

# EmbodiedEval: Evaluate Multimodal LLMs as Embodied Agents

Zhili Cheng<sup>\*†</sup> Yuge Tu\* Ran Li\* Shiqi Dai\* Jinyi Hu<sup>\*‡</sup> Shengding Hu  
Jiahao Li Yang Shi Tianyu Yu Weize Chen Lei Shi Maosong Sun<sup>†</sup>

Tsinghua University

{chengz122, hu-jy21}@mails.tsinghua.edu.cn

## Abstract

*Multimodal Large Language Models (MLLMs) have shown significant advancements, providing a promising future for embodied agents. Existing benchmarks for evaluating MLLMs primarily utilize static images or videos, limiting assessments to non-interactive scenarios. Meanwhile, existing embodied AI benchmarks are task-specific and not diverse enough, which do not adequately evaluate the embodied capabilities of MLLMs. To address this, we propose EMBODIEDEVAL, a comprehensive and interactive evaluation benchmark for MLLMs with embodied tasks. EMBODIEDEVAL features 328 distinct tasks within 125 varied 3D scenes, each of which is rigorously selected and annotated. It covers a broad spectrum of existing embodied AI tasks with significantly enhanced diversity, all within a unified simulation and evaluation framework tailored for MLLMs. The tasks are organized into five categories: navigation, object interaction, social interaction, attribute question answering, and spatial question answering to assess different capabilities of the agents. We evaluated the state-of-the-art MLLMs on EMBODIEDEVAL and found that they have a significant shortfall compared to human level on embodied tasks. Our analysis demonstrates the limitations of existing MLLMs in embodied capabilities, providing insights for their future development. We open-source all evaluation data and simulation framework at <https://github.com/thunlp/EmbodiedEval>.*

## 1. Introduction

In recent years, Multimodal Large Language Models (MLLMs) [53, 67, 82] have demonstrated strong understanding and reasoning capabilities on visual and language tasks. With the rapid development of MLLMs, a rich set of benchmarks for image understanding [25, 45, 56, 91] and video analysis [27, 63] has emerged. However, these benchmarks are non-interactive and insufficient in eval-

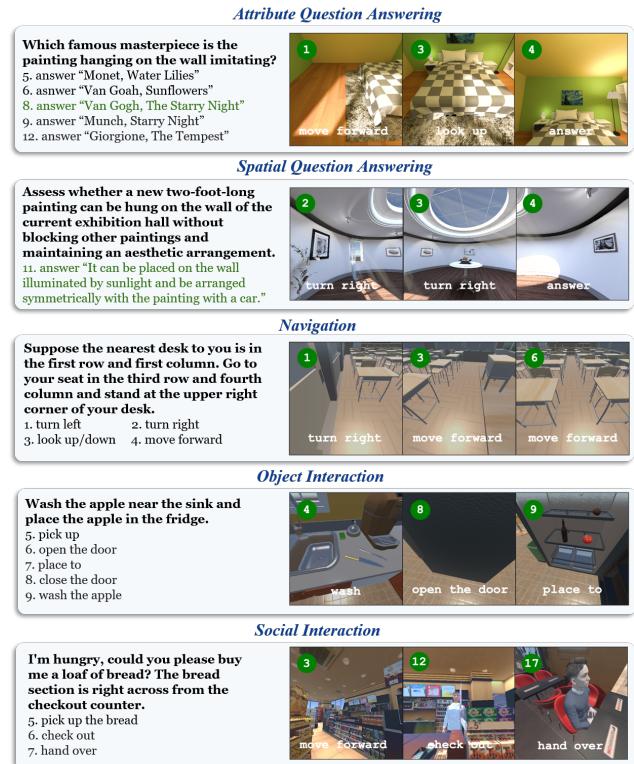


Figure 1. Examples of the five task categories in EMBODIEDEVAL. On the left are the task text and part of the action space. On the right are observations from specific steps, along with the actions taken in the expert demonstration at those moments.

ating MLLMs' ability to handle tasks in real-world scenarios. Beyond these basic tasks which focus on non-interactive visual scenes, researchers are actively trying to expand MLLMs as embodied agents in interactive environments, which require the model to interpret multimodal inputs into actions [1, 10, 22, 62, 66, 84, 99]. To accomplish this, MLLMs are expected to integrate a multitude of capabilities that enable them to interact effectively with the environment, including ego-centric perception [15], visual

\*Core contributors, †Project Lead, ‡Corresponding Author

grounding [4, 96], spatial reasoning [8], episodic memory [63], among others.

However, the comprehensive evaluation of MLLMs in embodied tasks remains largely unexplored. Existing benchmarks for embodied AI greatly lack diversity in tasks and scenes, which limits their evaluation to specific aspects. EQA [18] dataset is restricted to only 9 template questions such as queries about object color and existence, while ALFRED [76] contains only 7 template tasks such as “pick and then place” within 4 room types. Moreover, many of embodied AI benchmarks require specific forms of input and output, making the evaluation of mainstream MLLMs inefficient or even infeasible. For example, R2R [4] uses 3D points as both input and output, REVERIE [71] requires predicting the bounding box of a target object, while ALFRED requires an object segmentation mask for interaction.

To address this gap, we present the first comprehensive evaluation benchmark for evaluating MLLMs’ embodied capabilities in interactive environments, distinguishing it from the existing three types of evaluation benchmarks: static MLLMs benchmarks, which are non-interactive; embodied AI datasets, which are not comprehensive or diverse enough; and LLM agent benchmarks [54, 77], which heavily rely on textual environment states and have overly abstract actions (e.g., go to bathroom), thus downplaying or overlooking the critical embodied agent capabilities such as visual grounding and spatial reasoning. The key features of EMBODIEDEVAL are as follows:

**Diverse Interactions.** EMBODIEDEVAL provides a simulation framework that supports a variety of interactions, such as locomotion, question-answering, and interactions with objects and humans in realistic 3D scenes. Agents interact with the environment to gather new information or change its state to complete the task.

**Diverse Tasks.** In contrast to previous work that used task templates or tasks with minimal variation, our tasks have been systematically generated and carefully selected for high quality and diversity. EMBODIEDEVAL featuring a large number of novel tasks that involve a wider range of abilities to assess the comprehensive capabilities of the model as shown in Figure 1, which are categorized into five major categories.

**Diverse Scenes.** Unlike previous work, which was limited to household scenes, our scenes feature significant diversity in terms of objects and spaces, covering small rooms, large residences, and public spaces such as gym, store, office, among others. This approach can reduce the impact of scene types on the evaluation of the model’s generalization, making the assessment more comprehensive.

## 2. Related Works

**Multimodal Large Language Models.** By connecting vision modules with LLMs, LLaVA [53] pioneers research

Benchmark	Scene.	Task.	Disc.	Ego.	Nav.	Obj.	So.	Ans.
Video-MME [26]	-	✓	✓	✗	✗	✗	✗	✓
EgoPlan etc. [11, 14]	-	✓	✓	✓	✗	✗	✗	✓
OpenEQA [63]	-	✓	✓	✓	✗	✗	✗	✓
EQA etc. [18, 81, 88]	✗	✗	✓	✓	✓	✗	✗	✓
ALFRED [76]	✗	✗	✗	✓	✓	✓	✗	✗
BEHAVIOR[79]	✗	✓	✗	✓	✓	✓	✗	✗
EQA-MX [35]	✗	✗	✓	✓	✗	✗	✓	✓
<b>EMBODIEDEVAL</b>	✓	✓	✓	✓	✓	✓	✓	✓

Table 1. Comparison of EMBODIEDEVAL with previous benchmarks. The abbreviations in the table headers, from left to right, represent: **Scene** diversity (beyond household scenes), **Task** diversity (beyond task templates), **Discrete** action space (for MLLMs evaluation), **Egocentric** vision, **Navigation** involved, **Object** interaction involved, **Social** interaction involved, and **Answering** questions involved.

in MLLMs through visual instruction tuning, and obtains impressive multimodal chat capabilities. Many work further improves the MLLMs from various aspects, including detailed captioning [9], trustworthy response [89, 90], multilingual multimodal capabilities [32, 80] and visual grounding [70, 87]. Beyond single-image understanding, some work explores more complicated tasks. For example, KOSMOS-1 [33] and VILA [49] focus on image-text interleaved understanding, while Video-LLaVA [48] and VideoChat [47] focus on video understanding.

**Evaluation for MLLMs.** Mainstream benchmarks for MLLMs mainly focus on perception and cognitive evaluation, such as MME [25], MMB [56] and MMMU [91]. As existing MLLMs excel in these benchmarks, some benchmarks propose more challenging tasks, such as mathematical reasoning [31, 60, 93], OCR capability [57, 64, 78] and scientific knowledge [59, 91]. However, these benchmarks lack evaluation on egocentric vision, which is essential for broader applications of MLLMs. To address this gap, EgoVQA [24], EgoPlan-Bench [11], EgoThink [14], and OpenEQA [63] propose to evaluate the reasoning and planning capabilities of MLLMs given the first-person perspective images or videos. However, these benchmarks still use static question-answering pairs without interacting with environments.

