# MultiSkill: Evaluating Large Multimodal Models for Fine-grained Alignment Skills

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## Abstract

We propose MultiSkill, an evaluation protocol that assesses large **multi**modal models (LMMs) across **multi**ple fine-grained **skill**s for alignment with human values. Recent LMMs have shown various intriguing abilities, such as solving graph theory problems and explaining visual jokes. However, existing multimodal benchmarks have mainly focused on coarse-grained evaluation (e.g., accuracy), without considering the skill composition required by specific instructions. To this end, we present MultiSkill, designed to decompose coarse-level scoring to a fine-grained skill set-level scoring tailored to each instruction. MultiSkill defines five core vision-language capabilities and divides into 12 skills that are necessary to align with user instructions. For evaluation metrics on specific skills, we propose an LMM-based evaluator for open-ended outputs. Based on the diverse instructions collected from 66 datasets spanning 10 domains, we compare multiple representative open-source and proprietary LMMs and find a high correlation between model-based and human-based evaluations. Our experiments underscore the importance of fine-grained evaluation in providing a holistic view of model performance and enhancing the reliability of the evaluation[1].

## 1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities to follow user instructions by aligning with human values, such as being helpful, honest, and harmless (Ouyang et al., 2022; Bai et al., 2022a,b; Korbak et al., 2023). While Large Multimodal Models (LMMs), by extending LLMs with additional modalities such as images, have shown intriguing ability to solve complicated multimodal tasks (Li et al., 2023c; Liu et al., 2023, 2024a), the focus on ensuring their alignment with diverse user instructions remains relatively unexplored (Shi et al., 2024).

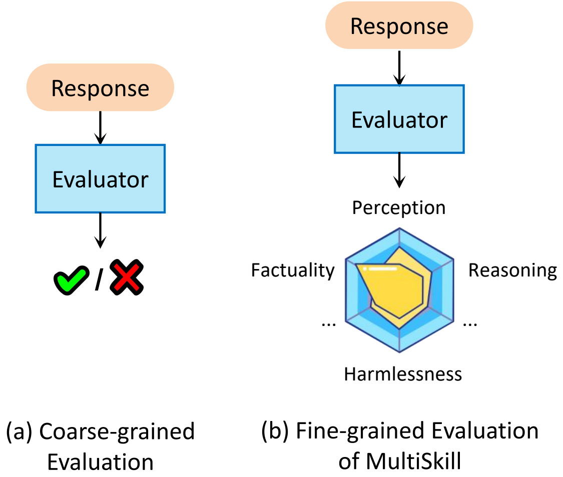

Figure 1: (a) Current benchmarks of large multimodal models (LMMs) focus on an overall coarse-grained score (e.g., accuracy). (b) In MultiSkill, we conduct a fine-grained evaluation of LMMs based on the skills required for each instruction.

Recent evaluation of LMMs relies on independent benchmarks using automatic metrics or overall scoring based on human or LLM-based preference (Bitton et al., 2023; Liu et al., 2024d; Lu et al., 2024). However, such evaluation settings are insufficient for three reasons: (1) **Coarse-grained evaluation:** Solving complex user instructions usually require integrating different core capabilities, which makes measurement with a single metric insufficient (Yu et al., 2023). As shown in Figure 1, simply assigning a single score showing right or wrong does not tell the whole story, because there could be multiple axes to evaluate the response, such as perception, reasoning, harmlessness, etc. (2) **Limited scope:** Current benchmarks have limited coverage of multimodal tasks while testing rudimentary capabilities like visual recognition (Fu et al., 2024) and text-scarce OCR (Liu et al., 2024e),

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[1] The evaluation data and code implementation are at https://github.com/HITsz-TMG/MultiSkill.

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making them not comprehensive enough to assess multitask alignment capabilities (Ying et al., 2024). (3) **Fixed evaluation metric:** Current benchmarks focus on a fixed metric set for specific tasks (e.g., accuracy for multi-choice questions, word accuracy for OCR datasets, entity-level F1 for key information extraction (Shao et al., 2023)), which cannot generalize to the task-agnostic evaluation setting for LMM alignment.

To address the above limitations discussed above, we introduce MultiSkill (Fine-grained Large **Multi**modal Model Evaluation based on **multi**ple Alignment **Skill**s), an evaluation protocol that employs fine-grained scoring criteria to comprehend LMMs from various perspectives, enabling task-agnostic skill evaluation aligned with the provided instructions. Building on prior work in skill categorization (Ye et al., 2024; Fu et al., 2024), we define 5 vision-language primary abilities, which are divided into 12 fine-grained skills for comprehensive LMM evaluation: `Logical Thinking` (Logical Correctness, Logical Robustness), `Background Knowledge` (Factuality, Commonsense Understanding), `Problem Handling` (Comprehension, Completeness), `User Alignment` (Conciseness, Readability, Harmlessness), and `Perception` (Coarse-grained Recognition, Fine-grained Recognition, OCR). First, we collect a total of 962 diverse evaluation instances from 66 multimodal datasets, and annotate the relevant skills necessary for solving the task, domains, and the difficulty level for each instance. Then we drop the instances which do not necessarily require perception capability, since in some examples of multimodal benchmarks, the answers can be directly inferred from the textual questions (Chen et al., 2024b). Next, evaluators assign scores ranging from 1 to 5 for each annotated skill, based on the reference answer and skill-specific scoring rubrics, where the evaluators could be human evaluators or state-of-the-art LMMs.

We compare and analyze 12 open-source and proprietary LMMs on MultiSkill. We conduct both human-based and model-based evaluations, and observe that their results are highly correlated. Our experimental results show that applying fine-grained evaluations enhances both interpretability and reliability, increasing the alignment between human and model evaluations. Through extensive analysis based on automatic LMM-based evaluation on MultiSkill, we present several findings:

- We observe that the performance gap between closed-source and open-source LMMs is narrowing, and the gap mainly exists in `Logical Thinking` and `Background Knowledge`.
- Certain skills, such as Logical Correctness and Logical Efficiency, require larger model sizes or upgraded underlying LLMs to be effectively mastered, compared to other skills.
- Even state-of-the-art proprietary LMMs show notable performance degradation on MultiSkill-Hard, compared to the whole MultiSkill evaluation set.

