UNO-Bench: A Unified Benchmark for Exploring the Compositional Law Between Uni-modal and Omni-modal in Omni Models

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Abstract

Multimodal Large Languages models have been progressing from uni-modal understanding toward unifying visual, audio and language modalities, collectively termed omni models. However, the correlation between uni-modal and omni-modal remains unclear, which requires comprehensive evaluation to drive omni model's intelligence evolution. In this work, we introduce a novel, high-quality, and **UN**ified **O**mni model benchmark, **UNO-Bench**. This benchmark is designed to effectively evaluate both **UN**i-modal and **O**mni-modal capabilities under a unified ability taxonomy, spanning 44 task types and 5 modality combinations. For omni-modal evaluation, we provide 1,250 human-curated samples with 98% cross-modality solvability, which is well-suited to real-world scenarios, particularly within the Chinese context. For uni-modal evaluation, we construct a dataset of 2,480 samples automatically distilled from 18 public benchmarks. This compressed dataset reduces evaluation costs by 90% while maintaining 98% consistency with the full-scale benchmarks. In addition to traditional multi-choice questions, we propose an innovative multi-step open-ended question format to assess complex reasoning. A general scoring model is incorporated, supporting 6 question types for automated evaluation with 95% accuracy. Experimental result shows the **Compositional Law** between omni-modal and uni-modal performance and the omni-modal capability manifests as a bottleneck effect on weak models, while exhibiting synergistic promotion on strong models. Our code and data are available at GitHub.

1 Introduction

Multimodal artificial intelligence has undergone extensive research in visual language model and audio language model, with current advancements progressing toward unifying visual, audio and language modalities, collectively termed omni models. The evaluation paradigm for these models has consequently expanded from assessing uni-modal understanding capabilities (i.e. visual understanding, audio understanding) to the next-level of intelligence, omni-modal understanding.

The ideal omni model should simultaneously preserve visual understanding capabilities, speech interaction proficiency, and cross-modal integration capacity. However, current evaluation paradigms employ disjointed benchmark suites for separate capability testing, creating resource-intensive evaluation processes and disconnected modality assessments. Beyond uni-modal, omni-modal capability introduces advanced challenges across image, video and audio modality. However, 77% questions from WorldSense are solvable without vision or audio, and 25% questions from OmniBench contain erroneous answers. These issues limit the evaluation and analysis of omni models' capabilities.

Due to the limited quality and coverage of existing benchmarks, we introduce a novel and unified benchmark, UNO-Bench, to provide a comprehensive evaluation of omni models.

Main Contributions:

1. We propose the first **UN**ified **O**mni model benchmark, **UNO-Bench**, which efficiently assesses both **UN**i-modal and **O**mni-modal understanding capabilities. UNO-Bench reveals the **Compositional Law** between omni-modal and uni-modal capability. The omni-modal capability manifests as a bottleneck in weaker models, while exhibiting synergistic enhancement in stronger models.

2. We establish a high-quality and diverse dataset through a construction pipeline that integrates human curation and automated data compression. As a result, UNO-Bench comprises 1250 human curated samples for omni-modal with 98% cross-modality solvability, and 2480 enhanced samples for uni-modal, across 44 task types and 5 modality combinations. The human-created omni-

Dataset	Omni-modal	Uni-modal	Acc.	Solvable	Source	#Tasks	#QA Pairs	QA Type	Language
MMBench	✗	I	-	-	80% private	20	3217	MC	EN/CH
MMAU	✗	A	-	-	15% private	27	10000	MC	EN
MVBench	✗	V	-	-	public	20	4000	MC	EN
OmniBench	I+A	✗	75%	90%	public	8	1142	MC	EN
AV-Odyssey	I+V+A	✗	91%	99%	public	26	4555	MC	EN
WorldSense	V+A	✗	99%	23%	public	26	3172	MC	EN
Daily-Omni	V+A	✗	94%	59%	public	6	1197	MC	EN
UNO-Bench-omni	I+V+A	-	100%	98%	90% private	44	1250	MC/MO	EN/CH
UNO-Bench-uni	-	I/V/A	-	-	40% private	44	2480	MC	EN/CH

Table 1: Comparison of MultiModal Benchmarks, with I, A, V, and T representing image, audio, video, and text modalities, respectively. It reports on the accuracy of question-answer pairs and the percentage of questions requiring omni-modal solutions, labeled as Acc. and Solvable. The Source category specifies the origin of the materials. Private sources, as opposed to public ones, can prevent data contamination. QA types include MC for multi-choice questions and MO for multi-step open-ended questions. EN and CH denote English and Chinese languages. UNO-Bench includes 1250 human-curated samples in the omni-modal section (referred to as -omni) and 2480 enhanced samples in the uni-modal section (referred to as -uni).

modal dataset is well-suited to real-world scenarios, particularly within the Chinese context. The automatically compressed uni-modal dataset reduces evaluation costs by 90% while maintaining 98% consistency with the full-scale benchmarks. Its comprehensive quality and efficiency significantly surpasses existing datasets.

3. Beyond conventional multiple-choice questions, we introduce an innovative **Multi-Step Open-Ended Question (MO)** format to enable a more realistic and discriminative assessment of complex reasoning, especially for cross-modal tasks. To facilitate this, we propose a **General Scoring Model** supporting 6 question types, which achieves 95% accuracy on out-of-distribution models and benchmarks.

2 Related Work

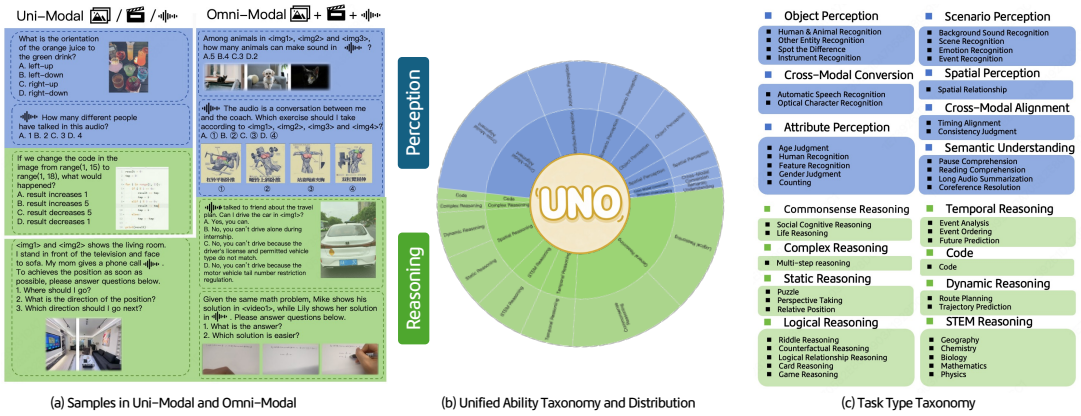
2.1 Uni-Modal Benchmarks

Based on large language models, vision language models (VLMs) (Bai et al., 2025; Xiaomi, 2025; Zeng et al., 2025) and audio language models (ALM) (Ding et al., 2025; Wu et al., 2025) introduce the general intelligence to vision modality and audio modality respectively. Various uni-modal benchmarks conduct comprehensive evaluations on VLMs (Liu et al., 2024b,c; Mathew et al., 2021; Li et al., 2024a; Fu et al., 2024) and ALMs (Ardila et al., 2019; Wang et al., 2021; Yang et al., 2024; Ao et al., 2024). For image modality, MMBench(Liu et al., 2024b) proposed a systematically designed benchmark to evaluate general image understanding on 20 different tasks. Focused on mathematics, MathVision(Wang et al., 2024b) collected questions from 19 mathematical competitions to evaluate VLMs complex reasoning ability. For video modality, MVBench(Li et al., 2024a) aggregated 11 public video benchmarks and incorporated data enhancement process to cover 20 dynamic video understanding tasks. For audio modality, MMAU(Sakshi et al., 2025) provides general audio understanding assessment across speech, sounds and music domains, featuring diverse audio samples. There are massive uni-modal benchmarks covering diverse model abilities on vision modality and audio modality separately.

2.2 Omni-Modal Benchmarks

Omni models have arisen in recent years(Comanici et al., 2025; Xu et al., 2025b; AI et al., 2025; Li et al., 2025), as the pioneer, Gemini(Comanici et al., 2025) shows a strong ability in understanding both vision and audio, while Qwen-3-Omni(Xu et al., 2025b) provides leading performance in open-source models. However, there are less omni-modal benchmarks that can evaluate the modality combination across image, video and audio. OmniBench(Li et al., 2024b) inserted audio as a context into the image understanding task and made up an omni-modal benchmark, while the data quality needs further improvement. WorldSense(Hong et al., 2025) emphasized audio-visual data in real world scenarios with high data quality, while most audio-visual questions can be solved by audio or video alone, which cannot assess the cross-modality ability. Other datasets focus on audio (Gong et al., 2024) or video (Zhou et al., 2025) and cover limited task types.

For instance, in Figure.3(b), the problem can be resolved using either the audio modality or the visual modality, whereas in Figure.3(c), only the visual modality is necessary to address the problem.



(a) Samples in Uni–Modal and Omni–Modal (b) Unified Ability Taxonomy and Distribution (c) Task Type Taxonomy

Figure 1: Illustration of the unified ability taxonomy proposed in UNO-Bench. (a) exemplarily presents the way to unify uni-modal and omni-modal samples. (b) shows the three-layer hierarchical structure of the unified ability taxonomy and its distribution in UNO-Bench. Among the 13 abilities, (c) demonstrates the 44 diverse task types that cover a large range of real world scenarios.

These instances are likely to exaggerate the capabilities of the omni model, making it crucial to evaluate the cross-modality solvable problem (illustrated in Figure.3(a)) to accurately assess omni-modal capability (refer to Section.4.3 for more details).

Addressing these limitations, we propose a novel and unified benchmark, UNO-Bench, that enables comprehensive model assessment and pushes omni models to the next-level of intelligence.

