

# SWITCH: Benchmarking Modeling and Handling of Tangible Interfaces in Long-horizon Embodied Scenarios

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## Abstract

*Autonomous intelligence requires not only perception and reasoning, but critically, effective interaction with the existing world and its infrastructure. Everyday environments are rich in tangible control interfaces (TCIs)—e.g., light switches, appliance panels, and embedded GUIs—that demand commonsense/physics reasoning, but also causal prediction and outcome verification in time and space (e.g., delayed heating, remote lights). Moreover, failures here have potential safety implications, yet current benchmarks rarely test grounding, partial observability (video), or post-hoc verification in situated settings. We introduce SWITCH (Semantic World Interface Tasks for Control & Handling), an embodied, task-driven benchmark created through iterative releases to probe these gaps. Its first iteration, SWITCH-Basic, evaluates five complementary abilities—task-aware VQA, semantic UI grounding, action generation, state-transition prediction, and result verification—under egocentric RGB video input and device diversity. Across 351 tasks spanning 98 real devices/appliances, commercial and open LMMMs exhibit inconsistent performance even on single-step interactions, often over-relying on textual cues and under-using visual/video evidence (and high aggregate scores can mask such failures). SWITCH provides data, code, and held-out splits to enable reproducible evaluation and community contributions toward more challenging future iterations of the benchmark and the creation of training datasets. Benchmark resources are available at: <https://github.com/BAAI-Agents/SWITCH>.*

## 1. Introduction

Intelligent behaviour requires not only perception and reasoning, but also effective interaction with the existing world and the infrastructure in it. Despite significant progress in

computer vision (CV), large multi-modality models (LMMs), and interactive agents, research efforts have largely overlooked understanding and operating tangible control interfaces (TCIs)<sup>1</sup>, from light switches and appliances to on-device GUI panels — the primary medium of **everyday human-device interaction**.

Recent benchmark efforts (e.g., [3, 4, 8]) have probed models’ ability to understand common-sense causality or physics-based outcomes and consistency. However, TCI interfaces require modeling causality beyond these dimensions only, as the effects of TCI interactions can depend on specific devices (e.g., same device type has different behaviours), present temporal delays (e.g., pre-heat an oven), and even may require spatial verification (e.g., pressing a switch in one room to turn a light in another one).

Moreover, despite over two decades of “smart home” and IoT efforts, the vast majority of deployed devices remain **non-API-enabled** or, if automatable at all, expose fragmented proprietary protocols: buildings, offices, and homes today still operate through knobs, panels, and remotes that require **eyes, hands**, and potentially **device-specific knowledge**, rather than programmatic control. As a result, evaluating whether **current foundation models** can function in everyday settings requires moving beyond text-image benchmarks and into embodied tasks where success depends on using these interfaces correctly and verifying their effects in situ.

Similarly to the work on manipulating GUIs, grounding is critical for proper **situated interaction** with TCIs. However, current benchmarks and simulators either don’t cover such interfaces or don’t model them in enough detail transferable to real-world settings.

These issues highlight the critical need for models that can understand and operate within such interaction-centric environments, bridging not only perception, reasoning, and

<sup>1</sup>We use the term TCI (Tangible Control Interfaces) to clearly specify this type of interaction interface in tangible form. As well as avoid ambiguity with usage of UI (usually associated directly with GUIs), TUI (which refers to physically interacting with the digital world through tangible assets [11], not our scenario), and HMI (Human-Machine-Interface, terminology used in industry for visual control interfaces for settings as complex machinery or facilities [19], e.g., control of a power plant).

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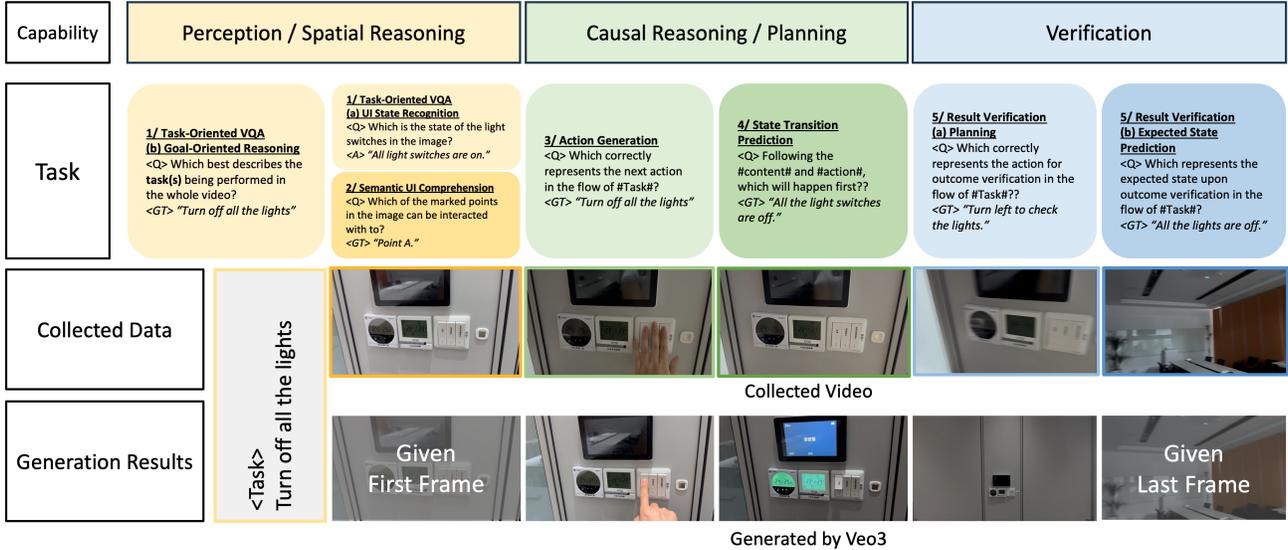


Figure 1. An overview of the SWITCH benchmark, using the case “Turn off all the lights” as a running example. SWITCH covers the **collection and annotation** of real-world TCI interaction data (“Collected Data”), which we systematically structure into **five distinct tasks**. These tasks are designed to evaluate models across **three crucial capability dimensions**: Perception/Spatial Reasoning, Causal Reasoning/Planning, and Verification. Furthermore, we leverage the benchmark to evaluate advanced generative models, like Veo3 [10]. By comparing generated videos against ground truth, we illustrate how current models still exhibit significant room for improvement in logical consistency and fine-grained interaction for real-world use, thus underscoring the importance of SWITCH’s target scenarios.

action; but also **verification of outcomes and adaptation**. As well as ways to evaluate them in both higher-level causality understanding and planning of actions, but also in grounded realistic execution of interactions.

To address this gap, we introduce **SWITCH** (Semantic World Interface Tasks for Control and Handling), a new effort towards a unified task-driven benchmark designed to evaluate models’ abilities to perceive, reason about, and interact with complex dynamic environments via TCI elements and understand and verify the effects of such interactions. SWITCH’s initial iteration, **SWITCH-Basic**, emphasizes five complementary capabilities: 1/ Task-Aware Visual Question Answering: answering questions conditioned on multimodal observations and task goals; 2/ Semantic UI Comprehension: grounding and interpreting actionable UI elements in context; 3/ Action Generation: planning and executing context-aware actions aligned with user intent; 4/ State Transition Prediction: reasoning about the causal consequences of UI-actions; 5/ Result Verification: post-hoc evaluation to determine task success. Figure 1 illustrates the benchmark design dimensions.

Each task is explicitly designed to bridge the gap between virtual reasoning and real-world applicability, requiring models to understand UI layout and functionality, anticipate consequences of actions, and verify outcomes. Unlike existing datasets, which often consider only object-level interactions or abstract digital actions, SWITCH evaluates practical, generalizable interactive skills that reflect realistic

human-device interactions.

We take an iterative benchmark design approach to both allow timely analysis of current model capabilities and collect feedback for upcoming more in-depth iterations of the benchmark. This iterative process will also allow the future creation of an effective dataset to train models for such scenarios.

This first SWITCH-Basic iteration of the benchmark focuses on single-step iterations and an initial analysis of current model capabilities through a set of multi-choice questions (MCQ) in different modalities to match availability of models and for ease of automatic evaluation. Using the same tasks we also perform a case study using a recent powerful video generation model, not restricted to pre-defined answer options.