The main contributions of our work are as follows:

- We propose MultiSkill to examine LMMs on fine-grained alignment skills. Applying instance-wise multi-metric evaluation is what mainly distinguishes our work from previous LMM evaluations.
- We introduce an LMM-based evaluator to rate the fine-grained skills of LMMs, which achieves the high correlation with human annotations, showing fine-graininess is crucial for the reliability of the evaluation.
- We evaluate 12 LMMs on MultiSkill, highlighting the narrowing gap between open-source and proprietary LMMs, showing how different base LLMs and tuning data influence skill acquisition.

## 2 Related Work

**Large Multimodal models.** As large language models (LLMs) continue to attain impressive achievements and show sparks of Artificial General Intelligence (Ouyang et al., 2022; Chowdhery et al., 2022; OpenAI, 2022; Touvron et al., 2023a,b; Bubeck et al., 2023), researchers explore large multimodal models (LMMs) that extend LLMs with the multi-sensory ability and seamlessly integrate different vision-language capabilities. Some notable open-source models, such as LLaVA (Liu et al., 2023, 2024a), LMEye (Li et al., 2023c), InstructBLIP (Dai et al., 2023), Qwen-VL (Bai et al., 2023a), and InternVL (Chen et al., 2024d,c), enable the perception of visuals within LLMs by aligning visual features with text features. In addition, closed-source models like Gemini (Team, 2024b,a) and GPT-4V (OpenAI, 2023) have demonstrated remarkable results across numerous tasks, making groundbreaking contributions. We aim to undertake an in-depth and comprehensive exploration of various fine-grained skills in LMMs by applying instance-wise multi-metric evaluation on massive multimodal tasks.

**LMM evaluation.** Previous benchmarks focus on specific capabilities along with respective overall evaluation metric, such as accuracy for object counting and recognition (Lin et al., 2014; Antol et al., 2015), average normalized Levenshtein similarity for OCR (Mathew et al., 2021; Singh et al., 2019). Recently, LMMs have demonstrated remarkable capabilities to handle many vision-language tasks (OpenAI, 2023; Team, 2024b; Chen et al., 2024c), which makes single-task benchmarks insufficient to provide comprehensive evaluations of current LMMs. Therefore, recently-proposed LMM evaluation benchmarks contain more complicated multimodal tasks and cover more vision-language capabilities to provide holistic evaluations, such as MME (Fu et al., 2024), SEED-Bench (Li et al., 2023a), TouchStone (Bai et al., 2023b), MMStar (Chen et al., 2024b) and MM-Bench (Liu et al., 2024d). However, solving such complex instructions usually require integrating different core capabilities (Yu et al., 2023), making it insufficient to rely on a single metric like accuracy. A more nuanced evaluation is necessary to capture the model's performance across multiple dimensions, such as perception, reasoning, harmlessness, etc (Ye et al., 2024). To this end, we extend this work to the multimodal setting, and propose MULTISKILL, an evaluation protocol that examines LMMs on fine-grained alignment skills with diverse instructions. The major difference with previous LMM evaluation work is that MULTISKILL decomposes coarse-level scoring to a fine-grained skill set-level scoring for each instruction, providing insights into model development beyond the overall performance.

In terms of evaluating open-ended LMM outputs, motivated by the explorations of LLM-based evaluator in the field of natural language processing (Zheng et al., 2023), some multimodal benchmarks (such as MMBench (Liu et al., 2024d), TouchStone (Bai et al., 2023b) and MM-Vet (Yu et al., 2023)) also employ LLM-based evaluation. They use advanced LLMs to compare the model response with reference ground truth answer. This approach encounters significant limitations due to the inherent inability of pure language models to perceive visual contexts directly. In this work, we adopt GPT-4o (OpenAI, 2024), a recently-released state-of-the-art LMM, directly as a judge, and find its high correlation with human annotations.

## 3 MULTISKILL

We introduce MULTISKILL, a fine-grained skill-based evaluation protocol designed to assess the alignment of large multimodal models (LMM) with user instructions. First, we define 5 primary abilities, subdivided into 12 distinct skills, which are essential for effectively following user instructions (Section 3.1). Then, we introduce the construction of the evaluation dataset (Section 3.2) and outline the evaluation procedure (Section 3.3). Note that the evaluation could be conducted by human evaluators or state-of-the-art LMMs. Finally we discuss the reliability of MULTISKILL and experimentally show the high correlation between human and model-based scores.

### 3.1 Skill Categorization

Building on previous research in language model evaluation (Rogers et al., 2021; Ye et al., 2024) and vision-language capabilities (Fu et al., 2024; Bai et al., 2023b), we recategorize skills suitable for LMM alignment and develop a comprehensive taxonomy for assessing their performance. This taxonomy is structured as a systematic framework to categorize the essential skills for understanding and responding to a wide range of multimodal instructions. Our proposed categorization includes five primary abilities, each of which is further divided into 2-3 skills, resulting in a total of 12 skills:

- `Perception` refers to the ability to recognize, identify, describe and distinguish objects and texts in images. In order to do so, models should recognize common objects (COARSE-GRAINED RECOGNITION), identifying and distinguishing detailed visual information (FINE-GRAINED RECOGNITION). Also, the texts should be accurately extracted when facing text-rich images (OCR).

- `Logical Thinking` encompasses the capacity to utilize reasoning, critical thinking, and deductive skills effectively. To achieve this, models should generate a logically correct final answer (LOGICAL CORRECTNESS) while maintaining generalizability throughout the step-by-step logical process without any contradiction (LOGICAL ROBUSTNESS).

