INTERFEEDBACK: UNVEILING INTERACTIVE INTELLIGENCE OF LARGE MULTIMODAL MODELS VIA HUMAN FEEDBACK

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ABSTRACT

Existing benchmarks do not test Large Multimodal Models (LMMs) on their interactive intelligence with human users, which is vital for developing general-purpose AI assistants. We design InterFeedback, an interactive framework, which can be applied to any LMM and dataset to assess this ability autonomously. On top of this, we introduce InterFeedback-Bench that evaluates interactive intelligence using two representative datasets, MMMU-Pro and MathVerse, to test 10 different open-source LMMs. Additionally, we present InterFeedback-Human, a newly collected dataset of 120 cases designed for manually testing interactive performance in leading models such as OpenAI-o1 and Claude-3.5-Sonnet. Our evaluation results indicate that even the state-of-the-art LMM, OpenAI-o1, struggles to refine its responses based on human feedback, achieving an average score of less than 50%. Our findings point to the need for methods that can enhance LMMs' capabilities to interpret and benefit from feedback.

1 INTRODUCTION

In this paper, we are curious about the question ***"Can Large Multimodal Models evolve through Interactive Human Feedback?"*** It is central to developing general-purpose AI assistants with Large Multimodal Models (LMMs). While these models show exceptional performance on tackling multimodal tasks directly, their ability to interact with humans remains largely unknown. We argue that an LMM functioning as the general assistant should possess two capabilities: 1) exceptional problem-solving ability and 2) the ability to improve itself through feedback (e.g., human feedback, execution results). In this work, we focus on the latter capability, which has been rarely examined in existing benchmarks.

Humans are highly adaptive, continuously refining their skills through feedback–a fundamental process for acquiring knowledge and solving problems. Likewise, advanced LMM models should be designed to learn from feedback, ensuring better alignment with real-world needs and enhancing their problem-solving capabilities in Human-AI Interaction (HAI). Recently, a surge of large multimodal models (LMMs) (OpenAI, 2023; Wang et al., 2024; Deitke et al., 2024; Zhao et al., 2024b; Li et al., 2024a; Zhao et al., 2024a; Chen et al., 2024b) have been developed to handle various tasks, including general vision-language understanding (Liu et al., 2023b; Li et al., 2023), expert-level multimodal understanding (Yue et al., 2024a;b), and scientific reasoning (Lu et al., 2022; 2024; Zhang et al., 2024). However, these LMMs are primarily tested in a static way, overlooking their great potential in an interactive process such as interactive coding (Jimenez et al., 2024; Yang et al., 2025), computer usage (Zhao et al., 2025; Lin et al., 2024; Gao et al., 2024; Xie et al., 2024), and clinical reasoning (Li et al., 2024e). Consequently, the interactive intelligence of LMMs, as illustrated in Figure 1, remains largely unexplored, and the development of a standard benchmark for evaluating their interactive intelligence remains an open challenge.

The key challenge in evaluating the interactive intelligence of LMMs is the automatic model tests. In practice, for the same query, different LMMs often produce varied responses, necessitating that humans offer tailored feedback for each conversation round. To address this issue, we propose
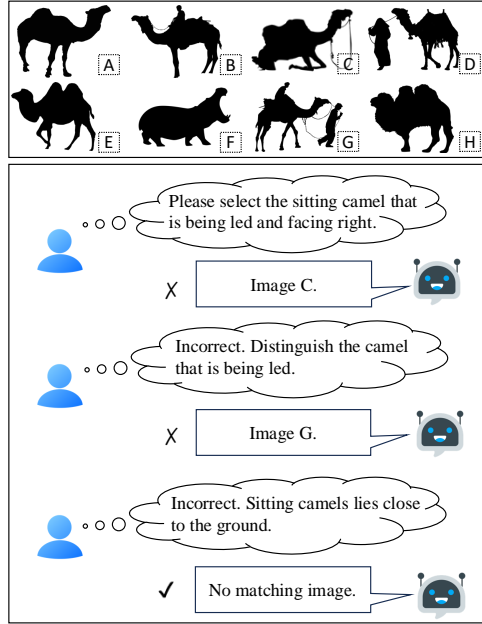
Figure 1: Illustration of an interactive feedback scenario. When models generate incorrect responses, human users provide pertinent feedback to iteratively refine the answers without leaking the GT answer.

InterFeedback a straightforward problem-solving framework that enables any LMM to tackle multimodal tasks interactively by leveraging leading models such as GPT-4o (OpenAI, 2023) to simulate humans, inspired in previous studies (Yao et al., 2025; Chen et al., 2024a; Yoon et al., 2024; Luo et al., 2024).

On top of this framework, we present **InterFeedback-Bench**, a benchmark designed to comprehensively evaluate LMMs for two purposes: 1) **the ability to interactively solve problems** and 2) **the capability of interpreting the feedback to improve themselves**. We demonstrate with two challenging pre-existing datasets: MMMU-Pro (Yue et al., 2024b) and Mathverse (Zhang et al., 2024). Additionally, for a more in-depth investigation, we conduct human evaluation on four closed-source leading models: GPT-4o (OpenAI, 2023), OpenAI-o1 (OpenAI, 2024), Claude-3.5-Sonnet (Anthropic, 2024), and Gemini-2.0 (Gemini, 2025) with a trained user acting as the feedback provider. Finally, we manually collected a dataset **InterFeedback-Human** containing 120 samples for this assessment.

Our experimental results reveal several compelling insights: 1) Interactive process could improve the performance of most LMMs in solving challenging problems; 2) Existing LMMs exhibit suboptimal performance in interpreting and incorporating feedback; 3) Accuracy result may not truly reflect the model's intelligence; 4) High-quality feedback is essential, as subpar feedback can degrade performance even more than a simple binary (0/1) correctness signal; 5) LMM may not truly reasoning, we find out that LMMs resort to guessing answer even on a simple question according to human. These findings point to the need for methods that can enhance the LMM's capability to interpret and benefit from feedback. In summary, our contributions are:

- We take the first step toward exploring the interactive intelligence of LMMs in improving themselves through human feedback.

- We propose a straightforward and extensible framework InterFeedback which allows any LMM to interactively solve problems.

- We construct InterFeedback-Bench, a novel and universal benchmark for assessing the ability of interactive problem-solving of LMMs.

- We conduct comprehensive evaluations and in-depth analysis, providing several compelling insights for future model alignment.