Results on multiple commercial and open foundation models show that, even for simpler single-step interactions, model performance is inconsistent; with models showing strong reliance on textual cues from multi-choice answers and difficulty in properly leveraging image and video data.

By providing an open, extensible, and reproducible benchmark in fast iterations, **SWITCH** encourages the development of models that integrate perception, reasoning, planning, and self-evaluation, pushing the boundaries of embodied AI research. We believe this benchmark is particularly important for advancing AI systems capable of robust generalization across diverse environments and interaction modalities, moving closer to truly intelligent agents that can

operate effectively in the real world.

In summary, our work makes two main contributions. First, we introduce **SWITCH**, a benchmark effort that starts to address previously underexplored challenges in TCI-centric interactive intelligence, and release it under a permissive license to support open and reproducible research. Second, we conduct a comprehensive evaluation of state-of-the-art large multimodal models (LMMs) on this benchmark - SWITCH-Basic, providing detailed analysis of their strengths and limitations, thereby offering insights to guide future model development in real-world interactive tasks.

We hope this benchmark effort will help foster further research to address this overlooked gap and we invite community feedback and collaboration for future iterations of the benchmark. SWITCH will also host a leaderboard for each iterations and difficulty levels, with held out answers for fair comparison against different approaches. The benchmark is available on our GitHub repository<sup>2</sup>.

## 2. Related Work

Evaluating LMMs in realistic, interactive environments remains a critical challenge for advancing embodied intelligence. While a wide range of benchmarks has emerged—spanning perception, reasoning, action planning, tool use, and interface control [6, 14, 23, 25, 27]—many lack the combined focus on semantic user interfaces, contextual control, and post-action verification that real-world interaction demands. We divide existing efforts into two main categories—Multimodal & World-Model Evaluation, and User Interface Control Interaction—and discuss how our benchmark uniquely addresses the gaps.

### 2.1. Multimodal & World-Model Evaluation

Recent benchmark efforts have aimed at assessing models’ capacity for perception, reasoning, and planning across modality. For instance, the work on PhysBench [4] introduces a large-scale benchmark for vision-language models to evaluate physical-world understanding across object properties, relationships, and scene dynamics. While valuable, it emphasises physical object phenomena rather than user-interface control semantics. Besides, WorldPrediction [3] targets the high-level, more abstract world modeling, and evaluating capabilities in both action choosing and long procedural planning. Furthermore, WorldModelBench [13] concentrates on video generation models, with a special focus on nuanced world modeling violations and alignment with human preferences. Meanwhile, WorldScore [7] proposes a unified benchmark for world generation and scene prediction—next-scene tasks driven by camera trajectories and layout dynamics. It centres on scene generation and layout controllability and overlooks interac-

tive device/appliance control via their interfaces. More recently, BEHAVIOR-1K [12] presents a large-scale human-centered embodied AI benchmark covering 1,000 everyday activities across 50 scenes with rich object annotations. Although BEHAVIOR-1K enhances scene diversity and long-horizon manipulation, it remains object-manipulation focused and does not systematically target semantic interface control, TCI-to-environment causality, or verification of control-action outcomes. These works provide strong foundations but leave interface-control reasoning and outcome verification under-explored.

### 2.2. User Interface Control Interaction

A second line of research investigates agents controlling digital interfaces or tools via screen-based or scripted simulation environments. Benchmarks such as WebShop[26], AndroidWorld [16], Cradle [20], and OSWorld [22], require agents to click buttons, navigate GUIs, or perform scripted operations from textual instructions. These tasks advance procedural reasoning and interface grounding, but remain within virtual or digital regimes and rarely involve real-world UI elements or their downstream environmental effects. In contrast, our benchmark—SWITCH—focuses explicitly on tangible control interfaces (TCIs) that combine UI semantics, physical device states, and user intent. SWITCH tasks include UI comprehension, action generation, state-transition prediction, task-aware VQA, and outcome verification, placing emphasis on models’ ability to understand control panels, predict the effect of toggling switches, and verify whether the goal has been achieved.

In summary, existing benchmarks either emphasise physical-world embodiment (object states, scene generation) without semantic interface control, or focus on digital UI interaction without grounding in real-world device state and verification. SWITCH fills this gap by providing a comprehensive benchmark that systematically evaluates a model’s ability to perceive, manipulate and verify real-world UI-based interactions—a key capability for interactive and embodied multimodal intelligence.

## 3. Semantic World Interface Tasks

Despite significant progress in world modeling, embodied AI, and interactive agents, existing benchmarks typically focus on either purely digital interactions or physical interactions with objects/tools (*e.g.*, PhysToolBench [27]). They largely overlook the critical domain of physical TCI interactions. Human environments are fundamentally shaped by physical tangible interfaces beyond basic tool affordances. These systems encode human intent into switches, buttons, displays, and smart appliances that control and regulate the spaces we live and work in. For AI to transition from passive perception toward truly embodied assistance, it must gain the ability to interpret and operate these widespread

<sup>2</sup><https://github.com/BAAI-Agents/SWITCH>.

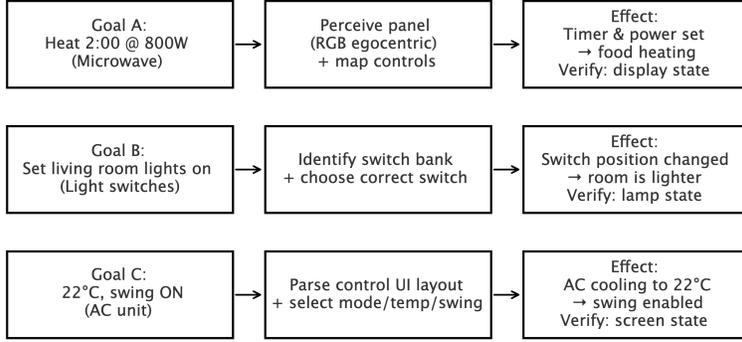


Figure 2. Example tasks modeled in SWITCH. Device Instruction (Goal) - Interface Understanding & Action - Effect / Verification.



Figure 3. Example of a one-step task. The agent interprets the user ask and identifies related TCI elements (timer, power), generates corresponding actions (only a timer change is needed). The state transition occurs as the switch settings change. Since the agent is close to the device during operation, result verification planning involves moving back to capture the full view of the microwave for reliable result verification and waiting.

designed affordances. Mastering “physical UI” interactions therefore represents a crucial milestone in realizing AI agents that can meaningfully collaborate with humans in the real world. Semantic understanding of capabilities, grounding of the interface itself and action planning and control, effect causality (including possible safety issues), and verification of results, all present challenges. See Figure 2 for examples of challenges covered in the benchmark.

To address this gap, the SWITCH benchmark provides a unified, task-driven framework to systematically evaluate models’ ability to perceive, reason about, and interact with such complex, dynamic real-world environments involving interactive TCIs. By bridging the gap between virtual, physical, and control-centric interactions, this benchmark enables a more comprehensive assessment of models’ embodied intelligence and world modeling capabilities. We introduce the design principles behind the benchmark in Section 3.1. Next, we provide detailed descriptions of the data curation process in Section 3.2.

### 3.1. Benchmark Design

In modern human environments, a wide variety of smart devices—from household appliances to office equipment—are increasingly ubiquitous. Among the simplest and most universal mechanisms for interacting with these devices are switches and control interfaces, which serve as the primary means by which humans manipulate their states and outcomes. To build models that can operate effectively

in such environments, it is essential for them to understand how switches function, including the actionable regions for interaction, the appropriate modes of interaction, and the causal consequences of triggering these controls. Furthermore, models should be capable of predicting potential outcomes of physical switch activations across diverse devices and contexts, as well as verifying whether the intended effect has been successfully achieved, potentially using additional tools or observation mechanisms. By designing tasks around these principles, our benchmark ensures that models are evaluated on practical, generalizable interactive skills that reflect real-world challenges.