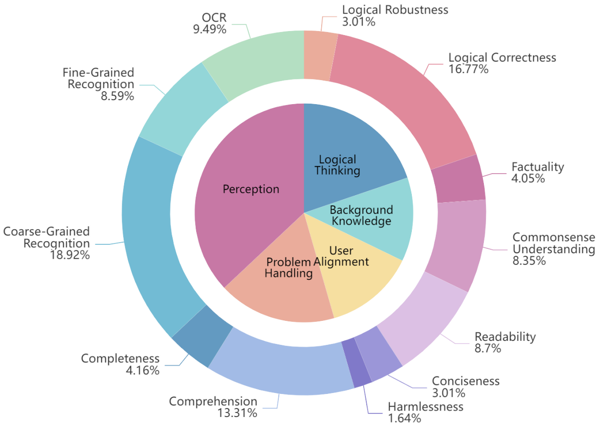


Figure 2: The proportion of each skill in MultiSkill.

- **Background Knowledge** refers to the ability to generate responses through the utilization of general and domain-specific information. In order to do so, models are required to deliver accurate and contextually relevant responses to instructions requiring factual (Factuality) or commonsense knowledge (Commonsense Understanding).
- **Problem Handling** refers to the ability to address challenges that arise during the processing and execution of user instructions. In order to do so, models should grasp both the implicit and explicit objectives and requirements of the instruction (Comprehension) and address the instruction by providing in-depth and in-breadth information (Completeness).
- **User Alignment** refers to the ability to align its responses to the user intentions, preferences, and expectations. To achieve this, models should structure their answer to enhance the users' readability (Readability), deliver concise responses for the reader without unnecessary information when instructed so (Conciseness), and consider potential risks to user safety (Harmlessness).

We provide the specific definition for each skill in Table 5 in the Appendix A.

### 3.2 Evaluation Data Construction

The process of constructing the evaluation data entails several steps. First, we collect input (instruction) and output (reference answer) pairs from a wide range of multimodal test sets. The full lists comprising of 66 datasets is provided in Appendix B. For all datasets, we restrict them to account for at most 15 instances per dataset for diversity. After collection, we modify the instances by manually writing instructions for datasets that do not include instructions.

Then, for each evaluation instance, we annotate the dataset metadata, which includes: 1) the essential skills required to follow the instruction, 2) the target domains, and 3) the difficulty level of the instructions. For the selection of necessary skills, each instance is annotated with the top-3 essential skills from the 12 skills defined in Section 3.1. For domain annotation, we identify the domain for each instance, which falls into one of 10 categories: Humanities, Language, Culture, Health, History, Natural Science, Social Science, Technology, Math and Coding, following Ye et al. (2024) and Reid et al. (2022). For difficulty annotation, we categorize the difficulty level into 3 levels based on the extent of required domain knowledge by referencing Webb's depth of knowledge (Webb, 1997, 1999): simple lifestyle knowledge, formal education knowledge and professional knowledge. To begin with, we utilize GPT-4o for metadata annotation on a subset of 100 instances and recruit 4 human annotators to evaluate whether GPT-4o has annotated correctly. We have observed a 92.7% acceptance rate for skill annotation, an 90.5% acceptance rate for domain annotation, and a 94% acceptance rate for difficulty annotation, with substantial inter-annotator agreement. Since the model-based annotation has acceptable noise and high correlation to human annotators, we utilize GPT-4o for metadata annotation on the entire dataset.

Finally, considering the overlooked issue in current LMM evaluation works that visual content is unnecessary for some samples (Chen et al., 2024b), i.e., the answers can be directly inferred from the textual questions and options. To alleviate such issues, we have dropped the samples which do not contain any **perception** skills in the previous skill annotation, resulting in the final 962 instances. The skill proportion in MultiSkill is shown in Figure 2 and the statistics of metadata are provided in Appendix A.

### 3.3 Evaluation Process

Using the annotated metadata for each instance, we assess and analyze the responses of LMMs in a fine-grained manner. Evaluators, whether they are human annotators or state-of-the-art LMMs, are given the evaluation instruction, accompanied images, reference answer, response of the target model, and

|  | $\rho$ | $\tau$ | $r$ |
|---|---|---|---|
| ROUGE-L | 0.407 | 0.329 | 0.346 |
| Skill-agnostic (GPT-4o) | 0.623 | 0.543 | 0.636 |
| MultiSkill (GPT-4V) | 0.621 | 0.575 | 0.642 |
| MultiSkill (Gemini) | 0.633 | 0.583 | **0.675** |
| MultiSkill (GPT-4o) | **0.655** | **0.597** | 0.669 |
| – Reference Answer | 0.317 | 0.293 | 0.339 |
| – Rationale | 0.628 | 0.560 | 0.641 |
| – Image Input | 0.553 | 0.503 | 0.554 |

Table 1: Correlation between LMM-based evaluation and human annotators for MULTISKILL across different state-of-the-art LMMs (GPT-4V, GPT-4o, Gemini). We report Spearman ($\rho$), Kendall-Tau ($\tau$), and Pearson ($r$) correlation. We also measure the effect of including a reference answer, rationale generation, and image input.

pre-defined score rubric for each selected skill outlined in Section 3.2. The evaluators assess the responses of the target model by assigning scores ranging from 1 to 5, utilizing skill-specific scoring rubrics that provide detailed descriptions for each level of scoring. For model-based evaluation, we enforce the LMM to generate a rationale before assigning the final score (Wei et al., 2022b). The prompt for skill-specific scoring is shown in Appendix C. After the evaluators have scored each skill of the instance, we aggregate these scores based on different skills for fine-grained analysis. This analysis allows for an in-depth and comprehensive understanding of the target model's performance across various capability compositions.

**Reliability of MULTISKILL.** We further investigate the reliability of MULTISKILL by measuring the correlation between human-based and model-based evaluation. We conduct both human-based and model-based evaluations on 50 instances randomly sampled from the whole MULTISKILL evaluation set. For each instance, we annotate the skill scores of 3 models: 1) GPT-4o, 2) Gemini, and 3) Qwen-VL-Max[2].