2 RELATED WORK

Large Multimodal Models. The LLaVA-series works (Liu et al., 2023a; 2024a;b; Li et al., 2024a) demonstrate that training with supervised fine-tuning (SFT) multimodal data and expand the vision lens would produce compatible multimodal reasoning ability. By adopting a large-scale image-text corpus for instruction tuning, Qwen2-VL (Wang et al., 2024), CogVLM (Wang et al., 2023), InternVL2 (OpenGVLab, 2024) have achieved exceptional performance on various multimodal abilities. Moreover, Molmo (Deitke et al., 2024) proposes to train an LMM from scratch with only the human-annotated data. Unlike these large models, MiniCPM-V (Yao et al., 2024) and Phi-3.5-Vision (Abdin et al., 2024) propose to train lightweight yet SOTA LMMs. Despite their exceptional performance on multimodal benchmarks of varying difficulty, such as MMMU-Pro (Yue et al., 2024b) and MathVista (Lu et al., 2024), it remains unclear how well these LMMs demonstrate interactive intelligence in Human-AI Interaction scenarios. In this paper, we conduct the evaluation of these LMMs to explore this basic yet vital capability (i.e., evolve through interactive human feedback).

Multimodal Benchmarks. Traditional vision-language benchmarks focus on visual question answering (Goyal et al., 2017), image captioning (Chen et al., 2015; Plummer et al., 2015; Agrawal et al., 2019), as well as other benchmarks for specialized scenarios such as scene text understanding (Singh et al., 2019; Sidorov et al., 2020), commonsense reasoning (Zellers et al., 2019), outside knowledge (Marino et al., 2019; Schwenk et al., 2022). The recent development of LMM posts a strong need for modernized multimodal benchmarks (Zhao et al., 2025; Liu et al., 2023b; Li et al., 2023; Yu et al., 2023; Yue et al., 2024a; Lu et al., 2024; Zhang et al., 2024; Li et al., 2024d) such as MMBench (Liu et al., 2023b), MMMU-pro (Yue et al., 2024b), and MathVerse (Zhang et al., 2024) which involve comprehensively evaluating current LMMs on various multimodal abilities. However, these benchmarks primarily focus on static testing processes, overlooking the interactive testing process that is vital in human-AI interaction scenarios.

Human-AI Interaction. Investigating how humans and AI systems communicate and collaborate is critical for shaping applications such as virtual assistants (Virvou, 2022), personalized recommendations (Dodeja et al., 2024), autonomous vehicles (Zhang et al., 2021), and healthcare diagnostics (McKinney et al., 2020). Recent LLMs-driven techniques such as memory (Park et al., 2023) and iterative (Zhang et al., 2023) mechanisms offer expert-level collaboration. While LMMs (Deitke et al., 2024; Wang et al., 2024) excel in multimodal tasks, their potential for HAI problem-solving (Zhao et al., 2025; Yang et al., 2025; Li et al., 2024e) remains underexplored. By offering a unified framework and meticulously curated data, our InterFeedback-Bench enables evaluation of LMMs on these capabilities and lays a foundation for advancing multimodal HAI problem-solving.

User Stimulation with LLM. Recently, previous work in order to build multi-agent system (Khan et al., 2024), stimulate human-AI interaction (Yao et al., 2025), evaluate LMMs in video analysis (Luo et al., 2024), stimulate the real user in a web shopping scenario Chen et al. (2024a), evaluate the conversational recommender systems (Yoon et al., 2024) determine to use LLM or LMM to stimulate the user. However, previous works have overlooked the importance of ensuring the reliability of LLMs or LMMs that are used to stimulate the users. In this paper, we curate test data by selecting only the samples that LMMs correctly address, minimizing unreliable interaction results.

3 INTERFEEDBACK-BENCH

In this section, we first introduce the automated interactive benchmarking process in Section 3.1. We begin by formulating the concept of interactive problem-solving, followed by a discussion of the data curation process. We then present the proposed interactive framework, InterFeedback. Next, in Section 3.2, we elaborate on the human benchmarking component, detailing the data collection and the proposed feedback providing strategy.

3.1 AUTOMATED INTERACTIVE BENCHMARKING

3.1.1 FORMULATION

The InterFeedback-Bench formalizes the interactive problem-solving process with feedback in a partially observable Markov decision process (POMDP) $(\mathcal{S}, \mathcal{O}, \mathcal{A}, \mathcal{T}, \mathcal{R})$ with state space $\mathcal{S}$, observation $\mathcal{O}$, action space $\mathcal{A}$, transition function $\mathcal{T}\colon \mathcal{S} \times \mathcal{A} \to \mathcal{S}$, and reward function $\mathcal{R}\colon \mathcal{S} \times \mathcal{A} \to \mathbb{R}$.
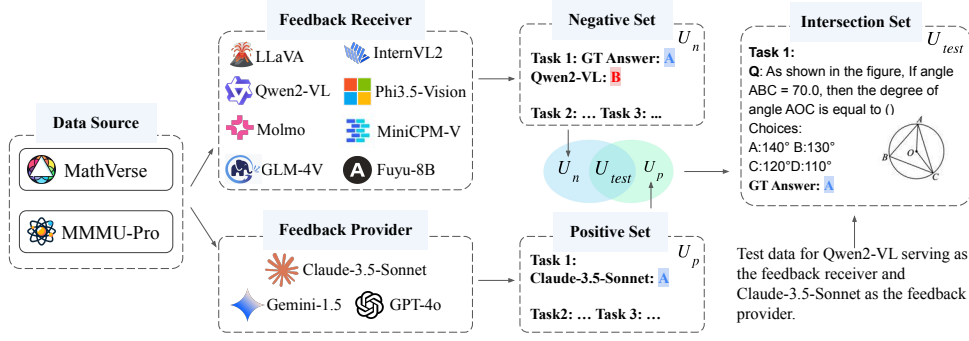
Figure 2: Overview of the test data construction process for InterFeedback-Bench. For each LMM serving as the feedback receiver, we process each instance from a target dataset (e.g., MathVerse) and collect the error cases to form a negative set. The feedback provider then processes the same instances to build a positive set. Finally, we curate test data by selecting the intersection of both sets.

In our setting, given a natural language question q (e.g., *Please select the sitting camel that is being led and facing right*) and the input image v, the model first gets the observation $o_t \in \mathcal{O}$ from the state $s_t \in \mathcal{S}$ in the execution environment and then generate the action $a_t \in \mathcal{A}$. The a_t is the response from models in natural language. The reward function $\mathcal{R}: \mathcal{S} \times \mathcal{A} \rightarrow \{0, 1\}$ here returns a binary value indicating the task correctness status. It is implemented by the exact match: returning 1 if the predicted answer exactly matches the ground-truth, and 0 otherwise. The observation o_t includes both the correctness signal from the reward function and the feedback from the humans.

