

VIGiA: Instructional Video Guidance via Dialogue Reasoning and Retrieval

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Abstract

We introduce VIGiA, a novel multimodal dialogue model designed to understand and reason over complex, multi-step instructional video action plans. Unlike prior work which focuses mainly on text-only guidance, or treats vision and language in isolation, VIGiA supports grounded, plan-aware dialogue that requires reasoning over visual inputs, instructional plans, and interleaved user interactions. To this end, VIGiA incorporates two key capabilities: (1) multimodal plan reasoning, enabling the model to align uni- and multimodal queries with the current task plan and respond accurately; and (2) plan-based retrieval, allowing it to retrieve relevant plan steps in either textual or visual representations. Experiments were done on a novel dataset with rich Instructional Video Dialogues aligned with Cooking and DIY plans. Our evaluation shows that VIGiA outperforms existing state-of-the-art models on all tasks in a conversational plan guidance setting, reaching over 90% accuracy on plan-aware VQA.¹

1 Introduction

Assisting in the execution of complex instructional plans (e.g. cooking and DIY projects), in a conversational manner, is a recent task (Choi et al., 2022) that requires Large Vision and Language Models (LVLMs) to understand and reason about logical sequences of actions. As illustrated in Figure 1, this task presents a unique challenge due to the nature of the setting, where models need to be able to attend to various and complex instructions (Choi et al., 2022; Fischer et al., 2024) arbitrarily interleaved throughout the dialogue, while remaining grounded in the instructional plan and tracking explicit and implicit plan progress. Although some works address text-only plan guidance (Zhu et al., 2022; Glória-Silva et al., 2024a; Zhu et al., 2025),

¹Model, code and dataset can be found at <https://github.com/dmgcsilva/vigia>.

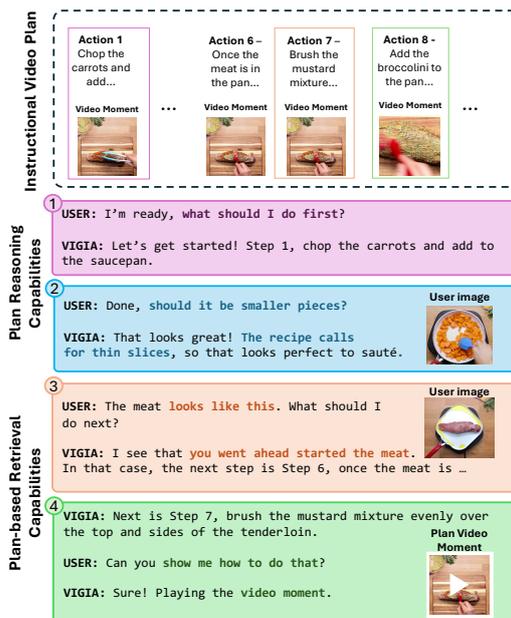


Figure 1: VIGiA is grounded on complex multimodal instructional plans, delivering unified multimodal alignment over dialogue turns by providing text-based guidance (Goal 1), plan-aware visual question answering (Goal 2) aligning plan actions and visual context (Goal 3), and retrieving relevant video moments (Goal 4).

only a few consider multimodality (Glória-Silva et al., 2024b) and yet image-grounded reasoning tasks remain largely unexplored, a particularly challenging scenario, as it requires the model to ground its answer on the provided image, the instructional plan, the dialogue history, and its encoded knowledge.

In this paper, we address the challenge in a comprehensive manner and propose VIGiA (Visual and Instructional Guiding Assistant), a complete conversational plan guidance model with strong multimodal support. To allow for a wide array of request types, VIGiA has two key capability types: (1) **multimodal plan reasoning** capabilities and (2) **plan-based retrieval** capabilities. The first enables it to reason about uni- and multimodal requests,

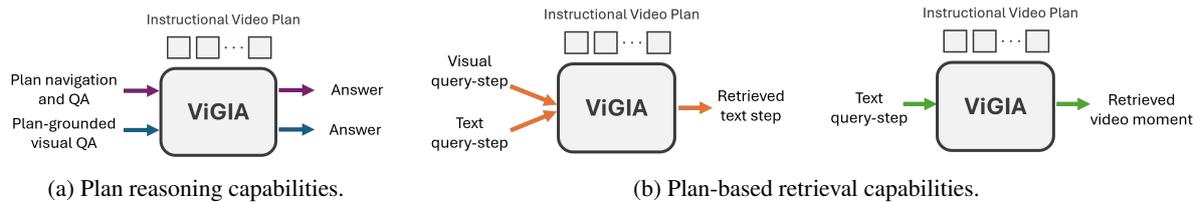


Figure 2: ViGiA is an LVLMM model that processes instructional video plans to navigate through steps of the plan, perform QA, VQA and retrieval of arbitrarily random text steps or video moment steps.

ground and align them on a multimodal plan, and answer accurately. The second allows it to align multimodal input queries against the instructional plan and perform both in-context retrieval of a plan action text or retrieval of the video moment of that action.

To address both plan reasoning and retrieval capabilities, ViGiA’s multi-goal architecture is purpose-built to support the multiple output and input modalities, and trained in a multi-objective learning paradigm using a novel dataset, InstructionVidDial. This dataset incorporates all of these supported goals via semi-automatic dialogue generation and expands the scope by considering multiple plan domains. A multi-stage training approach progressively delivers ViGiA capacity to follow complex plan-oriented multimodal instructions and support for multi-goal unified plan-guidance (Figure 2), generalizable to multiple domains. Our main contributions are:

- **ViGiA:** A novel model that dialogues and reasons about multi-step instructional plans, while allowing for arbitrary retrieval of plan actions both in text and visual domain.
- **InstructionVidDial:** We built a novel multimodal dialogue dataset that pushes plan-guidance into the complex and diverse domains of Cooking and DIY tasks.

Our evaluation compared ViGiA to existing state-of-the-art models and results showed that it was the best model on plan-grounded reasoning QA and VQA tasks, while also delivering top performance across all plan-grounded retrieval tasks.

2 Related Work

LVLMMs are models that are able to process not only text but also visual input (images and videos). These models combine the strengths of language decoders with visual encoders, enabling multimodal input and, in some cases, multimodal output.

LVLMMs have benefited from the advances in pre-trained Large Language Models (Dubey et al., 2024; DeepSeek-AI, 2024; Team et al., 2024) as they can be paired with pretrained visual encoders such as CLIP (Radford et al., 2021) or SigLIP (Zhai et al., 2023) to form an LVLMM connected via a connector module. Several architectures have been proposed for the connector, ranging in complexity. While examples like the LLaVA family of models (Liu et al., 2023; Sun et al., 2024; Liu et al., 2024a; Zhang et al., 2023) use a linear or MLP module, others used more complex approaches, an example is the QFormer in BLIP models (Li et al., 2023; Dai et al., 2023) or the Perceiver (Jaegle et al., 2021) in Flamingo (Alayrac et al., 2022).

The need for modality equilibrium in LVLMMs is key to their success, as performance in text-only settings needs to be maintained while also being able to attend to rich multimodal inputs. This led to increasingly more complex training approaches, with modern LVLMMs training in a multistage paradigm (Chen et al., 2024c; Yang et al., 2024; Liu et al., 2024a,b; Laurençon et al., 2024b,a), allowing to progressively build up capabilities in a structured manner, while preventing catastrophic forgetting (McCloskey and Cohen, 1989) of previously learned tasks. The increased complexity of this has also led some works (Laurençon et al., 2024a; Tong et al., 2024; Zohar et al., 2024) to measure and verify the benefit of multistage training.

Instructional plan guidance is the multifaceted task of guiding users through complex manual instructional plans in a user-led conversational manner. Although early work has focused on a text-only setting (Choi et al., 2022; Mo et al., 2023; Fischer et al., 2024; Glória-Silva et al., 2024a), these plans are inherently multimodal and often accompanied by instructional videos. The availability of large instructional video datasets (Sener and Yao, 2019; Zhukov et al., 2019; Tang et al., 2019) makes the application of LVLMMs particularly suitable for this task. This was the case of MM-PlanLLM (Glória-

Silva et al., 2024b), however, it lacked the ability to answer image-grounded questions. While VQA has been studied and applied to several domains (Mathew et al., 2020; Lobry et al., 2020; Ren and Zhou, 2020; Tapaswi et al., 2015), its application in instructional plan guidance remains unexplored.

3 Definitions and Problem Formulation

Let $P_k = \langle (a_{k,1}, vm_{k,1}), \dots, (a_{k,m}, vm_{k,m}) \rangle$ be the instructional plan k , composed of actions $a_{k,j}$ with the text action description, which is also illustrated by the video moment $vm_{k,m}$. An instructional plan has an associated sequence of video moments $V_k = \langle vm_{k,1}, \dots, vm_{k,m} \rangle$ illustrating the execution of the plan P_k . Each video moment $vm_{k,m} = \langle f_{k,start}, \dots, f_{k,end} \rangle \subseteq V_k$ range from a starting frame to an ending frame. Text actions and video moments are ordered in a logical sequence, where $a_{k,j}$ or $vm_{k,j}$ must be completed before $a_{k,j+1}$ or $vm_{k,j+1}$.

Let D_k be a dialogue that is composed of multimodal interactions and associated with a specific instructional plan, and an instructional video that covers all actions. Formally, each dialogue instance is defined as $D_k = (P_k, T_k)$ where $T_k = \langle t_{k,1}, t_{k,2}, \dots, t_{k,n} \rangle$ is the sequence of turns that constitutes the dialogue interaction for d_k . Each turn $t_{k,j}$ is defined as $t_{k,j} = (u_{k,j}, r_{k,j}, I_{k,j})$, where $u_{k,j}$ is the human input (question or request) during the j -th turn, $r_{k,j}$ is the system response, and $I_{k,j} \in \mathcal{I} \cup \{\text{None}\}$ is an optional image provided by the user during that turn.