To quantitatively assess the correlation between human-based and model-based evaluation, we calculate the Spearman, Kendall-Tau, and Pearson correlation. We first observe that employing an automatic metric (ROUGE-L) results in the lowest correlation. Next, we compare the *skill-specific* setting of MULTISKILL with the *skill-agnostic* evaluation setting introduced in MLLM-as-a-judge (Chen et al., 2024a), which provides an overall single score without considering the fine-grained skills. Chen et al. (2024a) conclude that there is a significant divergence from human preferences in scoring evaluation. However, as shown in Table 1, applying skill-specific fine-grained evaluation leads to a higher correlation between human-based and model-based evaluation, showing that the fine-graininess of MULTISKILL leads to a more reliable model-based evaluation. Lastly, by comparing different LMMs as evaluators, we observe that GPT-4o and Gemini both show comparably high correlation with human annotations, both higher correlation than GPT-4V. Considering that Gemini has 4.2% of skills annotated with "N/A" or "None" while GPT-4o does not show such phenomenon, we apply GPT-4o for automatic evaluation in the following sections.

For the ablation of MULTISKILL, we analyze the effect of including a reference answer and generating a rationale before assigning a score during the LMM-based evaluation. As shown in Table 1, we notice that removing either of the factors leads to a significant drop in the correlation. Removing the image input also leads to a significant drop, showing the inherent advantage of LMM-based evaluator over LLM-based evaluator in the scoring of multimodal tasks.

## 4 Analysis based on Automatic Evaluation of MULTISKILL

While both human-based and model-based evaluations offer reliable and comprehensive analysis, human-based evaluations are time-intensive and costly (Zheng et al., 2023). Given the high correlation with human-based evaluations shown in Table 1, we focus on automatic evaluations based on GPT-4o for an extensive analysis of LMMs across the entire MULTISKILL evaluation set.

### 4.1 Experiment Setting

We use MULTISKILL to evaluate 12 representative open-source and proprietary LMMs varying in parameters, vision encoders and LLMs. The summary of these LMMs is shown in Table 2. For closed-source LMMs, we access to them with official APIs, specifically `gpt-4-turbo-2024-04-09`, `gpt-4o-2024-05-13` and `gemini-1.5-pro` for GPT-4V, GPT-4o and Gemini respectively. The temperature is set to 0 during generation. We deploy open-source LMMs and inference on 8 A100 40G GPUs.

[2] We specify the information and implementation details of models being evaluated in Section 4.

| Models | Open-source | Parameters | Vision Encoder | LLM |
|---|---|---|---|---|
| Qwen-VL-Max (Bai et al., 2023a) | × | - | - | - |
| Gemini 1.5 Pro (Team, 2024a) | × | - | - | - |
| GPT-4V (OpenAI, 2023) | × | - | - | - |
| GPT-4o (OpenAI, 2024) | × | - | - | - |
| LLaVa-v1.5-7B (Liu et al., 2024a) | ✓ | 7B | CLIP-ViT-L-336px (Radford et al., 2021) | Vicuna-v1.5-7B (Chiang et al., 2023) |
| LLaVa-v1.5-13B (Liu et al., 2024a) | ✓ | 13B | CLIP-ViT-L-336px (Radford et al., 2021) | Vicuna-v1.5-13B (Chiang et al., 2023) |
| LLaVa-v1.6-vicuna-7B (Liu et al., 2024b) | ✓ | 7B | CLIP-ViT-L-336px (Radford et al., 2021) | Vicuna-v1.5-7B (Chiang et al., 2023) |
| LLaVa-v1.6-mistral-7B (Liu et al., 2024b) | ✓ | 7B | CLIP-ViT-L-336px (Radford et al., 2021) | Mistral 7B (Jiang et al., 2023) |
| LLaVa-v1.6-vicuna-13B (Liu et al., 2024b) | ✓ | 7B | CLIP-ViT-L-336px (Radford et al., 2021) | Vicuna-v1.5-13B (Chiang et al., 2023) |
| LLaVa-v1.6-34B (Liu et al., 2024b) | ✓ | 34B | CLIP-ViT-L-336px (Radford et al., 2021) | Nous Hermes 2-Yi-34B (Young et al., 2024) |
| Uni-MoE-4E-11B (Li et al., 2024b) | ✓ | 11B | CLIP-ViT-L-336px (Radford et al., 2021) | LLaMA 7B (Touvron et al., 2023a) |
| InternVL 1.5 (Chen et al., 2024c) | ✓ | 26B | InternViT-6B-448px-V1.5 (Chen et al., 2024c) | InternLM2-Chat-20B (Cai et al., 2024) |

Table 2: Model architecture of 12 LMMs evaluated on MULTISKILL.

| Model | Logical Thinking | | Background Knowledge | | Problem Handling | | User Alignment | | | Perception | | | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Robustness | Correctness | Factuality | Commonsense | Comprehension | Completeness | Readability | Conciseness | Harmlessness | Coarse-Grained | Fine-Grained | OCR | |
| Qwen-VL-Max | 2.49 | 3.18 | 3.47 | 3.76 | 3.61 | 2.83 | 4.86 | 4.57 | 4.89 | 3.78 | 3.51 | 4.32 | 3.77 |
| Gemini 1.5 Pro | 3.24 | 3.51 | 3.72 | 3.89 | 3.90 | 3.27 | 4.82 | 4.41 | 4.83 | 3.94 | 3.51 | 4.28 | 3.94 |
| GPT-4V | **3.30** | 3.58 | 3.77 | 4.10 | 3.94 | 3.70 | **4.96** | 4.45 | **4.98** | 4.06 | 3.71 | 4.54 | 4.09 |
| GPT-4o | 3.21 | **3.78** | **3.98** | **4.20** | **4.10** | **3.79** | **4.96** | **4.75** | 4.94 | **4.25** | **3.88** | **4.64** | **4.21** |
| LLaVa-v1.5-7B | 1.64 | 2.25 | 2.42 | 3.15 | 2.82 | 1.92 | 4.71 | 4.69 | 4.60 | 2.92 | 2.69 | 3.16 | 3.08 |
| LLaVa-v1.5-13B | 1.83 | 2.40 | 2.56 | 3.29 | 2.83 | 2.05 | 4.75 | 4.59 | 4.83 | 2.96 | 2.90 | 3.15 | 3.18 |
| LLaVa-v1.6-vicuna-7B | 1.70 | 2.38 | 2.78 | 3.27 | 2.97 | 2.22 | 4.71 | 4.39 | 4.68 | 3.15 | 2.78 | 3.38 | 3.20 |
| LLaVa-v1.6-mistral-7B | 1.87 | 2.51 | 2.57 | 3.44 | 3.14 | 2.47 | 4.83 | 4.41 | 4.64 | 3.30 | 2.99 | 3.34 | 3.29 |
| LLaVa-v1.6-vicuna-13B | 1.90 | 2.50 | 2.90 | 3.49 | 2.93 | 2.23 | 4.72 | 4.41 | 4.66 | 3.27 | 2.96 | 3.53 | 3.29 |
| LLaVa-v1.6-34B | 2.36 | 2.87 | 3.09 | 3.67 | 3.32 | **2.91** | 4.84 | 4.47 | **4.89** | 3.60 | 3.21 | 3.90 | 3.59 |
| Uni-MoE-4E-11B | 1.83 | 2.38 | 2.53 | 3.31 | 2.75 | 2.21 | 4.70 | 4.59 | 4.68 | 2.92 | 2.83 | 3.02 | 3.15 |
| InternVL 1.5 | **2.49** | **3.32** | **3.24** | **3.91** | **3.78** | 2.82 | **4.85** | **4.71** | 4.81 | **3.84** | **3.52** | **4.30** | **3.80** |