To illustrate the breadth and depth of our evaluation framework, we present two canonical examples. Figure 3 breaks down a simple, single-step task (heating food) into the fundamental stages of our benchmark: from semantic comprehension and action generation to state transition and result verification. Figure 4 then demonstrates how these stages are composed to address a complex, multi-step task (printing a document), which requires sequential reasoning, adaptation to dynamic UI changes, and the completion of a full perception-action-verification loop. These scenarios are enabled by our five core tasks, which we define as follows:

**1/ Task-Aware Visual Question Answering (VQA):** Most VQA datasets focus on static images or generic reasoning, often ignoring task relevance, user intent, and interaction context. In contrast, our benchmark defines a task-aware VQA setting composed of two complementary sub-



Figure 4. Example of a multi-step document printing task demonstrating complex interaction reasoning. Given the a user instruction, the agent must perform sequential Semantic UI Comprehension to interpret changing interface layouts, and execute corresponding Action Generation steps (A1–A4). Throughout the process, the model observes state transitions as the UI updates after each interaction, requiring adaptive planning based on visual context. Finally, through Result Verification Planning, the agent repositions to check the printed output, completing the full perception–action–verification loop in a dynamic, real-world setting.



Figure 5. Examples of two action categories. Left: UI Action. Right: Procedural Action.

tasks: **(a) UI State Recognition:** assessing whether the model can recognize and describe the current state of TCI elements within the scene; and **(b) Goal-Oriented Reasoning:** testing whether the model can interpret the purpose and outcome of actions observed in dynamic video sequences, reasoning about whether these interactions successfully achieve the intended task goals. Together, these sub-tasks measure a model’s ability to ground semantics in visual context, comprehend high-level task objectives, and reason about the operational consistency between actions and outcomes.

**2/ Semantic UI Comprehension:** Existing visual recognition and interactive datasets focus on object detection or purely digital virtual elements, largely ignoring TCI components and their functional roles. However, in real-world human-computer and human-robot interactions, understanding interactive UI elements and their spatial-functional relationships is essential. This task tests whether a model can accurately localize and interpret actionable TCI elements in cluttered or dynamic settings, reasoning about their spatial and functional relationships while inferring human intent.

**3/ Action Generation:** Previous action prediction datasets typically emphasize isolated motion sequences or simulations, lacking the need to comprehend TCI functions and layouts, user goals, or environmental context. In realistic interactive scenarios, models must integrate these elements to select meaningful actions. This task evaluates a model’s ability to infer intent and plan executable, context-aware action sequences that achieve user objectives. **(a) UI Action Identification:** Detect the relevant interaction region, recognize its affordances, and predict the appropriate mode of interaction; **(b) Action Execution Planning:** Generate the necessary physical actions to perform the intended TCI operation, such as moving toward the interface or manipulating its components.

**4/ State Transition Prediction:** Previous state prediction benchmarks often assume deterministic, object-centric transitions, overlooking the diverse causal effects of TCI controls and their dependency on environmental context. This task focuses on predicting the immediate consequences of an executed action—capturing how TCI states, physical surroundings, and observable views change in response. It evaluates a model’s capacity for causal reason-

Categories	Devices
Environment Controls	Light Switch
	Air Conditioner Panel
	Air Purifier
	Fan
	Humidifier
Office Equipments	Printer
	Adjustable Standing Desk
	Robot Lifter
	PC Power Switch
	Power Strip Switch
	Water Dispenser
Kitchen & Home Appliances	Microwave
	Washing Machine
	Kitchen Hood
	Kettle
	Air Fryer
	Stove
	Electric Cooker
	Coffee Machines
Building Infrastructure	Elevator

Table 1. Categories and devices / appliances types covered in the collected data for SWITCH-Basic.

ing, short-term prediction, and fine-grained understanding of action–state dynamics in interactive environments. **(a) UI-State Transition:** Predict changes in the visual or functional state of TCI elements after an action (*e.g.*, switch toggled, button activated). **(b) Environment-State Transition:** Predict corresponding updates in the surrounding physical or visual environment (*e.g.*, lights turning on, revealing a new scene or perspective). **(c) Coupled Transition:** Reason about interdependent updates where TCI and environment states jointly change as part of the same causal event (*e.g.*, pressing a control panel triggers a screen update and changes ambient light level).

**5/ Result Verification:** Existing benchmarks rarely assess post-hoc verification or causal reasoning in interactive contexts. However, verifying whether an intended action has successfully achieved its goal is essential for reliable real-world deployment—especially when diverse UI controls and device responses introduce uncertainty. **(a) Verification Planning:** Test whether the model can infer what actions or checks are required to verify the outcome of a previous operation, such as observing key indicators, querying system feedback, or performing follow-up interactions. **(b) Expected State Prediction:** Assess whether the model can predict what the expected state should look like after a successful interaction, providing a causal grounding for evaluating success or failure.

Categories	Statistics	Number
Collected Data	Video Samples	193
	High-level Actions	193
	Fine-grained Actions	508
	- UI Action	350
	- Procedural Action	81
Annotated Data	- Verification	77
	Overall States	772
	- UI-State Transition	509
	- Environment-State Transition	263
	Unique Pairs	1,782
Processed Questions	- 1/ Task-Aware VQA	699
	- 2/ Semantic UI Comprehension	288
	- 3/ Action Generation	351
	- 4/ State Transition Prediction	373
	- 5/ Result Verification	71

Table 2. Detailed statistics of the SWITCH-Basic Benchmark, with overall video duration of 74m12s.

### 3.2. Data Curation

The data curation process is organized into three key parts: Video Collection, Data Annotation, and Question Processing, ensuring a structured and systematic approach. Detailed statistics for the curated dataset can be found in Table 2.

**1/ Video Collection** To build a comprehensive dataset, we designed a collection methodology focused on capturing rich and diverse human interactions with physical user interfaces in realistic settings. The process spanned a wide array of common living and working environments, including devices from four main categories: (1) environmental controls (*e.g.*, light switches), (2) office equipment (*e.g.*, printers), (3) kitchen and home appliances (*e.g.*, coffee machines), and (4) building infrastructure (*e.g.*, elevator). A detailed list of the specific scenarios can be found in Table 1.

Beyond ensuring fundamental video quality (clarity, stability, and a first-person perspective), the key principle of our methodology was the capture of complete, task-oriented interaction sequences over isolated, atomic actions. This approach ensures our data reflects the full spectrum of user behavior, which includes not only direct manipulations, but also crucial reasoning steps. Specifically, we recorded:

- **UI Action:** Direct TCI element interactions like pressing, swiping, or rotating elements. A UI action example ("Press the *Down* button", when calling the elevator) is shown on the left side of Figure 5.
- **Procedural Action:** Behaviors and camera view changes when a user is uncertain of action outcome, such as moving closer for inspection, visually scanning the interface, or pausing to wait for system feedback. An procedural action example ("Move away from the elevator", to see which one arrives) can be seen in the right side of Fig-

Models	1/ Task-Aware VQA	2/ UI Compr.	3/ Action	4/ State Transition Prediction		5/ Verification		
	(a) UI State Recognition					(a) Planning	(b) Expected State Prediction	
Question Format	IT	IT	IT	IT	II	IT	IT	II
Claude Sonnet 4 [2]	51.78	45.49	<b>34.19</b>	71.31	<b>63.54</b>	81.48	79.55	<b>50.00</b>
Gemini 2.5 Flash [5]	54.15	58.33	32.19	72.12	45.04	74.07	<b>81.82</b>	34.09
Qwen3-VL-235B-Instruct [24]	<b>59.68</b>	<b>68.40</b>	33.90	<b>72.65</b>	37.27	<b>85.19</b>	<b>81.82</b>	40.91

Table 3. Accuracy (%) results on SWITCH-Basic for different baselines, using image in questions and text or image answers. IT: image in question, text choices as answers, and II: image in question, image choices as answers.

Models	1/ Task-Aware VQA	3/ Action			4/ State Transition Prediction		5/ Verification				
	(b) Goal-Oriented Reasoning						(a) Planning		(b) Expected State Prediction		
Question Format	VT	VT	IV	VV	VT	VI	VT	IV	VV	VT	VI
Gemini 2.5 Flash [5]	59.07	<b>31.91</b>	24.79	23.93	68.36	41.42	85.19	48.15	<b>51.85</b>	68.18	47.73
Qwen3-VL-235B-Instruct [24]	<b>60.10</b>	31.62	<b>29.34</b>	<b>24.22</b>	<b>73.99</b>	<b>75.54</b>	<b>88.89</b>	<b>51.85</b>	11.11	<b>79.55</b>	<b>61.36</b>

Table 4. Accuracy (%) results on SWITCH-Basic for different baselines using video in either questions or answers. VT: video in question, text choices as answers, IV: image in question, video choices as answers, VV: video in question, video choices as answers, and VI: video in question, image choices as answers. Failure to return a response was counted as an incorrect prediction.

ure 5.