**Benchmarks for Embodied Agents.** The datasets for embodied agents cover areas such as navigation, interaction, and question answering: (1) **Navigation** The R2R [4] dataset was the first to evaluate an agent’s navigation ability under natural language instructions, followed by R4R [36] and RxR [44], which improve the fine-grained evaluation of the navigation process. In navigation tasks, object navigation is a crucial task because it serves as a prerequisite step for an embodied agent to interact with any object. There are many object navigation datasets with different fo-

cus and features, including SOON [98], REVERIE [72], DOZE [61] and GOAT-Bench [40]. (2) **Interaction ALFRED** [76] is the most representative interaction dataset, requiring the agent to follow instructions to complete tasks involving interactions such as picking up and placing objects. Additionally, there are datasets focusing on moving objects [28, 86], rearrangement [6, 83], tidying up a room [38], and household activities [42, 46, 65, 79]. (3) **Question Answering** EQA [18] first proposes the navigate-then-answer mechanism. Subsequently, more diverse EQA datasets have emerged, including those with questions involving multiple objects [88], requiring knowledge integration [81], set in realistic scenes [73], and handling situational queries [21]. Additionally, IQA [30] requires interaction with the environment to gather more observations in order to answer questions. EQA-MX [34] requires understanding non-verbal human expressions, such as body movements. However, existing benchmarks are limited in task variety, lacking comprehensive assessments of navigation, object interaction, and question-answering. They rely on highly repetitive task templates, failing to adequately capture the wide spectrum of embodied capabilities. Additionally, the task-specific observation spaces and continuous action spaces in many benchmarks are inadequate for effectively evaluating MLLMs. We summarize the comparison between EMBODIEDEVAL and other representative benchmarks in Table 1.

### 3. EmbodiedEval

EMBODIEDEVAL consists of rich scenes and tasks to comprehensively evaluate the capabilities of embodied agents. We have implemented a unified simulation and evaluation framework and conducted meticulous data annotation to create the final dataset. First, we introduce the task categories involved in EMBODIEDEVAL in Section 3.1, followed by a detailed explanation of the simulation and evaluation framework in Section 3.2. After that, we describe the data collection and annotation process for this framework in Section 3.3. Finally, we show the data statistics of EMBODIEDEVAL in Section 3.4.

#### 3.1. Task Categories

To comprehensively assess the capabilities of MLLMs as embodied agents, we synthesized and expanded upon existing embodied tasks while incorporating novel additions, broadly categorizing the tasks into five categories. Each category encompasses a diverse set of tasks and involves various capabilities. The task categories and sample tasks are shown in Figure 1.

**Navigation.** The navigation task involves coarse-grained and fine-grained natural language instructions, requiring the agent to navigate from its initial position to a target location and find a specific object if the task demands it.

**Object Interaction.** In object interaction tasks, agents must change the state of the environment through direct interaction with objects, such as moving objects, opening/closing doors and drawers, and operating electrical devices. These tasks possibly involve multiple objects and require multi-step actions, such as using a tool to operate another object and rearranging items to meet certain requirements.

**Social Interaction.** Social interaction tasks encompass human-agent interactions, including item delivery, perspective-taking capabilities, human feedback interpretation, and non-verbal communication comprehension such as gestural cues.

**Attribute Question Answering (AttrQA).** AttrQA tasks necessitate exploring the environment to address questions regarding object and scene attributes. While incorporating traditional EQA tasks, AttrQA significantly broadens the scope of inquiry. It encompasses comprehensive attribute queries of objects and scenes, including but not limited to category, shape, material, color, function, state, location, existence, quantity, comparative analysis and reasoning across multiple attributes.

**Spatial Question Answering (SpatialQA).** Spatial understanding [8, 13, 23, 37, 51, 75] is a fundamental capability for embodied agents. SpatialQA requires agents to answer spatial-related questions through actions and observations, such as queries about size, height, position, distance, area, path, layout, spatial relationships, and more.

### 3.2. Evaluation Framework

We implemented a unified simulation framework based on LEGENT [17] platform. The framework aims to holistically evaluate embodied abilities through diverse tasks, rather than focusing on specific tasks with particular input-output requirements. The observation space consists of task descriptions and egocentric vision. The action space consists of movement space, interaction space and answering space, which varies in each task instance. The action space is reasonably discretized and semantically understandable, while preserving the core evaluation objectives.

#### 3.2.1 Action Space

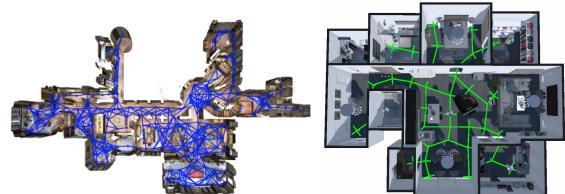


Figure 2. A comparison of navigation graphs between R2R [4] dataset (left) and EMBODIEDEVAL (right).

**Movement Space** We use navigation graph as the movement space where the agent can rotate its view at a point or move between adjacent navigation points. Compared to continuous movement, it discretizes motion without imposing great restrictions on the high-level tasks in practice [4]. Different from grid-world movement, this approach is more natural and adaptable to all kinds of scenes. Through sampling algorithms and manual adjustment, we constructed navigation graphs for each scene. To ensure realism, the navigation points are always walkable locations with no obstacles among them. Due to the greater diversity of our scenes and tasks compared to previous work, the density of navigation points varies based on the size of the scene and the task, ensuring that the number of steps required for tasks remains reasonable. For example, in complex interaction tasks within large scenes, the navigation points are more sparse and critical. In contrast to previous datasets, our navigation points are better organized as shown in Figure 2, and the connections between these points indicate clear semantics. MLLMs are not required to make choices from a set of 3D positions, but only need to make directional decisions among navigation points. Specifically, the action space consists of three types of actions: *move forward* (moving to the facing navigation point), *turn left/right* (rotating to face a new navigation point), and *look up/down* (adjusting the vertical view).

**Interaction Space** We follows the discrete interaction space of previous embodied AI tasks that involves object interaction such as IQA [30], CHAI [65], RoomR [83] and OVMM[86] rather than continuous space [76, 79]. This choice is based on two main considerations: (1) In continuous spaces, interactions are tightly related to specific methods and types of embodiment, which contradicts the goal of generality in evaluations and goes beyond the core issues of our research. (2) Due to the high complexity of continuous space, MLLMs cannot output reasonable values without being trained on specialized numerical trajectory, leading to infeasible evaluations. In EMBODIEDEVAL, we use an open vocabulary for the actions and objects in interactions to make them as rich as possible. Each interaction action has a brief action text, operable objects, and conditions for successful interaction. For example, the “pick up” action requires the target object to be within sight and very close, the “wash” action requires the agent and the target object to be next to a sink, and the “hand over” action requires the agent to hold an object and be next to a person. In a given test case, several interaction actions will be involved, including those necessary to complete the task and other distracting actions.

**Answering Space** Unlike EQA and IQA, which require outputs of specific categories or use a very limited vocabulary, our answer space is very open. Responses are written by annotators and rigorously verified, encompassing a vari-

ety of possible replies to the question. For QA tasks, before exceeding the maximum allowed steps, there is no specified step at which the agent must respond; it can continue to explore until it believes it can select an answer. Once an answer is chosen, the task is immediately judged as correct or incorrect.

In this way, the action space is discretized and each action has a semantic text. EMBODIEDEVAL directly input the list of actions into the MLLM to decide the next action.

### 3.2.2 Success Criteria

We automatically and accurately evaluate task completion through predicate functions. Each predicate maps the state of the simulation environment to a boolean value indicating success. For example, the *agent\_at* predicate requires a designated navigation point as a parameter and returns true when the agent reaches this location at the end of the episode. Beyond evaluating only the final state, EMBODIEDEVAL also includes predicates that assess the entire process, similar to R4R [36]. For example, the *agent\_pass* predicate becomes true once the agent passes a specified navigation point.

A task is considered successful when all predicates evaluate to true at the end. Consider the task “*Please go to the kitchen, then come back and tell me if there are any extra cups*”. This task involves three predicates: *agent\_pass*, *agent\_at*, and *choose*. These predicates verify that the agent passes through the kitchen doorway, returns to the initial position in front of the person, and selects the correct answer, respectively.

### 3.2.3 Evaluation Process

The process of an evaluation episode is as follows: (1) The simulator initializes the 3D scene and navigation graph. The agent is positioned at a designated starting point, and the initial first-person view image is saved into the observation history. (2) In each subsequent step, the agent chooses an action from a given list of options, including movement, interaction and answering, based on the observation history. The environment executes the action, changes the state accordingly, returns new observations, along with feedback indicating whether the action was successful. The observation, action, and feedback are then appended to the observation history.

This process continues until all success criteria are met resulting in task success, or the task fails due to an incorrect answer or exceeding the maximum allowed steps. For evaluating MLLMs designed for video understanding, image sequences are no longer used in the observation history. Instead, at each step, the simulator will output an egocentric video from the start to the current moment and use it as input for the MLLM.



Figure 3. The dataset construction pipeline of EMBODIEDEVAL.

### 3.3. Dataset Construction

The dataset construction process of EMBODIEDEVAL consists of three parts: scene collection, task collection, and task annotation. Each sample in the dataset requires substantial effort and undergoes rigorous annotation. Figure 3 illustrates our dataset construction pipeline.

#### 3.3.1 Scene Collection

The diversity of scenes allows for a more accurate assessment of the agent’s generalization capabilities. Our scenes are more varied in source and type than previous benchmarks, curated from four different sources: (1) **Objaverse Synthetic**. To expand our object variety, we utilize the Objaverse [20] dataset as our object database, which contains a vast collection of objects. Using procedural generation methods [19], we created numerous scenes from these objects. From these procedurally generated scenes, we manually selected and refined dozens of high-quality environments. (2) **AI2THOR**. We extracted and structured scenes from AI2THOR [43], focusing on indoor rooms with highly interactive objects. (3) **HSSD**. We included scenes from the Habitat Synthetic Scenes Dataset (HSSD) [39], which provides high-quality, realistic and complex scenes featuring extensive and diverse navigable spaces, including houses, villas, yards, and more. (4) **Sketchfab**. We enhanced our scene collection with selected free 3D scenes from Sketchfab<sup>1</sup>. These scenes are highly realistic and diverse, ranging from classrooms and supermarkets to offices and exhibitions, enriching the scope of our evaluation. These collected scenes serve as the basis for subsequent task annotation.