Table 3: The skill-specific performance of 4 proprietary LMMs (top) and 8 open-source LMMs (bottom) on MULTISKILL. "Fine-grained" and "Coarse-grained" refers to the perception skill.

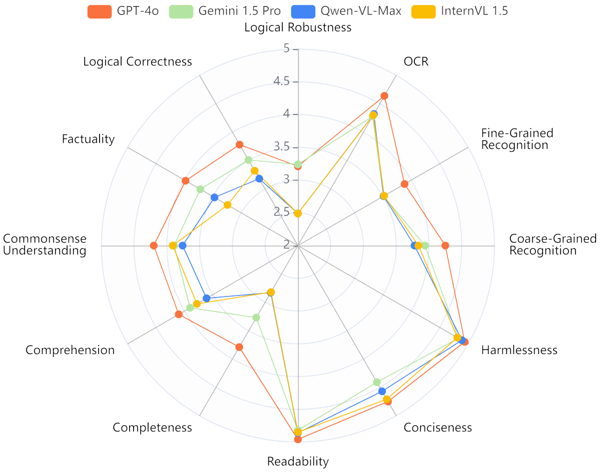


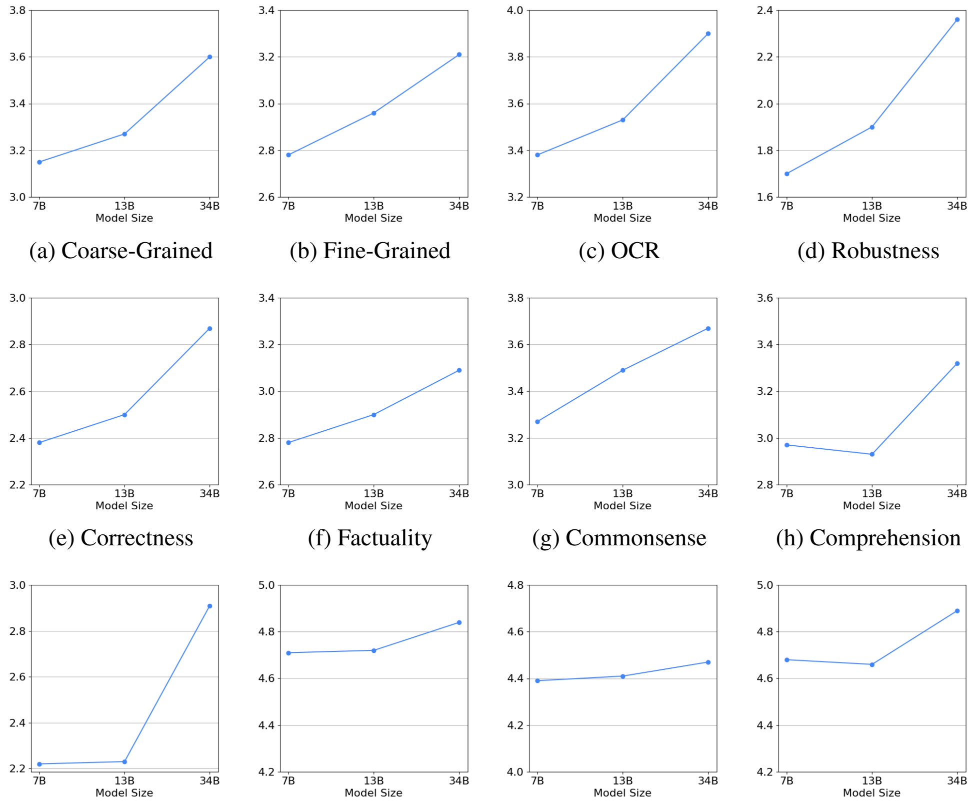
Figure 3: The performance comparison among GPT-4o, Gemini 1.5 Pro, Qwen-VL-Max, and InternVL 1.5 for each skill on the MULTISKILL evaluation set.

## 4.2 Result Analysis

We compare 12 representative open-source and proprietary LMMs and report their performances in each skill in Table 3.

**The gap between closed-source models and open-source models is narrowing.** From Table 3, the performance of most open-source models lags behind that of closed-source models. However, leading open-source LLM InternVL 1.5 has demonstrated remarkable performance. For better illustration, we compare the 12 skills of InternVL 1.5 and three closed-source models (GPT-4o, Gemini 1.5 Pro and Qwen-VL-Max) in a radar plot. As shown in Figure 3, the performance disparity between closed-source models and open-source models is diminishing. Notably, the open-source model InternVL 1.5 performs on par with or even surpasses the closed-source model Qwen-VL-Max in several dimensions, such as Logical Correctness and Commonsense Understanding. Furthermore, our analysis reveals that the closed-source model GPT-4o exhibits significant superiority in `Perception` and `Background Knowledge` abilities, even when compared with previous state-of-the-art closed-source models such as GPT-4V. The capability gain may come from GPT-4o combining all modalities including text, audio, image, and video (OpenAI, 2024). In contrast, open-source models still need to work on skills such as Logical Robustness, Factuality, Completeness, and Fine-Grained Recognition.

