

MENTISOCULI: Revealing the Limits of Reasoning with Mental Imagery

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Abstract

Frontier models are transitioning from *multimodal large language models* (MLLMs) that merely ingest visual information to *unified multimodal models* (UMMs) capable of native interleaved generation. This shift has sparked interest in using intermediate visualizations as a reasoning aid, akin to human *mental imagery*. Central to this idea is the ability to form, maintain, and manipulate visual representations in a goal-oriented manner. To evaluate and probe this capability, we develop MENTISOCULI, a procedural, stratified suite of multi-step reasoning problems amenable to visual solution, tuned to challenge frontier models. Evaluating visual strategies ranging from latent tokens to explicit generated imagery, we find they generally fail to improve performance. Analysis of UMMs specifically exposes a critical limitation: While they possess the textual reasoning capacity to solve a task and can sometimes generate correct visuals, they suffer from compounding generation errors and fail to leverage even ground-truth visualizations. Our findings suggest that despite their inherent appeal, *visual thoughts do not yet benefit model reasoning*. MENTISOCULI establishes the necessary foundation to analyze and close this gap across diverse model families.

1. Introduction

Words [...] do not seem to play any role in my mechanism of thought. The psychical entities which seem to serve as elements in thought are certain signs and more or less clear images which can be ‘voluntarily’ reproduced and combined.

— Albert Einstein (18)

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Vision–language models (VLMs) and even recent *multimodal large language models* (MLLMs) relegate vision to a passive, input-only modality. However, we are now witnessing a shift towards *unified multimodal models* (UMMs) capable of native, interleaved generation. Frontier models like Emu3.5, Gemini 2.5 / 3 and many others are trained to not only perceive but also actively generate text, images, video, and audio (e.g., 6; 14; 16; 15; 8; 26; 33; 40; 45; 2).

With more capable multimodal models comes a growing awareness that complex reasoning tasks need not be tackled in language alone (30; 49; 11; 3; 19; 42; 24). The premise is that dense visuals, spatial information, physical interaction, or object dynamics—in short, the complexities of real-world environments—are intrinsically difficult to textualize and may be better handled visually (47).

From an anthropocentric perspective, this is plausible: Our thinking inherently involves *mental imagery*—quasi-sensory experiences we can *observe* and, crucially, *manipulate* in the absence of external stimuli (35). For example, designing a dress entails visualizing its different panels and making adjustments based solely on imagined observations of their composition. This capacity is not only *reproductive* but *constructive*; mental imagery is believed to play an important role in problem-solving and has been linked to the generation of new knowledge (31).

Translating the concept of mental imagery to foundation models is an active field of study, with approaches spanning a spectrum of explicitness: On the *implicit* end, McCarty & Morales (29) suggest that LLMs can solve pictorial tasks using only internal representations, though others argue that these mental visualizations are fragile (37). Moving toward *explicit* imagery, interleaved visual aids ranging from latent visual tokens (e.g., 48) to generated images in UMMs (50; 22) find some success—though performance gains are inconsistent, especially in multi-step settings (23). Finally, on the *natively visual* end of the spectrum, Wiedemer et al. (43) show that image editing models and video models can solve some reasoning tasks entirely visually, directly modifying pixels of the input image.

Overall, the utility of *machine mental imagery* is unclear. While the *capacity* for multimodal generation exists, attempts to leverage it for reasoning yield ambiguous results.

Crucially, it remains unclear whether failures stem from fundamental reasoning deficits, flawed image generation, or an inability to interpret self-generated cues—and the field lacks a rigorous framework to disentangle these factors across different modalities.

We propose MENTISOCULI¹ to comprehensively study frontier models’ ability to form, maintain, and repeatedly manipulate visual representations in a goal-oriented manner. MENTISOCULI consists of five multi-step visual reasoning tasks designed to be difficult to textualize yet intuitive for humans to solve visually. All tasks are procedurally generated across stratified difficulty levels. This design yields ground-truth visual chain-of-thought solutions for granular analysis and allows us to calibrate complexity while ensuring the benchmark’s longevity through future extensions.

Benchmarking state-of-the-art MLLMs, UMMs, a latent reasoning model, and a generative video model, we find that explicit visual thoughts are currently ineffective; no visual intervention reliably outperforms text-only baselines. Further analysis of UMMs exposes a critical issue: Models often possess the *textual* reasoning capacity to solve a task and the *generative* capacity to (at least sometimes) create correct visualizations. However, they fail to integrate these skills—suffering from compounding generation errors over multiple steps and, surprisingly, even failing to leverage ground-truth visual aids. Our results suggest that despite the intuition behind mental imagery, architectures cannot yet bridge the gap between generation and reasoning.