To guarantee the diversity of interaction styles and minimum quality of collection, we utilized a team of 10 pre-trained data collectors. Their work produced a final (post-filtering) corpus of 193 high-quality video sequences, covering 508 fine-grained actions, forming the foundation of the SWITCH benchmark.

We have also surveyed for related reusable datasets. Unfortunately, only two such datasets (COIN [21] and HP-EPIC [15]) included possibly reusable videos covering TCI scenarios. Even those still presented issues and would require additional filtering and pre-processing for use in SWITCH. In the COIN dataset, angles change too frequently (often cutting procedural actions), speed varies during videos, and many videos include textual instructions across video frames. In HP-EPIC, which focuses on kitchen tasks, multiple cases including appliances suffer from strong occlusion and all potential videos after filtering would still require segmentation by TCI-related action. Thus, in this iteration of the benchmark, we utilize only newly collected videos.

**2/ Data Annotation** Inspired by Ego4D’s goal-step [18], our annotation process captures the fine-grained causal relationship between an agent’s actions and resulting changes in the world state. To achieve this, we model each interaction as a sequence of (pre-condition state, action, post-condition state) tuples, which explicitly links every action to its immediate outcome.

**(a) State Annotation:** We provide a detailed description for each state, capturing both the **UI-State Transition** (e.g., indicator lights, on-screen text, panel settings) and the **Environment-State Transition** (e.g., brightness, or an open door). Crucially, we also annotate the evidential source for each state component, specifying how a human

infers the state (e.g., from visual cues on the UI or observations of the physical world).

**(b) Action Annotation:** Our hierarchical action annotation first distinguishes actions by their primary intent. They are categorized as either Task-Execution Actions or a distinct Verification category. Task-Execution Actions are the primary operations performed to make progress on the task. These are further subdivided into the two categories mentioned previously: **UI Actions** and **Procedural Actions** (examples of both types are shown in Figure 5). To account for real-world complexities, we further annotate actions for attributes such as error occurrence, corrective measures, and whether an action is optional for the task. Verification Actions are those aimed specifically at confirming a system’s status or the outcome of a prior action.

**3/ Question Processing** We then transformed our rich annotations into a structured question-answer (QA) benchmark encompassing the five previously mentioned tasks. For standardized and automated evaluation, we uniformly adopted a MCQ format. Each question consists of one correct answer, derived from our annotations, and several plausible distractors, randomly generated from available similar annotated cases.

Furthermore, to push models to perform genuine reasoning rather than relying on superficial environmental cues, we implemented a ground-truth substitution strategy, inspired by methodologies from the WorldPrediction benchmark [3]. For specific Tasks (3, 4, and 5), we alter the visual context of ground-truth by using sentence similarity.

Additionally, for Tasks 3, 4, and 5, we designed questions that present context in diverse formats, including text, images, videos, and more complex combinations of images and videos. Finally, following all automated processing, the entire dataset was manually reviewed to ensure its final

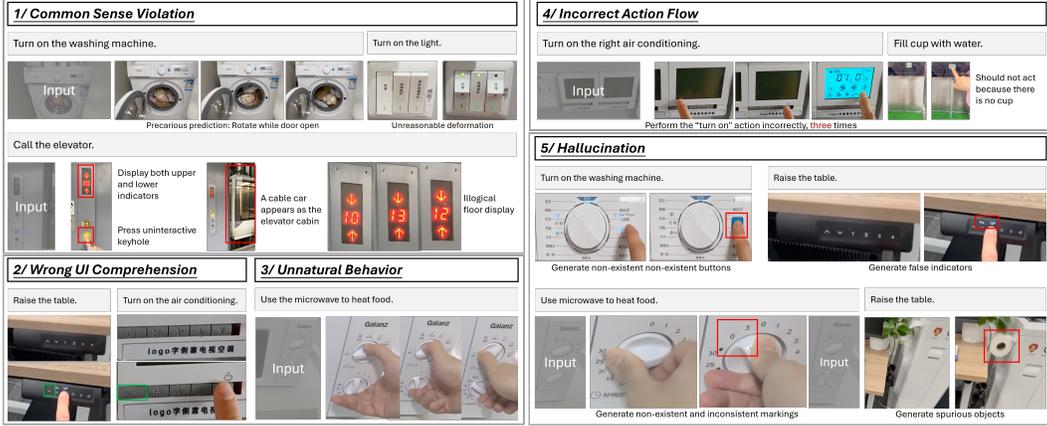


Figure 6. Case studies of representative errors in video generation. Examples using Veo3. Cropped image frames to focus on issues.

quality and correctness.

## 4. Experiment Results

To validate the utility of our benchmark and systematically assess the capabilities of existing LMMs, we conduct an evaluation of open and closed models on SWITCH. Our primary goal is to provide a detailed analysis of existing LMMs, shedding light on their strengths and limitations in tasks requiring interactive intelligence. Beyond this, we also conduct some experiments with a leading video generation model to probe its world modeling ability.

### 4.1. Experimental Setup

**Models Evaluated:** We selected a representative set of state-of-the-art LMMs, categorized into two groups:

- General-purpose proprietary models: These are leading closed-source models known for their powerful general reasoning abilities. We evaluated **Claude Sonnet 4** [2] and **Gemini 2.5 Flash** [5]. Claude Sonnet 4 accepts text and static images as input, while Gemini 2.5 Flash accepts video inputs in addition to text and images.
- General-purpose open models: To represent the frontier of publicly available research, we evaluated **Qwen3-VL-235B-Instruct** [24]. A key advantage of this model is its native support for text, image, and video inputs, which makes it well-suited for the full range of tasks in SWITCH.

**Evaluation Protocol:** Each model was evaluated on all tasks compatible with its input modalities. Consequently, Claude Sonnet 4 was benchmarked on image-based tasks, while Gemini 2.5 Flash and Qwen3-VL were evaluated across the full suite of tasks, including those with video. For each question, we provided the model with the multi-modal context (text, image, and/or video) and the multiple-choice questions in a zero-shot setting. The model’s task was to select the correct answer from the provided options.

Illustrative examples of our question-answer pairs and their prompts are provided in Figure 1.

**Implementation Details:** We use accuracy as the primary evaluation metric and we evaluate each baseline official implementation or API. All evaluation scripts and annotations are to be publicly released for transparency.

### 4.2. Observations and Challenges

The overall performance results of the evaluated models across tasks are summarized in Tables 3 and 4<sup>3</sup>. Analysis of these results and case studies reveals the following key observations<sup>4</sup>:

**1/ Fine-Grained Visual Perception Dependencies as a Bottleneck in Action Generation:** As shown in Table 3, there is a notable performance gap between Task 3 (Action Generation) and other tasks. Compared with other tasks, Action Generation has a greater dependency on perceiving fine-grained visual details to accurately determine the device’s current state before predicting next steps. In contrast, tasks as Verification or State Transition Prediction tend to provide more textual hints in the prompt itself, potentially allowing the model to reason about outcomes with less reliance on subtle visual information. Case studies further illustrate this finding: In failure case example (a) (Figure 7 in Appendix), Gemini fails to recognize that "where to print from" had not been selected. In example (b) (Figure 8), Claude incorrectly chooses to select mode rather than starting the machine due to a misunderstanding that a mode was already selected.

**2/ Limited Generalization from Abstract UI Semantics to Diverse Visual Implementations:** For Task 2 (UI Comprehension), the results show that while models possess a general "common sense" about UI conventions, they

<sup>3</sup>Due to their more limited number of cases, the results of Task 5 Verification may be less representative than others.

<sup>4</sup>Detailed examples can be found in Appendix A.2.

struggle to apply this knowledge correctly to the diverse and customized layouts of real-world interfaces (as seen in Example (c) and (d) in Figure 9, 10). In Example (c), Claude correctly infers the need to read the file from the USB flash disk. However, it fails to identify the correct icon among the options presented on that specific printer’s interface. In Example (d), Gemini is not able to distinguish between the "power on" and the "start" buttons on a washing machine. This gap leads to errors in identifying the correct interactive elements.