This problem setting requires a model that aligns the instructional plan with the dialogue context and accurately perform complex reasoning and plan retrieval operations.

4 Methodology

Addressing the problem outlined above, requires multimodal, context-aware, and plan-grounded reasoning, which will be integrated by design into ViGiA’s architecture and training strategies, as detailed in the next sections. In addition, we will also detail the supporting InstructionVidDial dataset.

4.1 Multimodal Plan Guidance LVLMS

Due to the required set of capabilities and input diversity, optimizing a single learning objective is infeasible. We address this by defining dedicated

learning objectives for each type of dialogue capability.

4.1.1 Plan-grounded reasoning capabilities

The first set of dialogue capabilities support the core requests to navigate and interact with the instructional plan.

Plan-Grounded Answer Generation. The task of textual plan-grounded answer generation encompasses every textual request that requires the generation of a response based on the dialogue and the instructional plan, such as plan navigation requests and questions. Here, a textual request $u_{k,j+1}$, a instructional plan P_k and the previous conversation turns $T_{k,1:j} \in D_k$, the model needs to generate $r_{j+1} = \{w_1, w_2, \dots, w_t\}$ that accurately answers the request. In ViGiA, the loss function for this task is the negative log-likelihood of the generated response tokens:

$$\mathcal{L}_{PGAG} = - \sum_{t=1} \log P(w_t | T_{k,1:j}, u_{k,j+1}, P_k) \quad (1)$$

Plan-aware Visual Question Answering (pVQA).

This task extends the previous one to include requests that require the comprehension of user-provided images. When provided with an image $I_{k,j+1}$ and a request $u_{k,j+1}$, the model must reason about the dialogue history $T_{k,1:j}$, the instructional plan P_k , and the given image, to generate a text response. For this task, we extend the same objective as in PGAG, now also conditioned on the provided image $I_{k,j+1}$. The loss function is defined as:

$$\mathcal{L}_{pVQA} = - \sum_{t=1} \log P(w_t | T_{k,1:j}, u_{k,j+1}, I_{k,j+1}, P_k) \quad (2)$$

It is important to note that, to support pVQA, the model develops a disambiguation capability that grounds its answers in the visual question rather than the instructional video.

4.1.2 Plan-step retrieval capabilities

The second set of model capabilities aim at retrieving an arbitrary plan step: a text step or a video moment with a text only or image query.

Visually-Informed Step Generation (VSG).

Given an unseen user-query-image, the model needs to align it with the plan to generate the corresponding action $a_j \in P_k$. This generation occurs with an in-context retrieval strategy that copies the step from the plan that is in the context of the model.

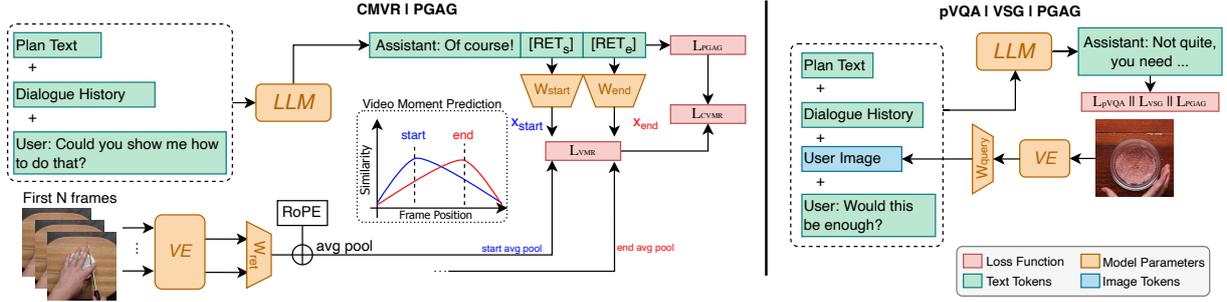


Figure 3: Global view of VIGiA’s architecture. To handle multimodal inputs VIGiA combines a visual encoder and an LLM using an MLP as a connector module. For conversational video moment retrieval, VIGiA outputs a dedicated video moment start and end representation that can be used for start and end frame retrieval.

The objective function is similar to the previous one:

$$\mathcal{L}_{VSG} = - \sum_{t=1} \log P(w_t | T_{k,1:j}, u_{k,j+1}, I_{k,j+1}, P_k) \quad (3)$$

Again, the model acquires novel reasoning capabilities that allow it to navigate to a specific instructional plan action and not answer a visual question.

Conversational Video Moment Retrieval. The CVMR task involves retrieving a relevant video moment $vm = \langle f_{k,start}, \dots, f_{k,end} \rangle \in V_k$ that corresponds to the current plan step, addressed in the request $u_{k,j+1}$. We tackle this in a principled manner by retrieving the start and end frames of the relevant video moment. Specifically, we introduce two dedicated textual tokens, [RET_s] and [RET_e], whose output embeddings are trained to approximate the average representation of the first and last N frames of the relevant video moment, respectively. This is optimized using a contrastive loss, specifically InfoNCE (van den Oord et al., 2018), which tries to maximize the similarity between the [RET_s] and [RET_e] tokens output representations and the target representations and uses in-batch samples as negative examples. We add the PGAG loss to regularize the model to generate coherent responses to these requests. The loss function is defined as:

$$\begin{aligned} \mathcal{L}_{RET} = & \text{InfoNCE} \left(g([\text{RET}_s]), \frac{1}{N} \sum_{i=0}^{N-1} v_{frame}(f_{start+i}) \right) \\ & + \text{InfoNCE} \left(g([\text{RET}_e]), \frac{1}{N} \sum_{i=0}^{N-1} v_{frame}(f_{end-i}) \right) \\ \mathcal{L}_{CVMR} = & \frac{\mathcal{L}_{RET}}{2} + \mathcal{L}_{PGAG} \end{aligned} \quad (4)$$

where $g(x)$ denotes the projected retrieval token x embedding and $v_{frame}(f)$ the retrieval representation of f (both defined later in Section 4.2).

	VIGiA	MM-PlanLLM
VQA support	✓	×
Vision Tokens	257 tokens	1 token
CVMR Retrieval	Start & End Frame	Mid Frame
Multiple Domains	✓	×

Table 1: Direct comparison of VIGiA with current procedural plan guidance SotA MM-PlanLLM (Glória-Silva et al., 2024b)

4.2 Model Architecture

We design a custom multi-goal architecture (see Figure 3) designed to effectively integrate multimodal information, while being flexible enough to accommodate the defined tasks:

Language Model (LM) & Vision Encoder (VE). For the LM backbone, we adopt a pretrained LLM to leverage the knowledge and capabilities learned during pretraining and instruction tuning. We use a pretrained vision encoder, $ve(\cdot)$, to obtain region-level visual features for target retrieval video frames and uploaded images. We follow Chen et al. (2024b); Laurençon et al. (2024b) and use all visual features as vision tokens. To bridge the modalities, we follow Liu et al. (2024a) and connect these 2 backbones using a 2-layer projector, W_{query} .

Retrieval Projectors. To deliver retrieval capabilities, two linear projection layers are learned $W_{start} \in \mathbb{R}^{d_{lm} \times d}$ and $W_{end} \in \mathbb{R}^{d_{lm} \times d}$, where d is the dimension of the shared retrieval space and d_{lm} is the output dimension of the LM backbone. A third layer $W_{ret} \in \mathbb{R}^{d_{fv} \times d}$ is learned to map the visual encoder [CLS] token to the retrieval space. Following MM-PlanLLM, video temporal information is encoded by applying RoPE (Su et al., 2024) to the W_{ret} output features, using each frame’s relative position in the video. Formally, our set of

generative retrieval features are learned as:

RET Start Tok.: $g([\text{RET}s]) = W_{\text{start}} \cdot h([\text{RET}s])$

RET End Tok.: $g([\text{RETe}]) = W_{\text{end}} \cdot h([\text{RETe}])$

where h is the last hidden layer embedding of the LM backbone. Target and candidate video frames are mapped to the same retrieval space as:

$$v_{\text{frame}} = \text{RoPE}(W_{\text{ret}} \cdot ve(f_{k,\text{pos}}), \text{pos}) \quad (5)$$

here pos is an integer with the position of the frame in the video and $ve(\cdot)$ is the vision encoder.

To highlight VIGiA’s novelty, Table 1 summarizes VIGiA key distinctions to current SotA model in procedural plan guidance, MM-PlanLLM (Glória-Silva et al., 2024b).

4.3 Training

Multistage LVLm training has been the predominant training paradigm, with several works highlighting its benefit (Tong et al., 2024; Zohar et al., 2024; Chen et al., 2024a). VIGiA is trained with the following structure (shown in Table 8):²

Stage 1: Initialization. The initial stage targets bridging the modality gap between modalities, by aligning the visual features extracted by the VE with the LM representation space, with both remaining frozen. The W_{query} connector is trained on a captioning task, and the retrieval-specific projection layers, W_{ret} , W_{start} , and W_{end} , are initialized with a text-to-image retrieval task.

Stage 2: Visual Instruction Tuning. This stage is aimed at introducing strong general image understanding, in an effort to improve the final model’s performance on unseen tasks. For pVQA and VSG, the model is trained end-to-end on general visual instruction datasets, whereas for retrieval captioning datasets are repurposed for image retrieval.