3.1.2 DATA CURATION

Data sources. To ensure the quality and difficulty of multimodal tasks, inspired by previous benchmarks demonstrated on pre-existing datasets (Yang et al., 2023; Li et al., 2024c), we choose to test LMMs on two challenging datasets: MathVerse (Zhang et al., 2024) and MMMU-Pro (Yue et al., 2024b). MathVerse is a visual math benchmark that includes various mathematical problems, and 3,940 samples (testmini set) are used in our work. MMMU-Pro is a comprehensive multimodal benchmark and we use 1,730 expert-level questions (single image mode). Both datasets are challenging even for the model GPT-4o which achieves only 64.7% accuracy on MMMU-Pro (Standard 4 options).

Data selection process. We choose to use leading LMMs, such as GPT-4o, for stimulating the humans to give feedback mimicking human-AI interactions. The primary challenge, however, is ensuring that the feedback generated by these models is reliable, as even models like GPT-4o and Claude-3.5-Sonnet still do not perform correctly on all test samples. Therefore, we construct the test data by selecting the intersection set that feedback provider M_p solves correctly while M_r does not, as shown in Figure 2. Specifically, the pipeline includes three parts: 1) feedback receiver LMM locally-running; 2) feedback provider LMM API-calling; and 3) intersection set selection. Such a data construction process leads to each tested LMM having a different test data set.

Specifically, given a test dataset D, we begin by having the feedback receiver model M_r process every instance in D to produce a negative set U_n consisting of tasks it fails to solve correctly. Next, the feedback provider model M_p processes the same dataset to generate a positive set U_p comprising tasks it solves correctly. We then define U_{test} as the intersection of U_n and U_p, i.e.,

$$U_{\text{test}} = U_n \cap U_p,$$

which means that U_{test} contains tasks that M_p solves correctly but M_r does not. This approach ensures that the feedback generated by M_p is both relevant and reliable.

3.1.3 INTERFEEDBACK FRAMEWORK

To enable an interactive problem-solving process, we propose a new straightforward framework **InterFeedback**. It includes two roles: feedback receiver M_r and feedback provider M_p, as shown in Figure 3. The feedback receiver is the candidate LMMs (e.g., Qwen2-VL) ready for the benchmark
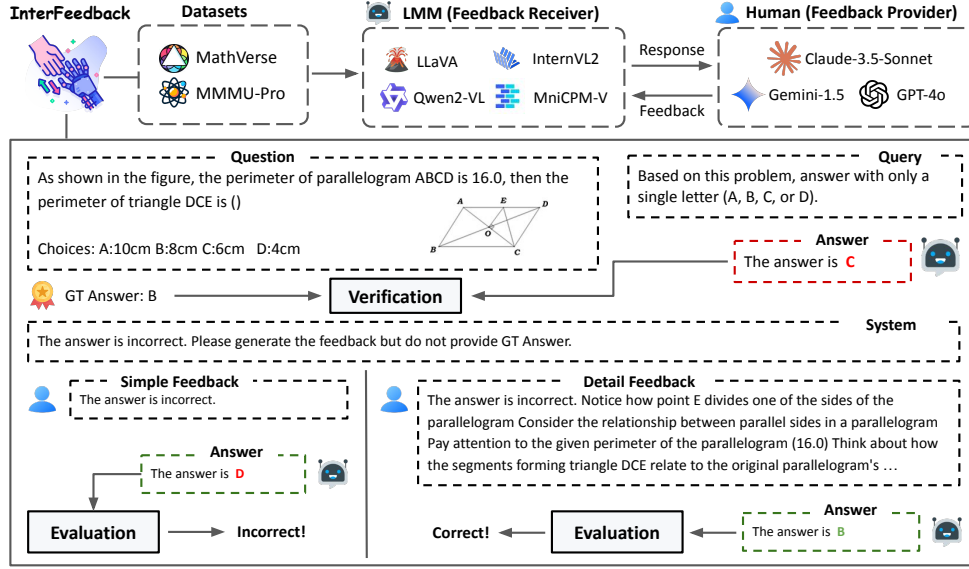
Figure 3: Overview of the proposed framework InterFeedback for assessing an LMM's ability to improve itself through feedback. The model interacts with humans to progressively solve a problem, and after each conversation round, we verify the correctness of the answer. If the answer is incorrect, an LMM-stimulated human will provide constructive feedback. We implement two types of feedback to investigate the behavior of LMMs.

and the feedback provider is the SOTA LMM (e.g., GPT-4o) for providing the pertinent feedback in each time step in place of a human. Consider at timestep t, the output of M_r is a_t, and the feedback provider M_p has to follow the policy that provides the feedback f_t from the mapping : $F(a_t, s_t) \rightarrow f_t$. The s_t denotes the correctness signal from the verification process via the reward function. We record the model outputs for the final evaluation.

Feedback types. Additionally, we propose a simplified feedback mechanism that only indicates correctness (i.e., correct or incorrect), without a detailed explanation. In summary, we evaluate the models using two feedback types: *Detail* and *Simple*. The *Detail* feedback comprises both *Simple* feedback and detailed LMM-generated explanation.

3.2 HUMAN BENCHMARKING

In the previous section, we employed leading LMMs as feedback providers. Naturally, how well do these models perform when receiving feedback? We begin to assess the leading LMMs with a human-in-the-loop process. The feedback provider M_p is a trained user who fully understands all the questions in the newly curated dataset InterFeedback-Human. The feedback receiver M_r is the closed-source leading LMMs including OpenAI-o1, GPT-4o, Gemini-2.0, and Claude-3.5-Sonnet. This evaluation aims to assess how effectively these leading models can serve as assistants in a human-AI interaction system.

3.2.1 DATA COLLECTION.

We gather challenging data examples across diverse domains: visual logic, mathematics, and coding. These were selected to probe the cognitive depth of the models, especially when confronted with complex, multi-step reasoning problems. The visual logic data is manually collected from publicly available resources. The emphasis on visual logic tasks reflects the growing demand for models to handle image-based reasoning challenges, such as pattern recognition (Wei et al., 2025) (e.g., determining the next shape in a sequence) and character-based logic (e.g., interpreting transformations between symbols). We also collect the multimodal mathematics data from the existing dataset MathVerse (Zhang et al., 2024) and the multimodal expert-level data from MMMU-Pro (Yue

et al., 2024b). Additionally, we also involve the natural language task into InterFeedback-Human to analyze such capability in the NLP area.