**3/ Coarse-Grained Recognition Inadequate for Precise Grounded Physical Interaction:** For most tasks, it was observed that while models may understand the high-level goal, they often lack the fine-grained procedural knowledge of how the action physically manifests or what the immediate feedback on a specific UI will be. For instance, in Examples (e) and (f) (Figure 11, 12), the model fails to identify that only the upper part of the switch is functional or to predict the precise outcome of lowering the temperature on an air conditioner.

**4/ Performance Degradation from the Burden of Abstraction:** An interesting trend in the results is that adding additional visual context (*e.g.*, images or videos) can lead to performance degradation in certain tasks, such as (Task 4 (State Transition Prediction), where Qwen’s performance drops from 72.65% (IT) to 37.27% (II) (Table 3), and Task 3 (Action Generation), where Gemini’s performance drops from 32.19% (IT in Table 3) to 25.78% (IV) and 24.85% (VV) (Table 4).

This phenomenon may be attributed to the abstraction burden required to process raw visual data—a step bypassed when using text-based inputs. Unlike text, which provides pre-summarized information, models must independently extract key cues from dense and often noisy visual scenes. This challenge is further amplified by our experimental design, which changes the origin image/video in correct options, requiring models to perform true abstraction rather than relying on scene matching. For instance, in Example (g) (Figure 14), a text option might explicitly state, "the elevator has arrived" (*e.g.*, Option C in Figure 13), but Qwen fails to infer this information from the corresponding image option.

### 4.3. Probing World Modeling in Generative Models

To push beyond discriminative QA and its limitations, and to directly probe the internal world models [1, 9, 17] of generative systems, we conducted further experiments using Google’s Veo3 [10], a state-of-the-art video generation model. We tested its ability to simulate physical-temporal TCI-related dynamics in two settings:

- **State Transition Prediction:** Analogous to Task 4, the model is provided with an initial frame and a textual description of an action, tasking it to generate the subse-

quent frames depicting the outcome. For instance, in the top-left example in Figure 6, when given an image of a washing machine and the instruction "Turn on the washing machine", Veo3 generates a coherent sequence of future frames.

- **Action Generation:** Analogous to Task 3, the model is given the initial and final frames of the state change with a high-level action description. The task is to generate the intermediate video showing the specific action that connects them. As an example, for the microwave shown in the bottom-right corner of Figure 6, the model receives the first and last frames along with the action "Use microwave to heat food" and is expected to generate the intermediate frames.

Analysis of the generated results reveals several fundamental error patterns, indicating limitations in the model’s physical and causal understanding (see Figure 6 for examples):

- **1/ Common Sense Violation:** A frequent failure mode is the model’s inability to maintain physical realism and logical consistency, leading to the generation of implausible and nonsensical scenarios. As shown in the top-left of Figure 6, these violations can be categorized as follows:
  - (1) Violations of Physical Constraints:** The model disregards fundamental real-world principles. For example, it generates a video of a washing machine’s drum rotating while the door is wide open—a clear breach of physical safety interlocks.
  - (2) Violations of Physical Inconsistency:** The model fails to maintain the physical consistency of objects. In the light switch example, it generates an "Unreasonable deformation" of the solid switch panel.
  - (3) Violations of Functional Logic:** The model produces functional impossible outcomes. The elevator case exhibits multiple such failures: illuminating both the up and down indicators simultaneously, generating a nonsensical scene where a cable car appears inside the elevator cabin, and displaying floor numbers in a non-sequential illogical order.
- **2/ Incorrect UI Comprehension:** The model fails to correctly interact with the appropriate UI elements. This includes attempting to raise a table or turn on an air conditioner by pressing an incorrect area on the respective control panels (shown in the bottom-left cases of Figure 6).
- **3/ Unnatural Behavior:** The model performs actions in a manner that is inefficient, or unlike how a human would. The bottom-left example of "3/ Unnatural Behavior" in Figure 6 shows the use of a microwave by trying to rotate the two knobs at the same time with one hand.
- **4/ Incorrect Action Flow:** The model executes a logically incoherent sequence of actions or violates necessary preconditions, such as performing the "Turn on" action for an air conditioner incorrectly *three* times or dispensing water from a machine with no cup present (even if

explicitly mentioned in the instruction) in the top-right cases of Figure 6.

- **5/ Hallucination:** The model exhibits a tendency to fabricate visual content that does not exist in the input and contradicts physical reality. As shown in the bottom-right cases of Figure 6, these hallucinations can be categorized as follows: **(1) Fabrication of UI Elements:** Generating non-existent markings or indicators. For example, it generates inconsistent and non-existent markings on a washing machine’s dial, creates a false indicator "up" on a standing desk’s control panel, and adds phantom numbers to a microwave’s timer knob (which are also inconsistent). **(2) Generation of Spurious Objects:** Introducing contextually irrelevant objects into the scene. A clear example is the generation of a roll of toilet paper attached to an office air purifier when the task prompt was to "Raise the table", or transforming an air-purifier into a printer as the camera view pans.

## 5. Conclusion

In this work, we introduce SWITCH, a benchmark effort designed to evaluate how large multimodal models perceive, reason about, and act upon semantic TCI user interfaces in real-world contexts. Unlike prior datasets and benchmarks that focus either on fully virtual simulations or object-centric physical interactions only, SWITCH targets a critical but overlooked scenario in embodied AI — the interactive layer between humans and smart environments and their appliances/devices, mediated through TCIs (*i.e.*, switches, buttons, and control panels).

Through five systematically designed tasks, SWITCH examines complementary dimensions of interactive intelligence — from perceiving UI semantics and generating purposeful actions, to predicting causal state transitions and verifying task outcomes. Our evaluation across mainstream LMMs reveals consistent weaknesses in understanding affordances, anticipating environmental effects, and verifying causal consequences, highlighting key challenges toward achieving well grounded world models.

By open-sourcing both the benchmark’s initial iteration (SWITCH-Basic) and the evaluation toolkit, we aim to provide the community with a standardized and extensible platform for studying perception-action reasoning in multimodal agents, on which to build upon. We believe SWITCH serves as a step toward bridging digital and embodied intelligence, advancing models that not only see and describe the world, but can also understand, control, and verify their interactions within it effectively and autonomously. We invite community feedback and collaboration, which will be incorporated on each upcoming iteration of the benchmark, covering more in-depth and challenging settings.

## 6. Future Steps

The current release of SWITCH represents only the first phase of our benchmark. In the upcoming stages, we plan to expand both the scale and diversity of the dataset. Specifically, we aim to increase the coverage of TCI-centric environments by incorporating a broader range of device interaction scenarios, as well as multiple variants of similar devices with distinct layouts, control mechanisms, and capabilities.

Crucially, we will also include evaluation beyond the current discriminative QA format, enhance the evaluation dimensions of existing tasks, and propose metrics to more precisely evaluate models’ world modeling and ground abilities. In Task-Oriented Visual Question Answering, for example, future extensions will assess models’ ability to perform context-aware inference — evaluating whether models can infer (TCI and world) states from indirect environmental cues when the interface itself is partially occluded or not directly visible.

As the collected dataset grows, we intend to partition it into training, validation, and test splits, enabling the community to use SWITCH not only for evaluation but also for training or adaptation of novel models.

Moreover, since many real-world interactions require multi-step operations before their outcome can be verified, the current benchmark data includes fewer Result Verification samples compared to other tasks. As we expand it, the number and diversity of verification examples should increase accordingly, allowing more comprehensive assessment of models’ ability to reason about important delayed or multi-stage effects.

A focus point for next iterations is also to cover cases of adapting to incorrect actions and adapting to retry. SWITCH-Basic currently only covers 5 instances of situations where an interaction needs to be canceled or restarted.

Finally, we will introduce multi-level difficulty settings across tasks, designed to more comprehensively evaluate models’ reasoning depth, generalization, and adaptability. We envision SWITCH evolving into a collaborative progressively richer and more diagnostic-oriented benchmark for studying the foundations of interactive and embodied intelligence in multimodal models.