Stage 3: Domain-specific Training. The third stage focuses on domain specialization using datasets with in-domain dialogues or instructions to start to expose the model to the target domain. For video datasets, such as YouCook2 (Zhou et al., 2018) and CrossTask (Zhukov et al., 2019), we use instructional video annotations to construct instructional training samples where the model needs to identify the plan step to which 4 provided frames belong. For retrieval, the model is trained to retrieve the relevant video moment provided a plan step and title. The FoodDialogues (Yin et al., 2023) and

²For more details on each stage see Appendix A

FoodReasonSeg (Yin et al., 2023) datasets are used for their dialogues with domain-specific knowledge.

Stage 4: Task-specific Training. The final stage trains the model for conversational instructional plan guidance, exposing the model to the domain-specific conversational patterns, CVMR, and VSG. The visual encoder $ve(\cdot)$ is frozen to avoid inserting a plan-specific bias that hinders the model’s generalization capabilities, as the tasks are limited. Here, we train solely on InstructionVidDial, described in Section 4.4.

4.4 InstructionVidDial Dataset

One of our core contributions is the introduction of a conversational plan-guiding dataset that extends TastyVidDial (Glória-Silva et al., 2024b), including both cooking and DIY plans, and adding plan-grounded visual question answering. Thus greatly widening the dataset scope and allowing for a more comprehensive evaluation on instructional plan guidance. Below we outline the details of each step of the dataset construction process:

DIY Plans. To improve plan diversity and promote more generalizable learning, we leverage the COIN (Tang et al., 2019) dataset to include DIY instructional plan dialogues. To do this, for each type of task in COIN, we randomly select 4 videos and then replicate the dialogue generation process from TastyVidDial. As COIN videos are not paired with instructional plans, we produce a step-by-step plan from the textual video annotations by prompting Claude 3.5³ to rewrite the annotation sequence into a instructional plan. This results in 700 additional dialogues.

InstructionVidDial Curation. TastyVidDial contains 1.5k illustrated recipes, with a total of 50k generated dialogues, with an average of 33 dialogues per recipe. This led to redundancy within the dataset, as many of the dialogues share the same plan. To mitigate this, we trim the dataset keeping only the 4 dialogues per plan that contained the most multimodal turns.

Visual Question Answering Augmentation. To introduce pVQA requests into the already generated dialogues, we navigate the dialogues and introduce a 30% chance of inserting a pVQA request after each time the user progresses to a new action in the plan. For each, we select the middle frame of the relevant video moment to mimic a user-uploaded

³<https://www.anthropic.com/news/claude-3-5-sonnet>

image, and prompt Claude 3.5 to generate a (question, answer) pair based on the image, the provided dialogue context, and the instructional plan. This results in dialogues where pVQA requests are naturally woven into the conversation (Appendix F).

5 Experimental Setup

5.1 Multitask Training Details

As VIGiA is trained in a multitask setup, we use a custom trainer, where each minibatch is sampled from multiple dataloaders to ensure a balanced task mix. Training batches are limited, per epoch, to the size of the smaller dataloader, ensuring a 1:1 sample ratio. As retrieval samples tend to have less tokens, task-specific batch sizes are used, which is beneficial for the InfoNCE retrieval loss as it uses as in-batch negatives. For retrieval, we set $d = 512$, and $N = 5$.⁴

5.2 Datasets

During our multistage training, the training data size progressively decreases at each stage as specialization occurs. For stage 4, InstructionVidDial has 6760 dialogues, which leads to a total of $\approx 114k$ dialogue turns, with a mix of multimodal requests (pVQA, VSG, CVMR) and textual plan-grounded answer generation. During training, we consider the 4 previous turns, and split the dataset in 90/5/5 for train/dev/test, with no plan overlap between splits. To reduce the frame count, for retrieval, only 1 in every 20 frames of the instructional video is kept.⁴

5.3 LM & Vision Backbones

For the LM we adopt LLaMa 3 8B (Dubey et al., 2024), but we compare different model sizes in Appendix C. For the VE, following previous findings (Tong et al., 2024; Zohar et al., 2024; Laurençon et al., 2024b,a), we use SigLIP SO400M (Zhai et al., 2023) as the VE with an image size of 224x224 and a patch size of 14, for a total of 257 patches per image.

5.4 Metrics

For **PGAG** we use text generation metrics: METEOR (Banerjee and Lavie, 2005), ROUGE-L (Lin, 2004), and BERTScore (Zhang et al., 2020). For **VSG** we use ROUGE-L and Exact Match, where a match is if the generated text contains the exact step text. For **pVQA** we complement ROUGE-L with Accuracy as measured by the majority vote

⁴Appendix B includes more details on the training setup.

of 3 LLMs (Claude 3.5 Sonnet (Anthropic, 2024), LLaMa Vision 90B (Dubey et al., 2024), and Pixtral Large (Team, 2024)), which are prompted with the image, dialogue context, instructional plan, and the system response, and asked to evaluate the accuracy of the response, more details in Appendix H. For **CVMR**, we consider two candidate extraction approaches: “*firm*” - where candidate video moments are determined by the most similar frames to the [RETs] and [RETe] token embeddings, and “*adjusted*” - where the start and end frame are the frames where the similarity with the produced [RETs] and [RETe] tokens representation drops below a certain threshold, respectively.⁵ We use Recall@k, where $k \in \{1, 5\}$ with Intersection over Union (IoU) with $m \in \{0.5, 0.7\}$.

5.5 Baselines

Due to the limited amount of domain-specific models and models capable of performing CVMR, we complement our baseline models with general-purpose models. Specifically, we consider the following baselines:

MM-PlanLLM, the current in-domain SotA model. A 7B model capable of generating plan-grounded responses and retrieving video moments, but with no pVQA training. For CVMR, as it only retrieves the middle frame, we leverage their observation that the produced retrieval embedding has high similarity with the target video moment frames so we obtain candidate video moments by considering all frames adjacent to the retrieved frame with a similarity greater than 0.3.

TRACE (Guo et al., 2025), a VMR-specific model that has strong performance in the QVHighlights (Lei et al., 2021) dataset. This is a generative model, so we can only report Recall@1 results.

We also consider six recent $\approx 7B$ general-purpose baselines that have shown strong performance across multiple computer vision tasks and domains: **LLaVA-1.5** (Liu et al., 2024a), **Idefics2** (Laurençon et al., 2024b), **LLaVA-OV** (Li et al., 2024), **InternVL 3.5** (Wang et al., 2025), **Qwen2.5VL** (Bai et al., 2025b), and **Qwen3VL** (Bai et al., 2025a).

5.6 Dataset Quality Annotation

As we add pVQA turns to the InstructionVidDial-dataset, we perform data annotation using volunteer annotators to obtain a quality estimation. In this annotation, we asked five annotators to, once shown

⁵See Appendix D for more details and examples.

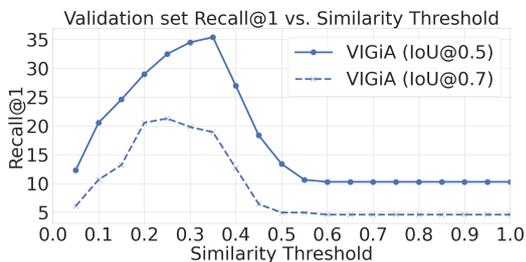
Table 2: Results on the in-domain tasks: PGAG, pVQA, and VSG. Underlined scores are the best among the baselines. *Accuracy is measured using the majority vote of three independent LLMs (See Section 5).

Model	Plan Reasoning			Plan-based Retrieval			
	PGAG			pVQA		VSG	
	ROUGE-L	METEOR	BERTScore	ROUGE-L	Accuracy*	ROUGE-L	EM
Idefics2	37.16	45.09	67.55	21.22	44.49	20.16	5.85
LLaVA-1.5	42.47	40.84	70.55	26.77	64.11	16.07	4.21
Qwen 2.5 VL	31.61	41.51	63.91	26.39	75.14	16.65	9.47
LLaVA-OV	41.18	40.85	70.70	27.02	77.38	32.28	17.89
InternVL 3.5	41.62	46.20	69.22	<u>28.31</u>	<u>91.40</u>	26.30	14.21
Qwen 3 VL	44.71	46.31	71.94	24.72	91.21	33.38	25.26
MM-PlanLLM	<u>58.85</u>	<u>59.34</u>	<u>80.03</u>	7.49	0.37	<u>44.70</u>	<u>40.00</u>
VIGiA	75.30	76.67	88.72	33.65	94.02	55.66	57.37

Table 3: Results on the CVMR task.

	Model	CVMR			
		Recall@1		Recall@5	
		$m=0.5$	$m=0.7$	$m=0.5$	$m=0.7$
firm	TRACE	5.97	1.63	—	—
	VIGiA	10.49	2.89	30.38	11.75
adj.	MM-PlanLLM	25.32	12.48	31.46	16.46
	VIGiA	30.74	15.37	51.18	26.94

Figure 4: Comparing R@1 performance with varying values for the similarity threshold on InstructionVidDial’s dev set.



the complete plan, the reference image, the question, and the answer, rate (from 1 to 3) the turn on three independent measures: **Relevance** of the question to both the image and instructional plan, **Plausibility** of the question in a real setting, and **Accuracy** of the provided answer. This annotation was carried out using 250 pVQA turns.