<sup>1</sup><https://sketchfab.com>

#### 3.3.2 Task Collection

For task collection, we first gather seed tasks from over 30 existing datasets and benchmarks for embodied agents. Using these tasks as seeds, we prompted several advanced large language models to generate diverse task examples. To enhance task complexity, we designed some tasks to incorporate various capabilities, including complex grounding, episodic memory, spatial reasoning, quantitative reasoning, common sense reasoning, and planning, which resulted in many novel tasks. From this extensive task pool, experts selected over 300 distinct candidate tasks. During task annotation, each task text could only be selected from this candidate set and used once. We chose this approach rather than allowing annotators to write tasks for given scenes, as it ensures task diversity, prevents repetition, and reduces dependency on individual annotators’ creativity or preferences.

#### 3.3.3 Task Annotation

**Annotation Content** Task sample annotation begins with an annotator selecting a task from the candidate pool and matching it to an appropriate scene. The annotator configures the action space detailed in Section 3.2.1, which includes movement space (via navigation graph adjustment), interaction space (via action options), and answering space (via answer options). Finally, the annotator defines success criteria as outlined in Section 3.2.2 through predicate function instantiation.

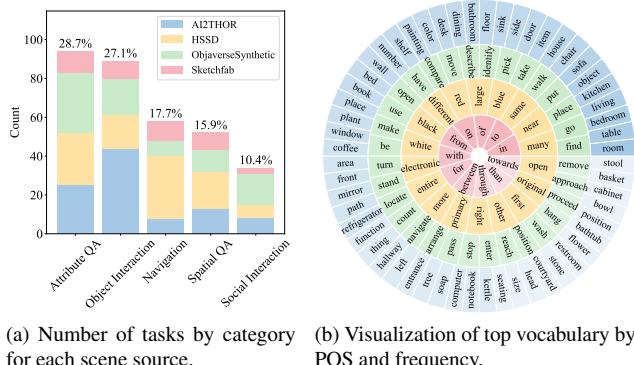
To maintain the validity and quality of the dataset, all task annotations must satisfy the following criteria. (1) All tasks must be unambiguous within the given scene. (2) Question-answering tasks must require scene observation,

with each task providing eight answer options that vary in difficulty and include misleading options to reduce the chance of guessing the correct answer. (3) Once a task is correctly annotated, the tasks must be executable in the simulator with a well-designed navigation graph and accurate action options. Annotators must verify task feasibility using the same observational constraints as agents.

**Annotation System** To ensure both efficiency and precision in the complex annotation process, we developed an annotation system based on Unity<sup>2</sup>. The system provides comprehensively function, which encompassing scene and task import/export, flexible content viewing, visualized action space, and a guided annotation workflow that adheres to predefined guidelines (See Section 3.3.3).

**Annotation Process** Eight expert annotators are recruited to perform the annotations. Before starting the annotation process, we conducted systematic training on annotation requirements and system usage. To ensure the dataset’s high quality, each annotated task was independently evaluated for correctness and quality by at least three reviewers. Furthermore, we validated task feasibility by providing expert demonstrations for each task and testing human performance with non-expert participants.

### 3.4. Dataset Statistics



EMBODIEDEVAL consists of 328 human-annotated tasks divided into 5 categories, distributed across 125 unique scenes and demonstrating a high level of visual diversity and complexity. Figure 4a shows the distribution of the task across 5 task categories and 4 scene sources. Overall, the dataset comprises 575 predicate instances and 1,533 action options excluding movement space, including 1,213 answers and 320 interactions, with each episode averaging 10.72 steps based on expert demonstrations. Task descriptions average 16.09 words in length, while options average 5.72 words. To showcase the lexical diversity in EMBODIEDEVAL, Figure 4b presents a visualization of the most frequent words categorized by grammatical type.

<sup>2</sup><https://unity.com/>

## 4. Experiments

### 4.1. Evaluation Settings

We evaluate the models using the evaluation process described in Section 3.2.3. For multi-image MLLMs, we input the task prompt, history information (egocentric image observation history, action history, feedback history), and the action space (movement, interaction, answering) into the model, which then outputs the corresponding action option to be executed in the environment. For video MLLMs, we replace the image observation history with egocentric video. We set the maximum number of attempt steps for each task to 24, as all tasks are completed within this number of steps in the expert demonstration. We use an image resolution of 448×448.

We evaluate 22 MLLMs on EMBODIEDEVAL including closed-source MLLMs, open-source multi-image MLLMs and open-source video MLLMs demonstrating strong performance on MLLM benchmarks like MMMU [92] and Video-MME [12]. For reference, we also introduce two special agents: (1) *Random* agent uniformly samples actions from the available option set at each timestep. (2) *Human* agent involves non-expert humans unfamiliar with the tasks, performing actions in the simulator’s user interface using the same observation and action space as the models.

### 4.2. Evaluation Metrics

We evaluate agent performance using three metrics. (1) **Success Rate (Succ.)** [2, 43, 55, 74, 97] is the primary metric we use to measure the percentage of tasks that the agent fully completes. (2) For multi-goal tasks, **Goal-condition Success (GcS)** [41, 76] measures partial success by calculating the proportion of goal conditions achieved, as specified by predicate functions. (3) **Success weighted by Path Length (SPL)** [3, 7] is a path-weighted metric to evaluate task execution efficiency in navigation and interaction tasks. SPL assesses an agent’s performance by considering both task success and the path efficiency relative to the expert demonstration.

### 4.3. Main Results

**EMBODIEDEVAL Reveals Limitations of Current MLLMs on Embodied Tasks.** As shown in Table 2, Success rates across various models on EMBODIEDEVAL remain notably low. The best-performing model, GPT-4o, achieves only a 25.00% overall success rate and a 32.42% GcS score. This is in stark contrast with non-expert humans, who reach a nearly perfect success rate of 97.26%, highlighting the difficulty these models face in executing embodied tasks that humans find trivial. This performance deficit is further underscored by significantly lower SPL scores, indicating that the models struggle to find optimal solutions. This shows the challenges for deploying MLLMs

Model	Attr. QA		Spatial QA		Navigation			Object Interaction			Social Interaction			Overall	
	Succ.	GcS	Succ.	GcS	SPL	Succ.	GcS	SPL	Succ.	GcS	SPL	Succ.	GcS	Succ.	GcS
Random	11.58	7.69	3.45	8.76	3.45	0.00	6.18	0.00	2.94	8.33	2.94	5.49	8.66		
Human	98.95	92.31	96.55	97.84	82.28	97.75	99.44	90.73	100.00	100.00	89.96	97.26	97.94		
<i>Closed-Source Multi-Image MLLMs</i>															
GPT-4o [68]	35.79	<b>32.69</b>	<b>31.03</b>	<b>42.53</b>	<b>22.23</b>	<b>10.11</b>	24.25	<b>5.94</b>	<b>11.76</b>	<b>26.72</b>	6.74	<b>25.00</b>	<b>32.42</b>		
GPT-4o-Mini [68]	31.58	15.38	27.59	39.51	15.34	2.25	17.42	1.50	5.88	22.06	2.98	17.68	25.58		
Gemini-Pro [29]	27.37	9.62	17.24	25.86	9.78	4.49	12.36	3.00	5.88	18.14	3.44	14.33	19.26		
Gemini-Flash [29]	26.32	13.46	5.17	17.10	3.51	2.25	7.58	0.96	2.94	12.50	1.47	11.59	16.13		
Qwen-VL-Max [5]	<b>37.89</b>	17.31	24.14	30.03	16.87	7.87	<b>24.91</b>	5.62	8.82	22.06	<b>6.86</b>	21.04	28.07		
Qwen-VL-Plus [5]	10.53	11.54	3.45	10.49	3.45	0.00	2.43	0.00	2.94	8.82	1.68	5.79	8.31		
<i>Open-Source Multi-Image MLLMs</i>															
InternVL2-40B [69]	14.74	5.77	6.90	12.93	3.06	0.00	7.68	0.00	<b>5.88</b>	<b>19.12</b>	2.16	7.01	11.54		
InternVL2-8B [69]	13.68	13.46	8.62	18.25	4.04	0.00	7.43	0.00	<b>5.88</b>	18.63	<b>2.45</b>	8.23	13.27		
InternVL2-Llama3-76B [69]	21.05	13.46	3.45	9.48	2.18	0.00	9.08	0.00	2.94	13.73	1.14	9.15	13.79		
LLaVA-NEXT-72B [12]	23.16	5.77	<b>12.07</b>	22.99	<b>7.83</b>	<b>3.37</b>	<b>9.74</b>	<b>2.21</b>	0.00	12.25	0.00	10.67	15.60		
LLaVA-OneVision-72B [52]	<b>26.32</b>	<b>19.23</b>	10.34	<b>23.28</b>	7.53	1.12	7.81	1.12	0.00	12.75	0.00	<b>12.80</b>	<b>18.23</b>		
LLaVA-OneVision-7B [52]	16.84	17.31	5.17	9.05	3.28	1.12	8.15	0.80	2.94	9.80	1.68	9.14	12.45		
VILA-40B [50]	17.89	7.69	0.00	5.75	0.00	0.00	3.93	0.00	0.00	8.58	0.00	6.40	9.53		
VILA-8B [50]	15.79	9.62	1.72	8.91	0.96	0.00	3.46	0.00	2.94	6.37	1.68	6.71	9.27		
<i>Open-Source Video MLLMs</i>															
LLaVA-NeXT-Video-32B-Qwen [94]	21.05	7.69	6.90	14.08	5.34	0.00	8.61	0.00	2.94	<b>12.01</b>	0.98	8.84	13.39		
LLaVA-Video-72B-Qwen2 [95]	<b>27.37</b>	9.62	<b>15.52</b>	<b>24.28</b>	<b>9.62</b>	1.12	8.05	0.86	0.00	9.80	0.00	12.50	<b>16.95</b>		
LLaVA-Video-7B-Qwen2 [95]	20.00	<b>19.23</b>	3.45	4.89	1.88	1.12	<b>8.80</b>	0.27	0.00	5.15	0.00	9.76	12.63		
Oryx-34B [58]	18.95	3.85	5.17	13.07	4.89	1.12	7.02	1.00	0.00	8.33	0.00	7.32	11.33		
VideoLLaMA2-72B [16]	<b>27.37</b>	9.62	12.07	18.68	6.35	<b>2.25</b>	7.49	<b>1.38</b>	<b>5.88</b>	10.78	<b>2.39</b>	<b>12.81</b>	15.91		
VideoLLaMA2-7B [16]	21.05	9.62	6.90	17.53	4.88	0.00	1.63	0.00	2.94	7.35	1.38	9.20	11.99		

Table 2. Results of different models on EMBODIEDEVAL (%). The best-performing model in each category is bolded.

in embodied scenarios.