In summary, we provide

1. MENTISOCULI: A procedural, stratified benchmark for multi-step reasoning with mental imagery, designed to challenge frontier models (Section 2).
2. An analysis of the spectrum of machine mental imagery, covering MLLMs, latent reasoning, UMMs, and video models (Sections 4.1 and 4.2).
3. Evidence that the failure of UMM visual reasoning stems from an inability to maintain consistency and to leverage visual aids (Section 4.3).
4. Human reference data, highlighting different reasoning budget allocation in humans and frontier models (Section 4.5).

2. Designing MENTISOCULI

The term *visual reasoning* as it is used for a myriad of benchmarks targeting VLMs and MLLMs is ambiguous: The vast majority of existing benchmarks do not consider *reasoning*

¹Latin for *eyes of the mind*, the concept of which goes back at least to Cicero (5)

visually, but instead evaluate *reasoning about visual information* (e.g., 46; 19; 27). Instead, we aim to benchmark models’ ability to *reason with mental imagery*: to use a more or less explicit, self-maintained visual representation space that can be modified at will to aid in reasoning.

To this end, we propose the following task desiderata:

1. **Visual nature** Tasks should test understanding of spatial relations, geometric constraints, or object transformations, rather than common knowledge or mere logic. While mental imagery might aid abstract reasoning, visualizations that are not grounded in the problem statement are hard to verify and evaluate.
2. **High information density** To be inefficient to solve via pure text, tasks should avoid grid-worlds or other symbolic arrangements that are trivially isomorphic to low-token text descriptions (e.g., “Piece A is at (0, 1)”, or representing a maze as a grid of X for walls and O for corridors). Instead, tasks should involve complex shapes, continuous and off-grid transformations, or fine-grained visual details.
3. **Sequential manipulation** To evaluate a model’s ability to *Maintain* a consistent visual state over time, tasks should require repeated updates to mental imagery, and actions should depend on the outcomes of previous manipulations. Solution sequences should be discrete to enable evaluation of models limited to image generation.
4. **Procedural** Tasks should be easy to generate, including a ground-truth solution with visualizations, enabling deeper analysis. Additionally, procedural generation provides a mechanism to address data contamination in the future, ensuring the benchmark’s longevity.
5. **Stratified** Tasks should have a clear knob to control complexity (e.g., number of steps or objects). This allows us to identify the breaking point of frontier models and maintain the benchmark into the future by releasing higher-complexity problem instances.
6. **Generative feasibility** Current model constraints should be respected. This includes visual states that are representable in 2D projections (i.e., not involving ambiguous depth cues or occlusions) and details that remain legible at standard resolutions.

While several benchmarks examine reasoning with interleaved images, they frequently fall short of our desiderata: Zebra-CoT and MIRA violate the visual nature requirement by relying on prior knowledge (22; 50). STARE and similar benchmarks (23; 19; 44; 4; 34) exhibit low information density, utilizing grid-based layouts that are trivially transcribed. Many tasks proposed by Chollet (4); Lyu et al. (27); Ramakrishnan et al. (34); Huang et al. (20); Sepehri et al. (37) lack