Our results show that the generated turns are composed of very relevant questions and accurate answers with a score of 2.67 and 2.75 respectively. Plausibility was the lowest rated measure at 2.22, although still strong. Based on annotator feedback and sample observation, we determine that the lower Plausibility score is linked to turns where, occasionally, the question is phrased as if the system is the one providing the image, not the user.⁶

⁶Additional details and an error analysis are provided in

6 Results and Discussion

In this section, we present and discuss the results of VIGiA on the various tasks considered. We start by evaluating on in-domain tasks using the InstructionVidDial test set. This is followed by an evaluation of general-purpose image understanding using MME.

6.1 Textual Plan-Grounded Answer Generation

Textual Plan-Grounded Answer Generation covers the majority of the requests seen in the InstructionVidDial dataset, and is a good benchmark of the model’s ability to generate coherent and contextually relevant responses based on the instructional plan dialogue. The evaluation of this task has all text-only requests from the test set, which includes a mix of questions, navigation requests, and more. The results are summarized in Table 2.

These results show that VIGiA outperforms all baselines and also reinforces the need for domain-specific training for instructional plans, as MM-PlanLLM, the only in-domain baseline, outperforms general purpose baselines.

6.2 Multimodal Answer Generation

Regarding multimodal answer generation, we test the model on tasks where direct image understanding is needed to respond accurately. Specifically, we evaluate VIGiA’s performance, against the baselines, on the VSG and pVQA turns of the test set and present the results in Table 2. The pVQA results attest the benefit of in-domain pVQA training as VIGiA has a 94.02% accuracy, a meaningful jump over most baselines, while MM-PlanLLM, which was not trained for any type of VQA, has near-zero performance, highlighting the critical gap that we

Appendix G.

Table 4: Ablation of model training stages. Underlined scores represent improvements over the previous stage/row.

	Plan Reasoning				Plan-based Retrieval				General		
	PGAG		pVQA		VSG		CVMR R@1		MME		
	R-L	METEOR	R-L	Acc.	R-L	EM	m=0.5	m=0.7	Cog.	Per.	
Stages	4 Only	74.75	76.05	33.56	88.79	54.27	56.84	11.39	5.97	234	503
	1+4	74.67	<u>76.61</u>	<u>33.89</u>	<u>90.47</u>	54.17	56.32	<u>20.43</u>	<u>11.39</u>	211	501
	1+2+4	<u>74.99</u>	76.39	<u>34.20</u>	<u>91.03</u>	54.12	<u>56.84</u>	9.58	5.06	<u>223</u>	<u>708</u>
	1+2+3+4	<u>75.30</u>	<u>76.67</u>	33.65	<u>94.02</u>	<u>55.66</u>	<u>57.37</u>	<u>30.74</u>	<u>15.37</u>	<u>229</u>	<u>717</u>

are the first to address. **VSG** results are similar with **VIGiA** strongly outperforming all baselines. General purpose baselines struggle as this task demands aligning the provided image with the textual plan, requiring a strong understanding of instructional plan structure on both modalities. We also hypothesize that the inclusion of in-domain pVQA in the training data elicits richer plan understanding as we outperform MM-PlanLLM by over 25% despite training on 5x less in-domain data.

6.3 Conversational Video Moment Retrieval

The **CVMR** task requires retrieving a specific video moment from an instructional video, based on the dialogue context, and, as covered in Section 5.4, we evaluate two moment extraction approaches. For the “*adjusted*” approach the threshold was set to 0.35, based on our observations on the validation set, shown in Figure 4. Table 3 shows the results of this evaluation. **VIGiA** substantially improves on the previous SotA for this task, with a decent improvement over MM-PlanLLM. Comparing the “*firm*” and “*adjusted*” settings, we note that the latter effectively leverages the representations learned by our retrieval-specific layers and highlights the benefit of learning start/end region representations, with much higher R@1 scores. **TRACE** while a strong baseline for general VMR struggles in our domain-specific task likely due to the conversational setting, showing that off-the-self models are not viable for this task.

6.4 General Task Performance

Domain-specific models still benefit from rich general image understanding to better address unseen plans and domains. We use **MME** (Fu et al., 2023), a benchmark of 14 image understanding sub-tasks, as a proxy to measure flexibility and the impact of domain-specific training.

From Table 5 we see the expected performance plot with general purpose models excelling. Regarding **VIGiA**, we confirm that Stage 2 training instills

Table 5: MME performance across stages.

Model	Stage 2		Stage 4 / Final	
	Cog.	Per.	Cog.	Per.
MM-PlanLLM	—	—	34	1
Idefics2	—	—	328	1474
LLaVA-1.5	—	—	314	1483
LLaVA-OV	—	—	418	1580
Qwen 2.5 VL	—	—	638	1685
InternVL 3.5	—	—	663	1686
Qwen 3 VL	—	—	639	1733
VIGiA	263	1344	229	717

Table 6: Dialogue-level evaluation ($N = 54$) with LLM-as-a-judge to measure guidance quality.

Model	State Tracking	Instruction Clarity	Plan Adherence
MM-PlanLLM	1.61	2.11	2.24
Qwen 2.5 VL	2.31	2.41	2.74
Llava OV	1.87	2.59	3.00
InternVL 3.5	2.52	2.44	3.13
Qwen 3 VL	2.85	2.35	3.39
VIGiA	3.30	4.06	4.26

rich image understanding but, after Stage 4, there is a performance drop, a trade-off of as the model begins to be specialized. In general, **VIGiA** retains general image understanding capabilities even after instructional plan guidance specialization, particularly compared to MM-PlanLLM.

6.5 Dialogue-level Evaluation

Our evaluation follows previous works’ protocol where the evaluation is conducted at turn level. While this is useful to measure model performance on each task, it fails to capture model performance on extended dialogue reasoning. To address this gap, we collected all test set dialogues without **CVMR** turns (54 dialogues) and evaluated dialogue level performance. We generated full dialogue trajectories by appending model responses to the context turn-by-turn, using the original user inputs as a static simulator. This exposes the model to error

Table 7: Ablation different pVQA data amounts.

pVQA Data %	PGAG		pVQA		VSG	
	R-L	M	R-L	Acc.	R-L	EM
0%	75.62	77.03	23.30	71.59	53.54	56.32
10%	75.63	76.98	31.66	85.23	53.55	54.74
20%	75.56	76.97	32.41	85.42	53.17	55.79
50%	76.09	76.54	34.00	88.79	56.01	57.89
100%	75.30	76.67	33.65	94.02	55.66	57.37

propagation. For evaluation we use an LLM-as-a-judge approach and judge each dialogue on 3 dimensions (in a 1-5 scale): State Tracking (accuracy of tracking the user progress across the conversation), Instruction Clarity (absence of added unwanted commentary that hinders instruction comprehension), and Plan Adherence (faithfulness to the plan, not hallucinating any steps or ingredients/tools). More details on this evaluation setup are provided in Appendix I.

Table 6 shows the results of this evaluation. Here we see that VIGiA performs strongly on all three dimensions with a significant lead in Instruction Clarity. Qualitatively, baseline models tend to be extremely verbose, often adding markdown notation and additional commentary, resulting in poor Instruction Clarity, an important factor when guiding user unfamiliar with the task. Finally, State Tracking emerges as the most challenging dimension, reinforcing the difficulty of tracking user progress through both visual and textual inputs over extend dialogue sessions where progress is rarely linear, one of the core challenges of procedural plan guidance.

6.6 Ablation Studies

To evaluate and measure the impact of each training stage on the different tasks, we performed an ablation study by progressively adding additional training stages. Table 4 shows our ablation of multistage training. We see an incremental benefit of each added training stage. Although the single-stage approach presents a strong baseline, it lacks CVMR and MME performance, which are then addressed in the latter stages. The first and third stage collectively improve CVMR performance, up 20 points on R@1 with $m=0.5$. The 2nd stage improves model flexibility with an MME Perception increase of 200 points, without a significant loss on in-domain tasks. We also ablated RoPE usage for frame position encoding and found that not using it degraded performance, with R@1 $m=0.5$ dropping

13%, from 30.74 to 26.76 and R@1 $m=0.7$ dropping 29% from 15.37 to 11.03.

Additionally, we evaluated the impact of pVQA data volume in training. From Table 7, we highlight two key findings: 1) including pVQA data yielded a notable improvement in VSG performance, likely due to their shared MLP module; and 2) performance across most metrics peaks with 50% pVQA data, with a minor decrease when all pVQA samples are used, likely due to task saturation. A further ablation of a text-only version of VIGiA is included in Appendix E.

7 Conclusion

This paper proposes VIGiA, the first LVLM model for conversational instructional plan guidance, that jointly addresses the key goals of the task: 1) rich image understanding for Plan-grounded pVQA, 2) conversational video moment retrieval, 3) multi-modal plan alignment and 4) plan-grounded answer generation. An extended cross-modal architecture is designed, supporting unified plan-grounded dialogue and generative video moment retrieval.

In our detailed evaluation, we compare VIGiA against both domain-specific and general-purpose LVLMs and find that it consistently and significantly outperforms both types of baselines, with over 90% accuracy in plan-grounded in-context VQA. We complement our analysis with an evaluation on a general image understanding benchmark and show that VIGiA remains far more capable than the in-domain state-of-the-art.

8 Limitations

The very limited amount of instructional plans paired with an annotated instructional video lead to a dataset with not enough training examples diverse enough to perform a full training, without needing auxiliary datasets. As presented in Table 5, VIGiA is trained with different datasets over different phases. These are intended to equip the model with increasingly complex capabilities, to mitigate the knowledge gaps of the latter stages.