## References

- [1] Arslan Ali, Junjie Bai, Maciej Bala, Yogesh Balaji, Aaron Blakeman, Tiffany Cai, Jiaxin Cao, Tianshi Cao, Elizabeth Cha, Yu-Wei Chao, et al. World simulation with video foundation models for physical ai. *arXiv preprint arXiv:2511.00062*, 2025. 9
- [2] Anthropic. Introducing Claude4, 2025. 7, 8
- [3] Delong Chen, Willy Chung, Yejin Bang, Ziwei Ji, and Pascale Fung. Worldprediction: A benchmark for

- high-level world modeling and long-horizon procedural planning. *arXiv preprint arXiv:2506.04363*, 2025. 1, 3, 7
- [4] Wei Chow, Jiageng Mao, Boyi Li, Daniel Seita, Victor Guizilini, and Yue Wang. Physbench: Benchmarking and enhancing vision-language models for physical world understanding. *arXiv preprint arXiv:2501.16411*, 2025. 1, 3
- [5] Gheorghe Comanici, Eric Bieber, Mike Schaeckermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, et al. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities. *arXiv preprint arXiv:2507.06261*, 2025. 7, 8, 13
- [6] Mengfei Du, Binhao Wu, Zejun Li, Xuan-Jing Huang, and Zhongyu Wei. Embspatial-bench: Benchmarking spatial understanding for embodied tasks with large vision-language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 346–355, 2024. 3
- [7] Haoyi Duan, Hong-Xing Yu, Sirui Chen, Li Fei-Fei, and Jiajun Wu. Worldscore: A unified evaluation benchmark for world generation. *arXiv preprint arXiv:2504.00983*, 2025. 3
- [8] Aaron Foss, Chloe Evans, Sasha Mitts, Koustuv Sinha, Ammar Rizvi, and Justine T. Kao. CausalVQA: A physically grounded causal reasoning benchmark for video models. *arXiv preprint arXiv:2506.09943*, 2025. 1
- [9] Pascale Fung, Yoram Bachrach, Asli Celikyilmaz, Kamalika Chaudhuri, Delong Chen, Willy Chung, Emmanuel Dupoux, Hongyu Gong, Hervé Jégou, Alessandro Lazaric, et al. Embodied ai agents: Modeling the world. *arXiv preprint arXiv:2506.22355*, 2025. 9
- [10] Google. Veo: a text-to-video generation system, 2025. 2, 9
- [11] Hiroshi Ishii and Brygg Ullmer. Tangible bits: Towards seamless interfaces between people, bits and atoms. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI'97)*. ACM, 1997. 1
- [12] Chengshu Li, Ruohan Zhang, Josiah Wong, Cem Gokmen, Sanjana Srivastava, Roberto Martín-Martín, Chen Wang, Gabrael Levine, Michael Lingelbach, Jiankai Sun, et al. Behavior-1k: A benchmark for embodied ai with 1,000 everyday activities and realistic simulation. In *Conference on Robot Learning*, pages 80–93. PMLR, 2023. 3
- [13] Dacheng Li, Yunhao Fang, Yukang Chen, Shuo Yang, Shiyi Cao, Justin Wong, Michael Luo, Xiaolong Wang, Hongxu Yin, Joseph E Gonzalez, et al. World-modelbench: Judging video generation models as world models. *arXiv preprint arXiv:2502.20694*, 2025. 3
- [14] Xiao Liu, Tianjie Zhang, Yu Gu, Iat Long Iong, Yifan Xu, Xixuan Song, Shudan Zhang, Hanyu Lai, Xinyi Liu, Hanlin Zhao, et al. Visualagentbench: Towards large multimodal models as visual foundation agents. *arXiv preprint arXiv:2408.06327*, 2024. 3
- [15] Toby Perrett, Ahmad Darkhalil, Saptarshi Sinha, Omar Emara, Sam Pollard, Kranti Kumar Parida, Kaiting Liu, Prajwal Gatti, Siddhant Bansal, Kevin Flanagan, et al. Hd-epic: A highly-detailed egocentric video dataset. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 23901–23913, 2025. 7
- [16] Christopher Rawles, Sarah Clinckemaiellie, Yifan Chang, Jonathan Waltz, Gabrielle Lau, Marybeth Fair, Alice Li, William Bishop, Wei Li, Folawiyi Campbell-Ajala, et al. Androidworld: A dynamic benchmarking environment for autonomous agents. *arXiv preprint arXiv:2405.14573*, 2024. 3
- [17] Luke Rivard, Sun Sun, Hongyu Guo, Wenhui Chen, and Yuntian Deng. Neuralos: Towards simulating operating systems via neural generative models. *arXiv preprint arXiv:2507.08800*, 2025. 9
- [18] Yale Song, Eugene Byrne, Tushar Nagarajan, Huiyu Wang, Miguel Martin, and Lorenzo Torresani. Ego4d goal-step: Toward hierarchical understanding of procedural activities. *Advances in Neural Information Processing Systems*, 36:38863–38886, 2023. 7
- [19] Keith Stouffer, Michael Pease, CheeYee Tang, Timothy Zimmerman, Victoria Pillitteri, Suzanne Lightman, Adam Hahn, Stephanie Saravia, Aslam Sherule, and Michael Thompson. Guide to Operational Technology (OT) Security. Technical Report NIST Special Publication (SP) 800-82, Rev. 3, National Institute of Standards and Technology, 2023. 1
- [20] Weihao Tan, Wentao Zhang, Xinrun Xu, Haochong Xia, Gang Ding, Boyu Li, Bohan Zhou, Junpeng Yue, Jiechuan Jiang, Yewen Li, Ruyi An, Molei Qin, Chuqiao Zong, Longtao Zheng, Yujie Wu, Xiaoqiang Chai, Yifei Bi, Tianbao Xie, Pengjie Gu, Xiyun Li, Ceyao Zhang, Long Tian, Chaojie Wang, Xinrun Wang, Börje F. Karlsson, Bo An, Shuicheng Yan, and Zongqing Lu. Cradle: Empowering foundation agents towards general computer control. In *Forty-second International Conference on Machine Learning, ICML 2025*, 2025. 3
- [21] Yansong Tang, Dajun Ding, Yongming Rao, Yu Zheng, Danyang Zhang, Lili Zhao, Jiwen Lu, and Jie Zhou. Coin: A large-scale dataset for comprehensive instructional video analysis. In *Proceedings of the*

*IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1207–1216, 2019. 7

- [22] Tianbao Xie, Danyang Zhang, Jixuan Chen, Xiaochuan Li, Siheng Zhao, Ruisheng Cao, Toh J Hua, Zhoujun Cheng, Dongchan Shin, Fangyu Lei, et al. Osworld: Benchmarking multimodal agents for open-ended tasks in real computer environments. *Advances in Neural Information Processing Systems*, 37:52040–52094, 2024. 3
- [23] Xinrun Xu, Pi Bu, Ye Wang, Börje F. Karlsson, Ziming Wang, Tengtao Song, Qi Zhu, Jun Song, Zhiming Ding, and Bo Zheng. Deepphy: Benchmarking agentic vlms on physical reasoning. *arXiv preprint arXiv:2508.05405*, 2025. 3
- [24] An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chujie Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, Huan Lin, Jialong Tang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiayi Yang, Jing Zhou, Jingren Zhou, Junyang Lin, Kai Dang, Keqin Bao, Kexin Yang, Le Yu, Lianghao Deng, Mei Li, Mingfeng Xue, Mingze Li, Pei Zhang, Peng Wang, Qin Zhu, Rui Men, Ruize Gao, Shixuan Liu, Shuang Luo, Tianhao Li, Tianyi Tang, Wenbiao Yin, Xingzhang Ren, Xinyu Wang, Xinyu Zhang, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yinger Zhang, Yu Wan, Yuqiong Liu, Zekun Wang, Zeyu Cui, Zhenru Zhang, Zhipeng Zhou, and Zihan Qiu. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*, 2025. 7, 8, 13
- [25] Rui Yang, Hanyang Chen, Junyu Zhang, Mark Zhao, Cheng Qian, Kangrui Wang, Qineng Wang, Teja Venkat Koripella, Marziyeh Movahedi, Manling Li, et al. Embodiedbench: Comprehensive benchmarking multi-modal large language models for vision-driven embodied agents. *arXiv preprint arXiv:2502.09560*, 2025. 3
- [26] Shunyu Yao, Howard Chen, John Yang, and Karthik Narasimhan. Webshop: Towards scalable real-world web interaction with grounded language agents. *Advances in Neural Information Processing Systems*, 35: 20744–20757, 2022. 3
- [27] Zixin Zhang, Kanghao Chen, Xingwang Lin, Lutaotao Jiang, Xu Zheng, Yuanhuiyi Lyu, Litao Guo, Yinchuan Li, and Ying-Cong Chen. Phystoolbench: Benchmarking physical tool understanding for mllms. *arXiv preprint arXiv:2510.09507*, 2025. 3

## A. Appendix

### A.1. Successful Response Rates of Baselines with Videos

Table 5 presents the successful response rates (%) of various baseline models when evaluated on video-based questions. Each value indicates the percentage of questions for which the model was able to return a valid response. This table provides additional details on model robustness and response consistency in the video setting.