3 Method

In this section, we first introduce the omni-modal dataset construction pipeline in Section.3.1. For uni-modal dataset, an quality improvement method and a general dataset compression method to improve the evaluation efficiency are introduced in Section.3.2. Finally, the novel multi-step open-ended questions are presented alongside a general scoring model in Section.3.3

3.1 Omni-modal Dataset Construction

We have established a human-centric data construction pipeline (Figure.2) that efficiently empower human intelligence to produce high-quality and high-diversity dataset.

3.1.1 Model Ability Taxonomy

Through cumulative experiences on multimodal evaluation from both model-side and user-side, we summarize the capabilities of uni-modal and omni-modal into a unified model ability taxonomy. As shown in Figure.1, the omni model's capabilities are systematically categorized into two primary dimensions: Perception and Reasoning.

Perception dimension structured through seven recognition types including Object Perception, Attribute Perception, Scenario Perception, Spatial Perception, Cross-Modal Conversion, Semantic Understanding. In addition, we incorporate Cross-Modal Alignment to assess information synchronization across modalities.

Reasoning dimension extends conventional reasoning categories (including General, STEM, Code) with Spatial Reasoning (including Static Reasoning and Dynamic Reasoning), Temporal Reasoning, and Complex Reasoning (which indicates multi-conditional, multi-step problem).

For example, Scenario Perception includes the recognition of visual scenes and the judgment of audio scenes. Based on this taxonomy, we create a diversity dataset with 44 task types illustrated in Figure.1(c). Detailed definitions and examples can be found in the Appendix.I.

3.1.2 Annotation Pipeline

Based on the unified taxonomy, we construct the dataset through three steps: Material Collection, QA Annotation and Quality Inspection. Details can be found in Appendix.3.1.

- **Material Collection.** To eliminate the cross-modal information redundancy and the risk of data leakage, we collect diverse innovative data sources and replace all the original audio dialogues to annotator recordings based on each task.
- **QA Annotation.** Combined with human experts and high quality crowd-sourced users, we integrates a human-centric approach to

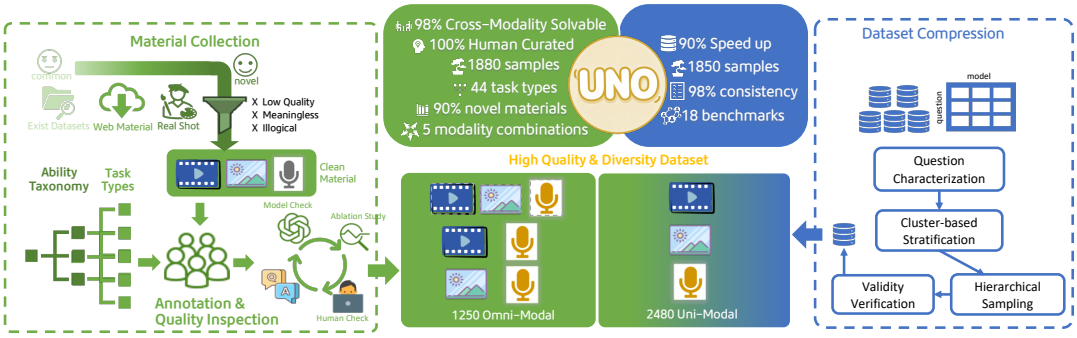


Figure 2: Dataset Construction Pipeline includes human crafted process (left side) and automated data compression (right side). First, we collect diverse and novel materials to prevent data contamination. Second, with the proposed unified ability taxonomy, human annotators including experts will craft questions, answers and record audios in real-world scenarios. Finally, with model checking, ablation study and human experts revision, we achieves high quality and diversity dataset. Regarding automated data compression, we use model performances as the sample feature, employing clustering and resampling to achieve a 90% dataset compression.

construct high quality QA pairs that simulates real-world scenarios.

- **Quality Inspection.** To ensure the data quality, we establish a multi-stage, cyclically validated quality assurance system composed of automated tools and manual review.

3.2 Uni-modal Dataset Improvement

3.2.1 Quality Improvement

Existing public uni-modal datasets are bothered by data leakage issue(Xu et al., 2024). To verify the influence, we adopt privatization improvement on the widely used public dataset MMBench(Liu et al., 2024b). As shown in Figure.9, the performance of models have better distinguishability after dataset improvement, reflecting the true capability differences between models.

3.2.2 Dataset Compression

Regarding the existing large-scale uni-modal benchmarks, to reduce the evaluation costs of LLM yet still maintain the consistence with the full scale, we designed a **clustering-guided hierarchical sampling (CGHS)** method as shown in Figure.2. CGHS is a general method for dataset compression, which utilizes model performance metrics as features rather than the content of questions to select important samples that impact model performance. The introduction of CGHS is outlined in the following steps:

Question Characterization: Represent each question as an x-dimensional vector, where dimensions correspond to scores from different models on that question.

Cluster-based Stratification: Utilize the Kmeans++(Arthur and Vassilvitskii, 2007) algorithm to categorize questions into k clusters, each representing a "model performance similar" question type (e.g., easy questions, difficult questions, etc.).

Hierarchical Sampling: Determine the sample size for each stratum based on cluster size proportions, and construct the final evaluation subset through simple random sampling.

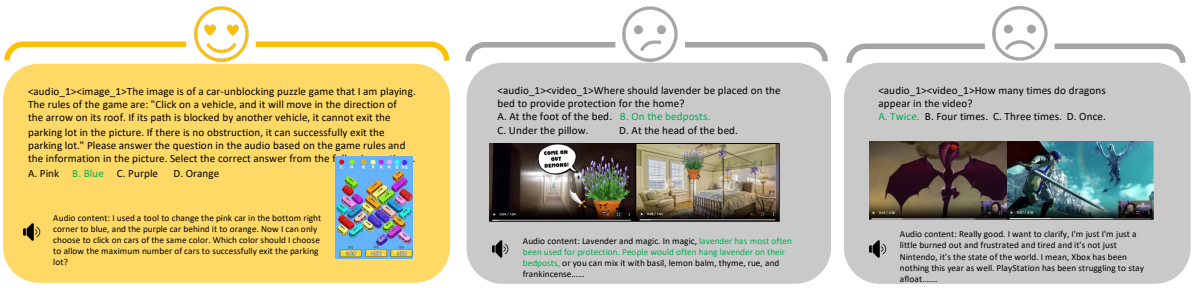
Validity Verification: To verify the compression performance, we define these metrics: Spearman's Rank Correlation Coefficient (SRCC) for ranking consistency, Pearson's Linear Correlation Coefficient (PLCC) for linear value consistency, Root Mean Square Error (RMSE) for numerical precision, Margin of Error (MoE) for quantifying estimation uncertainty, and Confidence Interval Coverage (CIC) for statistical reliability.

To ensure statistical stability, we repeat the above steps by using 5 random splits and performing 10-fold cross-validation. This approach identifies the optimal sample size via cost-benefit curve analysis, leading to a reduction in evaluation costs by over 90% while preserving accuracy, as shown in Figure.8.

3.3 Multi-Step Open-Ended Questions

3.3.1 Question Type Definition

Evaluating the multi-step reasoning capabilities of omni models presents a significant challenge. Real-world problems require models to integrate multi-modal information and execute a sequence of logical steps. However, current automated benchmarks, often relying on Outcome Reward Models



(a) Need both audio and visual modality (b) Need either audio or visual modality (c) Need visual modality only

Figure 3: Illustration of the cross-modality solvable sample.

(ORMs), typically provide only a binary pass/fail judgment. This approach fails to distinguish between a model that completes 80% of a task and one that fails at 20%, a crucial gap that human evaluators easily perceive. While alternatives like Process Reward Models (PRMs)(Lightman et al., 2023) or multi-turn dialogues(Reddy et al., 2019) exist, they are hampered by high implementation difficulty, low accuracy, or poor efficiency. Moreover, the prevalence of multiple-choice formats in existing benchmarks is unrepresentative of real-world, open-ended user queries and may conceal the weaknesses of models.

To address these issues, we propose an innovative Multi-Step Open-Ended Question (MO) type, designed for granular and realistic assessment. In the construction of MO dataset, complex problems are first deconstructed by human experts into a series of progressive, interdependent sub-questions. Each sub-question is assigned a score based on its importance, summing to a total of 10 points. During testing, all sub-questions are posed in a single turn, requiring the model to generate a step-by-step open-ended response. This method allows us to precisely quantify how far along a complex reasoning chain a model can proceed, offering a more accurate and insightful measure of its true capabilities. An example is shown in Figure.4.

3.3.2 General Scoring Model

Besides the dataset construction, multi-step open-ended question introduces a new challenge of automated evaluation. We propose a general scoring model based on Qwen3-14B (Yang et al., 2025) to evaluate diverse tasks ranging from multi-choice to multi-step open-ended questions. This model takes the *(question, reference, model prediction)* triplet as input and outputs a scalar score. The construction of our training dataset is illustrated in Figure 5. One of the critical way to improve

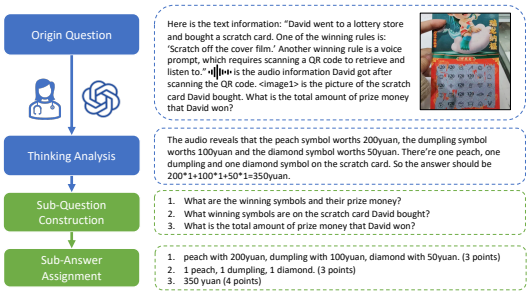


Figure 4: Construction Pipeline of Multi-Step Open-Ended Questions.

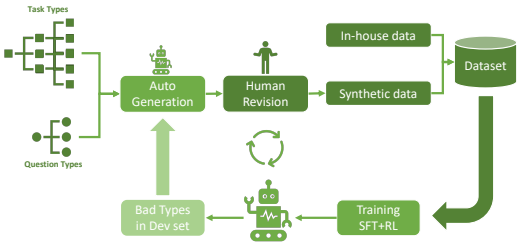


Figure 5: Training dataset construction and model training pipeline for general scoring model.

accuracy is to group questions into finer types and define appropriate criteria for each types. See details in Appendix.H.