The datasets and instructional plans used for domain-specific training (Stage 3 & 4) might have a western bias, as they were sourced from English sources. Because of this, we posit that for other cultural contexts model performance can vary as the model is not as familiar with region-specific terminology and techniques. However, we do not believe that core functionalities, such as navigation

and context-dependent QA, are affected because these functionalities depend on task structure rather than external knowledge.

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A Training Dataset Details

In this section, we provide additional details on the datasets used to train VIGiA. We include the specific number of samples used in each stage, as shown in Table 9.

A.1 Multitask Trainer

As there are 2 losses being optimized in our model, passing through task-specific components, we need to employ a dual dataloader trainer that allows us to train on both tasks at the same time without needing to format our batches in a multitask format, something that is not doable for pVQA, Visual Instruction Tuning, and CMVR. This is achieved by alternating the dataloaders when sampling batches, allowing for an even distribution of training batches.

A.2 Dataset Transformations

As we target instructional plans in a conversational manner, we needed to adapt and transform some of the datasets to train our model. In this section, we detail the transformations applied to each dataset:

LAION400M - For LAION400M we use the image-caption pairs to train the model in a Image-to-Text task and Text-to-Image retrieval.

ShareGPT4o - This dataset is used as is, with no alterations.

MAMMoTH-VL - This dataset is used as is, with no alterations. We only consider the first 1M multimodal samples.

VQAv2 & GQA - These datasets are framed as an instruction following task using templates to convert the question into an instruction, the answer is kept as is.

ShareGPT4v, LLaVA-Pretrain, Pixmo-cap - These datasets are used as is, with no alterations. Pixmo is framed as a user request for a detailed image caption.

FoodDialogues - This dataset includes special tags, such as [CARB], to indicate nutritional info estimation in system answers, we remove these tags and preserve the rest of the text.

FoodReasonSeg - This dataset includes requests for segmentation mask along with ingredient identification, we focus on the latter and remove the segmentation mask requests. We also rewrite the user utterances using a Llama 3 model, to improve naturalness and fluency.

YouCook2, Crosstask, COIN - These datasets are made up of instructional videos with annotated video segments. To adapt them to our needs, for

each annotated video segment, we extract 4 frames and train the model to predict the annotated text. For retrieval, we instead provide the model with the task name and annotated video segment text and train the model to retrieve the start and end frames of the video segment. In this case we adopt the strategy of picking N frames from the start and end, and the model is trained to approximate the average of the embeddings of these frames. This allows us to train the model to retrieve a single frame, while also allowing for some flexibility in the candidate video moment limits.

B Training Details

In this section, we provide additional details on the training setup and hyperparameters used to train VIGiA. The hyperparameters are shared across all models and are shown in Table 10, for each training stage. The training was performed using NVIDIA A100 GPUs with 80GB of memory each, connected with SXM4.

On stage 2 and 3 we leverage our dual dataloader training approach to utilize larger batch sizes for retrieval, this was possible as the retrieval samples are smaller than the captioning samples. This approach benefits retrieval training as we utilize in-batch samples as negatives for the contrastive loss calculation.

For stage 4 we use a single dataloader with a batch size of 32, and the different mode samples are uniformly sampled from the dataset, with this sampling logic being handled by the sampler instead.

In Table 10, CAP refers to the connector between the Vision Encoder and the LLM, RET refers to the retrieval-specific layers used in the model (W_{start} , W_{end} , W_{ret}).

C LM Backbone Size Variance

To measure how model performance varies across LM backbone sizes, we ran some experiments with other Llama 3 model sizes. Specifically, we tested with Llama 3 1B and 3B, the results for all tasks are shown in Table 11.

Here we see that, with some exceptions, the smaller models have very strong performances, considering their reduced size, whilst also being clear the benefit of increase LM backbone size. For CVMR VIGiA 1B outperforms 3B, we hypothesize that it is caused by 3B training with a smaller batch size, which slows down convergence as In-fonCE loss uses in-batch negatives, meaning that

Table 8: Overview of the multistage training process for VIGiA. Status indicators: 🔥 = Trainable, ❄️ = Frozen.

Stage	Specialized Layers	LLM	VE	Datasets
Initialization	🔥	❄️	❄️	Laion400M (Schuhmann et al., 2021)
Visual Instruction Tuning	🔥	🔥	🔥	ShareGPT4o (Cui et al., 2024), MAMmoTH-VL (Guo et al., 2024), VQAv2 (Goyal et al., 2017), GQA (Hudson and Manning, 2019), ShareGPT4v (Chen et al., 2024a), PixMo-Cap (Deitke et al., 2024), LLaVA-Pretrain (Liu et al., 2023)
Domain-specific Tuning	🔥	🔥	❄️	FoodDialogues (Yin et al., 2023), FoodReasonSeg (Yin et al., 2023), Youcook2 (Zhou et al., 2018), COIN (Tang et al., 2019), Crosstask (Zhukov et al., 2019)
Task-specific Training	🔥	🔥	❄️	InstructionVidDial (ours)

Table 9: Overview of the datasets used to train VIGiA.

Stage	Dataset	Type	Samples #
1	LAION400M	Cap + Ret	10M+10M
2	ShareGPT4o	Cap	≈57k
	MAMmoTH-VL	Reasoning	1M
	VQAv2	pVQA	≈444k
	GQA	pVQA	943k
	ShareGPT4v	Ret	≈1.25M
	Pixmo-cap	Ret	≈698k
3	LLaVA-Pretrain	Ret	≈558k
	FoodDialogues	Domain	≈26k
	FoodReasonSeg	Domain	≈14k
	YouCook2	Cap+Ret	≈10k+≈10k
	Crosstask	Cap+Ret	≈17k+≈16k
4	COIN	Cap+Ret	≈43k+≈39k
	InstructionVidDial	All	≈110k

smaller batches can slow down convergence. Focusing on **pVQA** the benefit of higher parameter count is very accentuated with significant improvements as we scale up the LM. As this is a task that requires the models to encode external knowledge acquired during training thus smaller models have more limited external knowledge remembrance capacity. Whereas for **PGAG**, where most requests are context-dependent, the models all have impressively similar performance. **MME** emerges as an outlier, having similar performance to the 3B variant, despite the increased LLM size. We hypothesize that this is caused by training the 8B LM backbone using LoRA (Hu et al., 2022), due to memory constraints, from stage 2 onward, which means that only a small number of parameters are being updated, thus suffering from decreased learning capacity, as studied in Biderman et al. (2024).

Table 10: Shared hyperparameters used to train all models. For Stage 1, LLM-specific hyperparameters only affect the [RET] tokens input and output embeddings, along with the language modeling head.

Stage	1	2	3	4
Batch Size	512	64	128	32
RET Batch Size	512	96	192	—
Acc. Steps	4/4/8	4/8/8	4/8/8	4/8/16
Train Steps	19500	15000	866	3252
Parallel	DDP	DDP	DDP	DDP
GPU #	4	8	4	1
Model DType	BF16	BF16	BF16	BF16
LLM LR	$1 * 10^{-3}$	$5 * 10^{-5}$	$2 * 10^{-6}$	$5 * 10^{-5}$
VE LR	—	$5 * 10^{-5}$	—	—
CAP LR	$5 * 10^{-4}$	$5 * 10^{-4}$	$5 * 10^{-4}$	$2 * 10^{-4}$
RET LR	$1 * 10^{-3}$	$1 * 10^{-3}$	$1 * 10^{-3}$	$1 * 10^{-3}$
Scheduler	Constant	Constant	Constant	Constant
Optimizer	AdamW	AdamW	AdamW	AdamW
LLM Decay	0.03	0.01	0.0	0.0
VE Decay	—	0.0	—	—
CAP Decay	0.03	0.03	0.01	0.01
RET Decay	0.03	0.03	0.01	0.01
LoRA (Only for 8B)				
LoRa DType	—	FP32	FP32	FP32
LoRa Rank	—	32	32	32
LoRa α	—	128	128	128
LoRa Dropout	—	0.03	0.03	0.03

Table 11: Ablation of LM backbone sizes on model performance across all considered tasks.

	Plan Reasoning				Plan-based Retrieval				General	
	PGAG		pVQA		VSG		CVMR R@1		MME	
	R-L	METEOR	R-L	Acc.	R-L	EM	m=0.5	m=0.7	Cog.	Per.
VIGiA 1B	75.44	76.67	29.35	58.69	51.53		26.22	13.92	203	632
VIGiA 3B	76.51	77.72	30.16	71.59	52.15	53.68	23.33	15.91	214	808
VIGiA 8B	75.30	76.67	33.65	94.02	55.66	57.37	30.74	15.37	229	717

Algorithm 1: Candidate video moment extraction in the “adjusted” setting.

Input : Start representation r_{start} ,
End representation r_{end} ,
Encoded Frames $\mathcal{V} = \{v_1, v_2, \dots, v_T\}$,
Similarity threshold τ

Output : Temporal segment indices (t_{start}, t_{end})

```

1  $idx_s \leftarrow \arg \max_{i \in \{1, \dots, T\}} \text{Sim}(v_i, r_{start})$ 
2  $idx_e \leftarrow \arg \max_{i \in \{1, \dots, T\}} \text{Sim}(v_i, r_{end})$ 
3  $t_{start} \leftarrow idx_s$ 
4 for  $i \leftarrow idx_s$  down to 1 do
5   if  $\text{Sim}(v_i, r_{start}) < \tau$  then
6     break // Stop if similarity drops
7   end
8    $t_{start} \leftarrow i$ 
9 end
10  $t_{end} \leftarrow idx_e$ 
11 for  $i \leftarrow idx_e$  to T do
12   if  $\text{Sim}(v_i, r_{end}) < \tau$  then
13     break // Stop if similarity drops
14   end
15    $t_{end} \leftarrow i$ 
16 end
17 return  $(t_{start}, t_{end})$ 

```

D CVMR Evaluation

Although the task of CVMR is formulated by retrieving the start and end frame of a relevant video moment, realizing the lack of flexibility of such an approach, specifically in a setting where adjacent images are largely similar, we train our model to instead produce the representation of the averaged N frames around the target frame. Based on this, it is fair to say that our model is trained to predict a start and end region representation rather than only retrieving a individual start and end frames.