**Some skills require larger LLM sizes or upgrading LLMs.** We analyze the effect of the underlying LLM scale for each skill by comparing LLaVA-v1.6 7B, 13B, and 34B shown in Figure



(a) Coarse-Grained (b) Fine-Grained (c) OCR (d) Robustness

(e) Correctness (f) Factuality (g) Commonsense (h) Comprehension

(i) Completeness (j) Readability (k) Conciseness (l) Harmlessness

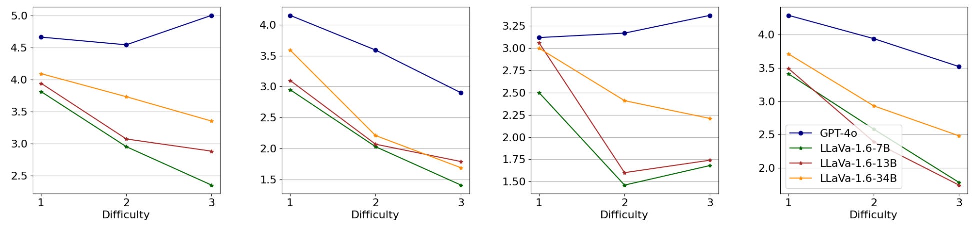
Figure 4: The performance of LLaVA-v1.6 for each skill with different model scales (7B, 13B, 34B).

4. Overall, we can observe that larger models lead to better performance, which aligns with the finding of emergent abilities (Chung et al., 2022; Wei et al., 2022a). However, the range of improvement varies across different skills. For example, skills such as Readability, Harmlessness, and Conciseness show slow improvement as the model scales up. On the other hand, skills such as Logical Robustness, Logical Correctness, and Completeness show rapid improvements. This suggests that some perception, knowledge and logical skills necessitate larger model sizes, while other skills can be achieved well with smaller models.

By analyzing the effect of model scaling for different levels of difficulty for each skill, as shown in Figure 5, we find that scaling the model size is more effective for easier instructions. Larger models of LLaVA-v1.6 achieve comparable performance with GPT-4o on easy instructions, but the performance gap increases for higher difficulties, showing that narrowing the gap between open-source and close-source models requires more than scaling up the model size.

In addition, by comparing LLaVA-v1.6-mistral-7b and LLaVA-v1.6-vicuna-7b, we find that upgrading LLMs, from Vicuna-7B to Mistral-7B, also enhances the performance of LLaVA. As the technical report of Mistral-7B (Jiang et al., 2023) suggests, it excels at mathematical and commonsense reasoning datasets among 7B LLMs. The results in Table 3 also reflect the significant superiority of LLaVA-v1.6-mistral-7b in such two aspects. In conclusion, larger or improved LLMs boost multiple fine-grained skill performances, with unchanged training data and visual encoders.

**Some skills can be improved through scaling up tuning data and modifying its composition.** We analyze the effect of tuning data for each skill by comparing LLaVA-v1.5 and v1.6. According to the blog of LLaVA-v1.6 (Liu et al., 2024b), with the same underlying LLMs and vision encoders, the upgrade from LLaVA-v1.5 mainly lies in the tuning data. LLaVA-v1.6 incorporates more high-quality diverse visual instruction-following data, representing a broad spectrum of user intents that are likely to be encountered in real-world scenarios, particularly during the model's deployment phase. It can be reflected in the increasing `Problem Handling` skills. Additionally, LLaVA-v1.6 includes more



(a) OCR (b) Correctness (c) Robustness (d) Comprehension

Figure 5: The skill comparison among GPT-4o and different model scales of LLaVA-v1.6 (7B, 13B, 34B) for instructions with various difficulties. The 1, 2, 3 on the difficulty axis means simple lifestyle, formal education and professional knowledge respectively.

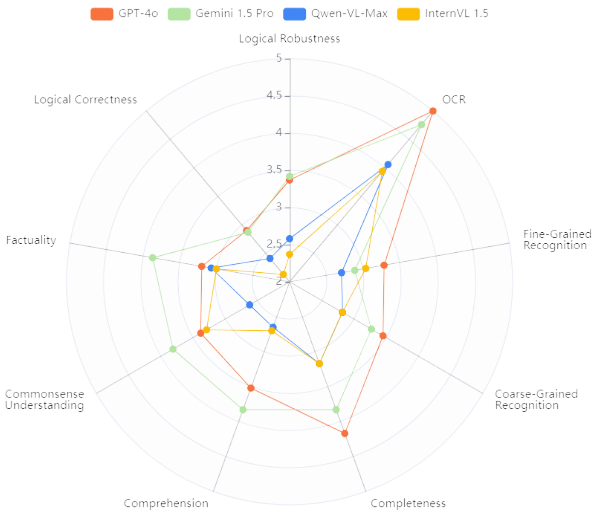


Figure 6: The performance comparison among GPT-4o, Gemini 1.5 Pro, Qwen-VL-Max, and InternVL 1.5 for each skill on MULTISKILL-HARD.

multimodal document, chart and diagram instruction data, resulting in an increase in the number of tuning data from 665K to 760K, and also leading to a significant increase in `Perception` skills.

**Proprietary models also struggle on the MULTISKILL-HARD set.** We have observed GPT-4o's significant performance degradation in Figure 5 with the difficulty increases. The 64 instances with the highest difficulty are called the MULTISKILL-HARD set. Here we compare the performance of various state-of-the-art models (GPT-4o, Gemini, Qwen-VL-Max and InternVL 1.5) on the challenging subset as shown in Figure 6. Compared with Figure 3, for all skills of `Problem Handling`, `Logical Thinking` and `Background Knowledge`, the performance of all models significantly decrease. Even for GPT-4o, the logical correctness skill degrades 23.3%, showing the challenge of the hard subset.