Empirical evaluations demonstrate the effectiveness of this approach. As detailed in Appendix H, our scoring model achieves a 95.05% accuracy on the internal MO benchmark, outperforming strong baselines like GPT-4.1(OpenAI, 2023), while maintaining robust performance on the public single-step benchmark EVOUNA(Wang et al., 2023).

Experiments in Section.C.1 show that compared with single-step evaluation method (e.g. multiple-choice questions), multi-step open-ended questions can effectively observe the ability decay of models in long-chain reasoning, providing a more realistic difficulty for advanced models with stronger discrimination.

Table 2: General performance of omni models in UNO-Bench for both uni-modal capability and omni-modal capability, where omni-modal benchmark includes multi-choice questions (Omni-MC) and multi-step open-ended questions (Omni-MO). Metrics are accuracy for all tasks except Omni-MO, which employs keypoint-based scoring.

Model	Audio	Visual	Omni-MC	Omni-MO
Qwen-2.5-Omni-3B	54.40	42.67	27.80	24.76
MiniCPM-O-2.6	56.50	42.27	28.60	23.76
Ming-lite-Omni-1.5	58.30	46.28	28.90	25.48
Baichuan-Omni-1.5	54.10	44.66	29.70	21.04
Qwen-2.5-Omni-7B	60.20	50.68	32.60	27.72
Qwen-3-Omni-30B-A3B	79.40	63.29	42.10	37.08
LongCat-Flash-Omni	**80.20**	**67.06**	**49.90**	**42.68**
Gemini-2.0-Flash	70.70	62.76	44.90	38.56
Gemini-2.5-Flash	79.50	69.54	54.30	47.08
Gemini-2.5-Pro	88.40	78.67	70.90	57.32
Gemini-3.0-Flash-Preview	87.80	83.61	74.70	68.16
Gemini-3.0-Pro-Preview	**89.80**	**84.30**	**76.30**	**76.68**

4 Experiment and Analysis

4.1 Experiment Setting

We evaluate omni models that support text, visual, and audio inputs simultaneously, including open-source models: Longcat-Flash-Omni(Team, 2025), Qwen-3-Omni-30B-A3B-Instruct(Xu et al., 2025b), Qwen-2.5-Omni-3B, Qwen-2.5-Omni-7B(Xu et al., 2025a), Baichuan-Omni-1.5(Li et al., 2025), MiniCPM-O-2.6(Yao et al., 2024), and Ming-lite-Omni-1.5(AI et al., 2025), as well as closed-source models: Gemini-3-Pro-Preview, Gemini-3-Flash-Preview, Gemini-2.5-Pro, Gemini-2.5-Flash, and Gemini-2.0-Flash(Comanici et al., 2025). To have a fair comparison between instruct model and thinking model, we adopt similar way in Qwen-3(Xu et al., 2025b) that limits thinking budget to 128 tokens. We apply this restriction to Gemini-2.5-Pro and disable the thinking mode for both Gemini-2.5-Flash and Gemini-2.0-Flash. All the other model integrations strictly adhere to official implementations. In video processing, each model receives raw video and performs frame sampling according to its own sampling strategy.

In the subsequent sections, we perform detailed experiments on UNO-Bench and aim to address the following questions:

1. How do current omni models perform, and what are their limitations?

2. How are uni-modal and omni-modal capabilities related?

3. Is the UNO-Bench capable of effectively evaluating the omni model?

4.2 Model Performance

4.2.1 Overall Analysis

Our main evaluation, summarized in Table.2, reveals a clear performance hierarchy where proprietary models, particularly Gemini-3-Pro, establish the state-of-the-art across all benchmarks. Meanwhile, progress within the open-source community is notable, with increased model scale and more training data, exemplified by Longcat-Flash-Omni, leading to substantial improvements. Furthermore, we observe a strong positive correlation between a model's performance on the foundational Audio and Visual tasks and its scores on the more demanding Omni benchmarks, suggesting that robust uni-modal perception is a prerequisite for advanced omni-modal understanding.

On the Omni-MC benchmark, which evaluates omni-modal comprehension, smaller open-source models exhibit performance marginally surpassing the random guess baseline (25%), achieving scores between 27.80% and 29.70%. The larger Qwen-3-Omni-30B marks a significant leap, with a score of 42.10% that approaches the performance of entry-level proprietary models like Gemini-2.0-Flash (44.90%). Nevertheless, a substantial performance deficit persists when compared to the leading Gemini-3-Pro (76.30%). This gap highlights the profound difficulty of advanced omni-modal comprehension, even in a multiple-choice format.

The Omni-MO benchmark presents a considerably greater challenge, as evidenced by the universal and marked degradation in performance for most models relative to their Omni-MC scores. This degradation reveals a systemic limitation in multi-step omni-modal reasoning. The open-

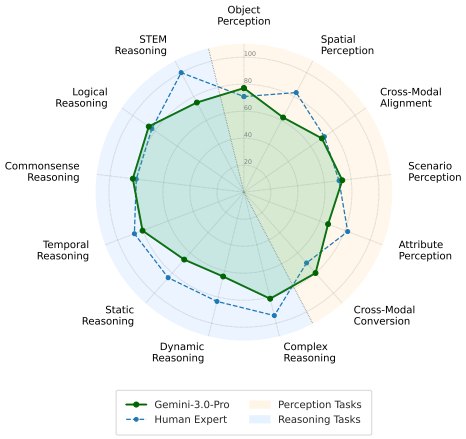


Figure 6: The competition between human experts and Gemini-3.0-Pro. Gemini-3.0-Pro shows comparable perception capability but lower reasoning capability.

source model with the highest score, LongCat-Flash-Omni, achieved only 42.68%. However, Gemini-3.0-Pro achieved 76% on both benchmarks, demonstrating a significant improvement in reasoning capabilities. We attribute this significant gap primarily to the scarcity of high-quality, modality-synergistic reasoning benchmarks and instruction data within the open-source community.

Further ablation studies are conducted to deep dive into the enhancement from vision and audio modality in Appendix.B.1 and Appendix.B.2 respectively.

4.2.2 Top-tier Analysis

In which direction should the SOTA model be improved? To answer this question, we invited human experts for a competition. It's important to highlight that, unlike the dataset annotators, these experts had no prior exposure to the questions or the answers.

Finding 1. Gemini-3.0-Pro has reached human comparable perception ability in omni-modal perception, yet there remains a gap in its reasoning performance. Compared to human experts, Gemini-3.0-Pro exhibits similar performance in perception, but falls behind in reasoning. The comparison of scores for specific ability items can be seen in Figure.6. Upon examining ability analysis, we observe an intriguing phenomenon: humans are more proficient in reasoning as opposed to perception (81.3% compared to 74.3%), which contrasts with the model's performance. By interviewing various human experts, it becomes evident that humans might miss some information in video or audio formats, and their world knowledge is more limited compared to large language models.

4.3 Uni-Modal v.s. Cross-Modal

To investigate the relationship of uni-modal and omni-modal understanding ability, we conduct regression analysis and ablation experiments. Thanks to the unified ability taxonomy and the high quality of omni-modal samples in UNO-Bench, we find some interesting observations.

Finding 2. Compositional Law: the effectiveness of omni-modal capability is related to the product of the performances of individual modalities by a power-law. Observing the results in Table.2, we identify a strong correlation between a model's omni-modal performance and its uni-modal capabilities. To formalize this, we derive a Compositional Law from a general functional form by applying two simplifying principles dictated by the omni-modal tasks proposed in our UNO-Bench. Let's elaborate on the specifics below.

General Model & Task Constraints. We begin by positing that the omni-modal performance $\mathcal{P}_{\text{Omni}}$ is a function of uni-modal performances $\mathcal{P}_{\text{A}}$ and $\mathcal{P}_{\text{V}}$. A general model can be written as:

$$\begin{aligned}\mathcal{P}_{\text{Omni}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) = f_{\text{A}}(\mathcal{P}_{\text{A}}) + f_{\text{V}}(\mathcal{P}_{\text{V}}) \\ + f_{\text{I}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) + b\end{aligned} \tag{1}$$

where $f_{\text{A}}, f_{\text{V}}$ represent modality independent path contributions, f_{I} the interaction, and b a baseline performance constant (e.g. random guess).

We arrive at the **Omni-modal Compositional Law** based on task constraints (including 100% omni-modal solvable assumption), and the detailed derivation process is provided in the Appendix.F.

$$\mathcal{P}_{\text{Omni}} = C \cdot (\mathcal{P}_{\text{A}} \times \mathcal{P}_{\text{V}})^{\alpha} + b \tag{2}$$

where α is the synergistic exponent, C is a scaling coefficient, and b is a baseline bias. A non-linear regression on data from leading models is shown in Figure.7, with a coefficient of determination (R^2) of 0.9759. Analysis of the fitted parameters reveals a clear transition from limited gains to emergent capabilities, driven by the super-linear nature of the law.

Power-law Synergy and Emergent Ability. The exponent $\alpha \approx 2.19$ is the most critical discovery, revealing a powerful **Power-law synergy**. Since $\alpha > 1$, the function is convex, implying that the performance improvements increase at an accelerating rate. This explains the transition from a

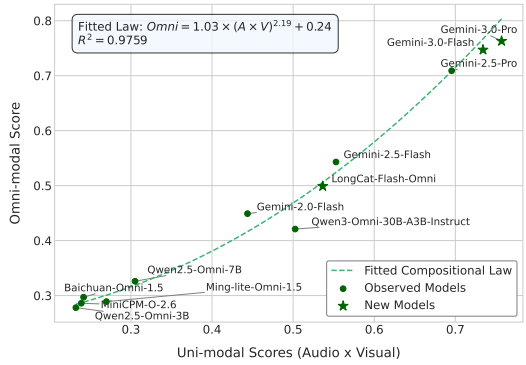


Figure 7: **The Compositional Law of Omni-modal Performance.** Observed omni-modal scores versus the product of their uni-modal scores. The dashed line represents our fitted law (Eq. 2), derived from 9 observed omni-modal models, and 3 additional new models are plotted to validate the fitting consistency. The convex, accelerating curve illustrates the Power-law synergy.