To account for this, during evaluation, we evaluate our models and MM-PlanLLM in what we call an “adjusted” candidate extraction setting where the limits of the candidate video moment are determined by the point/frame where the frame’s similarity to the produced representation drops below a given threshold. Specifically, in the “adjusted” ap-

proach, the extraction of candidate video moments follows the logic of Algorithm 1.

This leverages the observations of Glória-Silva et al. (2024b) that the model’s retrieval features show a decrease in similarity to video frames belonging to steps further away from the target step, suggesting that the model is able to effectively identify the target plan step and produce an adequate video region representation. This threshold is determined using the validation set, as seen in Figure 4, where we report R@1 values for mIoU = 0.5 and 0.7, with 20 different threshold values. Here we observe a constant CVMR performance improvement until threshold = 0.35 followed by a sharp decline when the threshold > 0.35, showing that the model has clearly learned region-level features. Interestingly, when mIoU=0.7 instead of a peak at 0.35 we see a plateau from 0.2 to 0.35, which reveals that the model is able to identify the moment’s core content at around 0.35 similarity with its outer limits having between 0.2 and 0.35 similarity with the retrieval features. The existence of a plateau reinforces that the model is capable of isolating the relevant video moment. Based on this, we set the threshold to 0.35, where the model is at or close to its performance peak.

To illustrate how similarity with the start and end retrieval representations varies across the video frames we included six plots in Figure 5. In these plots, the x axis is the frame position, and the y axis is the similarity score with the start (blue line) and end (red line) retrieval representations. Additionally, we plot two vertical lines that mark the ground truth video moment limits.

These plots provide an insight into how accurately the produced retrieval representations line up against the instructional video. In the first few examples we see clear cases where the produced representations have their similarity maximized in the target video moment frames, meaning that they correctly identified the video moment. Particularly

Table 12: Results comparing the full model training pipeline against a text-only training run. Underlined scores are the second best scores.

Model	PGAG		
	ROUGE-L	METEOR	BERTScore
Idefics2	37.16	45.09	67.55
LLaVA-1.5	42.47	40.84	70.55
Qwen 2.5 VL	31.61	41.51	63.91
LLaVA-OV	41.18	40.85	70.70
InternVL 3.5	41.62	46.20	69.22
Qwen 3 VL	44.71	46.31	71.94
MM-PlanLLM	<u>58.85</u>	<u>59.34</u>	<u>80.03</u>
VIGiA	75.30	76.67	88.72
VIGiA-Text	75.09	76.47	88.68

in the 5b plot where there’s a clear peak and plateau spanning the target moment almost exactly. The plots also show how the model is able to produce retrieval representations that “track” video progress with similarity monotonically increasing and decreasing when getting closer and further from the target moment, respectively, as seen in plots 5a and 5c. This same pattern is visible in 5d however here the similarity seems to start dropping slightly earlier than the end of the target video moment. The plots 5e and 5f also showcase this pattern, however here the representations maximize similarity on the moment immediately before the target moment, leading to incorrect candidate extraction. Overall, these plots show that the model is capable of producing very accurate retrieval representations that correctly identify the position of the target video moment in most cases. We also see that there are similarity “valleys” separating the moments, showing that the model is able to model a clear moment-to-moment barrier.

E Text-only Ablation

To measure the impact of multimodal training on the final text-only, PGAG, performance we also trained a llama directly on text-only in-domain data, meaning the model training solely on stage 4 and only on samples that do not involve multimodal inputs or outputs. We report these results in Table 12.

From these results, we can see a slight negative performance delta against VIGiA. This is likely due to the lack of the added multimodal training data that still exposes the model to the procedural plan guidance conversational patterns. This combined with the sacrifice of all multimodal capabilities, makes it far less capable for full procedural plan guidance.

Table 13: Results of the data quality annotation conducted on 250 pVQA turns from the test set of InstructionVidDial.

Plausibility	Relevance	Accuracy
2.22	2.67	2.75

F pVQA Generation Details

Of the two crucial extensions that we make to TastyVidDial is the addition of pVQA user requests. To achieve this, we used Claude 3.5 Sonnetv2 to generate user questions relevant to a provided image, the ongoing dialogue, and the instructional plan being executed. To determine whether a pVQA turn would be added we set a 30% chance of that after any time the user moved forward in the task (using the NextStepIntent annotation provided in TastyVidDial). Table 22 shows the prompt used to generate the visual question-answer pairs, and Table 15 shows an example from InstructionVidDial’s test set.

G pVQA Data Quality Annotation

To ascertain the quality of the generated turns we conducted a data quality annotation study followed by some error analysis study.

G.1 Quality Annotation

As LLMs were used to generate the pVQA turns in InstructionVidDial we find it important to conduct a data quality annotation study to ascertain the quality of the added turns on several metrics. To this end, we conduct an annotation study with five volunteer annotators and tasked them with annotating the following 3 criteria:

- **Plausibility** - Here we asked annotators to rate how plausible each turn is when considering the provided dialogue context in a real scenario. With this criteria, we aimed to measure how realistic the generated turns are and how well they pass for real user inputs.
- **Relevance** - For this criteria, we wanted to assess how relevant the generate user visual question was to both the selected image, and the instructional plan being executed. This is critical to understand if the generated turns are closely related to all of the surrounding context.

- **Accuracy** - It was also important to ensure that the generated turns were made up of questions that were adequately answered and did not contain inaccurate answers instead. In this criteria, we asked annotators to, considering the dialogue, instructional plan, and their own knowledge, rate if the provided answers were accurate to the generated user questions.

The selected annotators were volunteers all with higher education in the computer science field, all fluent in English, and familiar with data annotation tasks and user studies. In total 250 pVQA samples were randomly selected from InstructionVidDial’s test set. Annotators were shown the instructional plan, provided user image, generated user question, and generated system response. The specific instructions provided to the volunteers are shown in Table 14.

The results, shown in Table 13, highlight the quality of the generated pVQA turns with very high scores for both Relevance and Accuracy, meaning that the turns were closely related to the context they were inserted in and provided reliable answers. Plausibility scores were also very positive asserting that the generated user questions often fell into the scope of possible questions a user might ask in a realistic setting, a key factor to ensure high data quality.

G.2 Error Analysis

To understand the possible failure patterns presented in the generated data, we manually examined the worst 50 (as measured by the average score of the 3 criteria annotated) turns from the ones in the data quality annotation and noted the most common patterns: **1.** The generated question phrases the image as not being the user’s (20 occurrences) - In these cases, the question is framed as if the user is seeing the image somewhere, not that it is their image. **2.** Image contains text on screen (12 occurrences) – As images are extracted from instructional videos, occasionally they may contain some text on screen that renders their usage implausible for a user-uploaded image. **3.** Image-text mismatch (12 occurrences) – In some cases, the question mentions aspects (objects, tools, ingredients, etc.) that are not visible in the image.

To mitigate the above patterns, several approaches can be adopted:

- The first failure pattern can be tackled by identifying common wording patterns in these

cases and automatically rejecting samples with these patterns. Alternatively, a second LLM could be deployed with the sole task of annotating each sample on several criteria to automatically isolate low quality samples.

- The second pattern could be addressed by using an OCR model to try and extract text from the image. If text is successfully and confidently extracted, the image would be deemed unfit for usage.
- The third pattern poses a more challenging obstacle to address with no clear solution without relying on LVLMs, as it requires the extraction of entities in text and image and cross-referencing them to identify possible mismatches.

However, extrapolating this to the entire dataset, we highlight that this occurs in a small part of the dataset of **less than 10% of the samples** having at least one of these.

H pVQA Evaluation Details

For the evaluation of pVQA turns on the InstructionVidDial dataset, we utilize accuracy as measured by three LLMs. For this evaluation, we consider three large-scale LVLMs to maximize the quality of the annotations. Specifically, we utilize Claude 3.5 Sonnet v2, LLaMa Vision Instruct 90B, and Mistral Large.

For each model, we provided it with the relevant image, the previous 4 dialogue turns, and the instructional plan being followed. The prompt structure is present in Table 23. The majority vote of the three responses is then used to provide the final accuracy score.

I Dialogue-level Evaluation Details

To address the lack of a dialogue level measurement of model quality we conducted an additional test against the strongest baselines. As most baselines do not support CVMR, we collected all dialogues from the test set that did not contain any CVMR turns, this resulted in 54 dialogues out of 340. For each dialogue, the model was tasked with answering each user request in a turn-by-turn manner, with previous responses being added to the dialogue history and model context. This allows mistakes to be reflected in the context and propagate through the dialogue, thus impacting overall dialogue performance. As user simulation with dynamic image

inputs is not feasible, we opted to use the dialogue’s original user requests as the user inputs, while this means that the user does not acknowledge incorrect model responses, it still allows for an insight into long term model reasoning on extended conversations.