In summary, InterFeedback-Human encompasses a total of 120 tasks distributed across the five task types: 80 visual logic tasks, 10 mathematical logic tasks (sampled from NuminaMath (Li et al., 2024b)), 10 coding tasks (sampled from CodeComprehension (Imbue, 2024)), 10 MMMU-Pro tasks, and 10 MathVerse tasks.

3.2.2 HIERARCHICAL FEEDBACK

We design a hierarchical feedback generation scheme to gradually increase the information intensity. Specifically, we ask the human to give the following three-level feedback:

- Level 1: Provide a basic and simple description that leads to the correct answer.
- Level 2: Provide an expanded explanation that leads to the correct answer.
- Level 3: The correct answer is <u>GT Answer</u>. Provide a comprehensive and detailed explanation that leads to the correct answer.

Since most of our questions have four options, giving more than three rounds of feedback might let the model guess the answer by elimination rather than by reasoning. For example, if the correct answer is A and the model already gave B, C, and D, a third round of feedback is unnecessary. Therefore, we directly provide the <u>GT Answer</u> in Level 3 feedback prompts to test the models' ability to explain their thinking process.

3.2.3 EVALUATION INTEGRATION

To ensure fairness and consistency in our evaluation, we engaged only one experienced user. Since human-in-the-loop feedback is inherently subjective, involving multiple participants could introduce variability due to differences in background and expertise. This approach helps maintain the reliability of the relative performance comparisons across candidate LMMs.

4 EXPERIMENTS

4.1 EXPERIMENT SETUP

Evaluation Models. We evaluate the performance of foundation models served as the feedback receiver M_r across 10 representative LMMs: LLaVA-1.5-7B (Liu et al., 2024a), LLaVA-1.6-7B (Liu et al., 2024b) (Mistral-7B), LLaVa-OneVision-7B (Li et al., 2024a) (Qwen2-7B (Yang et al., 2024)), Qwen2-VL-7B (Wang et al., 2024), GLM-4V-9B (Wang et al., 2023), InternVL2 (OpenGVLab, 2024), Molmo (Deitke et al., 2024), MiniCPM-V (Yao et al., 2024), Phi-3.5-Vision (Abdin et al., 2024), and Fuyu-8B (Bavishi et al., 2023). The feedback provider M_p includes the three best available models from three model families: OpenAI (`gpt-4o-2024-08-06`), Gemini (`Gemini-1.5-Pro`), and Claude (`Claude-3.5-Sonnet-2024-10-22`).

Evaluation Metrics. In addition to the **Accuracy** metric, we leverage the **Correction Rate**, defined as the percentage of corrected answers of all erroneous samples. Let N denote the total number of samples, N_e the number of erroneous samples, and N_c the number of samples that have been corrected. The Accuracy and Correction Rate metrics can be formulated as follows:

$$\text{Accuracy} = \frac{(1 - N_e)}{N} \times 100\%, \quad \text{Correction Rate} = \frac{(N_c)}{N_e} \times 100\%. \tag{1}$$

Implementation Details. We set the temperature to 0 for all tested models and API models. The image resolution of the Qwen2-VL model we restrict to 512×512 to avoid the memory exceeded error. All evaluations were conducted on two NVIDIA RTX A6000 GPUs. To ensure the reliability of results, we obtain the intersection set for both the feedback receiver and provider models that are able to output the correct answer format. Based on our preliminary experiments, we limited the interactive benchmarking to a single round. This decision is driven by two observations: most models fail to provide correct answers in subsequent rounds, and multiple rounds tend to lead to answer guessing, which undermines the reliability of quantitative evaluation.

Table 1: **Correction Rate Results of three Feedback Providers on MathVerse Dataset. Acc (%)**: The average accuracy of MathVerse's *testmini* set. The results are tested by ourselves. **# Neg**: The number of negative samples produced by the model. **# Test**: The total number of test samples evaluated. **Detail (%)**: correction rate of using LMM-generated feedback. **Simple (%)**: correction rate of using simple feedback.

Model	Acc (%)	# Neg	GPT-4o			Gemini-1.5-Flash			Claude-3.5-Sonnet		
			# Test	Detail (%)	Simple (%)	# Test	Detail (%)	Simple (%)	# Test	Detail (%)	Simple (%)
LLaVa-OneVision-7B	25.6	2933	373	36.2	18.0	428	29.0	15.7	453	26.5	15.7
InternVL2-8B	38.1	2440	379	49.6	41.2	375	48.8	44.4	376	43.4	40.2
Molmo-7B	25.6	2931	452	55.1	52.0	507	36.5	38.9	597	37.4	40.0
MiniCPM-V	16.2	3301	552	28.4	20.3	741	16.6	25.4	772	18.7	27.1
GLM-4V-9B	20.2	3146	440	38.6	28.2	568	30.1	29.9	603	30.0	26.4
Phi3.5-Vision-4.2B	19.0	3192	534	36.1	33.7	579	31.3	33.7	616	26.8	29.1
LLaVa-1.5-7B	13.5	3409	763	23.2	14.3	678	18.0	14.7	816	8.3	11.2
LLaVa-1.6-Mistral-7B	14.8	3357	549	41.0	35.9	661	5.9	5.9	617	33.5	33.2
Fuyu-8B	21.8	3083	582	24.1	19.8	635	15.0	12.9	755	14.0	11.5
Qwen2-VL-7B	22.5	3052	295	66.8	72.2	470	41.9	44.9	505	50.5	52.7

Table 2: **Correction Rate Results of three Feedback Providers on MMMU-Pro Dataset.** We test models on a single image setting of MMMU-Pro.

Model	Acc (%)	# Neg	GPT-4o			Gemini-1.5-Flash			Claude-3.5-Sonnet		
			# Test	Detail (%)	Simple (%)	# Test	Detail (%)	Simple (%)	# Test	Detail (%)	Simple (%)
LLaVa-OneVision-7B	47.1	915	312	31.7	15.7	333	35.4	18.6	408	27.5	16.4
InternVL2-8B	45.7	939	343	50.1	41.4	329	57.1	50.2	437	50.1	41.2
Molmo-7B	43.8	973	362	51.7	48.9	383	41.5	43.1	436	29.8	27.5
MiniCPM-V	38.1	1071	410	27.3	23.7	503	21.5	21.7	540	24.4	23.3
GLM-4V-9B	46.0	935	327	38.8	30.0	359	38.7	31.5	441	34.9	27.9
Phi3.5-Vision-4.2B	43.2	983	366	44.3	42.3	396	40.9	39.6	484	39.9	38.0
LLaVa-1.5-7B	36.5	1099	506	31.9	12.3	470	20.0	16.0	595	13.9	13.4
LLaVa-1.6-Mistral-7B	38.8	1058	432	46.1	36.1	429	14.7	14.7	515	42.3	35.3
Fuyu-8B	34.1	1140	481	6.0	8.7	1140	3.7	3.5	612	9.5	6.9
Qwen2-VL-7B	48.1	898	268	50.4	44.8	322	39.4	37.6	389	42.9	37.3

4.2 Experimental Analysis on Automatic Benchmarking

To thoroughly investigate the ability of LMMs to integrate feedback and improve their problem-solving performance, we present evaluation results for various models on two datasets—MathVerse (Zhang et al., 2024) in Table 1 and MMMU-Pro (Yue et al., 2024b) in Table 2, respectively. Below, we provide a detailed discussion of key findings.