### A.2. Case Study Examples

Many of the following examples are referenced in the main text, and we include them here to provide additional context and visualization.

Models	1/ Task-Aware VQA			3/ Action			4/ State Transition Prediction		5/ Verification				
	(b) Goal-Oriented Reasoning			VT	IV	VV	VT	VI	(a) Planning			(b) Expected State Prediction	
	VT	IV	VV						VT	IV	VV	VT	VI
Question Format													
Gemini 2.5B Flash [5]	<b>100.00</b>	<b>100.00</b>	93.45	<b>96.01</b>	<b>99.73</b>		98.39		<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>
Qwen3-VL-235B-Instruct [24]	<b>100.00</b>		99.71	<b>96.01</b>	95.16	99.20	<b>99.73</b>		98.00	59.00	61.00	<b>100.00</b>	<b>100.00</b>

Table 5. Percentage of questions for which a valid response was successfully returned. VT: video in question, text choices as answers, IV: image in question, video choices as answers, VV: video in question, video choices as answers, and VI: video in question, image choices as answers.

Following the content of the image input, which of the four provided options correctly represents the next action in the flow of "print a file in the USB flash disk".

- A. Wait for the print.
- B. Select the file to print.
- C. Swipe to find the correct option.
- D. Select print from the USB flash disk.

Input Image:



Ground Truth:

D

Model Answer:

B

```

### Thinking Process
The user wants to know the next logical step after the action shown in the image. The image shows a finger pressing an option that says "Print from USB drive". This implies the user has already decided to print from a USB drive.

```

```

Let's analyze the options:

```

- A. Wait for the print: This would happen after selecting the file and confirming the print job, not immediately after selecting "Print from USB drive".
- B. Select the file to print: After choosing to print from a USB drive, the next logical step is to browse the files on the USB drive and select the one to print.
- C. Swipe to find the correct option: The user has already found and selected the "Print from USB drive" option, so swiping is not the next step.
- D. Select print from the USB flash disk: This action is "already happening" in the image. The finger is actively pressing this option.

```

Therefore, the most appropriate next action in the flow after selecting "Print from USB drive" is to select the specific file to be printed.

```

```

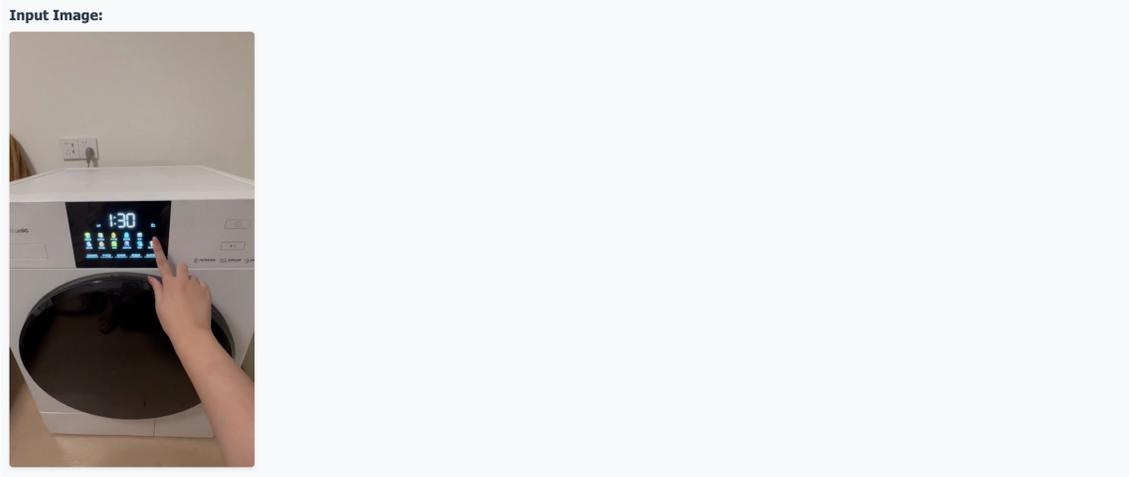
### Answer

```

B

Figure 7. Example (a): An example of Gemini 2.5 Flash on Task 3/ Action Generation in question format: Image in question, text as option. The model failed to recognize that "where to print from" has not been selected, thus giving the incorrect answer.

Following the content of the image input, which of the four provided options correctly represents the next action in the flow of "Select the correct drying mode".  
A. Press the mode button  
B. Wait until the washing machine start.  
C. Press the button to start.  
D. select mode



**Ground Truth:**  
C

**Model Answer:**  
A

```
### Thinking Process
The image shows a hand pressing a button on the control panel of a washing machine. The display shows "1:30", which likely indicates the remaining time or a selected program duration. The user is interacting with the touchscreen interface, which typically involves selecting a mode or program before starting the cycle.

Looking at the options:
- A. Press the mode button - This is plausible as the user is interacting with the control panel, and selecting a drying mode would involve pressing a mode button.
- B. Wait until the washing machine start - This is not relevant as the machine has not yet started, and the user is actively selecting settings.
- C. Press the button to start - This would be the next step after selecting the mode, but the current action is selection, not initiation.
- D. select mode - This is descriptive of what is happening, but it's more of a description than an action. The action being performed is pressing a button.

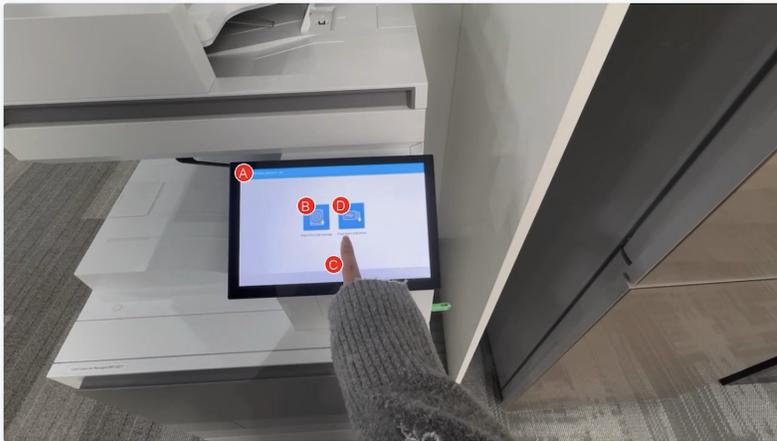
Given that the user is pressing a button on the control panel, the most accurate description of the next action in the flow of "Select the correct drying mode" is "Press the mode button". This implies selecting a specific drying mode by pressing the corresponding button.

### Answer
A
```

Figure 8. Example (b): An example of Claude Sonnet 4 on Task 3/ Action Generation in question format: Image in question, text as option. The model incorrectly chooses to select mode rather than starting the machine due to misunderstanding the mode not already been selected.

Which of the marked points in the image can be interacted with to select to print a file from the USB flash disk? Choose only one option.

**Input Image:**



**Ground Truth:**

D

**Model Answer:**

B

### Thinking Process  
Looking at this printer touchscreen interface, I can see several marked areas. The user is pointing at the screen and asking about selecting files from a USB flash disk for printing.

- Point A appears to be on a blue bar at the top, which looks like a status or progress bar rather than an interactive element for file selection
- Points B and D are both on blue rectangular icons that appear to be folder or storage device representations
- Point C is pointing to an area below the icons

For printing from a USB flash disk on a printer interface, you would typically interact with folder or storage device icons that represent external storage. These blue rectangular icons (B and D) are the most likely candidates for accessing files from a connected USB device, as they appear to be storage/folder representations on the printer's file browser interface.