"short-board effect" to an "emergent ability" seen in Figure.7:

- **Limited Gains at Low Performance:** For models with weaker uni-modal abilities (e.g., MiniCPM-O), the curve is relatively flat. Small improvements in the product of uni-modal scores yield only marginal gains in omni-modal performance. This can be seen as a "short-board effect", where the system is not yet capable of effectively leveraging the combined inputs.

- **Emergent Ability at High Performance:** As uni-modal abilities strengthen (e.g., Gemini-2.5-Pro), the curve steepens dramatically. The same amount of improvement in the uni-modal product now yields a much larger increase in omni-modal performance. This accelerating return on investment is the quantitative signature of emergence, where stronger foundational skills unlock disproportionately powerful combined capabilities.

Interpreting the Coefficients and Benchmark Coherence. The other parameters complete the picture. The bias term $b \approx 0.2422$ acts as a performance floor. As uni-modal performances approach zero, the system's output converges to this value, which is strikingly close to the 0.25 random-guess accuracy of our benchmark. The scaling coefficient $C \approx 1.0332$, being remarkably close to unity, indicates a harmonious and naturally scaled system. We attribute this harmony not only to the models' intrinsic fusion mechanisms but also to the coherent design of our benchmark itself.

Additional fitted models are presented in Appendix.G. We argue that our proposed model is the most natural and interpretable among them. It is worth emphasizing that this finding is directly attributed to the deliberate design of UNO-Bench. Specifically, it not only ensures a balanced distribution of capabilities across both uni-modal and omni-modal tasks, but also constructs the majority of questions to demand the joint processing of both modalities for resolution.

4.4 Benchmark Analysis

To verfiy the effectiveness of UNO-Bench, we conduct analysis on three aspects. First, the performance on MO questions captures the difficulty of complex reasoning ability and magnifies this critical capability gap between the SOTA and other models (Appendix.C.1). Second, the proposed dataset compression method achieves 0.98 SRCC and PLCC on only 10% percent of samples (Appendix.3.2.2). Finally, compared to current omni benchmarks, UNO-Bench has 100% accuracy on omni-modal dataset while 98% questions requires cross-modality to solve. It also provides both a clear performance ladder and a meaningful difficulty range (Appendix.C.3).

5 Conclusion

In this work, we introduce a high quality and diversity benchmark to evaluate omni models comprehensively. With unified data framework in UNO-Bench, we found that the omni-modal capability may not simply be a linear superposition of uni-modal capabilities, but rather follows a significant multiplicative relationship. The evaluation results show that it manifests as a bottleneck effect on weak models, while exhibiting synergistic promotion on strong models. In addition, we found that both uni-modal and omni-modal understanding capability of the Gemini series far surpasses existing open-source omni models. The Gemini-3-Pro shows comparable perception capability with human experts but still has a performance gap in reasoning aspect. Besides better dataset quality and evaluation efficiency, UNO-Bench can provide sufficient metric discriminability and a progressive difficulty scale to drive model capability growth.

Limitations

Scale versus quality. To ensure strict cross-modality dependency and high data quality, we prioritized a human-centric curation process over large-scale automated generation. Although UNO-Bench covers 44 distinct task types, the sample size for certain long-tail tasks may be insufficient to yield statistically significant results at a fine-grained level. Consequently, we recommend that researchers focus on performance comparisons at the capability level rather than the sub-task level. In future work, we aim to develop semi-automated pipelines to expand the dataset scale and improve the stability of fine-grained evaluations without compromising quality.

Generalizability of the Compositional Law. The proposed Compositional Law is empirically derived from 12 representative models. Although the predictive power has been validated on unseen models such as Gemini-3-Flash and LongCat-Flash-Omni, the law may require recalibration as model architectures and training paradigms continue to evolve. Furthermore, the applicability of this law to other omni-modal data distributions remains to be verified. Finally, while our work quantifies the mathematical relationship between uni-modal and omni-modal capabilities, the underlying mechanistic interpretation of how modalities synergize within the model's internal representations remains to be explored.

Ethics Statement

In the data construction process, we employed LLMs, primarily the Gemini series, to assist in two key aspects. First, we leveraged LLMs to creatively generate certain questions, providing inspiration and guidance for data construction. Second, to ensure appropriate difficulty and solvability, a preliminary model check was conducted on every constructed question.

We employed a professional annotation team from China. All members hold university degrees and possess extensive experience in data annotation. The annotation process was conducted on the AGI-Eval platform. Annotators received an average compensation of $8 USD per hour, a rate significantly exceeding the local average wage. All participants were fully informed that the annotated data would be used for public research release.

To mitigate privacy risks and copyright issues, all multimodal assets (images, audio, and video) were sourced from authorized public benchmarks, royalty-free platforms, or were self-recorded by the annotators. Following data construction, we implemented an enterprise-level content safety audit. This process integrated deep learning algorithms with a professional human review team to rigorously identify and eliminate potential violation risks across text, image, video, and audio modalities.

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Appendix

A Ability Taxonomy Analysis

To dissect the models' core capabilities, we perform a fine-grained analysis based on our proposed ability taxonomy, with detailed results presented in Table.3.

In perception, a notable trend emerges: while smaller models find Recognition easier than Alignment, more powerful models like Qwen-3-Omni-30B-A3B and the Gemini-2.5 series exhibit stronger Alignment capabilities. This suggests that advanced models develop a more sophisticated grasp of inter-modal relationships. Among open-source models, LongCat-Flash-Omni achieves the highest perception score 53.68%. Gemini-2.5-Pro leads overall significantly, with both its Alignment 74.35% and Recognition 70.05% exceeding 70%.

In reasoning, Spatial Reasoning is consistently the most challenging task across all models. Even the best-performing Gemini-3.0-Pro only achieves 65.83%, and LongCat-Flash-Omni demonstrates the best spatial reasoning among open-source models with a score of 29.17%.

Overall, reasoning proves to be a more challenging frontier than perception. This is highlighted by the performance gap between the leading proprietary model, Gemini-3.0-Pro, and the best open-source model, LongCat-Flash-Omni. The disparity is 17.15% in Perception (70.83% vs. 53.68%) but widens to a more substantial 32.82% in Reasoning (79.93% vs. 47.11%). This indicates that advanced reasoning remains a key differentiator and a primary bottleneck for current multimodal models.

B Ablation Experiment

B.1 Ablation Visual Understanding

To quantify the contribution of visual information, we conducted an ablation study with three settings: audio-only (Audio), audio plus high-quality textual captions of the visual scene (+ Caption), and the full audio-visual input (+ Visual). The captions were generated by Gemini-2.5-Pro to ensure descriptive richness. Results are detailed in Table.4.

With only audio input, most models' performance drops to a level near random guessing (around 20%-28%), confirming the critical role of visual context. A notable exception is Gemini-2.5-Pro, which scores 40.34%, suggesting an ability to leverage linguistic cues or shortcuts within the questions even without visual data.

The introduction of `Caption` information yields significant but highly variable performance gains. Powerful models like the Gemini series and Qwen-3-Omni-30B-A3B demonstrate a substantial leap in performance (gains of 20%-25%), showcasing their strong ability to reconstruct scenes from textual descriptions. In contrast, models like MiniCPM-O-2.6 and Ming-lite-Omni-1.5 show minimal improvement, indicating a weaker capacity for this text-to-vision reasoning.

Comparing `Caption` against full `Visual` input reveals a fascinating dichotomy. For the most capable model, Gemini-2.5-Pro, direct visual information provides a clear advantage over captions (70.90% vs. 65.10%), proving that raw visual data contains nuances that text cannot fully capture. However, for several other models, including Gemini-2.0-Flash and the powerful Qwen-3-Omni-30B-A3B, performance with captions is surprisingly on par with, or even slightly exceeds, that with direct visual input. This suggests that for these

Table 3: Analysis of Omni-MC on ability taxonomy. To simplify the analysis, Cross-modal Recognition refers to the set of other Perception capabilities except Cross-modal Alignment.

Model	Perception			Reasoning				Overall
	Cross-modal Alignment	Cross-modal Recognition	Overall	General Reasoning	Temporal Reasoning	Spatial Reasoning	Overall	
Qwen-2.5-Omni-3B	29.84	35.94	33.09	20.65	50.00	20.83	23.98	27.80
MiniCPM-O-2.6	26.70	30.88	28.92	26.62	42.42	26.67	28.40	28.60
Ming-lite-Omni-1.5	28.80	35.94	32.60	24.38	43.94	24.17	26.53	28.90
Baichuan-Omni-1.5	30.89	32.26	31.62	25.87	45.45	28.33	28.57	29.70
Qwen-2.5-Omni-7B	38.22	36.41	37.25	28.11	43.94	26.67	29.59	32.60
Qwen-3-Omni-30B-A3B	**53.40**	45.16	49.02	38.06	53.03	26.67	37.41	42.10
LongCat-Flash-Omni	51.31	**55.76**	**53.68**	**50.00**	**62.12**	**29.17**	**47.11**	**49.90**
Gemini-2.0-Flash	43.98	49.77	47.06	45.02	57.58	31.67	43.71	44.90
Gemini-2.5-Flash	56.02	50.69	53.19	61.44	68.18	27.50	55.27	54.30
Gemini-2.5-Pro	**74.35**	70.05	**72.06**	75.62	**84.85**	45.00	70.41	70.90
Gemini-3.0-Flash-Preview	67.02	**71.89**	69.61	83.08	83.33	59.17	78.23	74.70
Gemini-3.0-Pro-Preview	70.16	71.43	70.83	**84.08**	80.30	**65.83**	**79.93**	**76.30**

models, the language processing pathway may be more adept at extracting semantic meaning than their own visual encoders, highlighting a potential imbalance in their multimodal processing capabilities.

B.2 Ablation Audio Understanding

To isolate the impact of auditory information, we evaluated models under three conditions: visual-only (`Visual`), visual plus transcribed audio (`+Caption`), and the full audio-visual input (`+Audio`). We further divided the audio into three categories: the `Speech` category was annotated with ASR transcripts, while both the `Environment` and `Music` categories received textual descriptions. To ensure the robustness of our analysis and improve statistical reliability, the data-insufficient `Music` class was merged with the `Environment` class. The majority of the transcriptions were manually produced by human annotators, while a smaller subset was generated by a powerful multimodal model. The results are presented in Table.5.