Whether interactive process improve the performance of LMMs? As demonstrated in both tables, integrating our proposed framework InterFeedback enables most models to benefit from feedback provided by SOTA LMMs, such as GPT-4o and Claude-3.5-Sonnet. Notably, even the weaker model Fuyu-8B sees 24.1% of its erroneous samples corrected through GPT-4o's feedback.

Current LMMs struggle to enhance performance through feedback. As shown in the tables, most LMMs are unable to correct all erroneous samples, even when provided with feedback from SOTA closed-source models such as Claude-3.5-Sonnet and GPT-4o. For example, consider the two leading open-source models, Qwen2-VL-7B and Molmo. Qwen2-VL-7B achieves a 66.8% correction rate on the MathVerse dataset with GPT-4o's feedback, but only a 50.4% correction rate on the MMMU-Pro dataset. Similarly, Molmo-7B attains correction rates of 55.1% and 51.7% on the MathVerse and MMMU-Pro datasets, respectively. Overall, the correction rates for the rest models remain below 50%. This suggests that even with constructive feedback from advanced LMMs, current models struggle to enhance performance through feedback generally.

Accuracy result may not truly reflect the model's capability to improve itself from feedback. As shown in Table 1, although InternVL2-8B achieves a higher accuracy (38.1%), its correction rate is only 49.6%. In contrast, Qwen2-VL-7B, with a lower accuracy of 22.5%, attains the highest correction rate of 66.8% when using GPT-4o's feedback. Similarly, Molmo-7B surpasses InternVL2-8B in correction rate despite having lower accuracy. On the MMMU-Pro dataset (see Table 2), LLaVA-OneVision-7B records the second-best accuracy (i.e., 47.1%) but only a 31.7% correction rate, which is lower than that of several models who have inferior accuracy (e.g., InternVL2-8B, Molmo-7B, GLM-4v-9B, and Phi3.5-Vision-4.2B). This inconsistency between initial answering

Table 3: **Human Evaluation Results across LMMs on InterFeedback-Human.** Math$^{\text{Text}}$ and Coding$^{\text{Text}}$ represent two text-only task categories. The scores represent the average percentage of correct samples among all samples.

Model	Visual Logic	MMMU-Pro	MathVerse	Math$^{\text{Text}}$	Coding$^{\text{Text}}$	Average
Gemini-2.0	21.3	50.0	70.0	50.0	50.0	32.5
Claude-3.5	37.5	60.0	80.0	70.0	70.0	48.3
OpenAI-o1	28.8	60.0	90.0	90.0	90.0	46.7
GPT-4o	25.0	70.0	80.0	60.0	50.0	38.3

Table 4: **Correction Rate Results across various LMMs on InterFeedback-Human.** Math$^{\text{Text}}$ and Coding$^{\text{Text}}$ represent two text-only task categories. # Round denotes the number of interaction rounds. The correction rate is the percentage of corrected samples among all erroneous samples.

Model	# Round	Visual Logic	MMMU-Pro	MathVerse	Math$^{\text{Text}}$	Coding$^{\text{Text}}$	Average
Gemini-2.0-Flash	1	38.1	20.0	33.3	0.0	80.0	37.0
	2	20.6	0.0	33.3	20.0	20.0	19.8
	3	41.3	80.0	33.3	80.0	0.0	43.2
Claude-3.5-Sonnet	1	38.0	0.0	50.0	33.3	66.7	37.1
	2	32.0	25.0	50.0	33.3	66.7	30.6
	3	30.0	75.0	0.0	66.7	0.0	32.3
OpenAI-o1	1	38.6	0.0	100.0	11.1	100.0	39.1
	2	21.1	0.0	0.0	0.0	0.0	18.8
	3	40.4	100.0	0.0	0.0	0.0	42.2
GPT-4o	1	41.7	33.3	100.0	25.0	40.0	41.9
	2	31.7	0.0	0.0	0.0	0.0	25.7
	3	26.7	66.7	0.0	75.0	60.0	32.4

ability and self-improvement capability indicates that evaluating models solely on accuracy may not fully capture their true potential.

Simple feedback also enhances performance. In addition to using detailed LMM-generated feedback, we evaluated models with binary (0/1) feedback that simply indicates the correctness of their current response. Surprisingly, the results show that all models benefit from this simple feedback mechanism. This suggests that while LMMs have the inherent potential to generate correct answers, they may require additional prompting techniques to fully harness the problem-solving capabilities.

LMM-generated feedback is not always better than simple feedback. By comparing the results obtained using *Detail* feedback from GPT-4o with those using *Simple* binary feedback, we observe that most models perform better with detailed feedback. For example, on the MathVerse dataset, LLaVA-OneVision-7B achieves 36.2% with detailed feedback versus 18.0% with binary feedback; InternVL2-8B increases from 41.2% to 49.6%; and MiniCPM-V increases from 20.3% to 28.4%. The only exception is Qwen2-VL, which scores 66.8% with detailed feedback and 72.2% with simple feedback. Similarly, on the MMMU-Pro dataset, only Fuyu-8B performs worse with detailed feedback (6.0% vs. 8.7%).

The quality of feedback is crucial: low-quality feedback can degrade performance more than simply providing binary (0/1) feedback. We compare the feedback provided by GPT-4o and Gemini-1.5-Flash on the challenging MathVerse dataset, where most models achieve accuracies below 30%, highlighting the difficulty of its problem instances. We find that leveraging a suboptimal model (Gemini-1.5-Flash) to deliver simple binary feedback—merely indicating the correctness of the tested model's output—can outperform LMM-generated detailed feedback. Specifically, the correction rates using simple feedback exceed those with detailed feedback for several models: Molmo-7B (38.9% vs. 36.5%), MiniCPM-V (25.6% vs. 16.6%), Phi3.5-Vision-4.2B (33.7% vs. 31.3%), and Qwen2-VL-7B (44.9% vs. 41.9%).