**Performance Gap between Best Proprietary and Open-source Models.** Proprietary models demonstrate a consistent advantage across all tasks and metrics. GPT-4o leads in overall performance, with the highest success rate on four out of five tasks. Qwen-VL-Max ranks second, achieving the highest success rate in Attribute QA. In contrast, open-source models show a substantial performance gap. The top performing multi-image MLLM, LLaVA-OneVision-72B, achieves an overall success rate of 12.80%, barely competitive with proprietary models. The other multi-image MLLMs have accuracy rates of around 10% at best. Among the video MLLMs, VideoLLaMA2-72B achieves the highest success rate (12.81%), while LLaVA-Video-72B-Qwen2 achieves the highest GcS (16.95%). For open-source models, larger models often exhibit improved performance, but this trend is not universally observed.

**Model Performance across Different Task Types.** The results highlight a significant variation in model performance across different task types. GPT-4o demonstrates relatively strong results in QA and Navigation tasks, but

its performance drops notably for interaction tasks. This disparity is even more pronounced among other commercial models. For instance, most models perform reasonably well in Attribute QA but see a sharp decline in Spatial QA that requires spatial reasoning, often halving their success rates. The Navigation task shows substantial performance variability across models, such as Gemini-Flash, which achieves 26.32% in Attribute QA but drops to only 5.17% in Navigation. Overall, the scores for Object Interaction and Social Interaction are consistently lower across all models, underscoring the challenge these models face in scenarios that require a deeper understanding of affordance or social cues.

#### Challenges in Long-Horizon Tasks.

The performance of MLLMs shows a significant decline as the number of steps required for the task and the subgoals increase. As illustrated in Figure 5, models maintain relatively high success counts at lower required steps, but their performance drops fluctuatingly as tasks require longer sequences of actions. This drop in performance can be attributed to two primary factors: (1) the increased complex-

ity and reasoning demands associated with longer tasks and multiple subgoals, which challenge the models' planning and decision-making capabilities, and (2) the limitations in retaining and processing the long temporal context necessary for successful execution in extended tasks. These challenges highlight the need for further model improvements to enhance MLLM capabilities in handling complex, multi-step objectives over long horizons.

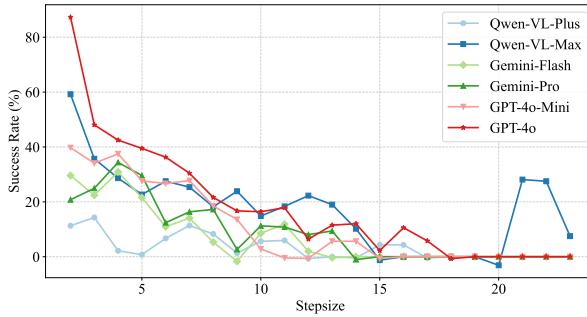


Figure 5. Success rate vs. number of steps required for the task.

**Studies on Temperature.** We find that all models perform slightly better at temperature = 1 compared to temperature = 0. Through observing cases, we believe this is because embodied tasks require a certain level of exploration, and when the temperature is set to 0, the determinism of the output causes the model to easily get stuck in repetitive errors. However, in this paper, we propose using a temperature of 0 as the evaluation standard, as this removes randomness from the evaluation, improving efficiency and better reflect the model's true capabilities, including its ability to recognize and escape from erroneous trajectories.

#### 4.4. Error Analysis

We summarize four primary error categories in MLLM-based embodied agents: **(1) Hallucination in Grounding:** Models misperceive the environment, hallucinating nonexistent objects or overlooking present ones. For example, models may confidently describe absent items or fail to locate small objects like laptops or keys, impacting both QA (e.g., providing answers based on imagined objects) and non-QA tasks (e.g., failing to navigate to or interact with target objects). **(2) Insufficient Exploration:** Agents employ suboptimal exploration strategies, hindering information gathering and goal finding due to incomplete environment coverage. They are often trapped in local areas, or answer before fully exploring the environment due to overconfidence. **(3) Lack of Spatial Reasoning:** Models struggle with understanding spatial relationships. They misinterpret directional instructions (e.g., “to my left”) and face difficulties navigating between locations, even for simple tasks such as moving to or around furniture. **(4) Wrong Planning:** Agents demonstrate poor state estimation and action

planning. This results in random or repetitive actions, such as aimless circling or repeatedly picking up objects. They also struggle to understand the outcomes of the action and adapt after failed attempts. Figure 6 provides illustrative examples of these errors.

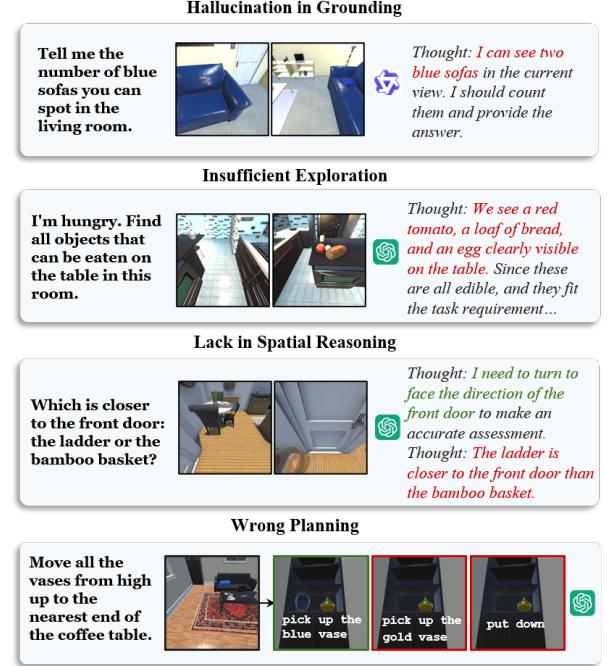


Figure 6. Case study of common error categories. In *Hallucination in Grounding*, the agent mistakenly identified a single blue sofa as two. In *Insufficient Exploration*, the agent failed to look for additional items. In *Lack in Spatial Reasoning*, the agent misestimated the distance between objects. In *Wrong Planning*, the agent did not organize the picking up and putting down of the vases in the proper order and at the correct positions.

## 5. Conclusion

In this paper, we propose EMBODIEDEVAL, the first interactive benchmark designed for MLLMs with comprehensive embodied tasks. We provide an efficient framework to interactively evaluate the capabilities of MLLMs on embodied tasks. To ensure the accuracy, diversity, and quality of the dataset, extensive efforts are devoted to the annotation process for each task sample.

Through experiments, we found that current MLLMs perform poorly on embodied tasks. However, we believe there will be more attention to improving the embodied capabilities of MLLMs upon the general capabilities learned from universal multimodal data. We hope EMBODIEDEVAL can help and guide the development of MLLMs to realize their potential in embodied intelligence.

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## 6. Appendix

### 6.1. Task Samples

We selected some representative examples to illustrate the diversity of the task set in Table 3.

### 6.2. Details of Evaluation Framework

#### 6.2.1 Evaluation Formulation

We formalize the evaluation process mentioned in Section 3.2.3 as follows. The prompt we used for the MLLMs during the evaluation is shown in Figure 8.

---

#### Algorithm 1 EMBODIEDEVAL Evaluation Process

---

**Input:** A Multimodal LLM  $\pi$ , an evaluation task including a scene  $x$ , a task description  $g$ , an option list  $\mathcal{C} = a_0, a_1, \dots, a_n$ , and a predicate list  $\mathcal{P}$ .

**Output:** A boolean indicating whether the task was successful *success*.

```

1:  $o, s \leftarrow E.reset(x)$             $\triangleright E$  is the simulator,  $o$  is the
   observed image,  $s$  is the world state
2:  $H_o \leftarrow \{o\}$                    $\triangleright$  observation history
3:  $H_a \leftarrow \emptyset$                  $\triangleright$  action history
4: for  $i \leftarrow 0$  to max steps do
5:    $a \leftarrow \pi.predict(g, \mathcal{C}, H_o, H_a)$ 
6:    $o, s \leftarrow E.step(a)$ 
7:    $H_o.append(o)$ 
8:    $H_a.append(a)$ 
9:    $done \leftarrow P.judge(s)$ 
10:  if  $done$  then
11:    return true
12:  else if  $a$  is answer action then
13:    return false                    $\triangleright$  wrong answer
14:  end if
15: end for
16: return false                   $\triangleright$  reach the max steps

```

---

#### 6.2.2 Interaction Actions

We provided more examples of the interaction space mentioned in Section 3.2.1 in Table 5.

#### 6.2.3 Predicates

All the predicate functions described in Section 3.2.2 are listed in Table 4.

### 6.3. Creation of Objaverse Synthetic

We use a wide variety of objects from Objaverse to procedurally generate diverse scenes and further refine them through interactive scene editing.

**Object Selection.** We curated a subset of indoor assets out of Holodeck’s [85] annotated realistic and diverse objects chosen from the Objaverse asset library [20]. To ensure quality, we employed GPT-3.5 to filter unsuitable outdoor objects and manually reviewed frontal renderings to remove low-quality assets. This process resulted in a database of about 15,000 objects spanning over 500 categories (see examples in Figure 9).