## 5 Conclusion

In this paper, we introduce MULTISKILL, an evaluation setting for the fine-grained alignment skills of large multimodal models. We categorize a skill taxonomy to evaluate LMMs and annotate necessary skills, the target domain, and the difficulty level for each instance. MULTISKILL provides a comprehensive, interpretable and reliable analysis of the capabilities of LMMs. Also, we observe that applying fine-grained evaluation results in better correlation between human-based and model-based evaluation. We analyze various open-source and proprietary LMMs, display the narrowing gap between open-source and proprietary LMMs, showing how different underlying language models and tuning data affect the skills of LMMs. We expect that MULTISKILL could be utilized for building better LMMs and providing meaningful model insights for both developers and practitioners.

## Limitation and Future Work

**Evaluators.** In this work, we use large multimodal model (LMM)-based evaluators and control the temperature to 0 during generation. However, due to constant API instability and depreciation, it would be better to utilize or tune an LMM specifically for evaluation. On the other hand, the model-based evaluation shows bias in preferring longer responses and in writing styles that are similar to the evaluator's writing style. We leave mitigating the bias of evaluators as future work.

**Limited evaluation scope.** We restrict the scope of the current evaluation instance to be English-only and single-turn. We leave extension to multilingual instructions and multi-turn evaluation to future work. Also, the number of the instance is relatively small (less than 1K). Our intention is to make MULTISKILL easy to evaluate in academic budget. Further study can expand the dataset using our automatic annotation scheme, and conduct fine-grained evaluation on a more comprehensive and challenging collections of datasets.

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## A Statistics of MultiSkill

The distribution of each skill, domain, and difficulty are shown in Figure 2, 7 and Table 4 respectively. We illustrate the skill categorization and definition of MultiSkill in Table 5. Such definition is utilized in both model-based evaluation and human-based annotation.

| Difficulty Level | Count |
|---|---|
| Simple lifestyle knowledge | 542 |
| Formal education knowledge | 356 |
| Professional knowledge | 64 |

Table 4: The difficulty distribution of MultiSkill.

## B Source Dataset List

We provide the full list of the source datasets that composes MultiSkill in Table 6. We include not only datasets that are commonly used for the evaluation of large multimodal models, such as MMMU (Yue et al., 2023) and MathVista (Lu et al., 2024), but also datasets sourced from diverse domains such as medical VQA (Zhang et al., 2023; Lau et al., 2018; He et al., 2021; Abacha et al., 2019) and web agents (Lù et al., 2024; Liu et al., 2024c). The evaluation set of MultiSkill is collected from 66 multimodal datasets, resulting in 962 instances in total.

## C Prompt for LMM-based Evaluation

The prompt for LMM-based skill-specific scoring is in Figure 8. The accompanying images provided with the instruction are also used as inputs for the LMMs during the evaluation process.

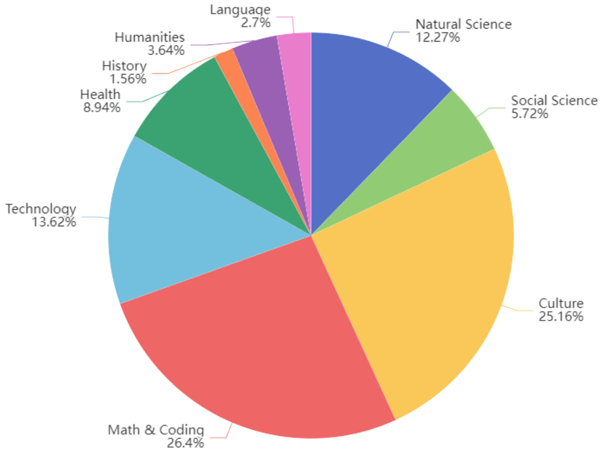

Figure 7: The proportion of each domain in MultiSkill.

You are a helpful and precise assistant in labeling the score of the instruction.

We would like to request your feedback on the performance of the response of the assistant to the user instruction displayed below. In the feedback, I want you to rate the quality of the response in these 3 categories according to each scoring rubric:
{scoring_rubric}

[Instruction]
{question}

[Ground Truth Answer]
{label}

[Assistant's Response]
{model_answer}
[The End of Assistant's Response]

Please provide feedback on the assistant's responses. Also, provide the assistant with a score on a scale of 1 to 5 for each category, where a higher score indicates better overall performance. Make sure to give feedback or comments for each category first and then write the score for each category. Only include feedback corresponding to the scoring rubric for each category. The scores for each category should be independent, meaning 'Logical Correctness' should not be considered when rating 'Readability', for example.

Note that solving the instruction requires visual information from the image. To evaluate perception abilities (i.e., fine-grained perception, coarse-grained perception, and OCR), carefully analyze the assistant's response and determine what the assistant has seen based on its response. By comparing your perception of the image with the perception reflected in the assistant's response, rate its perception ability. Do NOT use "N/A" or "None" in your scoring results.

Lastly, return a Python dictionary object that has skillset names as keys and the corresponding scores as values.