The `Visual`-only setting results in significantly lower performance across all models, with Overall scores ranging from 21.20% to 33.70%. This confirms the critical role of auditory context in multimodal understanding. The introduction of textual audio descriptions (`+Caption`) substantially boosts performance across the board. The improvement is particularly dramatic for high-capacity models like Gemini-2.5-Pro (+31.0% Overall) and Qwen-3-Omni-30B-A3B (+17.4% Overall), demonstrating their strong ability to integrate textual information.

The comparison between `+Caption` and `+Audio` reveals crucial insights into the models' raw audio processing capabilities. In environmental sound scenarios, understanding raw audio remains a significant challenge for most open-source models. For instance, Qwen-2.5-Omni-3B, MiniCPM-O-2.6, and Ming-lite-Omni-1.5 all exhibit considerably higher performance with textual descriptions (`+Caption`) than with the original audio (`+Audio`). This suggests that their audio encoders struggle to extract meaningful features from complex non-speech sounds, making them prefer clean textual summaries. In contrast, the most capable models—Gemini-2.5-Pro, Gemini-2.5-Flash, and Qwen-3-Omni-30B-A3B demonstrate superior audio understanding by scoring higher in the `+Audio` setting, indicating they can extract richer information directly from the audio signal than is present in the provided caption.

In conversational (Speech) scenarios, the results are more nuanced. The top-performing Gemini-2.5-Pro shows a substantial advantage with raw audio over ASR transcripts (`+Audio` 72.16% vs. `+Caption` 66.00%), indicating it effectively leverages paralinguistic cues such as tone, emotion, and prosody that are lost in transcription. Conversely, several other models, including the Qwen series and MiniCPM-O-2.6, perform slightly better with ASR transcripts (`+Caption`) than with raw audio. This points to a common bottleneck where imperfections in their audio encoders are a greater liability than the information lost during ASR, making clean text a more reliable input. Notably, Gemini-2.5-Flash achieves nearly identical scores in both settings, suggesting its ASR and audio understanding capabilities are exceptionally well-aligned.

C Benchmark Analysis

In this section, we verify the effectiveness of UNO-Bench on three aspects, the performance of

Table 4: Ablation of visual understanding ability. The three settings are audio-only (`Audio`), audio plus high-quality textual captions of the visual scene (`+Caption`), and the full audio-visual input (`+Visual`).

Model	Perception			Reasoning			Overall		
	Audio	+ Caption	+ Visual	Audio	+ Caption	+ Visual	Audio	+ Caption	+ Visual
Qwen-2.5-Omni-3B	17.76	29.13	33.09	20.07	21.43	23.98	19.12	24.60	27.80
MiniCPM-O-2.6	**29.44**	29.61	28.92	**27.21**	29.93	28.40	**28.13**	29.80	28.60
Ming-lite-Omni-1.5	26.28	31.07	32.60	23.13	21.43	26.53	24.42	25.40	28.90
Baichuan-Omni-1.5	22.14	32.04	31.62	23.81	26.70	28.57	23.12	28.90	29.70
Qwen-2.5-Omni-7B	22.14	30.10	37.25	20.41	25.34	29.59	21.12	27.30	32.60
Qwen-3-Omni-30B-A3B	27.01	**46.84**	**49.02**	18.71	**39.63**	**37.41**	22.12	**42.60**	**42.10**
Gemini-2.0-Flash	25.55	44.17	47.06	29.76	45.58	43.71	28.03	45.00	44.90
Gemini-2.5-Flash	22.63	49.03	53.19	29.08	53.23	55.27	26.43	51.50	54.30
Gemini-2.5-Pro	**37.71**	**63.83**	**72.06**	**42.18**	**65.99**	**70.41**	**40.34**	**65.10**	**70.90**

Table 5: Ablation of audio understanding ability. The three settings are visual-only (`Visual`), visual plus transcribed audio (`+Caption`), and the full audio-visual input (`+Audio`). We further divided the audio into two categories: Environment sounds, for which we provided textual descriptions, and Speech, for which we provided ASR transcripts.

Model	Environment			Speech			Overall		
	Visual	+Caption	+Audio	Visual	+Caption	+Audio	Visual	+Caption	+Audio
Qwen-2.5-Omni-3B	26.28	41.03	34.62	24.76	26.66	26.54	25.00	28.90	27.80
MiniCPM-O-2.6	26.92	39.74	34.62	**28.08**	28.44	27.49	**27.90**	30.20	28.60
Ming-lite-Omni-1.5	31.41	43.59	35.26	22.27	25.59	27.73	23.70	28.40	28.90
Baichuan-Omni-1.5	25.64	32.05	28.85	23.70	23.58	29.86	24.00	24.90	29.70
Qwen-2.5-Omni-7B	30.77	41.03	37.18	24.41	33.06	31.75	25.40	34.30	32.60
Qwen-3-Omni-30B-A3B	**32.05**	**48.08**	**48.72**	23.58	**41.23**	**40.88**	24.90	**42.30**	**42.10**
Gemini-2.0-Flash	25.00	48.08	45.51	22.87	48.93	44.79	23.20	48.80	44.90
Gemini-2.5-Flash	17.95	48.72	49.36	21.80	55.09	55.21	21.20	54.10	54.30
Gemini-2.5-Pro	**32.69**	**57.69**	**64.10**	**33.89**	**66.00**	**72.16**	**33.70**	**64.70**	**70.90**

multi-step open-ended question, the performance of dataset compression and the benchmark comparison with other open-source benchmarks.

C.1 Multi-Step Open-Ended Question Analysis

In this work, we introduce a new type of evaluation method, multi-step open-ended question, which effectively assess the complex reasoning ability, especially appears in cross-modality understanding.

As shown in Table.6, the experimental results on our multi-step open-ended questions reveal a clear performance stratification among models. Gemini-3.0-Pro establishes itself as the top-tier model with an overall score of 76.68%, with Gemini-3.0-Flash 68.16% and Gemini-2.5-Pro 57.32% forming a distinct second tier. Among open-source models, LongCat-Flash-Omni emerges as the clear leader with a score of 42.68%, significantly outperforming smaller-scale models like Qwen-2.5-Omni-7B 27.72%. This starkly illustrates that both advanced architecture and model scale are pivotal factors for success in complex, multi-turn multimodal tasks.

As the depth of questions increases from Q1 to Q3+, most models exhibit a general decline in performance, confirming the effectiveness of our dataset's progressive difficulty. For instance, the leading open-source model, Qwen-3-Omni-30B-A3B, sees its overall score drop from 18.08% on the first question (Q1) to 14.18% (Q2) and further to 11.42% (Q3+). This decay highlights a common challenge for current models in handling long-range dependencies, maintaining conversational context, and performing multi-step reasoning. However, a notable exception is `Gemini-2.5-Pro`, whose performance on the second question (Q2) surpasses its score on the first (24.48% vs. 23.44%), before declining on subsequent questions. This unique pattern suggests a superior ability to utilize the context from the initial turn to enhance its understanding and response in the subsequent turn, a capability not observed in other models.

Reasoning ability remains the key bottleneck that differentiates model performance. For all open-source models and the lower-tier Gemini models, scores on `Perception` tasks are considerably higher than on `Reasoning` tasks. The gap is particularly pronounced for Qwen-3-Omni-30B-A3B,

Table 6: Performance on Multi-Step Open-Ended (MO) Questions. Each MO question comprises multiple sub-questions. We denote the first sub-question as Q1, the second as Q2, and the third and subsequent sub-questions as Q3+. Results were evaluated using our general scoring model.

Model	Perception				Reasoning				Overall			
	Q1	Q2	Q3+	All	Q1	Q2	Q3+	All	Q1	Q2	Q3+	All
Baichuan-Omni-1.5	15.4	8.2	5.33	25.2	9.00	7.25	5.75	18.90	10.28	7.44	5.70	20.16
MiniCPM-O-2.6	20.0	6.2	11.33	29.6	9.05	9.55	8.02	22.30	11.24	8.88	8.43	23.76
Qwen-2.5-Omni-3B	19.8	12.2	5.33	33.6	10.70	7.20	8.86	22.55	12.52	8.20	8.42	24.76
Ming-lite-Omni-1.5	19.6	12.4	4.67	33.4	10.90	8.40	7.92	23.50	12.64	9.20	7.52	25.48
Qwen-2.5-Omni-7B	20.2	15.0	12.00	38.8	12.15	8.99	7.83	24.95	13.76	10.20	8.35	27.72
Qwen-3-Omni-30B-A3B	**25.0**	**22.8**	**20.00**	**53.8**	16.35	12.01	10.19	32.90	18.08	14.18	11.42	37.08
LongCat-Flash-Omni	**25.0**	19.2	18.00	49.6	**16.60**	**16.65**	**14.53**	**40.95**	**18.28**	**17.16**	**14.96**	**42.68**
Gemini-2.0-Flash	25.2	19.4	14.67	49.0	15.50	14.05	13.02	35.95	17.44	15.12	13.22	38.56
Gemini-2.5-Flash	31.6	22.6	12.00	57.8	18.35	17.35	16.42	44.40	21.00	18.40	15.87	47.08
Gemini-2.5-Pro	25.6	22.2	21.33	54.2	22.90	25.05	19.43	58.10	23.44	24.48	19.67	57.32
Gemini-3.0-Flash-Preview	36.2	32.2	**24.00**	75.6	26.45	28.85	21.13	66.30	28.40	29.52	21.49	68.16
Gemini-3.0-Pro-Preview	**40.4**	**33.8**	22.67	**81.0**	**28.50**	**33.95**	**24.81**	**75.60**	**30.88**	**33.92**	**24.55**	**76.68**

which scores 53.8% in Perception but only 32.9% in Reasoning. This indicates that while these models have developed solid foundational perception capabilities, converting this perceptual input into complex logical or causal reasoning remains a major hurdle. However, the gap between Perception and Reasoning is much smaller in Gemini-2.5-Pro and Gemini-3.0-Pro.