4.3 EXPERIMENTAL ANALYSIS ON HUMAN BENCHMARKING

In this section, we will introduce the human evaluation results of several well-known closed-source families: OpenAI (`GPT-4o`, `OpenAI-o1`), Claude (`Claude-3.5-Sonnet-20241022`), and Gemini (`Gemini-2.0-Flash-Exp`).

Overall accuracy results. In Table 3: (1) The best scores for each subcategory in our InterFeedback-Human are 37.5% (Claude-3.5-Sonnet), 70.0% (GPT-4o), 90% (OpenAI-o1), and
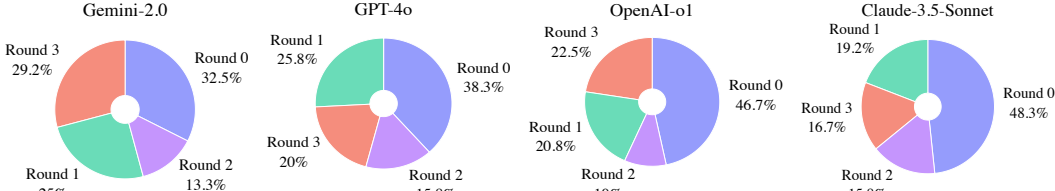
Figure 4: Distribution of samples being corrected in each round. We can observe that Claude-3.5-Sonnet achieves the best performance in round 0.

90% (OpenAI-o1), respectively. (2) Overall, Claude-3.5 achieves the highest average accuracy at 48.3%.

Correction rate results analysis. Comparing the correction rates across rounds in Table 4 reveals that GPT-4o benefits the most from human feedback in the first round, correcting 41.9% of erroneous samples, while Claude-3.5 exhibits its strongest correction performance in the second round, with 30.6% of erroneous samples corrected. Given that the ground truth answer is provided in the third round, all LMMs are able to supply their reasoning steps for selecting the correct answer.

Distribution of tasks corrected across rounds. Figure 4 illustrates the distribution of tasks solved by each LMM across the interaction rounds. Round 0 represents the initial accuracy before beginning human-AI interactions. For example, GPT-4o solved 38.3% of instances in Round 0, 25.8% in Round 1, and 20% in Round 2. Additionally, during the first two rounds, both OpenAI-o1 and Claude-3.5-Sonnet solved the same number of samples, achieving a performance of 67.5%.

Figure 5: Distribution of corrected samples across various task categories. The results are the average of the four tested models.

Distribution of corrected samples across various task categories. As shown in Figure 5, Visual logic tasks are mostly resolved within the first two rounds, whereas Math (Text-only) and MMMU-Pro tasks show few corrections in rounds 1 and 2. The results indicate that if the answers cannot be addressed at the first, following human feedback cannot help them improve their performance in the next rounds. According to Coding (Text-only) and Math-Verse tasks, these models exhibit obvious corrections during rounds 1 and 2. That means these models have the potential for solving Coding (Text-only) and MathVerse tasks by following the human feedback.

Summarization. (1) The closed-source SOTA LMMs can be improved through human feedback. (2) Most models show improvement after the first round of feedback. (3) After two rounds of human feedback, there are still 30-40% of questions that cannot be addressed.

5 CONCLUSION

In this work, we introduced InterFeedback-Bench, the first solution to concern the critical importance of evaluating the interactive intelligence of current LMMs. We build an interactive framework InterFeedback which can be applied to any LMM and dataset to bootstrap the testing in an interactive way. We conduct the comprehensive evaluations on 10 open-source LMMs by demonstrating with two representative datasets MathVerse and MMMU-Pro. Additionally, we present InterFeedback-Human, a new benchmark for manually testing the leading models such as OpenAI-o1 and Claude-3.5 with 120 curated samples. Our evaluation results show that even the SOTA LMM (like OpenAI-o1) can only correct their results through human feedback with less than 50%. Several findings point to the essential need for methods that improve the LMM's ability to receive feedback to improve themselves.
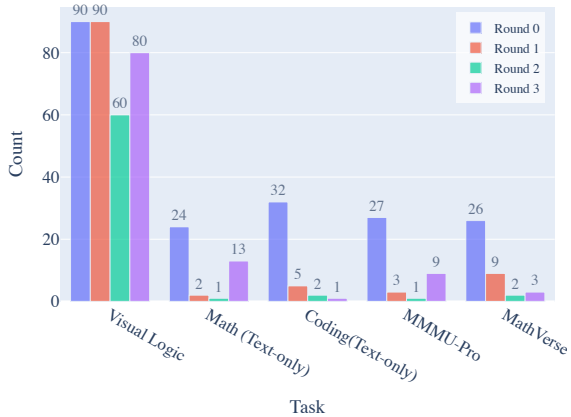
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A ADDITIONAL EXPERIMENTAL DETAILS

A.1 MODEL SOURCES.

For different LMMs, we select their latest models with sizes around 7B for evaluation. Table 5 presents the release time and model sources of LMMs used in InterFeedback-Bench.

Table 5: The release time and model source of LMMs used in our InterFeedback-Bench.

Model	Release Time	Source
Closed-source Models		
GPT-4o (OpenAI, 2023)	2024-08-26	https://openai.com/index/hello-gpt-4o/
OpenAI-o1 (OpenAI, 2024)	2024-12-17	https://openai.com/o1/
Gemini-1.5-Flash (Gemini, 2024)	2024-09-24	https://deepmind.google/technologies/gemini/
Gemini-2.0-Flash	2025-01-21	https://deepmind.google/technologies/gemini/
Claude-3.5-Sonnet	2024-10-22	https://www.anthropic.com/claude/sonnet
Closed-source Models		
LLaVA-One-Vision	2024-08-05	https://llava-vl.github.io/blog/2024-08-05-llava-onevision/
InterVL2-8B	2024-07-04	https://internvl.github.io/blog/2024-07-02-InternVL-2.0/
Molmo-7B	2024-09-24	https://huggingface.co/allenai/Molmo-7B-D-0924
MiniCPM-V	2024-08-03	https://huggingface.co/openbmb/MiniCPM-V
GLM-4V-9B	2024-11-01	https://huggingface.co/THUDM/glm-4v-9b
Pih3.5-Vision-4.2B	2024-08-20	https://huggingface.co/microsoft/Phi-3.5-vision-instruct
LLaVA-1.5-7B	2023-10-05	https://huggingface.co/liuhaotian/llava-v1.5-7b
LLaVA-1.6-Mistral-7B	2024-01-30	https://huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf
Fuyu-8B	2023-10-27	https://huggingface.co/adept/fuyu-8b
Qwen2-VL-7B	2024-08-30	https://huggingface.co/Qwen/Qwen2-VL-7B

A.2 QUALITATIVE ANALYSIS

Interactive process could improve the performance. In Figure 6, we provide the qualitative results of different models. For the same question, Claude-3.5-Sonnet gives the correct answer C without human feedback, Gemini-2.0-Flash uses two rounds while OpenAI-o1 uses three rounds. It indicates that 1) even the SOTA models like OpenAI-o1 can not fully address the visual logic problem which is worse than Claude-3.5-Sonnet, 2) the responses can be corrected by human feedback which shows that the models have the capability of interpreting and incorporating the feedback into their reasoning, 3) Different models shows a different level of this capability. Additionally, we provide another example in Figure 7.