For the evaluation protocol, we opt for an LLM-as-a-judge approach as it allows for flexible implementation and support for very long inputs (full dialog traces) with differing styles; for the judge model, we used Claude 3.5 Sonnet v2 (Anthropic, 2024). Specifically, we tasked the model with measuring performance on a scale of 1-5 in 3 dimensions:

1. **State Tracking** - This dimension seeks to measure how capable the model was at tracking user progress. This involves not only accurately understanding the user’s intent with each navigation request but also possessing strong visual-text plan alignment that allows the model to infer the new state in VSG turns.
2. **Instruction Clarity** - In a plan guidance setting it is crucial that the model is able to provide instruction in a clear manner with minimal additional and unwanted conversation filler. This dimension scores the model on how well it can keep the instructions clear and in line with user requests.
3. **Plan Adherence** - This dimension measures how strongly the model adheres to the plan without hallucinating additional steps, ingredients, or tools.

The complete prompt is shown in Table 16.

J Qualitative Examples

In Tables 17, 18, and 19 we share some examples of generated answers to plan-grounded pVQA turns from InstructionVidDial test set. In Tables 20 and 21 we compare how different model sizes answer the same user questions, highlighting their capabilities and limitations.

Table 14: Annotation instructions provided to annotate in-domain pVQA turns.

Consider a dataset of dialogues between users and a system designed to assist with manual tasks (recipes or DIY projects). The objective of these annotations is to quantify the quality of automatically generated VQA (Visual Question Answering) turns within that dataset.

Each line contains an example of a question-answer pair, along with the image that originates the question and the task to be performed. For each line, on a scale of 1 to 3 (from worst to best), annotate the following 3 criteria:

Relevance: The relevance of the question concerning the image and the task in question.

- 1 - The question has nothing to do with either the image or the task.
- 3 - The question is relevant to both.

Plausibility: How plausible the question is, considering a person trying to perform the task.

- 1 - A question that no one would ask in the context of that task.
- 3 - A completely plausible question to be asked during the execution of the task.

Accuracy: Based on the task and your own knowledge, how correct the given answer to the question is.

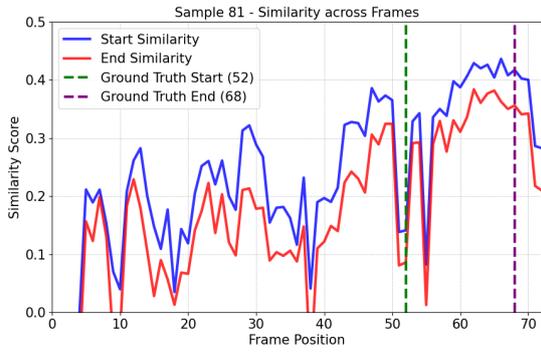
- 1 - An incorrect answer.
- 3 - A correct answer.

Consider each criterion separately. A question may not be at all relevant or plausible (in the context of the task) but still have a correct answer.

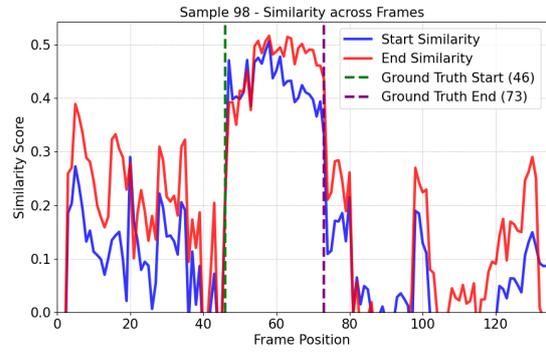
Table 15: pVQA test set examples

User Image	
	<p>Question: I'm adding the pasta to the boiling milk mixture now - is it normal that the liquid looks this white and creamy already, or did I add too much milk?</p> <p>GT Answer: The liquid consistency shown in the image looks perfect! The white, creamy appearance is exactly what you want at this stage. The milk should be bubbling and have this rich, creamy texture before adding the farfalle (bow-tie) pasta. Just remember to keep stirring frequently while the pasta cooks for about 10 minutes at medium heat to prevent it from sticking to the bottom of the pot and to ensure even cooking.</p>
	<p>Question: Based on the color of the chicken pieces in the pan, are they browned and cooked through enough to be removed from the pan?</p> <p>GT Answer: Yes, from what I can see in the image, the chicken pieces appear to have a nice golden-brown color and look properly cooked through. You can see they've lost their raw pink color and have taken on a light golden hue. They're being removed from the pan with a black spoon, which is exactly what you should be doing at this step. The bits of browned fond left in the pan will add great flavor to the next steps of the recipe.</p>
	<p>Question: Is the green and black cap shown in the image the correct type of cap for sealing a volumetric flask?</p> <p>GT Answer: Yes, that appears to be the correct type of cap for a volumetric flask. The cap shown in the image has a green band and black top which is a standard laboratory flask cap design. It's designed to create an airtight seal when properly attached to the volumetric flask. Make sure to screw it on firmly but not too tight to avoid damaging the threads.</p>

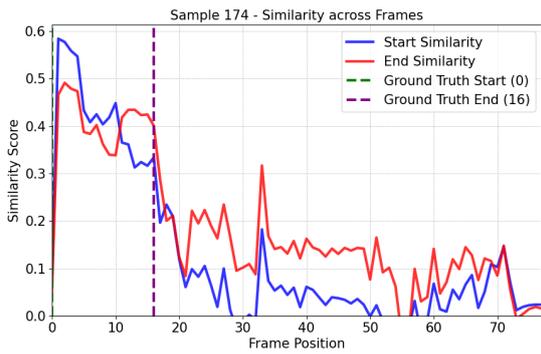
Figure 5: Six examples of how the similarity of the start and end retrieval representations with the video frames varies throughout the video.



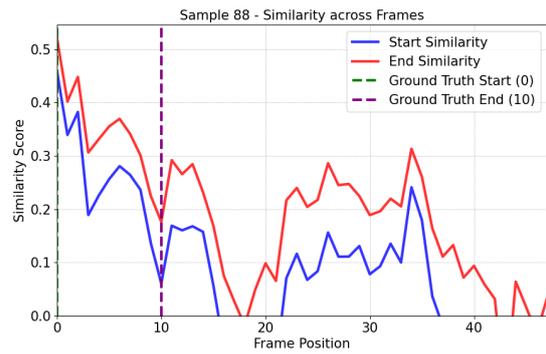
(a)



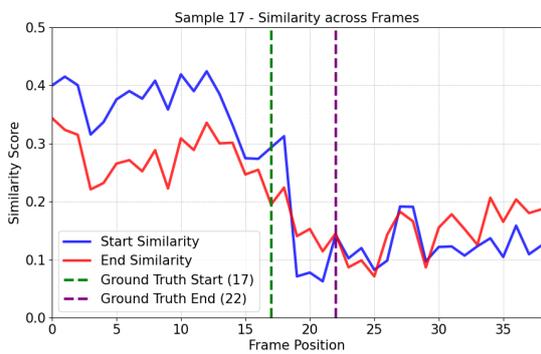
(b)



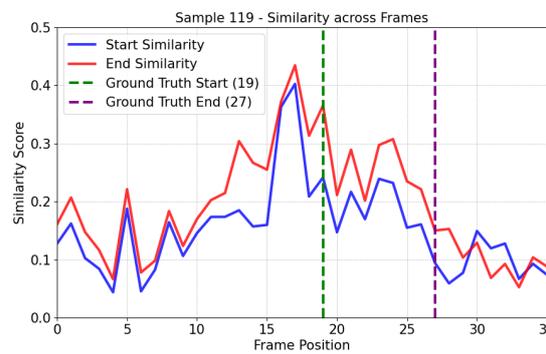
(c)



(d)



(e)



(f)

Table 16: Prompt used to evaluate the dialogues in the dialogue level evaluation described in Section 6.5

You are an expert evaluator for Multimodal Procedural Guidance Assistants.
Your task is to evaluate a full dialogue session between a User and a VLM Assistant.

For the purpose of this evaluation you are provided with:

- TASK: The official ground-truth procedural plan (recipe, manual, etc.).
- Dialogue Transcript: A chronological log of the interaction. Each turn contains:
- User Input: Text and (optional) Image Description.
- Assistant Response: The response you must evaluate.
- Ground-Truth Response: The ground truth response (useful for checking state/facts). DO NOT use this to score the assistant's style or tone, only for state verification.

Your task is to evaluate the entire interaction on these 3 dimensions (Score 1-5, where 1 is poor, 3 is acceptable, and 5 is excellent):

1 - State Tracking

- Does the Assistant correctly identify the user's progress through the TASK based on the User's text and images?
- If the User silently skips steps (evident in images or ground-truth response), does the Assistant correctly recognize this and jumps to the new step?
- Penalize drifting from the plan or failing to recognize visual completion of steps, but do so proportionally to the severity of the error.

2 - Instruction Clarity

- Does the Assistant provide direct, actionable instructions without excessive conversational filler or unwanted commentary?
- The goal is that the Assistant should be a tool, not a chatty companion. It should only speak when necessary to guide or warn, and prioritize instruction clarity.
- Do not penalize politeness or empathy.

3 - Plan Adherence

- Does the Assistant remain faithful to the TASK?
- Penalize hallucinating tools, ingredients, or steps that do not exist in the TASK.

OUTPUT FORMAT

1 - First, provide a concise reasoning block analyzing the dialogue. You may critique specific turns.

2 - End with a valid JSON block, with the following structure:

```
{  
  "state_tracking_score": int,  
  "succinctness_score": int,  
  "plan_adherence_score": int,  
}
```

Here is the TASK:
{task_description}

Here is the dialogue:
{dialogue}

Please provide your evaluation below.