**Scene Generation.** We leveraged GPT-3.5 to annotate object categories with their typical room occurrences (e.g., inLivingRoom, inKitchen), positions (e.g., onWall, onFloor, onEdge), and functions (e.g., receptacle, pickup). Gemini-1.5-Flash was used to annotate large objects’ orientations. Subsequently, a procedural approach was employed to randomly place architectural elements such as walls, doors, and windows. Large objects were then arranged on the floor either against the walls or in the center of the rooms, and smaller items were finally placed on surfaces of large receptacles. Hundreds of scenes were generated randomly, from which we selected 15 living rooms, 15 bedrooms, 10 two-room, 5 three-room, and 5 four-room for further editing.

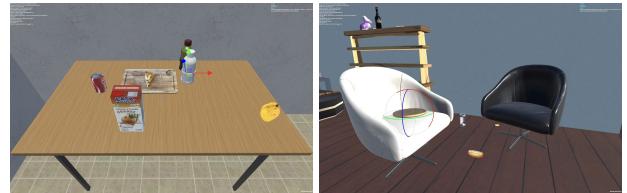


Figure 7. Interactive scene editor: adjust object position (left) and angle (right).

**Scene Editing.** To make the scene more organized and to avoid errors caused by automatic generation, we also edited the generated scene by developing a runtime scene editor. Users can view the type and description of objects, and adjust their position and orientation (see Fig 7). Once editing is complete, the scene can be saved as a JSON file, which can be imported to reproduce the environment.

Task	Characteristics
Please go to the kitchen, then come back and tell me if there are any extra cups.	scene memory
Imagine the house is rotated 90 degrees counterclockwise. How would this affect the natural light distribution in the room?	spatial imagination
Open a black locked drawer with a key found on the desk.	tool use
Pick up the kettle and the box labeled "BREAD" from the kitchen counter and place them on the table with the coffee machine.	optical character recognition
Optimize the display of artworks on the shelves as follows: place two items on each shelf, with one shelf featuring two items of the same shape. Complete the requirements in as few steps as possible.	reasoning and planning
Grab the object that is cylindrical and silver on the table next to the washing machine.	multiple attribute reference
Estimate the percentage of floor space occupied by furniture in the room you're currently in.	area estimation
Estimate the straight-line distance from the front door to the TV. Note that each step you take forward is approximately two meters.	distance estimation
Which is closer to the drink on the round table, the ginger or the ice cream?	distance comparison
If we were to host a birthday party, which area of the house could accommodate the most people while ensuring clear pathways to exits?	logic, space, and common sense
Describe the path from the kitchen to the living room.	path description
If you were to draw a straight line from the desk with a turned-on laptop to the bookshelf, which pieces of furniture would it intersect?	spatial reasoning
What is the object I am pointing at?	pointing comprehension
Pick up the watermelon on my right.	perspective-taking comprehension
My red glasses are missing. Please help me look for them in the room. Once you find them, bring them to me.	object searching and delivering
Get close to the lady in white and ask if she needs help.	social navigation
Wake up my dad. He is sleeping in the bedroom. The bedroom is the second room on your right as you walk forward.	finding someone
Enter the dining area and see if there is more than one door in the entire house.	object counting
Calculate the ratio of seating options to the number of rooms in the house.	counting and calculation
Tell me which objects have a handle in the kitchen.	attribute grounding
Evaluate whether the painting above the living room sofa is more colorful than the carpet.	attribute comparison
How many rooms are there in total?	room counting
Confirm if a garbage can is located on the floor in the living room.	object existence
Which room has more seating options, the kitchen or the living room?	quantity comparison
I'm hungry. Find all objects that can be used as ingredients. on the table in this room.	object functionality
Count the maximum number of identical clocks among all the rooms.	counting and attribute memory
What do you think the owner of this room probably studies?	common sense
Is there an egg inside the fridge?	interaction and answering
Open the drawer of the side table in the study room. If there is something inside, leave it open and put all similar items from the room into it. If there is nothing inside, close it.	logical execution

Table 3. Examples of the diverse tasks in EMBODIEDEVAL.

Predicate	Parameters	Success Conditions
<i>choose</i>	The right answer.	When the agent selects the correct answer.
<i>agent_at</i>	A navigation point.	When the agent finally arrives at this point.
<i>agent_pass</i>	A navigation point.	When the agent has passed through this point at least once.
<i>at</i>	An object and a specific point.	When the object is at this point.
<i>grab_once</i>	An object.	When the agent has picked up this object at least once.
<i>grab</i>	An object.	When the agent picks up the object.
<i>special_action_success</i>	An interaction action.	When this interaction action has been successful.

Table 4. The predicates involved in EMBODIEDEVAL.

Action Text	Execution Requirements
wash	When the agent is holding the target object and stand next to the sink.
hand over	When the agent is holding the target object and stand next to the person.
sit down	When the agent is next to the target chair.
unlock	When the agent is holding the target key and standing next to the drawer
greet	When the agent is near the person.
ask	When the agent is near the person.
mix	When several target beverages are on the table next to the agent.
wipe off the table	When the agent is holding an object for cleaning and standing next to the table.
check the results of the program	When the agent is next to the computer.

Table 5. Some cases of the interaction actions involved in EMBODIEDEVAL.

### Prompt for Multi-image MLLMs

You are an intelligent vision-language embodied agent skilled at solving tasks **and** answering questions **in** a 3D environment. Your job **is** to efficiently complete a specified task by choosing the optimal action at each timestep **from** a **set** of available actions. You are given a series of ego-centric images, **and** a history of previous actions with optional feedback (success/failure **or** human response). Each image shows what you see at a particular step **in** the action history, along with an extra image showing your current view.

```
Current task: {}
Action history (action -> feedback): {}
Visual history: {}
Current view: {}
For the current step, your available options are listed as "[Option_Number].Content" as follows
: {}
Choose your action from the above options by replying with "Thought:_Your_reasoning.\nChoice:_[Option_Number]_(e.g._[1])".
```

#### Note:

- If the task needs more information of the scene, navigate wisely to the required targets (objects, places, **or** people).
- Avoid repeated actions like useless forward motion **and** circling.
- You can only interact with objects **or** humans (e.g. pick/place/**open**/close/handover) **if** they are within your view **and** very close to you.
- You can only hold one **object** at a time. Put down **any** held **object** before picking up another.
- Tasks containing "**I**" **or** "**me**" are requested by a person **in** the scene.
- Reflect on why previous actions fail to avoid repeating mistakes **and** adjust your current action.
- You have a limited number of {} steps to complete the task.

Figure 8. Prompt for Multi-image MLLMs.



Figure 9. Examples of selected Objaverse assets and views of generated scenes.

## 6.4. Success Cases

We present successful cases accomplished by closed-source MLLMs to gain deeper insights into their current capabilities. As discussed in Section 4.3, the models generally scored low and successfully completed only a limited number of tasks. A closer examination of these successful tasks reveals that they are typically simpler, involve fewer steps and require interaction with fewer objects. To better illustrate these findings, we present representative cases from five task types. These examples highlight the underlying behavioral patterns and reasoning processes of the models during task execution.

### 6.4.1 Attribute QA

**Task:** What do you think the owner of this room probably studies?

**Options:**

- |                                                              |                                                          |
|--------------------------------------------------------------|----------------------------------------------------------|
| <input checked="" type="checkbox"/> answer "interior design" | <input type="checkbox"/> answer "comparative literature" |
| <input type="checkbox"/> answer "computer science"           | <input type="checkbox"/> answer "theoretical physics"    |
| <input type="checkbox"/> answer "molecular biology"          | <input type="checkbox"/> answer "digital marketing"      |
| <input type="checkbox"/> answer "music composition"          | <input type="checkbox"/> answer "industrial design"      |

**GPT-4o:** answer "interior design"



The current view doesn't provide enough information about the room's contents or any clues about the owner's field of study. I should study. I should examine the room further to gather more context.

The current view shows a desk with books and an open notebook, which might provide clues about the subject of study. I should study. I should examine the room further to make an informed decision.

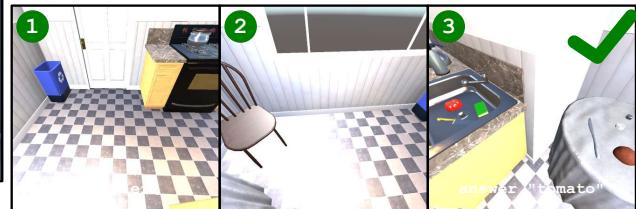
The current view shows books related to architecture and design, along with an open book that appears to have design content. This suggests that the owner of the room likely studies something related to design.

**Task:** What is inside the sink near the dining table?

**Options:**

- |                                          |                                                     |
|------------------------------------------|-----------------------------------------------------|
| <input type="checkbox"/> answer "potato" | <input type="checkbox"/> answer "soap"              |
| <input type="checkbox"/> answer "water"  | <input type="checkbox"/> answer "cup"               |
| <input type="checkbox"/> answer "bowl"   | <input type="checkbox"/> answer "steel wool"        |
| <input type="checkbox"/> answer "apple"  | <input checked="" type="checkbox"/> answer "tomato" |

**GPT-4o:** answer "tomato"



I need to locate the dining table and the sink. Since the current view shows a kitchen area, I should explore further to find the dining table and sink.

I need to locate the sink near the dining table. The current view shows a chair and a recycling bin, but no sink. I should continue exploring to find the sink.

The current view shows the sink, and I can see items inside it. I need to identify what is inside the sink near the dining table.