LMMs guess answers by elimination. In Figure 8, we find that the model will guess the answer. For the same question, we conduct two runs and find that OpenAI-o1 could not solve this problem at the beginning, but two different answers were given in these two runs. In the first run, the model outputs D at the beginning, while in the second run, the model outputs A at the beginning. In the following rounds, we provide the same prompts to ensure the fairness comparison, one can see that based on the same prompt, it outputs the same answer C in the second round. The left run in the figure shows the correct answer in the third round while the right run in the figure shows the incorrect answer D. We continue to give the third feedback for round 4, and the right run finally gives answer B. It is obvious that when a problem cannot be solved by a model, it will 1) answer randomly, and 2) output the answer through an elimination approach. These results may indicate that LMMs may not always truly reason, they may give the answer by guessing. Additionally, we provide another example in Figure 9 to illustrate that LMMs may guess answers when they can not solve the challenging problems.

LMMs still fail when the GT answer is not provided in the level 3 feedback. As discussed in the main submission, we include the GT answer in the level 3 feedback prompt to examine whether the model can generate the correct reasoning procedure that leads to the correct answer. When we remove the GT answer as in Figure 10, the model still fails to produce the correct answer, indicating its limited capability in solving challenging problems even when detailed feedback is provided as guidance.

Question:

Select the most appropriate option from four choices to complete a sequence or reveal a pattern.

GT Answer: **C.**

(*The key point of this question is that Figure 3 represents the common part of Figures 1 and 2*)
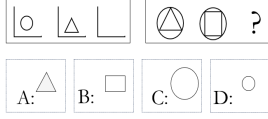
Claude 3.5 Sonnet

Select one answer from the options "A, B, C, D" to complete the sequence.

In the first box, there are three shapes in squares: circle, triangle, empty. In the second box, there are two shapes: a triangle inside a circle, and a square inside a circle.

The pattern appears to be: if a shape appears alone in the first box, it becomes 'encased' by a circle in the second box ... the answer is **C**.

Gemini 2.0 Flash

Select one answer from the options "A, B, C, D" to complete the sequence.

... the missing figure in the second row should have the same shape as the missing figure in the first row. Therefore, the missing figure in the second row should be a square, which corresponds to option B.

Incorrect. I recommend reevaluating the task from the perspective of "Relationships between graphs".

The missing figure (Figure 3, Right) must contain the shape that is common to both Figure 1 and Figure 2. Common Shape: The circle is present in both figures. The missing figure should be a circle. Therefore, the correct answer is **C**.

OpenAI-O1

Select one answer from the options "A, B, C, D" to complete the sequence.

Following that same cycle, the next (sixth) frame should be a circle enclosing a circle again. Among the given choices (A–D), that corresponds to choice D.

Incorrect. I recommend reevaluating the task from the perspective of "Relationships between graphs".

... So, by that same repeating pattern of "triangle → square" inside the circle, the missing sixth box should be a circle containing a triangle again. Hence, the best answer is A (triangle).

Incorrect. I suggest analyzing the problem from the perspective of "Figure 3 is the common part of Figures 1 and 2".

... Likewise, Figures 4 and 5 both use the same circular container but hold different shapes (triangle vs. square). So, Figure 6 should be just that common circular container (an empty circle). Among the choices, the empty circle is **option C**.

Figure 6: Qualitative results on different LMMs.

Question:

As shown in the figure, it is known that angle A = 80 °, angle B = 60 , DE parallel BC, then the size of angle CED is ___?

Choices: A: 40° B: 60° C: 120° D: 140°

GT Answer: D: 140°.
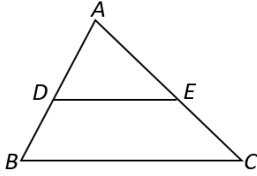
Claude 3.5 Sonnet

Select one answer from the options "A, B, C, D" to complete the sequence.

... Since we know ∠ A = 80° and ∠ B = 60 °, We can find ∠ C in triangle ABC: ∠ $C = 180° − ∠ A − ∠ B$, ∠ $C = 180° − 80° − 60° = 40°$.

Now, because DE is parallel to BC, ∠ CED = 180° - ∠C, ∠ CED = 180° - 40° = 140°.

Therefore, angle CED is 140°. The answer is **D: 140°.**

Gemini 2.0 Flash

Select one answer from the options "A, B, C, D" to complete the sequence.

Since DE is parallel to BC, the corresponding angles are equal. Angle CED is a corresponding angle to angle C. ..., Therefore, ... The correct answer is A: 40°.

Incorrect. I recommend reevaluating the task from the perspective of thinking about the triangle as 180° and the parallel lines' properties.

Since DE is parallel to BC, the consecutive interior angles on the same side of the transversal are supplementary. Therefore, ... The correct answer is **D: 140°**.

OpenAI-O1

Select one answer from the options "A, B, C, D" to complete the sequence.

Since DE ∥ BC, triangle ADE is similar to triangle ABC.

Line AC is a transversal of the parallel lines DE and BC, so the angle formed at E by CE and DB (i.e. ∠CED) corresponds to ∠ C in triangle ABC.

In triangle ABC, the angles are 80° (at A), 60° (at B), and thus 40° (at C).

Therefore, ∠CED = 40°.

Incorrect. I recommend reevaluating the task from the perspective of thinking about the triangle as 180° and the parallel lines' properties.

... The angles ∠BCE (at C) and ∠CED (at E) lie on the same side of this transversal, so they are co-interior angles and must sum to 180°.

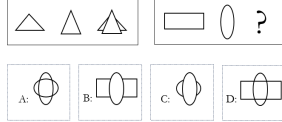∠BCE is the same as ∠BCA = 40°. Hence, ∠CED = 180° - 40° = **140°**.