Table 17: Examples of answers provided by VIGiA and some baselines to pVQA samples. In this example LLaVA-OV provided a very dangerous suggestion to the user, whereas both VIGiA and Qwen2.5 VL were able to provide adequate and safe answers.

<p>User Image</p>	
<p>Question:</p>	<p>I've added the oil and garlic to the pan as shown in the image, but how do I know if the heat is at the right temperature? I can see some garlic starting to sizzle but I don't want to burn it.</p>
<p>VIGIA 8B:</p>	<p>The heat appears to be at a good medium temperature as shown in the image. You can see the garlic is starting to sizzle and release its oil, which is the right reaction. If you're seeing this gentle sizzling and the garlic isn't browning too quickly, the heat is appropriate. Just keep an eye on it and stir occasionally to prevent burning. The garlic should be fragrant but not browned when you move on to the next step.</p>
<p>Qwen2.5VL:</p>	<p>To ensure the heat is at the right temperature, you can use a few methods:</p> <ol style="list-style-type: none"> 1. Sizzling Garlic: As you've noticed, the garlic is sizzling in the pan. This is a good sign because it indicates the oil is hot enough to start cooking the garlic without burning it. However, if the sizzling becomes too intense or the garlic starts to brown quickly, reduce the heat slightly. 2. Visual Check: If you can see the oil moving around the pan and the garlic pieces are moving as well, it's likely the oil is at a good temperature.
<p>LLaVA-OV:</p>	<p>To check if the heat is at the right temperature, you can use the "tongue test." Place the tip of your tongue close to the pan, but not touching it. If it feels warm but not uncomfortable, the heat is likely medium. If it feels too hot, reduce the heat. If it feels cool, increase the heat. Remember, it's better to start with a lower heat and adjust as needed to prevent burning.</p>

Table 18: Examples of answers provided by VIGiA and some baselines to pVQA samples. In this example, all three models provided adequate answers but general-purpose models tend to be more verbose.

<p>User Image</p>	
<p>Question:</p>	<p>How do I know if I've rolled the pastry out to the correct dimensions? Should I measure it or is eyeballing it okay?</p>
<p>VIGIA 8B:</p>	<p>For best results, you should measure your rolled pastry to ensure it's exactly 24 inches long and 8 inches wide. This is crucial because puff pastry needs to be rolled to the correct size to properly fold and layer. While eyeballing might work for some recipes, for puff pastry, precise measurements are essential to achieve the right texture and layers. You can use a measuring tape or ruler to check the dimensions while rolling.</p>
<p>Qwen2.5VL:</p>	<p>When rolling out the puff pastry, it's important to ensure that it reaches the desired dimensions to achieve the best results. Here's how you can check:</p> <p>### Measuring:</p> <ul style="list-style-type: none"> - Use a Ruler: Place a ruler next to the pastry and measure the length and width. This ensures accuracy and consistency. - Mark the Dimensions: If you're using a recipe, mark the dimensions on the pastry sheet with a pen or a small piece of paper to guide your rolling. <p>### Eyeballing:</p> <ul style="list-style-type: none"> - Experience: If you have experience with baking and are comfortable with your eye, you might be able to eyeball it.
<p>LLaVA-OV:</p>	<p>When rolling out puff pastry, it's important to ensure that the dimensions are correct for the recipe you're following. Here are a few ways to check if you've rolled the pastry out to the correct dimensions:</p> <ol style="list-style-type: none"> 1. Measurement: Yes, you should measure the pastry. Use a ruler or a measuring tape to ensure that the length and width of the rolled-out pastry are as specified in the recipe. This is crucial for puff pastry, as the thickness and size can affect the final texture and rise of the pastry. 2. Visual Inspection: While it's not as accurate as measuring, you can also visually inspect the pastry.

Table 19: Examples of answers provided by VIGiA and some baselines to pVQA samples. In this example, all three models provided adequate answers but general-purpose models tend to be more verbose.

<p>User Image</p>	
<p>Question:</p>	<p>I see the balance pointer is not quite centered at zero - should I adjust the calibration knob before weighing anything?</p>
<p>VIGIA 8B:</p>	<p>Yes, you should definitely calibrate the balance first. The image shows the balance is currently not zeroed, which means you'll need to adjust the calibration knob to ensure the indicator needle is centered at zero before proceeding to weigh any objects. This is a crucial first step to ensure accurate measurements throughout the process.</p>
<p>Qwen2.5VL:</p>	<p>Yes, it's important to ensure that the balance is properly calibrated before using it for any measurements. If the pointer is not centered at zero, it means the balance is not calibrated correctly, which could lead to inaccurate readings. Here's what you should do:</p> <ol style="list-style-type: none"> 1. Locate the Calibration Knob: Typically, there will be a small knob or screw near the base of the balance, often labeled "Calibration" or something similar. This is used to adjust the balance. 2. Adjust the Calibration Knob: Turn the knob slowly in the direction needed to bring the pointer back to the zero mark. Usually, turning clockwise
<p>LLaVA-OV:</p>	<p>Yes, you should adjust the calibration knob to ensure the balance is properly calibrated and reading zero before weighing anything. This is a crucial step to ensure the accuracy of the weight measurement.</p>

Table 20: Examples of answers provided by VIGiA and its variants. All 3 model sizes available are capable of providing an accurate and coherent answer to the user question, while also providing a brief explanation of the importance of the thickness of the cinnamon rolls.

<p>User Image</p>	
<p>Question:</p>	<p>Are my cinnamon roll discs being cut at the right thickness based on what's shown in the image?</p>
<p>VIGIA 8B:</p>	<p>Looking at the image, the cinnamon roll discs appear to be cut at a good thickness. You can see they're being cut into uniform, bite-sized pieces that are approximately 1-2 inches in diameter. This size is ideal for mini cinnamon roll bites as it ensures they'll cook evenly and be easy to eat. Just make sure to keep an eye on them while baking as the thickness may vary slightly depending on how you cut them.</p>
<p>VIGIA 3B:</p>	<p>From what I can see in the image, the thickness appears to be appropriate. The discs are being cut into small, uniform pieces that are about 1-2 inches in diameter, which is ideal for mini cinnamon roll bites. This size will allow them to cook evenly and be easy to handle. When baked, these will become crispy on the outside while remaining soft on the inside.</p>
<p>VIGIA 1B:</p>	<p>Yes, the thickness shown in the image appears to be appropriate for the recipe. The discs should be cut to be about 1/4 inch (6mm) thick, which is ideal for baking. If you cut them too thick, they might burn easily, and if too thin, they might burn too quickly. The uniform, flat shape shown in the image is also a good sign that you're working on the right material.</p>

Table 21: Examples of answers provided by VIGiA and its variants. The smaller model variants fail to accurately answer the user question, claiming that only a jar lid can be used whereas VIGIA 8B accurately clarifies that other objects can be used as long as they are dry and clean.

<p>User Image</p>	
<p>Question:</p>	<p>The pie crust in the image looks quite round - is a jar lid the only tool I can use to cut these circles, or can I use something else of similar size?</p>
<p>VIGIA 8B:</p>	<p>While a jar lid is the traditional tool for cutting pie crust circles, you can use other round objects of similar size as a substitute. Some alternatives include a clean, dry glass or a small bowl. Just make sure the object you use is completely dry and clean to prevent sticking. The most important thing is to have a consistent size for your circles so they'll bake evenly.</p>
<p>VIGIA 3B:</p>	<p>A jar lid is the only tool that will work for cutting the circular pie crust. The size of the jar lid (4 inches) is perfect for creating uniform, bite-sized pieces. Using a different tool could lead to unevenly sized pieces, which would be difficult to work with. Make sure you're using a clean, sharp jar lid and press it into the center of the pie crust to ensure a clean cut.</p>
<p>VIGIA 1B:</p>	<p>A jar lid is the correct tool for cutting the 12 4-inch (10 cm) circles. While the image shows a circular shape, a jar lid is specifically designed for this purpose. Using a jar lid will give you the most precise and uniform cuts needed for the pie crust. Make sure to press firmly into the crust to ensure the circles are firmly attached. The circular shape will help the crust hold its shape when baked.</p>

Table 22: Prompt used to generate the in-domain pVQA question-answer pairs.

You are a helpful assistant simulating a user interacting with a visual task guidance system. You will be provided with a task, a conversation history, the current step's description, and an image related to that step.

Based on the conversation context, the current step, and the image, generate one question-answer pair. The question should mimic a question a user might ask after uploading the provided image while seeking guidance on the current step, this is VERY important. The questions should be DIRECTLY related to the image and current task step, and should be relevant to the ongoing conversation. Make sure that these questions sound natural as if a real user had asked them. Use the conversation history, the task instructions and your knowledge to answer as accurately as possible. Some examples of questions you might generate include asking if the mixture in the image is the correct consistency, if the oven temperature is correct, or if the bolt in the image needs to be tightened, etc.

Output the question-answer pair in the following format:

Q: <Question>
A: <Answer>

Task:
{task_text}

Conversation History:
{conv_history}

Current Step: {step_number} -
{step_text}
Image:

Table 23: Prompt used to evaluate the in-domain pVQA responses.

You will be provided with an image and a bit of a dialogue. Your task is to tell me if the last system response accurately answers the last user question based on the image. Answer solely regarding the LAST user question and the last assistant response in the dialogue.

As I am parsing this automatically, please write your answer (YES or NO) immediately after the words "FINAL ANSWER:" in your response. Feel free to think and reason out loud in your response before you give the final answer.

Task Context:

{task_text}

Dialogue Context (up to 4 turns):
{conv_history}

Image: (provided in the request)