Figure 10

**Task: What color is the car parked around the house?**

**Options:**

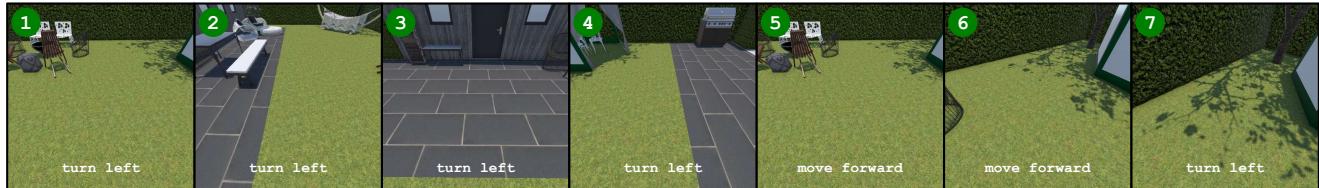
- answer "red"
- answer "black"
- answer "white"
- answer "blue"

- answer "black"
- answer "blue"

- answer "red and white"
- answer "blue and white"

- answer "black and white"
- answer "yellow"

**Gwen-VL-Max:** answer "red and white"



I need to find the car parked around the house. parked around the house. I should start by I should start by I should explore the area by turning left to see if there is a car nearby. I need to find the car parked around the house. I should explore the area by turning left to see if there is a car nearby. I need to find the car parked around the house. I should start by moving forward to explore the area by moving forward. I need to find the car parked around the house. I should explore the area by turning left to see if there is a car nearby.



I need to find the car parked around the house. parked around the house. I should explore the area by turning left to see if there is a car nearby. I need to find the car parked around the house. I should explore the area by moving forward. I need to find the car parked around the house. I should explore the area by turning left to see if there is a car nearby. The car parked around the house is red and white.

Figure 11

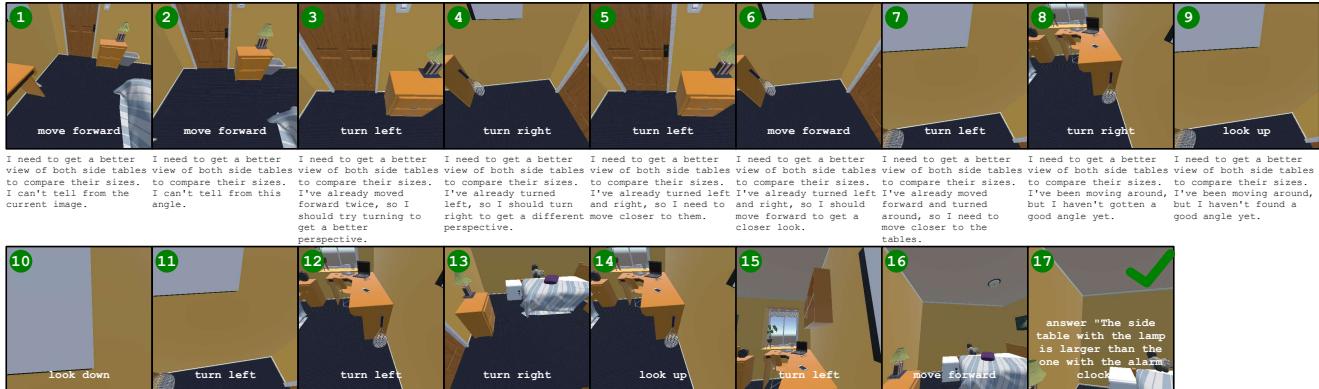
**Task: Compare the sizes of two side tables in the bedroom.**

**Options:**

- answer "The side table with the lamp is located near the window."
- answer "Both side tables are of equal size."
- answer "The side table with the alarm clock is larger than the one with the lamp."
- answer "The side table with the alarm clock is painted blue."

- answer "It's difficult to tell the difference in size between the two side tables."
- answer "The side table with the lamp is larger than the one with the alarm clock."
- answer "The side table with the alarm clock has a drawer."
- answer "The side table with the lamp has two drawers."

**Gemini-Flash:** answer "The side table with the lamp is larger than the one with the alarm clock."



I need to get a better view of both side tables to compare their sizes. I can't tell from this current image. I need to get a better view of both side tables to compare their sizes. I've already moved forward twice, so I should try turning to a better perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I need to get a better view of both side tables to compare their sizes. I've already turned left, so I should turn right to get a different perspective. I have been moving around the bedroom, trying to get a good view of both side tables. I can see that the side table with the lamp is larger than the one with the alarm clock.

Figure 12

## 6.4.2 Spatial QA

**Task:** Determine if the sofas on the left will fit through the front door.

**Options:**

- answer "There is no front door."
- answer "Yes, the front door is wide enough, and all the sofas can pass through easily in any orientation.."
- answer "No, only the smallest sofa can pass through."
- answer "Yes, but the sofas need to be stood upright to pass through."
- answer "No, the largest sofa cannot pass through."
- answer "No, none of the sofas can pass through."
- answer "There is no sofa."

answer "Yes, but the sofas need to be turned sideways to pass through."

**GPT-4o:** answer "Yes, but the sofas need to be turned sideways to pass through."

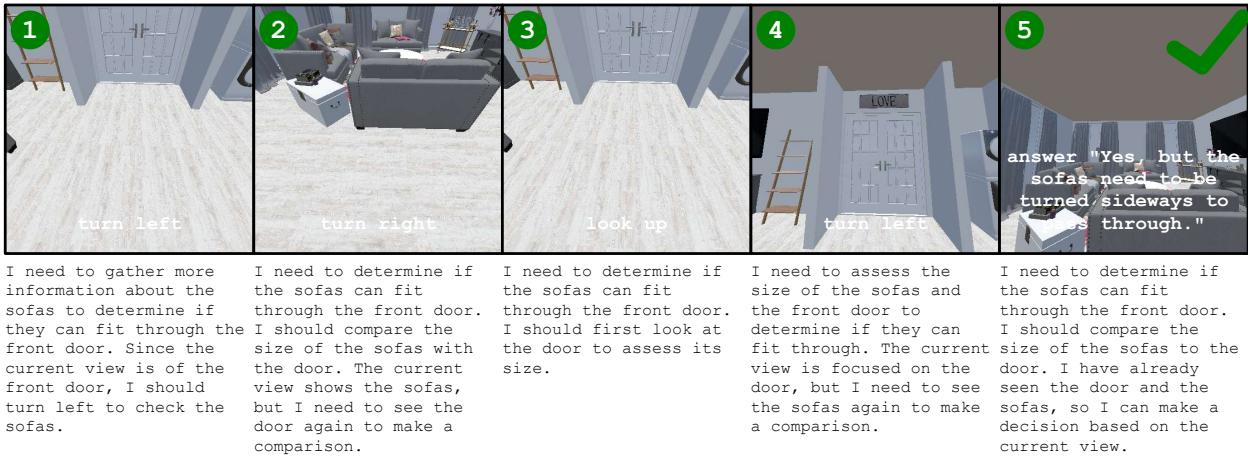


Figure 13

**Task:** What direction does the bedroom doorway face when looking out?

**Options:**

- answer "Opposite to the orientation of the table."
- answer "Opposite to the orientation of the chair with many objects on it."
- answer "Consistent with the orientation as the table."
- answer "Consistent with the orientation as the toilet."
- answer "Consistent with the orientation as the white cabinet."
- answer "Consistent with the orientation of the bed."
- answer "Consistent with the orientation as the fridge."
- answer "Opposite to the orientation of the bed."

**GPT-4o:** answer "Consistent with the orientation of the bed."

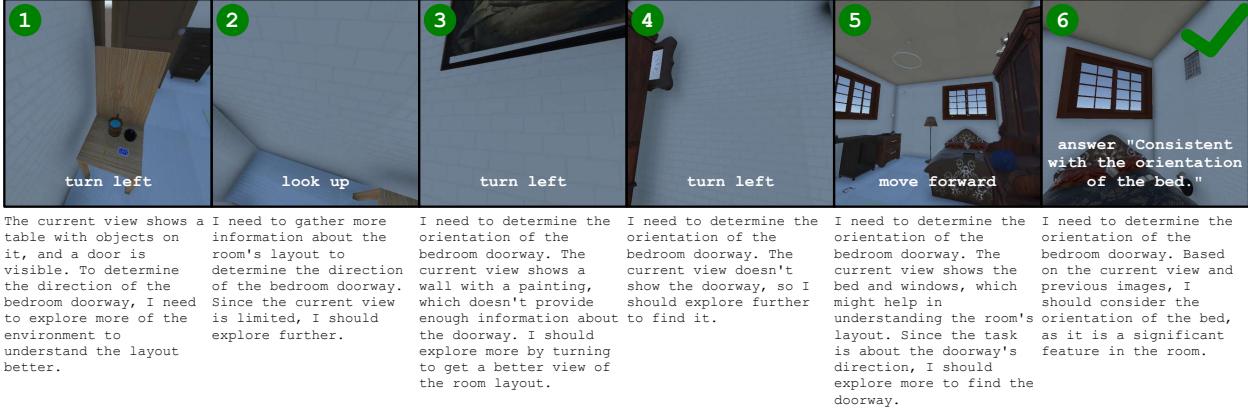
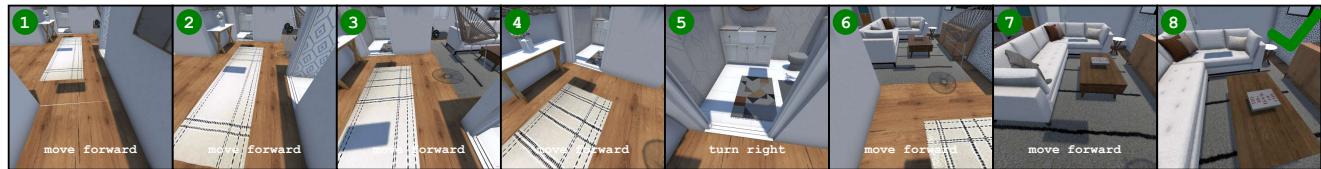


Figure 14

### 6.4.3 Navigation

Task: Walk straight past the kitchen on your left, turn right when you are almost at the bathroom door, and stop when you reach the book in the center of the sofa table.