C.2 Dataset Compression

We design a cluster-guided stratified sampling to compress the scale of benchmark. To evaluate the consistency of model ranking and the best size of compression data size, we conduct several experiments to analysis.

The baseline data set consists of 8000 samples including 18 open-source benchmarks (e.g. MathVista and MMAU, details see Appendix.E) and 20 models evaluation results on them, which split into 12/8 on models as training/test set. Kmeans++(Arthur and Vassilvitskii, 2007) is used to cluster with K=48. To eliminate the random factor, we conduct 5-fold settings and evaluate 10 times on each setting.

The experimental result is shown in Figure.8. At a 10% sampling rate, our method achieved excellent results on test-set. Both SRCC and PLCC exceeded 0.98, indicating near-perfect preservation of ranking and value relationships. The RMSE was below 0.02 with a corresponding MoE of 0.024; together, these values signify high numerical precision and a tight estimation range. Furthermore, the CIC was approximately 95%, confirming the statistical unbiasedness of the sample.

C.3 Benchmark Comparison

To ensure the quality of dataset, we conduct quality check on 10%-20% random samples in each benchmarks. As shown in Table.1, UNO-Bench has 100% accuracy on omni-modal dataset while 98% questions requires cross-modality to solve. It shows the highest quality among existing omni benchmarks.

An effective benchmark must provide both a clear performance ladder and a meaningful difficulty range. As shown in Figure.10, UNO-Bench is engineered to deliver on both fronts. It excels in discriminability, establishing substantial and remarkably linear intervals of ~10%-12% between adjacent models. This superior discriminability comes from a well-calibrated difficulty. UNO-Bench creates a vast 31.9% performance gap between the top and bottom models, effectively separating their capabilities. This approach avoids the pitfall of being universally difficult, a problem seen in AV-Odyssey where all models are compressed into a narrow, low-scoring band (34%-45%). By combining a structured performance ladder with a balanced challenge, UNO-Bench serves as a more reliable and insightful tool to gage genuine progress in the field.

D Dataset Construction Pipeline

D.1 Material Collection

In both data quality checks and experimental results, we found that the natural video with audio-visual synchronized data contains a large amount of information redundancy, only a few videos require both audio and visual modality simultaneously. Therefore, we begin with carefully designed

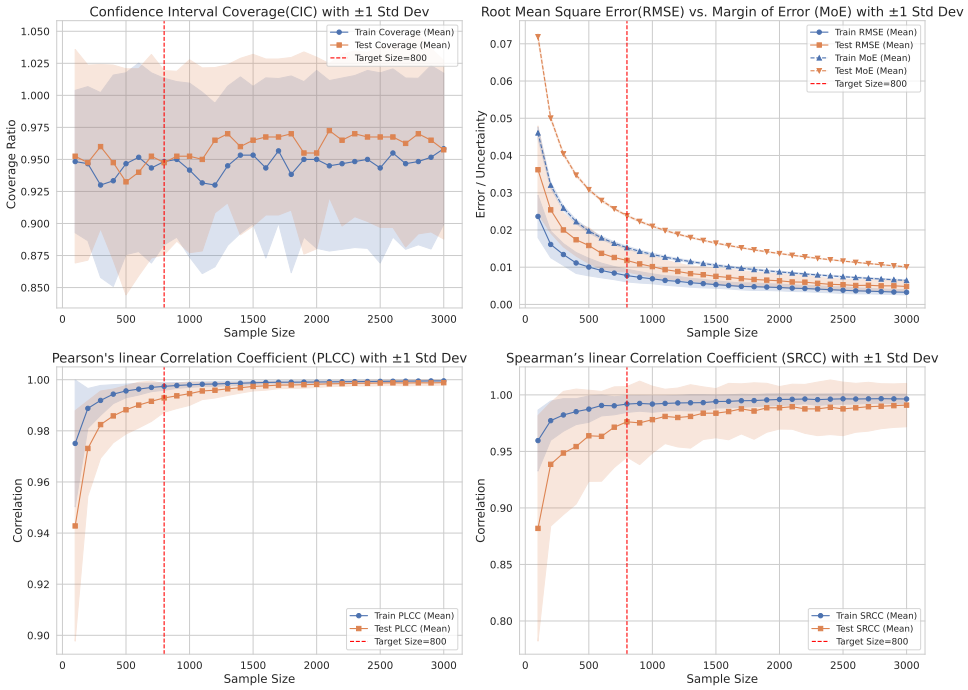

Figure 8: Data compression performance. The four subplots illustrate the evolution of CIC, RMSE/MoE, PLCC, and SRCC metrics as the sample size increases. The vertical red line highlights the chosen sample size (N=800), balancing data reduction with ranking consistency. Shaded areas denote ±1 standard deviation for training (blue) and test (orange) sets.

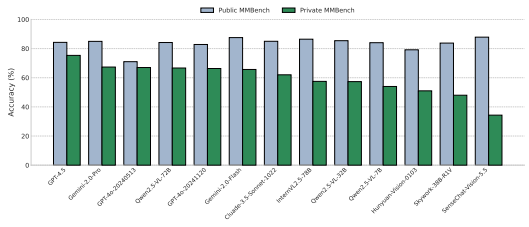

Figure 9: Performance comparison between public MMBench and our private MMBench. With our dataset improvement strategy, the performances among models are more distinguishable.

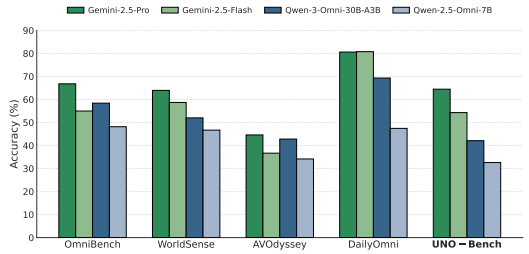

Figure 10: Evaluation of omni-models across five omni-modal benchmarks. The performances among models are more distinguishable on UNO-Bench.

material collection.

Our materials have the following three characteristics:

Diverse Sources. The majority of our materials are real-world photos and videos collected through crowd sourcing, and another portion sourced from copyright-free websites. Additionally, a small fraction comes from high-quality public datasets such as MMVU(Zhao et al., 2025), LongVideoBench(Wu et al., 2024), and VideoVista(Chen et al., 2025).

Rich and Diverse Topics. Our materials cover a broad spectrum of subjects, including society, culture, art, life, literature, science, and so on.

Live-Recorded Audio. Apart from background sounds and music, all dialogue is recorded by human speakers. With over 20 participants in the recording process, the audio features are rich and closely reflect the diverse vocal characteristics of the real world, such as Mandarin and Sichuan dialect.

Finally, we conduct material filtering. Eliminate meaningless, illogical, and low-quality materials, and categorize the remaining materials by theme to create a material library. Additionally, label the materials with more detailed information such as subject, event, scene, and style to facilitate subsequent

annotators to quickly find matching materials.

D.2 QA Annotation

Our annotators consist of human experts and high-quality crowd-sourced users. Human experts have extensive experience in cross-modal data construction and annotation, a deeper understanding of model capabilities, and thus ensure higher professionalism and specificity in the data they construct. Most crowd-sourced users are college students with rich experience in multimodal model interactions and diverse professional backgrounds, providing data with better authenticity and diversity.

First, annotators clarify the required image/video features based on task type definitions and filter appropriate materials from existing libraries using tags. Second, following data construction requirements, they then design prompts and corresponding answers. Finally, to enhance data authenticity, all dialogue audio is recorded manually. Through this workflow, we ultimately generate complete QA pairs encompassing three modalities: visual, auditory, and textual.

Compared to conventional methods limited to human intervention only during the quality assurance phase, our pipeline integrates a **human-centric** approach, ensuring continuous manual involvement from the initial data sourcing to the final output. This methodology not only prevents data leakage but also more accurately simulates real-world scenarios. Furthermore, the manually curated Chinese dataset genuinely captures user requirements in a Chinese linguistic context, compensating for the shortcomings of most existing English-centric datasets.

D.3 Quality Inspection

To ensure the data quality, we have established a multi-stage, cyclically validated quality assurance system composed of automated tools and manual review. Each question undergoes at least three rounds of independent quality inspection to maximize data quality. **Model Check**, a preliminary model check is conducted to filter out cases with ambiguous questions, non-unique answers, or those that do not conform to the task type. **Ablation Study**, through modality ablation experiments, we remove one modality of information from the QA pair to see if the model can answer based solely on the remaining information. If the question becomes unsolvable or ambiguous after removing any one modality, it proves the cross-modality solvability of the data. **Human Check**, finally manual quality inspection and revision are performed.

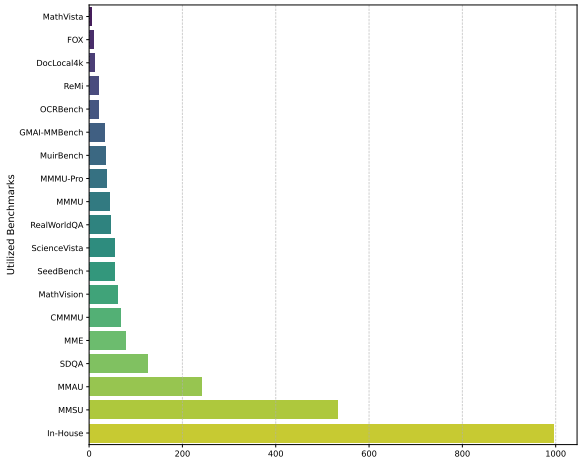

Figure 11: The distribution of the uni-modal benchmarks in UNO-Bench. In addition to publicly available benchmarks, we incorporated several in-house benchmarks both before and after compression to ensure the reasonableness of the data distribution.

