white mountain, while the mountain in the image is green, thus the evaluation is incorrect.



Figure 10: An example of AMBER-g evaluation. Hallucination is marked in red. The model response mentions several other players, while there are only two players in the image, thus the evaluation is incorrect.



Image	
Instruction	
Which electronic devi	ce is larger?
Ground Truth:	
The iPod touch on the	left is larger than the iPod nano on the right.
Model Response	
The iPod is larger than	the iPhone.
MMHal	
Without hallucinatio	n hall ucination score = 5

Figure 12: An example of MMHal evaluation. Hallucination is marked in red. The model response
 mentions iPhone, while there is no iPhone in the image, thus the evaluation is incorrect.



Instruction What is the man doing? Ground Truth: Smoking a cigarette.

Figure 14: An example of filtered low-quality image-instruction pairs which contain inaccurate instruction. The subject reference "the man" in the question is ambiguous, as there are two men in the image.

Instruction		
What is written on t	the bottom sticker on the toilet tank?	

Figure 15: An example of filtered low-quality image-instruction pairs which contain incorrect ground truth answer. The ground truth answer "ASAP" is incorrect, as the text is "ASCAP" in the image.

Image

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Input

Given the input instruction, ground truth answer and detailed image information, please determine whether the response provided by a Large Vision-Language Model (LVLM) contains any hallucination. Hallucination here refers to the situation that the generated response is inconsistent with the input image.

Please note that the ground truth answer and image information only contain factual information and may not be completely comprehensive in describing all the objects and their attributes. Detailed analysis or reasoning in LVLM response should be encouraged and not considered as hallucination.

To evaluate the LVLM responses, you need to provide brief evidence to support your judgment.

###Evaluation criteria:

-Without hallucination: The LVLM response is semantically similar to the ground truth answer and does not contain any contradictory factual claim with the provided information.

-With hallucination: The LVLM response is completely different from the ground truth answer, or
contains a contradictory factual claim about an object, action, attribute, or any other detail that is not
grounded in the provided information.

- 1215 ###Instruction:
- 1216 What are the horses doing? ###Ground Truth:
- 1217 Walking.
- 1218 ###Image Caption:
- 1219 Three horse wearing coats walk around a large field.

1220 ###Image Details:

- a brown horse in a field X:162 Y:160 Width:82 Height:82
- a brown horse in a field X:258 Y:141 Width:54 Height:54
- a brown horse in a field X:297 Y:161 Width:74 Height:74
- These are three horses X:108 Y:132 Width:285 Height:285
- The horses are wearing capes X:168 Y:158 Width:209 Height:209
- This is a purple cape X:260 Y:187 Width:37 Height:37
- This is a picture of small grass X:141 Y:235 Width:179 Height:179 The trees have no locues X:51 V:60 Width:67 Height:67
 - The trees have no leaves X:51 Y:69 Width:67 Height:67
- 1228The tree is very brown X:63 Y:57 Width:80 Height:801229...

###Model Response:

The horses are wearing blankets and standing in a field. There is a tree in the background and some buildings visible in the distance.

###Output Format: With/Without hallucination, [evidence].

GPT Output

With hallucination, The response includes information about buildings visible in the distance, which is not supported by the image details.

Figure 16: The 1st example of HQH evaluation. Hallucination is marked in red.

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1242 1243 1244 1245 1246 Image 1247 1248 1249 1250 1251 1252 1253 Input Given the input instruction and detailed image information, please determine whether the response 1255 provided by a Large Vision-Language Model (LVLM) contains any hallucination. Hallucination here 1256 refers to the situation that the generated response is inconsistent with the input image. 1257 Please note that the image information only contain factual information and may not be completely 1259 comprehensive in describing all the objects and their attributes. Detailed analysis or reasoning in LVLM response should be encouraged and not considered as hallucination. 1261 To evaluate the LVLM responses, you need to provide brief evidence to support your judgment. 1262 1263 ###Evaluation criteria: 1264 -Without hallucination: The LVLM response does not contain any contradictory factual claim with the 1265 provided information. 1266 -With hallucination: The LVLM response contains a contradictory factual claim about an object, action, 1267 attribute, or any other detail that is not grounded in the provided information. 1268 ###Instruction: List the main instances in the image. 1270 ###Image Caption: A small dog is running down the street carrying a frisbee. 1271 ###Image Details: 1272 the dog is running X:215 Y:76 Width:84 Height:84 the frisbee is pink and green X:211 Y:111 Width:66 Height:66 1274 the ground is gray X:0 Y:0 Width:497 Height:497 the dog is white X:187 Y:65 Width:149 Height:149 1276 the ground here is very sandy X:18 Y:144 Width:161 Height:161 ###Model Response: 1278 Here are the main instances in the image: 1. The dog is running with a frisbee in its mouth. 2. The 1279 dog's owner is holding a leash and looking on as the dog plays with the frisbee. 3. The dog is running 1280 across the beach with the frisbee in the air. 4. The dog is running towards the camera with the frisbee in 1281 its mouth. 5. The dog's owner is standing on the beach, looking at the dog play with the frisbee. 6. The 1282 background of the image is a beach with sand and water. 7. The sky is cloudy and there are some trees 1283 visible in the distance. 8. The dog's fur is white with black spots. 9. The dog's tail is wagging as it runs 1284 with the frisbee. 10. The dog's eyes are looking up and to the right as it runs with the frisbee. 1285 ###Output Format: With/Without hallucination, [evidence]. 1286 1287 **GPT** Output With hallucination, The response includes details not present in the image, such as the dog owner, a beach with sand and water. These elements are not supported by the image information provided. 1290

Figure 17: The 2nd example of HQH evaluation. Hallucination is marked in red.

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