Qwen-VL-Max:



I need to walk straight past the kitchen on my left, which means I should continue moving forward.

I need to walk straight past the kitchen on my left, so I should continue moving forward.

I need to walk straight past the kitchen on my left, which means I should continue moving forward.

I need to walk straight past the kitchen on my left, which means I should continue moving forward until I am almost at the bathroom door. Then, I will turn right.

I need to turn right after passing the kitchen and before reaching the bathroom door.

I need to walk straight past the kitchen on my left, which means I should continue moving forward until I reach the point where I need to turn right. The current view shows that I am still in the hallway, so I should keep moving forward.

I need to move closer to the sofa table to find the book.

Figure 15

Task: I want to find a human-shaped statue which is placed on the table below the wall where the iris painting hangs. Please navigate to it.

Qwen-VL-Max:



I need to find the human-shaped statue on the table below the wall where the iris painting hangs. I should start by painting. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by exploring the room and looking for any with the iris painting.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should start by looking around to identify any potential locations that match this description.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should move towards the area where the iris painting is located, which is visible in the background of the current view. Moving forward will bring me closer to the painting and potentially the statue.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should move towards the area where the iris painting is located, which is visible in the current view. Moving forward will bring me closer to the target location.

The task requires me to find a human-shaped statue on a table below the wall where the iris painting hangs. I should move towards the area where the iris painting is located, which is visible in the current view. Moving forward will bring me closer to the target location.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

The task is to find a human-shaped statue on a table below a wall where the iris painting hangs. I need to move closer to the table where the statue is located.

Figure 16

#### 6.4.4 Object Interaction

### **Task: Is there an egg inside the fridge?**

## Options:

- answer "Yes, and there are two eggs, one in the upper part and one in the lower part."  
 **answer "Yes, in the lower part of the fridge."**  
 answer "Yes, there are two eggs in the upper part of the fridge."  
 open the lower fridge door  
 answer "There is no fridge."  
 answer "No, there are no eggs in the fridge."  
 answer "Yes, in the upper part of the fridge."  
 open the upper fridge door  
 answer "Yes, there are two eggs in the lower part of the fridge."

**Qwen-VL-Max:** answer "Yes, in the lower part of the fridge."



I need to find the  
fridge first to check  
for eggs. The current  
view does not show the  
fridge, so I should turn  
to face it.

To determine if there is To check for eggs in the  
an egg inside the fridge, I need to go to the fridge, I need to go to the fridge, I need to go to the  
fridge, I need to first the fridge and open it, the fridge and open it, the fridge and open it.  
locate the fridge and The fridge is located to The fridge is located to The fridge is not  
then check its contents. the right of my current the right of my current visible in the current  
The current view does position. position. view, so I should move  
not show the fridge, so towards it.  
I should turn to find



To check for eggs in the I need to check inside the fridge, I need to approach the fridge and if there are any eggs. The current view shows the distance, so I should move closer to the fridge to determine if there are any eggs. Since I am already at the top of the fridge, I should open the doors to inspect the contents. I need to check inside the fridge to determine if there are any eggs. Since I am already at the top of the fridge, I should open the doors to inspect the contents. I need to check inside the fridge to determine if there are any eggs. The previous attempts to open the fridge were unsuccessful, so I will try again. I need to check inside the fridge to determine if there are any eggs. The previous attempts to open the upper fridge door were unsuccessful, so I should try opening the lower fridge door instead. I need to check if there is an egg inside the fridge. I should open the fridge doors to look inside. The task is to determine if there is an egg inside the fridge. I can see an egg inside. Therefore, I can confirm that there is an egg in the fridge.

Figure 17

**Task:** Pick all round objects into trash can.

**Options:**

pick up     place to the trash can

**Gemini-Pro:**

1



I have successfully picked up one round object, the basketball, and tried to place it in the trash can. I've been turning right eight times in the trash can. I've been placing it in the trash can, but I'm not facing it correctly. I've been working hard, but it hasn't worked; I need to turn around and locate the trash can. I will turn around and attempt to place the object again. I will turn right first to explore the room. I have picked up one basketball and tried to place it in the trash can. I've been turning right eight times in the trash can. I've been facing it correctly because I wasn't facing the trash can. I turned around and attempted again and located the trash can. I will turn around and attempt to place the object again. I will turn right first to face the desk, because the trash can was next to it.

I have successfully picked up one round object and tried to place it in the trash can. I've been turning right eight times in the trash can. I've been facing it correctly because I wasn't facing the trash can. I turned around and attempted again and located the trash can. I will turn around and attempt to place the object again. I will turn right first to face the desk, because the trash can was next to it.

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Figure 18

#### 6.4.5 Social Interaction

**Task:** Wake up my dad. He is sleeping in the bedroom. The bedroom is the second room on your right as you walk forward.

**Options:**

speak "get up"

GPT-4o-Mini:

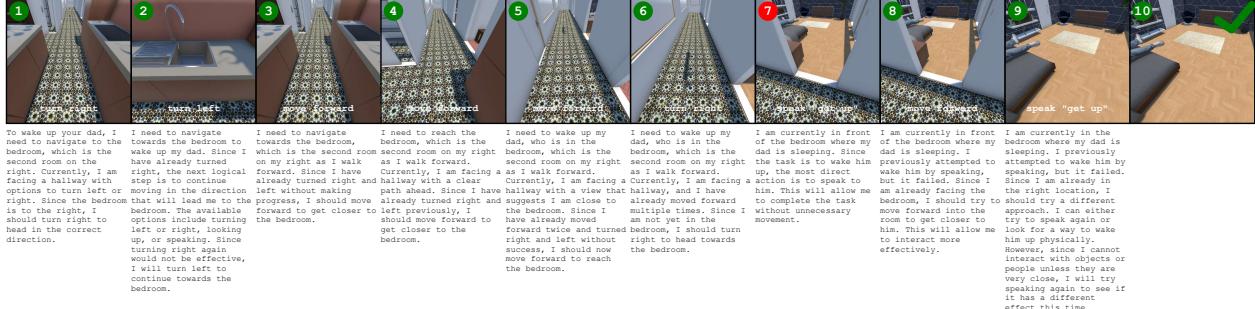


Figure 19

**Task:** Retrieve the magazine for the madam sitting on the chair.

**Options:**

pick up     hand over

**Gemini-Pro:**

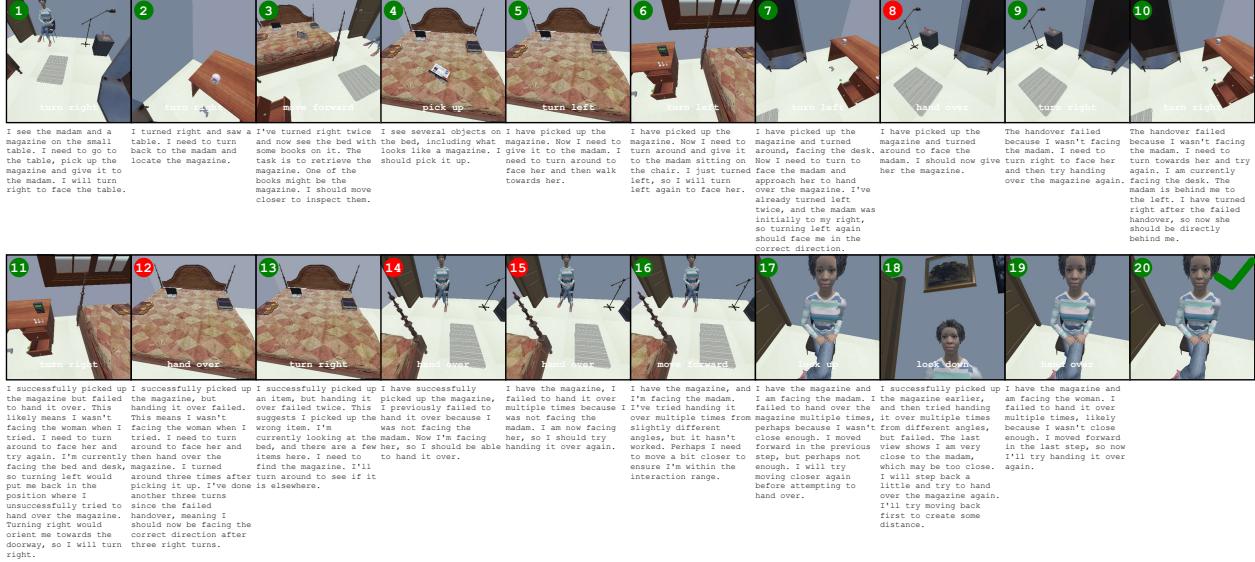


Figure 20

## 6.5. Error Cases

### 6.5.1 Attribute QA

**Task:** Locate any electronic devices in the bedroom.

**Options:**

- answer "flashlight, desk lamp, and phone"
- answer "laptop, desk lamp, and phone"
- answer "laptop, TV, and desk lamp"**
- answer "TV, laptop, and door"

**Qwen-VL-Max:** answer "laptop, desk lamp, and phone"



I need to explore the room to find electronic devices. I should start by turning left to see what's there.

I need to explore the room to find electronic devices. I should start by turning left to see more of the room.

I need to locate electronic devices in the bedroom. I have already seen a laptop and a desk lamp. I should explore the room further to find more devices.

I need to locate electronic devices in the bedroom. I have already seen a laptop and a desk lamp. I should continue exploring the room to find more devices.

I have already explored the room and found a laptop, desk lamp, and phone. I should report these findings to complete the task.