E Benchmarks Utilized in Dataset Compression

To construct our compressed datasets, we utilized a variety of benchmarks for both visual and audio modalities. For the visual component, we curated data from 15 public and several in-house benchmarks that assess a range of capabilities, including general visual question answering, document and chart comprehension, STEM/scientific reasoning, and multi-image understanding. For the audio component, we used 3 audio question answering benchmarks. The detailed composition of the resulting uni-modal dataset is presented in Figure.11. The public benchmarks utilized in this work are distributed under open-source licenses (e.g., Apache-2.0, MIT, CC-BY, and CC-BY-NC), and we adhere to their specific terms and intended usage. For the in-house benchmarks, we ensure they are constructed and used following standard ethical guidelines for data collection.

- **General visual question answering**, RealWorldQA(xAI, 2023), MME(Chaoyou et al., 2023), SeedBench(Li et al., 2023).
- **Document and chart understanding**, OCRBench (Liu et al., 2024c), Fox(Liu et al., 2024a), DocLocal4k(Ye et al., 2023).
- **Stem & reasoning**, MMMU(Yue et al.,

2024), MMMU-Pro(Yue et al., 2025), CMMMU(Ge et al., 2024b), MathVista(Lu et al., 2024), MathVision(Wang et al., 2024b), ScienceVista(Team et al., 2025), GMAI-MMBench(Ye et al., 2024).

- **Multi-image Understanding**, ReMi(Kazemi et al., 2024), MuirBench(Wang et al., 2024a).
- **Audio question answering**, MMAU(Sakshi et al., 2025), MMSU(Wang et al., 2025), SDQA(Faisal et al., 2021).

F Rigorous Derivation of the Compositional Law

Defining the **performance gain** as $\mathcal{P}'_{\text{Omni}} = \mathcal{P}_{\text{Omni}} - b$. From Eq. 1, we have:

$$\mathcal{P}'_{\text{Omni}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) = f_{\text{A}}(\mathcal{P}_{\text{A}}) + f_{\text{V}}(\mathcal{P}_{\text{V}}) + f_{\text{I}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) \tag{3}$$

Due to the high quality of our benchmark, where a task is unsolvable if either modality is absent, causing the performance to drop to its baseline (e.g. random guessing). we can have a strict boundary condition:

$$\begin{aligned} \mathcal{P}'_{\text{Omni}}(\mathcal{P}_{\text{A}}, 0) = 0 \quad \text{and} \\ \mathcal{P}'_{\text{Omni}}(0, \mathcal{P}_{\text{V}}) = 0 \quad \text{and} \\ \mathcal{P}'_{\text{Omni}}(0, 0) = 0 \end{aligned} \tag{4}$$

Applying the boundary condition of Eq. 4 to Eq. 3, we find that the gain is a second-order mixed difference of f_{I}:

$$\begin{aligned} \mathcal{P}'_{\text{Omni}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) = & f_{\text{I}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) - f_{\text{I}}(\mathcal{P}_{\text{A}}, 0) \\ & - f_{\text{I}}(0, \mathcal{P}_{\text{V}}) + f_{\text{I}}(0, 0) \end{aligned} \tag{5}$$

Substituting the Taylor series of f_{I} around $(0, 0)$ into Eq. 5, the performance gain is thus exactly equal to the sum of all pure interaction terms from f_{I}:

$$\mathcal{P}'_{\text{Omni}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) = \sum_{i \geq 1, j \geq 1} c_{ij} \mathcal{P}_{\text{A}}^{i} \mathcal{P}_{\text{V}}^{j} \tag{6}$$

where the coefficients c_{ij} are constants derived from the partial derivatives of f_{I} at the origin. For sufficiently small uni-modal performances, we can approximate this series by its leading-order term:

$$\mathcal{P}'_{\text{Omni}}(\mathcal{P}_{\text{A}}, \mathcal{P}_{\text{V}}) \approx c_{11} \mathcal{P}_{\text{A}} \mathcal{P}_{\text{V}} \tag{7}$$

This result strongly motivates modeling the interaction with the general multiplicative Cobb-Douglas form. Re-introducing the baseline b yields our final Compositional Law:

$$\mathcal{P}_{\text{Omni}} = C \cdot \mathcal{P}_{\text{A}}^{\alpha} \mathcal{P}_{\text{V}}^{\beta} + b \tag{8}$$

where C is a scaling constant, and exponents α, β model the interaction's elasticity.

We then posit a **fusion symmetry** assumption: in end-to-end omni models, the fusion mechanism does not inherently favor one modality over another (Xu et al., 2025b; Yao et al., 2024), implying symmetric scaling behavior. This leads to $\alpha = \beta$. Substituting this into Eq. 8, we arrive at the **Omni-modal Compositional Law**:

$$\mathcal{P}_{\text{Omni}} = C \cdot (\mathcal{P}_{\text{A}} \times \mathcal{P}_{\text{V}})^{\alpha} + b \tag{9}$$

G Model Selection for the Compositional Law

To validate our choice of the Compositional Law, we compared its performance against several alternative models. The fitting results for all candidate models on our 9-model dataset are summarized in Table.7.

As shown in Table.7, more complex models like the 'Generalized Power Law' achieve a near-perfect fit on the training data. However, this superior performance is misleading. These models yield parameters that are physically implausible, such as negative exponents (e.g., $P_{Audio}^{-1.59}$) or negative weights. Such parameters would illogically imply that improving a model's uni-modal capability could degrade its omni-modal performance. This is a classic symptom of overfitting, where a model with high capacity learns the noise in a small dataset rather than a generalizable underlying trend.

In contrast, our proposed **Symmetric Power Law** provides an excellent fit ($R^2 = 0.976$) while maintaining theoretical coherence. All its parameters are positive and have clear interpretations: a super-linear synergy ($\alpha = 2.19 > 1$) between modalities, a positive scaling factor ($C = 1.03$), and a reasonable baseline score ($b = 0.24$). Following the principle of Occam's Razor, we select this model as it offers the most parsimonious, robust, and interpretable explanation for the observed phenomenon.

Interestingly, while the parameters from the overfitted models are invalid, they consistently suggest a stronger influence from the visual modality (e.g., the large positive exponent for P_{Visual} in the 'Generalized Power Law'). This hints that while our

Table 7: Fitting results for all candidate models. While more complex models achieve higher fitting scores (R^2), their parameters lack physical interpretability (e.g., negative exponents), indicating severe overfitting on our small dataset. Our chosen **Symmetric Power Law** offers the best balance of a high R^2 value and theoretical soundness.

Model Name	R^2	RMSE	Fitted Equation
Generalized Power Law	**0.999**	**0.005**	$P_{Omni} \approx 1.33 \cdot P_{Audio}^{-1.59} \cdot P_{Visual}^{5.09} + 0.24$
Linear Interaction	0.995	0.010	$P_{Omni} \approx 0.97 - 2.01P_{Audio} - 0.59P_{Visual} + 2.85(P_{Audio} \times P_{Visual})$
Weighted Sum Power Law	0.995	0.010	$P_{Omni} \approx 1.19 \cdot (-0.20P_{Audio} + 1.20P_{Visual})^{3.83} + 0.24$
Symmetric Power Law	**0.976**	**0.022**	$\boldsymbol{P_{Omni} \approx 1.03 \cdot (P_{Audio} \times P_{Visual})^{2.19} + 0.24}$
Simple Linear	0.945	0.033	$P_{Omni} \approx -0.15 - 0.37P_{Audio} + 1.43P_{Visual}$

symmetric law captures the primary collaborative effect, the visual component may play a slightly more dominant role, a direction for future investigation.

H General Scoring Model

We employ Qwen3-14B (Yang et al., 2025) as the backbone for our general scoring model. This model is distributed under the Apache-2.0 license, and our usage is consistent with its intended terms. One of the critical way to improve accuracy is to group questions into finer types and define appropriate criteria for each types. We define six different question types in Table.9. We constructed a fine-tuning dataset consisting of 13,000 samples. The model was trained for 3 epochs using the Llama-Factory framework (Zheng et al., 2024). The training process was conducted on a compute node equipped with 8 NVIDIA A100 (80GB) GPUs and was completed in approximately 3 hours. For inference, we deployed the scoring service using vLLM (Kwon et al., 2023) to optimize throughput, achieving a processing speed of approximately 1 sample per second. To facilitate reproducibility, the complete evaluation code for UNO-Bench and the scoring model are publicly available in our github repository.

Table 8: Accuracy comparison across question types. Our scoring model outperforms baselines in the multi-step open-ended question type.

Model	Single-step		Multi-step
	EVOUNA-TQ	EVOUNA-NQ	In-house
Seed-1.5-VL	**95.90**	89.30	91.18
GPT-4.1	94.50	88.60	94.57
Ours	95.50	**89.30**	**95.05**

To validate the precision of our proposed general scoring model, we conducted a comparative analysis against state-of-the-art models, including Seed-1.5-VL(Ge et al., 2024a) and GPT-4.1(OpenAI, 2023). The evaluation covers two distinct domains:

- **Single-step:** We utilize EVOUNA to evaluate the scoring accuracy on single-step questions(e.g., multiple-choice questions).
- **Multi-step:** We utilize a curated internal dataset to evaluate the model's performance on complex, multi-step open-ended questions.

The detailed accuracy comparison is presented in Table 8. Our model demonstrates superior performance, achieving **95.05%** accuracy on the internal multi-step dataset and consistently competitive results on public benchmarks. Furthermore, our scoring model benefits from a smaller size, offering significant cost advantages.

I Model Ability Taxonomy

This section will provide specific definitions for each ability item and present examples of various task types.

The specific model abilities and task types of the Perception dimension can be seen in Table.10, and the Reasoning dimension can be seen in Table.11.

Specific examples are provided for each model ability. Examples of Perception ability including Object Perception, Spatial Perception, Cross-Modal Alignment, Attribute Perception, Scenario Perception, Cross-Modal Conversion and Semantic Understanding can be seen in Figure.12. Examples of Reasoning ability including Complex Reasoning, Temporal Reasoning, Spatial Reasoning, Life Reasoning, STEM Reasoning and Code can be respectively seen in Figure.13.

Table 9: Definition of finer question types for general scoring model.