Figure 7: Qualitative results on different LMMs.

Question:

Select the most appropriate option from four choices to complete a sequence or reveal a pattern.

GT Answer: B.

(*This question tests the concept of shape overlay, with attention to the fact that the obscured parts are not visible.*)

OpenAI-O1

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

✳️ ... only D shows that same offset-overlap arrangement of ellipse over rectangle, so D is the best fit.

👤 Incorrect. Please focus on the graphic overlay.

✳️ ... we want the ellipse in front with the rectangle partly showing behind. Option C is the choice that clearly shows the ellipse overlaid on the rectangle with the rectangle partially visible behind, matching the top-row overlay pattern.

👤 Incorrect. Please focus on the graphics are super-imposed and the obscured parts are invisible.

✳️ Among the answer choices, **B** clearly shows the ellipse in front with the rectangle's edges visible to the sides, mirroring the top-row overlap pattern.

OpenAI-O1

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

✳️ In both rows, there seems to be a progression of shapes with different orientations or alterations ... the answer is A.

👤 Incorrect. Please focus on the graphic overlay.

✳️ ... where the oval has an overlay in the middle, and this time it should be a 3D-like effect similar to the triangles in the first row. Option C has an oval with an overlay in the center, matching the pattern.

👤 Incorrect. Please focus on the graphics are super-imposed and the obscured parts are invisible.

✳️ Option D fits this pattern perfectly. It shows an oval with a new shape super-imposed, and the hidden parts of the shape are not visible ...

👤 Incorrect. The correct answer is **B**. The graphics are layered on top of each other, which means that any parts hidden underneath are not visible.

✳️ Option **B** features an oval with a different shape inside it, continuing the pattern of a shape inside an oval where parts of the shape are hidden.

Figure 8: An example that the model tends to guess answers.

Question:

Select the most appropriate option from four choices to complete a sequence or reveal a pattern.

GT Answer: A.

(*This question examines the type of figures. The first group of figures are all plane figures; the second group of figures are three-dimensional figures.*)
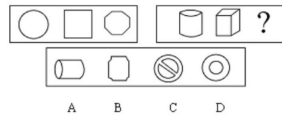
Claude 3.5 Sonnet

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

✳️ The answer is B, as it shows an octagonal prism, which is the 3D equivalent of the 2D octagon in the first box.

👤 Incorrect. Please focus on the type of figures.

✳️ Therefore, the answer is C, as it shows a circle with a line through it, which represents how an octagon would appear when viewed at an angle.

This is similar to how a circle remains a circle, and a square becomes a cube-like shape when viewed at an angle.

👤 Incorrect. Please focus on the type of figures. The first group of figures are all plane figures, and the second group of figures are solid figures.

✳️ ... Therefore, the answer is D, as it represents the circular view you would see when looking at an octagonal solid from above or below.

👤 Incorrect. Distinguish the solid and plane figures.

✳️ ... Therefore, the answer must be B - the octagonal prism. This maintains the pattern of converting 2D shapes into their 3D equivalents.

OpenAI-4o

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

✳️ The missing shape should be a 3D object that corresponds to an octagon, similar to how the cylinder corresponds to the circle and the cube corresponds to the square. The correct answer is the shape that represents an octagonal prism (Option B).

👤 Incorrect. Please focus on the type of figures.

✳️ The correct choice should be Option B, as it represents an octagonal prism, matching the pattern of transforming 2D shapes into their corresponding 3D versions.

👤 Incorrect. Please focus on the type of figures. The first group of figures are all plane figures, and the second group of figures are solid figures.

✳️ ... Therefore, the answer is D, as it represents the circular view you would see when looking at an octagonal solid from above or below.

👤 Incorrect. Distinguish the solid and plane figures.

✳️ ... The correct choice is B, as it represents a solid shape with an octagonal face, completing the pattern.
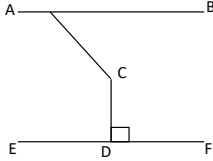
Figure 9: An example that the model tends to guess answers.

Question:

As shown in the figure, AB parallel EF, angle BAC = 50°, then angle ACD = ( )

Choices: A: 120° B: 130° C: 140° D: 150°

GT Answer: **C.**

GPT-4o with GT Answer

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

🤖 Since AB ∥ EF, $\angle BAC$ corresponding to $\angle ACD$ through the supplementary relationship of the interior angles. The sum of angles on a straight line is 180°. $\angle ACD = 180° - 50° = 30°$. The correct choice is B: 130°.

👤 Incorrect. When parallel lines (AB and EF) are intersected by a transversal (line AC), alternate interior angles are equal ...

🤖 Since AB ∥ EF and AC is a transversal, alternate interior angles are equal. Therefore, $\angle ACD = \angle BAC = 50°$. The sum of angles at point C along a straight line is 180°. So, $\angle ACD = 180° - 50° = 130°$. correct choice is B: 130°.

👤 Incorrect. Add a support straight horizontal line through point C to help you solve it.

🤖 ... use the Straight-Line Property: since angles on a straight-line sum to 180°. $\angle ACD = 180° - 50° = 130°$.

👤 Incorrect. The correct answer is C. angle ACD = 140 ...

🤖 Using the straight-line property. $\angle ACD = \angle ACG + \angle GCD = 50° + 90° = 140°$. Correct choice is **C.**

GPT-4o without GT Answer

👤 Select one answer from the options "A, B, C, D" to complete the sequence.

🤖 Since AB ∥ EF, $\angle BAC$ corresponding to $\angle ACD$ through the supplementary relationship of the interior angles. The sum of angles on a straight line is 180°. $\angle ACD = 180° - 50° = 30°$. The correct choice is B: 130°.

👤 Incorrect. When parallel lines (AB and EF) are intersected by a transversal (line AC), alternate interior angles are equal ...

🤖 Since AB ∥ EF and AC is a transversal, alternate interior angles are equal. Therefore, $\angle ACD = \angle BAC = 50°$. The sum of angles at point C along a straight line is 180°. So, $\angle ACD = 180° - 50° = 130°$. correct choice is B: 130°.

👤 Incorrect. Add a support straight horizontal line through point C to help you solve it.

🤖 ... use the Straight-Line Property: Since angles on a straight-line sum to 180°. $\angle ACD = 180° - 50° = 130°$.

👤 Incorrect. Please reconsider your answer.

🤖 Using the straight-line property. $\angle ACD + \angle DCF = 180°$. Substituting known values: $50° + \angle ACD = 180°$. Solving for $\angle ACD = 130°$.

Figure 10: Qualitative results by removing GT answer in level 3 feedback.