Between the two similar-looking icons, both could potentially provide access to USB files, but based on typical printer interface layouts, these types of storage icons are the logical interaction points for file selection.

### Answer

B

Figure 9. Example (c): An example of Claude Sonnet 4 on Task 2/ UI Comprehension in question format: Image in question, text as option. The model correctly inferred that it needs to read file from USB flash, but fails to identify the correct icon for it.

Which of the marked points in the image can be interacted with to press the button to turn on the washing machine? Choose only one option.

Input Image:



Ground Truth:

D

Model Answer:

C

### Thinking Process

Looking at this washing machine control panel, I need to identify which marked point corresponds to the power/on button. On most washing machines, the power button is typically located on the right side of the control panel and is often one of the more prominent buttons.

Examining the four marked points:

- Point A appears to be on the left side near cycle selection options
- Point B is in the center-left area of the panel
- Point C is positioned on the right side of the control panel where power buttons are commonly located
- Point D is on the far right

Based on typical washing machine design conventions, the power button is usually positioned on the right side of the control panel for easy access, and point C appears to be in this optimal location.

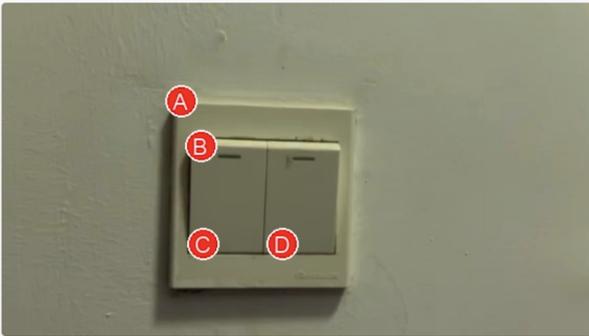
### Answer

C

Figure 10. Example (d): An example of Gemini 2.5 Flash on Task 2/ UI Comprehension in question format: Image in question, text as option. The model failed to distinguish the "power on" button and the "start" button on a washing machine.

Which of the marked points in the image can be interacted with to turn off the light in kitchen? Choose only one option.

Input Image:



Ground Truth:

B

Model Answer:

C

### Thinking Process

Looking at this image, I can see a double light switch mounted on the wall with four marked points (A, B, C, D). To turn off a light, I need to identify which point corresponds to an actual switch button that can be pressed.

- Point A appears to be on the wall above the switch plate
- Point B appears to be on the upper frame of the switch plate
- Point C appears to be positioned on the left switch button/rocker
- Point D appears to be positioned on the right switch button/rocker

Points A and B are on non-functional areas (wall and switch plate frame), while points C and D are on the actual switch buttons that can be pressed to control lights. Since this is a double switch setup, either C or D would be interactive elements that could control the kitchen light.

### Answer

C

Figure 11. Example (e): An example of Gemini 2.5 Flash on Task 2/ UI Grounding in question format: image in question, text as option. The model fails to identify that only the upper part of the light switch is functional, thus choosing an incorrect answer.

Following the content of the image input and the action "Lower down the set temperature of right panel.", which one of the four provided options will happen first?  
 A. The screen shows the remain time of washing. The pin code is set.  
 B. The fan is off.  
 C. elevator controller button is not activated  
 D. The set temperature of left panel is 22, the wind speed is low.

Input Image:



Ground Truth:

D

Model Answer:

B

```

### Thinking Process
Looking at the image, I can see two air conditioning control panels. The right panel shows:
- Current room temperature: 24°C
- Set temperature: 25°C
- Fan speed: High (高速)
- Mode: Cool (冷风)

The question asks what happens first when lowering the set temperature on the right panel.

Analyzing the options:
- Option A mentions washing time and pin codes, which are unrelated to air conditioning controls
- Option B mentions the fan turning off
- Option C is about elevator controls, which is unrelated
- Option D refers to the left panel, but we're adjusting the right panel

When lowering the set temperature on an air conditioning unit in cooling mode, if the new set temperature is at or near the current room temperature (24°C), the system may turn off the fan since the desired temperature would be reached. This would be the most immediate response from the system.

### Answer
B
  
```

Figure 12. Example (f): An example of Qwen3-VL-235B-Instruct on Task 4/ State Transition Prediction in question format: Image in question, text as option. The model fails to predict that the initial outcome of lowering the temperature on an air conditioner control is the change in the visible set temperature.

Following the content of the image input and the action "Call the elevator to go upstairs.", which one of the four provided options will happen first?  
 A. The selected floor is bright now.  
 B. The washing machine is working.  
 C. The elevator light is lit, the elevator has arrived  
 D. The fan is off now.

Input Image:



Ground Truth:

C

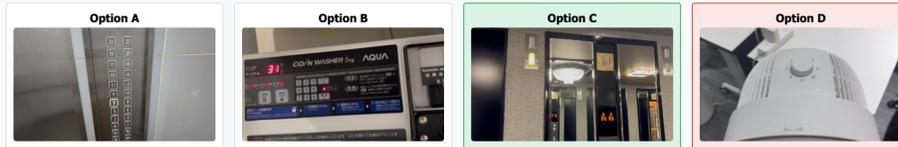
Figure 13. Example (g) in question format: Image in question, text as option. Text choices may provide reasoning shortcuts for models.

Answer the question based on the input image (current state) and the four image response options, marked as A/B/C/D. Following the content of the first image input and the action "Call the elevator to go upstairs.", which one of the four provided image options will happen first?

Input Image:



Option Images/Videos:



Ground Truth:

C

Model Answer:

D

### Thinking Process

The user's action is to "Call the elevator to go upstairs." The first image shows an elevator call button panel, which is the interface for initiating this action. After pressing the up arrow button (which is visible in the first image), the elevator will begin its journey upwards. The subsequent images show different scenes: an elevator interior with floor buttons (image 2), a coin washer (image 3), and an elevator at floor 30 (image 4), which would be the result of the elevator arriving. Image 5 shows a humidifier, which is unrelated to the action.

Therefore, after calling the elevator, the next logical step is for the elevator to move, which is depicted in image 2 (the floor selection panel inside the elevator) or image 4 (elevator at floor 30). However, since the user is calling the elevator to go upstairs, the immediate consequence is the elevator moving upwards, which would be shown by the elevator's internal display changing or the doors closing to start moving. Image 2 shows the floor buttons inside the elevator, which would be used after the elevator arrives at a floor, not immediately after being called. Image 4 shows the elevator at floor 30, which is the destination, but it's not the immediate next state after calling.

Actually, looking at the sequence again, image 2 shows the elevator's floor selection panel, which is typically seen when you are already inside the elevator. Image 4 shows the elevator at floor 30, which is the final destination after the call. But the question asks what happens "first" after calling the elevator. The most direct visual representation of the elevator responding to a call is seeing the elevator car moving, which might be inferred from the display showing the current floor (like 2 in image 1) and then the elevator starting to move. However, among the options, image 2 is the only one that directly relates to the elevator's operation (floor selection), while image 4 is the final state. Since we need the "first" thing that happens after calling, it's likely the elevator starts moving towards the requested floor. But none of the options explicitly show the elevator moving. Image 2 is the closest as it shows the interior controls, which would be used after entering. However, the action of calling the elevator should lead to the elevator moving, which isn't directly shown in any option. Given the choices, image 2 is the most relevant because it's the next step in using the elevator system after the initial call. But strictly speaking, after calling, the elevator should be seen moving, which isn't shown. Let me reconsider. Perhaps the first thing that happens after calling is seeing the elevator's internal display change or the doors close, but none of the options show that. Image 4 shows the elevator at floor 30, which is the destination, but that would happen after the call. So perhaps image 2 is the answer, as it's the most related to the elevator's operation. Or maybe none of them are correct, but we have to choose. Looking at the context, image 2 is the most logical choice as it represents the elevator's operational interface, which is the next step after calling.

Figure 14. Example (g): An example of Qwen3-VL-235B-Instruct on Task 4/ State Transition Prediction in question format: Image in question, images as option. The model fails to derive that "the elevator is arriving" from Option C, resulting in an incorrect answer.