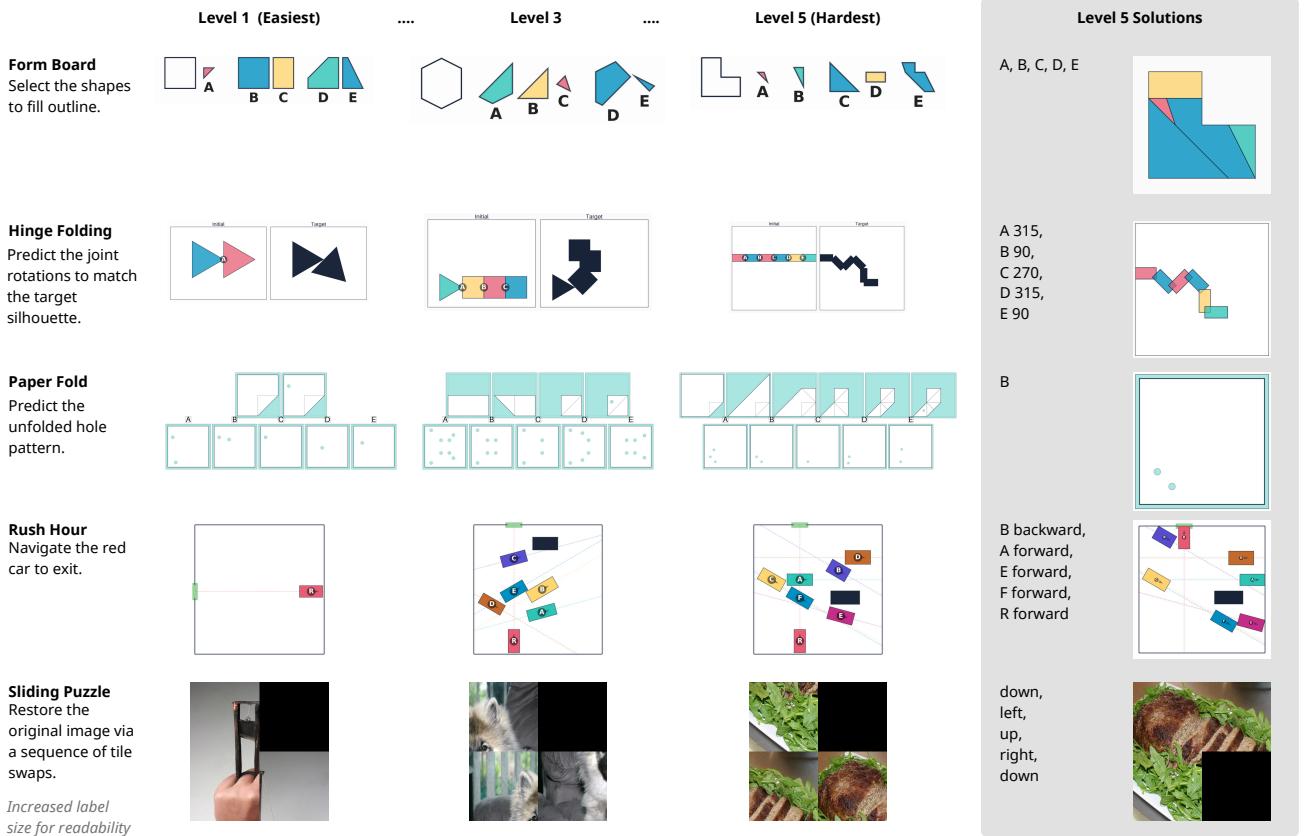


Figure 1. MENTISOCULI comprises five visual reasoning tasks designed to be best-solved with mental imagery. Collectively, the tasks require models to solve multi-step reasoning problems with geometric constraints. Success hinges on the ability to maintain a visual representation with high fidelity and consistent geometry under affine transformations. Each task is procedurally generated across five difficulty levels, scaling with the number of operations required from one (left) to five (right); see Section A for details.

sequential manipulation, requiring only a single rule application or fill-in-the-blank completion. Further, several are not strictly procedural due to manual crafting or a lack of generation code (e.g., MIRA), or suffer from limited sample variety and a lack of stratified difficulty levels (e.g., STARE). Finally, Artificial Phantasia proposes a purely linguistic task to measure mental imagery (29). While individual tasks in prior work occasionally satisfy our criteria (e.g. in VisFactor, 20), MENTISOCULI is the first benchmark exclusively dedicated to this rigorous category of mental imagery.

We release MENTISOCULI with the following procedural tasks, each at five levels of difficulty (see Figure 1).

FORM BOARD Derived from Ekstrom & Harman (10), this task probes the ability to *compare shapes*, *understand spatial constraints*, and *maintain geometry* under translation. Models must identify the subset of candidate shapes that cover the target silhouette without gaps or overlaps. Our implementation builds on Huang et al. (20).

HINGE FOLDING This task retains the need to *compare shapes* and *maintain geometry*, but introduces the complex-

ity of *mental rotation* and *object dependencies*. Models must predict the discrete rotation angle (in 45° steps) for each hinge in a chain of polygons to form a target silhouette.

PAPER FOLD Adapted from Ekstrom & Harman (10) and Huang et al. (20), this task requires maintaining spatial locations under *reflection symmetry*, demanding higher *spatial fidelity* than previous tasks. Given an image showing a sequence of folds and a hole punch applied to a paper sheet, models must identify the correct unfolded pattern.

RUSH HOUR This task tests *multi-step planning* under *dynamic geometric constraints*. Models must navigate the red vehicle out of a crowded lot by moving blocking vehicles. To prevent symbolic grid-based shortcuts, vehicles are not axis-aligned and have continuous-valued positions, though actions are discrete forward/backward commands.