Figure 21

**Task:** Are there more flower pots in the living room or the bedroom?

**Options:**

- answer "There are more flower pots in the living room, while no one in bedroom"
- answer "The bedroom has a few flower pots, but the living room has none."
- answer "The bedroom has only one flower pot, while the living room has several."**
- answer "There are no flower pots in the bedroom, only in the living room."
- answer "The living room has more flower pots, placed near the trash can."
- answer "There is only one flower pot in each room."
- answer "Both the living room and bedroom have the same number of flower pots."
- answer "Both rooms have flower pots, but the bedroom's pots are larger in size."

**Gemini-Pro:** answer "There are no flower pots in the bedroom, only in the living room."



I can see a flower pot in the living room. I need to explore the bedroom to compare the number of flower pots.

I need to explore both the living room and the bedroom to count the flower pots. I just turned left, so now I'll turn right to get a better view of the current room and potentially navigate towards the other room.

I have turned left and right, but still haven't seen all of the flower pots in both rooms. I will need to explore more before answering.

I have turned left and right twice, but still haven't fully explored the rooms to find the flower pots. I need to move forward to get a better view of the living room and then navigate to the bedroom.

I have turned left, right, right, and forward. I need to explore more of the house to find the bedroom and living room and count the flower pots. Moving forward seems like the best option to continue exploration.

I have explored the environment a bit. I believe I've seen both the living room and the bedroom. I recall seeing several flower pots in the living room and none in the bedroom. I'm ready to answer.

Figure 22

## 6.5.2 Spatial QA

**Task:** Determine the best location for a fire extinguisher that would be quickly accessible from both the kitchen and the living room.

**Options:**

- answer "Near the window."
- answer "Beside the flowerpot near the round carpet."
- answer "On the countertop."
- answer "Beside the black sofas."
- answer "In front of the stove."
- answer "Next to the piano."
- answer "Beside the white sofa."
- answer "Next to the irregular table with many books."

GPT-4o: answer "Beside the white sofa."

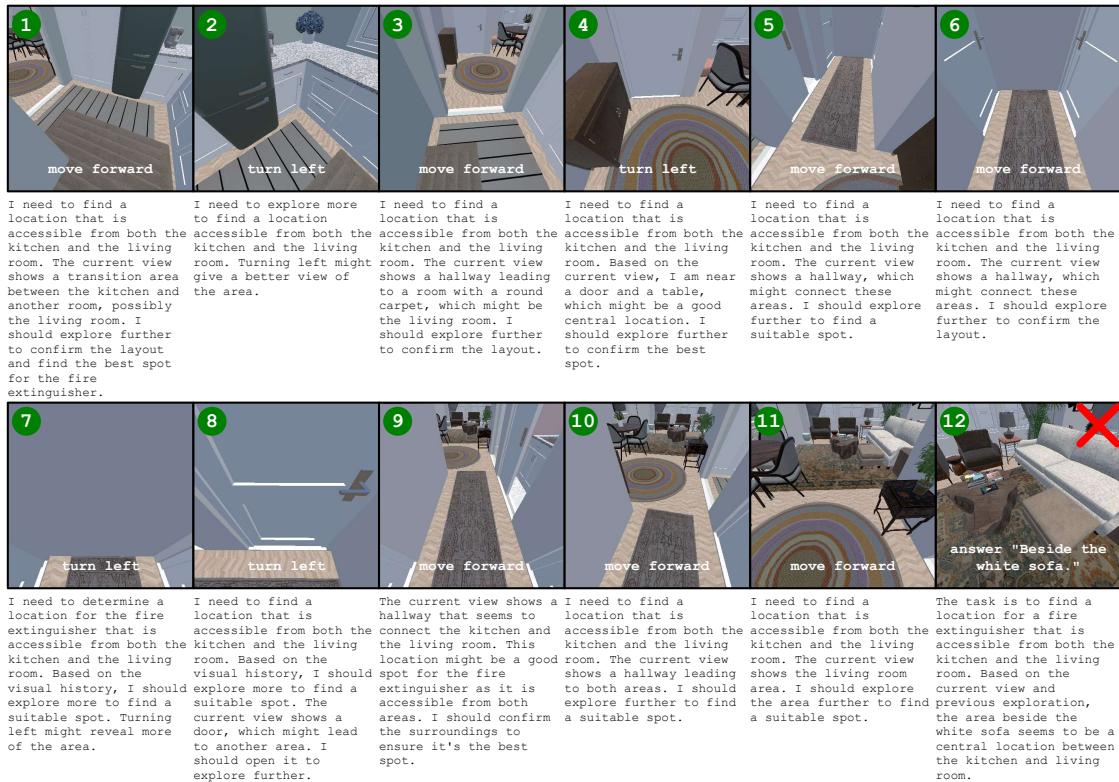


Figure 23

## 6.5.3 Navigation

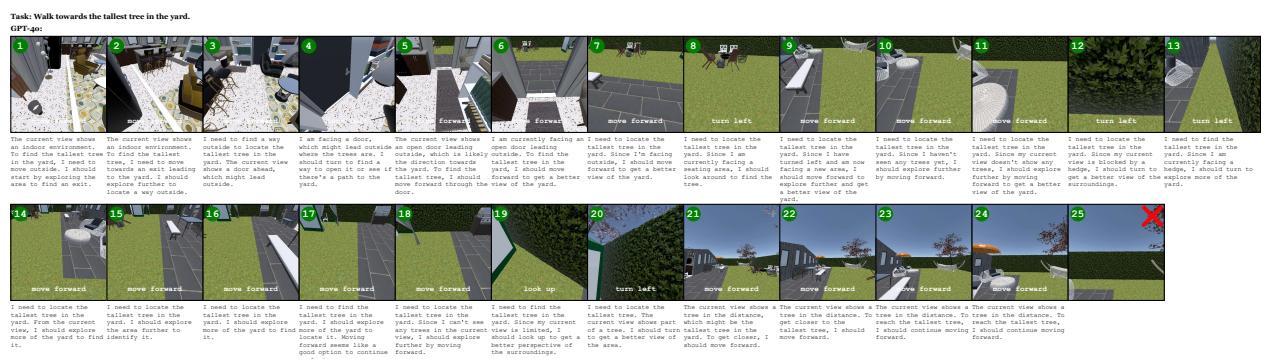


Figure 24

## 6.5.4 Object Interaction

**Task:** Retrieve the tied reading materials from the sofa in the living room and place it on the lounge chair.

**Options:**

place down    pick up

**GPT-4o:**



The task is to retrieve the tied reading materials from the sofa and place them on the lounge chair in the lounge chair. In the current view, I can see the sofa and the reading materials on it. The reading materials are visible. I need to pick up the reading materials from the sofa. I should move closer to the sofa to successfully pick them up.

The task is to retrieve the tied reading materials from the sofa and place them on the lounge chair. In the previous attempt to pick up the item failed, possibly because I wasn't close enough. The reading materials are visible on the sofa. I should move closer to the sofa to successfully pick them up.

The task is to retrieve the tied reading materials from the sofa and place them on the lounge chair. The current view shows the sofa and the lounge chair. Since the previous attempt to pick up failed, I need to ensure I'm close enough to the reading materials. I should move closer to the sofa to successfully pick up the materials.

The reading materials are likely on the sofa to my right, based on the previous images. I should turn right to face the sofa and locate the lounge chair.

The tied reading materials are visible on the sofa in the current view. I need to pick them up before moving to the lounge chair, which is visible in my current view. The lounge chair is to my left.

I have successfully picked up the reading materials. Now, I need to place them on the lounge chair. The current view shows the wall, so I need to turn to face the lounge chair.

I have successfully picked up the reading materials. Now, I need to place them on the lounge chair. The lounge chair, which is currently in my view.

I have successfully picked up the reading materials. Now, I need to place them on the lounge chair. The lounge chair, which is currently in my view.

Figure 25

## 6.5.5 Social Interaction

**Task:** Bring my credit card to me and return it back to its original place.

**Options:**

pick up the card    place down    hand over    place into trash can

**GPT-4o:**



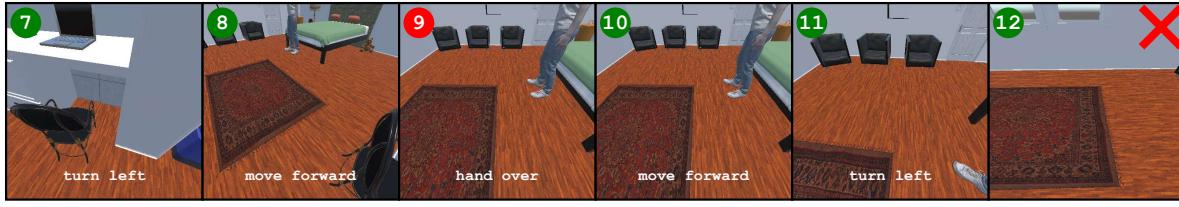
I need to locate the credit card first. The current view shows a trash can and part of a room. I should explore the area to find the card.

The current view shows a trash can, but I don't see a credit card. I should turn to explore the area further.

I need to locate the credit card before I pick it up. The current view shows a bed, a chair, and a desk. I should explore the area further to find the card.

The task is to bring the credit card to the person and return it to its original place. Currently, I don't see a credit card in my view. I should explore the room further to locate it. Turning right might give a better view of the room.

I have already picked up the card. The next step is to hand it over to the person in the room. The person is visible in the previous images, so I should hand over the card.



The task is to bring the credit card to the person who requested it and return it to its original place. The previous attempt to hand over the card failed, possibly because I was not in the correct position. I need to locate the person and try handing over the card again.

I am currently facing the person who requested the card. The previous attempt to hand over the card failed, possibly because I wasn't close enough. I should move closer to the person to successfully hand over the card.

I am currently facing the person who requested the card. The previous attempt to hand over the card failed, possibly because I wasn't close enough. I should move closer to the person to successfully hand over the card.

The previous attempts to hand over the card failed, possibly because I was not facing the person directly. I need to turn around to face the person and hand over the card.

I am currently facing the chairs, and the person is likely behind me. I need to turn around to face the person and hand over the card.

Figure 26