Question Type	Criteria	Example
Numerical Type	Requires the model's response to exactly match the numerical value in the reference answer, with no margin of error.	Question: In which year was the Beijing Olympics held? Reference Answer: 2008 Model Response: 2004 Scoring Result: Incorrect.
Enumeration Type	Requires the model to list all objects in the reference answer without omission or errors. Synonyms or semantically equivalent expressions are allowed. Order must be maintained if specified.	Question: Which animals appear in the image? Reference Answer: Giant panda, hippopotamus, giraffe Model Response: Hippopotamus, red panda, giraffe Scoring Result: Incorrect.
Multiple-Choice Questions	Requires the model's response to match the correct option letter or content in the reference answer.	Question: Which dynasty did the poet Li Bai belong to? A. Tang Dynasty B. Song Dynasty C. Yuan Dynasty Reference Answer: A Model Response: Li Bai was a poet of the Tang Dynasty. Scoring Result: Correct.
Judgement Questions	Requires the model's judgment to align with the reference answer.	Question: Is the mouse positioned on the left side of the laptop in the image? Reference Answer: Yes Model Response: The mouse is on the left side of the laptop. Scoring Result: Correct.
Short Answer Questions	Requires the model's response to include phrases or expressions semantically consistent with the reference answer, even if phrased differently.	Question: What was the final ingredient added to the pot in the video? Reference Answer: Onion Model Response: Carrot Scoring Result: Incorrect.
Discursive Questions	Requires the model's response to include core viewpoints from the reference answer.	Question: Briefly explain why biodiversity protection is important. Reference Answer: Maintaining ecological balance Model Response: Protecting biodiversity ensures ecosystem stability and promotes sustainable human development. Scoring Result: Correct.

Table 10: Definition of the Perception Dimension.

Model Ability Taxonomy	Task Type	Definition
Object Perception	Human and Animal Recognition	Recognize persons or animals by combining information from different modalities.
	Other Entity Recognition	Recognize other entities by combining information from different modalities, for example, plants, daily necessities, electronic products, etc.
	Spot the Difference	Completely identify the differences among multiple images or audio clips by combining information from different modalities.
	Instrument Recognition	Identify different musical instruments through sound by combining information from different modalities.
Spatial Perception	Spatial Relationship	Determine the spatial relationship between people/objects by combining audio and visual information.
Cross-Modal Alignment	Timing Alignment	Examine the matching between information from different modalities, for example, matching a single audio clip with multiple images/videos, or a single image/video with multiple audio clips.
	Consistency Judgment	Determine whether the information within the same modality is consistent.
Scenario Perception	Background Sound Recognition	Identify the background sound in the audio; determine the environment in the image/video based on the background sound.
	Scene Recognition	Recognize the environment in images/videos in conjunction with audio, such as identifying scenic spot names and various indoor/outdoor scenes.
	Emotion Recognition	Determine emotions (fear, anger, happiness, surprise, doubt, hesitation, etc.) based on the tone, pitch, and particles of speech of people/animals in the audio.
	Event Recognition	Recognize the overall scene in a video/image, for example, describing the actions of people in the entire scene and the corresponding scene description; analyzing ongoing events; identifying the chronological order of events.
Cross-Modal Conversion	ASR	Recognize speech content, including the recognition of various dialects.
	OCR	Recognize text, including both short and long texts.
Attribute Perception	Counting	Count entities or actions that appear in audio, images, and videos.
	Age Judgment	Determine a person's age by their timbre.
	Human Recognition	Identify the number of people by different timbres.
	Feature Recognition	Recognize all entity-related attributes, such as color, size, material, etc.
	Gender Judgment	Determine a person's gender by different timbres.
Semantic Understanding	Pause Comprehension	Recognize the different meanings expressed by pauses at different positions in speech within an audio.
	Reading Comprehension	Understand the ultimate meaning conveyed through a person's dialogue.
	Long Audio Summarization	Summarize the content of long audio information.
	Coreference Resolution	Understand the specific referents of various personal pronouns that appear in the audio through dialogue and other supplementary information.

Table 11: Definition of the Reasoning Dimension.

Model Ability Taxonomy	Task Type	Definition
Code	Code	Coding problems, including languages such as Python, C++, Java, etc.
Complex Reasoning	Multi-step Reasoning	Reasoning problems that require multiple steps to solve.
Spatial Reasoning	Route Planning	Provide action route planning according to the target by combining information from different modalities.
	Trajectory Prediction	Predict the subsequent action trajectory, direction, and motion state by combining information from different modalities.
	Puzzle	In jigsaw puzzle tasks, complete tasks such as puzzle restoration and fragment searching by combining spatial understanding abilities.
	Perceptive Taking	Examine the model's understanding of the positional relationship of objects in space from different perspectives.
	Relative Position	Determine the relative position, direction, angle, etc., of objects in space by combining information from different modalities.
Temporal Reasoning	Event Analysis	Analyze the causes and effects of events by combining information from different modalities.
	Event Ordering	Sort past events according to a certain objective order; or organize the correct sequence of an event based on fragmented information.
	Future Prediction	Predict future actions or events by combining information from different modalities.
General Reasoning	Social Cognitive Reasoning	Infer personal relationships, social culture, occupations, etc., by combining information from different modalities.
	Life Reasoning	Includes reasoning in various life scenarios, such as intelligent customer service, combining food delivery orders, common life knowledge, etc.
	Riddle Reasoning	Various riddles, escape room puzzles, and other similar questions.
	Counterfactual Reasoning	Given the conditions and result of an event, ask what result will occur if a certain condition is changed.
	Logical Relationship Reasoning	Involves various logical relationships such as causality and analogy, and requires reasoning according to given rules or logic.
	Card Reasoning	Questions related to chess and card games, including poker, mahjong, Chinese chess, etc.
	Game Reasoning	Various game-related questions, including board games, mobile games, computer games, etc.
STEM Reasoning	Geography	Geography-related disciplinary reasoning, with a difficulty range from middle school to university level.
	Chemistry	Chemistry-related disciplinary reasoning, with a difficulty range from middle school to university level.
	Biology	Biology-related disciplinary reasoning, with a difficulty range from middle school to university level.
	Mathematics	Mathematics-related disciplinary reasoning, with a difficulty range from middle school to university level.
	Physics	Physics-related disciplinary reasoning, with a difficulty range from middle school to university level.

Figure 12: Example of each ability in perception dimension.

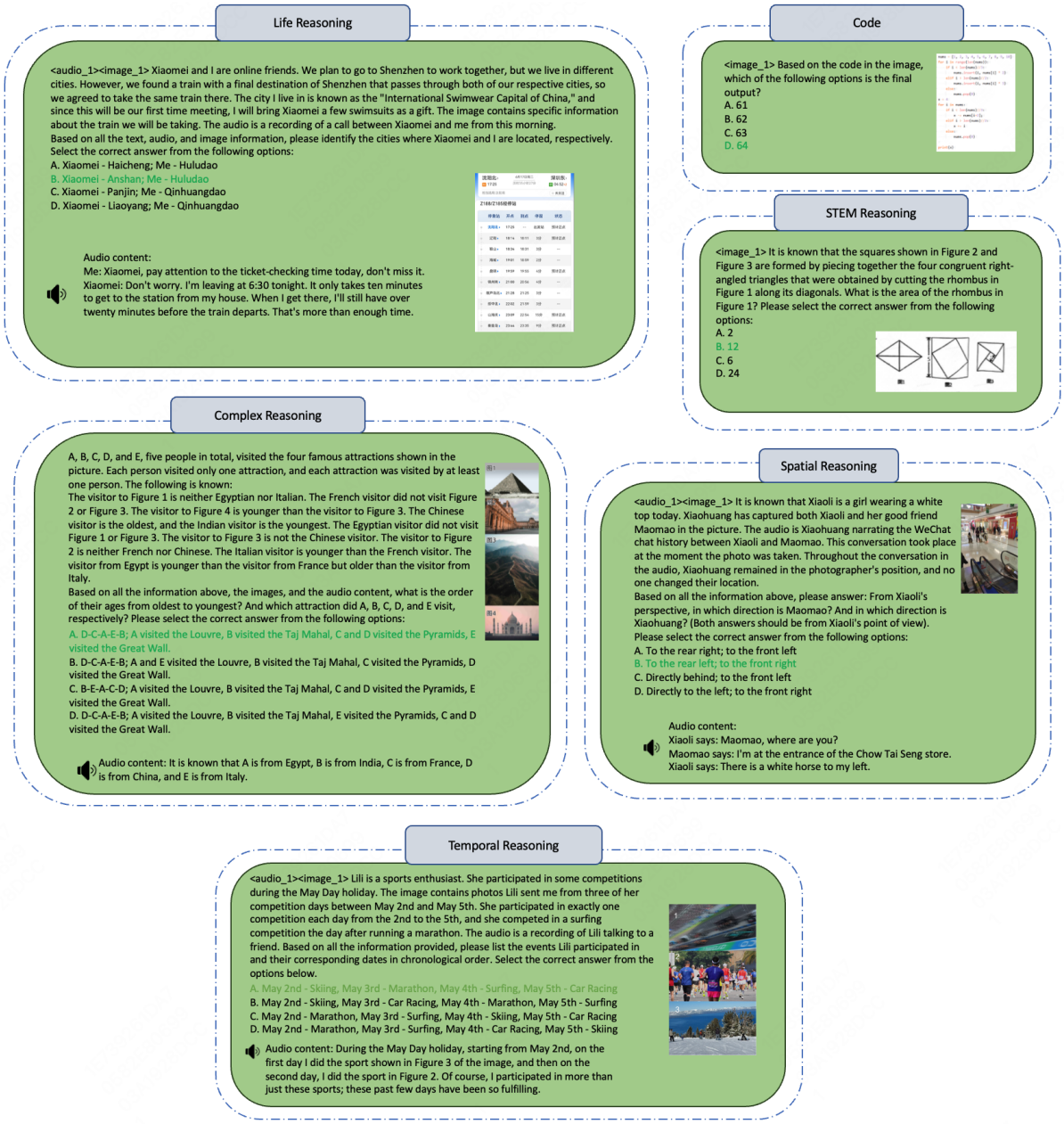

Figure 13: Example of each ability in reason dimension.