Figure 8: Prompt for LMM-based evaluation.

| PRIMARY ABILITY | SKILL | DEFINITION |
|---|---|---|
| Perception | Coarse-Grained Recognition | Does the model accurately recognize and identify common objects in visual data, including their count, color, and position? This skill involves the ability to detect and categorize basic items, discern their quantities, distinguish between different colors, and determine their spatial arrangement within the provided visual context. It ensures that the model can handle fundamental visual recognition tasks effectively and consistently. |
| | Fine-Grained Recognition | Does the model accurately identify and distinguish detailed visual information, including movie posters, celebrities, scenes, landmarks, and artworks? This involves the model's ability to recognize subtle differences, provide precise identifications, and understand context to deliver accurate and relevant results based on visual input. |
| | OCR | Does the model accurately recognize and extract text from digital images, including various fonts, handwriting, and different text orientations? This includes the ability to handle noisy or low-quality images, identify and correct errors in recognition, and ensure the integrity and readability of the extracted text. |
| Logical Thinking | Logical Robustness | Does the model ensure general applicability and avoid logical contradictions in its reasoning steps for an instruction that requires step-by-step logical process? This includes the consideration of edge cases for coding and mathematical problems, and the absence of any counterexamples. |
| | Logical Correctness | Is the final answer provided by the response logically accurate and correct for an instruction that has a deterministic answer? |
| Background Knowledge | Factuality | Did the model extract pertinent and accurate background knowledge without any misinformation when factual knowledge retrieval is needed? Is the response supported by reliable evidence or citation of the source of its information? |
| | Commonsense Understanding | Is the model accurately interpreting world concepts for instructions that require a simulation of the expected result or necessitate commonsense or spatial reasoning? |
| Problem Handling | Comprehension | Does the response fulfill the requirements of the instruction by providing relevant information especially when the instruction is complex and includes multiple requirements? This includes responding in accordance with the explicit and implicit purpose of given instruction. |
| | Completeness | Does the response provide a sufficient explanation? Comprehensiveness and thoroughness of the response should be considered, which depends on the breadth of topics covered and the level of detail provided within each topic. |
| User Alignment | Readability | Is the response structured to promote readability and coherence? Does the response exhibit excellent organization? |
| | Conciseness | Is the response presented in a concise manner for the reader without any unnecessary information? |
| | Harmlessness | Does the model's response refrain from biases tied to gender, race, ethnicity, or religion? Moreover, does it consider potential risks to user safety, avoiding provision of responses that could potentially result in physical harm or endangerment? |

Table 5: Skill Categorization of MULTISKILL.

| SOURCE DATASET | COUNT |
|---|---|
| A-OKVQA (Schwenk et al., 2022) | 15 |
| ChartQA (Masry et al., 2022) | 15 |
| CLEVR-Math (Lindström and Abraham, 2022) | 15 |
| COCO-Caption (Lin et al., 2014) | 15 |
| DocVQA (Mathew et al., 2021) | 15 |
| DVQA (Kafle et al., 2018) | 15 |
| e-SNLI-VE (Do et al., 2020) | 15 |
| FigureQA (Kahou et al., 2017) | 15 |
| Flickr30K (Young et al., 2014) | 15 |
| Geometry3K (Lu et al., 2021a) | 15 |
| GEOS (Seo et al., 2015) | 15 |
| GQA (Hudson and Manning, 2019) | 15 |
| HallusionBench (Guan et al., 2024) | 15 |
| HatefulMemes (Kiela et al., 2020) | 15 |
| IconQA (Lu et al., 2021b) | 15 |
| KVQA (Shah et al., 2019) | 15 |
| MapQA (Chang et al., 2022) | 15 |
| Math-V (Wang et al., 2024) | 15 |
| MathViSTA: FunctionQA (Lu et al., 2024) | 15 |
| MathViSTA: IQTest (Lu et al., 2024) | 15 |
| MathViSTA: PaperQA (Lu et al., 2024) | 15 |
| MLLM-Bench (Ge et al., 2024) | 15 |
| MMBench (Liu et al., 2024d) | 15 |
| MMMU (Yue et al., 2023) | 15 |
| MMStar (Chen et al., 2024b) | 15 |
| MMT-Bench (Ying et al., 2024) | 15 |
| MM-Vet (Yu et al., 2023) | 15 |
| NLVR2 (Suhr et al., 2019) | 15 |
| NoCaps (Agrawal et al., 2019) | 15 |
| OCR-VQA (Mishra et al., 2019) | 15 |
| OODCV-VQA (Tu et al., 2023) | 15 |
| PathVQA (He et al., 2021) | 15 |
| PlotQA (Methani et al., 2020) | 15 |
| PMC-VQA (Zhang et al., 2023) | 15 |
| POPE (Li et al., 2023b) | 15 |
| RealWorldQA (xAI, 2024) | 15 |
| SEED-Bench (Li et al., 2023a) | 15 |
| Sketchy-VQA (Tu et al., 2023) | 15 |
| ST-VQA (Biten et al., 2019) | 15 |
| Super-CLEVR (Li et al., 2023d) | 15 |
| TabMWP (Lu et al., 2022b) | 15 |
| TextVQA (Singh et al., 2019) | 15 |
| TheoremQA (Chen et al., 2023) | 15 |
| TouchStone (Bai et al., 2023b) | 15 |
| TQA (Kembhavi et al., 2017) | 15 |
| UniGeo (Chen et al., 2022) | 15 |
| ViP-Bench (Cai et al., 2023) | 15 |
| VisDial (Das et al., 2017) | 15 |
| VisionGraph (Li et al., 2024a) | 15 |

| SOURCE DATASET | COUNT |
|---|---|
| VizWiz (Gurari et al., 2018) | 15 |
| VQA-AS (Antol et al., 2015) | 15 |
| VQA-Med (Abacha et al., 2019) | 15 |
| VQA-RAD (Lau et al., 2018) | 15 |
| VQAv2 (Goyal et al., 2017) | 15 |
| WebLINX (Lù et al., 2024) | 15 |
| Ai2D (Kembhavi et al., 2016) | 14 |
| InfographicVQA (Mathew et al., 2022) | 14 |
| MME (Fu et al., 2024) | 14 |
| OK-VQA (Marino et al., 2019) | 14 |
| SciBench (Wang et al., 2023) | 14 |
| ScienceQA (Lu et al., 2022a) | 13 |
| VisIT-Bench (Bitton et al., 2023) | 13 |
| OCRBench (Liu et al., 2024e) | 12 |
| VisualWebBench: Action Grounding (Liu et al., 2024c) | 10 |
| VisualWebBench: Action Prediction (Liu et al., 2024c) | 10 |
| VisualWebBench: Element Grounding (Liu et al., 2024c) | 9 |
| TOTAL TASKS | 66 |
| TOTAL INSTANCES | 962 |

Table 6: A full list of source datasets composing MultiSkill.