SLIDING PUZZLE This task evaluates *multi-step planning* with a focus on *visual coherence*. The pieces of a natural image are permuted on a grid, with one piece missing. Models must output the sequence of moves (up, down,

left, right) of the empty tile to restore the image.

We control the difficulty of each task via the minimum number of steps (moves, folds, etc.) required to reach the solution. We generate 30 samples per level for the initial version of the benchmark; see Section A for details on the generators. As we will show, Level 5 is more than sufficient to challenge current models. We release our code to generate more challenging problem instances in the future.

3. Evaluation

3.1. Model families

We compare the following model families, spanning a spectrum from implicit to explicit visual reasoning. Prompts and hyperparameters are detailed in Sections F and H. We query models up to three times to obtain an answer and use the highest reasoning budget unless specified otherwise.

- **Multimodal large language models (MLLMs)** on the *implicit* end of the spectrum produce text-only outputs and don't expose or interleave visual representations. We query **Gemini 2.5** (Flash), **Gemini 3** (Pro), **GPT-5.1**, and **Qwen3-VL** (235B-A22B Thinking) (14; 16; 32; 41).
- **Latent visual reasoning models** produce text reasoning chains interleaved with visually-grounded latents. This category lacks widely-established models; we fine-tune Qwen2.5-VL-32B (1) on RUSH HOUR using the **Mirage** framework (48), which was explicitly designed for visual reasoning.
- **Unified multimodal models (UMMs)** can *explicitly* visualize states as images interleaved into the reasoning chain. We specifically prompt for and only evaluate samples with generated visualizations. In this category, we query **Gemini 2.5-I** (Flash Image) and **Gemini 3-I** (Pro Image) (14; 15).
- **Video models** represent the *natively visual* end of the spectrum, producing purely visual rollouts conditioned on a prompt and an initial frame. After comparing multiple video models (see Section E.2), we report results for **Veo 3.1** (13).

3.2. Automated scoring

Text outputs We evaluate **MLLMs**, **UMMs**, and **latent visual reasoning models** on the text output that they produce. For FORM BOARD and PAPER FOLD, we score answers as correct only if the model's predicted option(s) exactly match the ground-truth label(s). For HINGE FOLDING, RUSH HOUR, and SLIDING PUZZLE, we parse predicted action sequences and simulate them in the corresponding environment. Predictions are correct only if the

simulated terminal state satisfies the task goal (target silhouette matched/red car exits/original image reconstructed). Outputs that reference invalid identifiers (e.g., non-existent vehicles) or contain invalid moves (e.g., out-of-bounds actions) are scored as incorrect.

Visual outputs For RUSH HOUR, we follow Wiedemer et al. (43) and implement an automatic rater for **video model** output (see Section 4.2). The rater processes videos frame-by-frame, using color and spatial consistency to recover object identities and trajectories. From the trajectories, we extract an implied sequence of actions via a lenient heuristic: We only consider each vehicle's first move and relative order of moves, ignoring minor visual artifacts (color changes, minor distortions, etc.) and continued motion after reaching the goal. However, large scene changes, including the introduction of spurious objects, immediately invalidate a sample. Analogous to the text-based validity checks, parsed actions are verified by simulation.

3.3. Human reference data

To gauge top human performance, we conduct a psychophysical experiment on RUSH HOUR, which resembles standard IQ tests. Thus, we can assume performance to be normally distributed among the general population. Since we only require an upper bound, we investigate a small population of PhD students ($n = 5$, 2f/3m, mean age 27), yielding high-quality data. The population includes two of the first authors who were familiar with the task, while other participants remained naive. Crucially, all humans were instructed to respond as quickly as possible, such that response time is a proxy for perceived difficulty. For a comprehensive description of the experimental setup, see Section B.

3.4. Chance Performance

For FORM BOARD and PAPER FOLD, we assume a uniform distribution over possible answers. For HINGE FOLDING, we additionally assume the model to trivially infer the correct number of steps, such that chance performance decreases over levels. For the planning tasks RUSH HOUR and SLIDING PUZZLE, we report the probability that a random six-step action sequence reaches the goal state at any point, accounting for (limited) backtracking.

4. Results

4.1. SotA multimodal model performance across tasks

We begin by benchmarking the most capable models—state-of-the-art **MLLMs** with text-only reasoning and **UMMs** with interleaved text and image reasoning traces—on all tasks, see Figure 2.

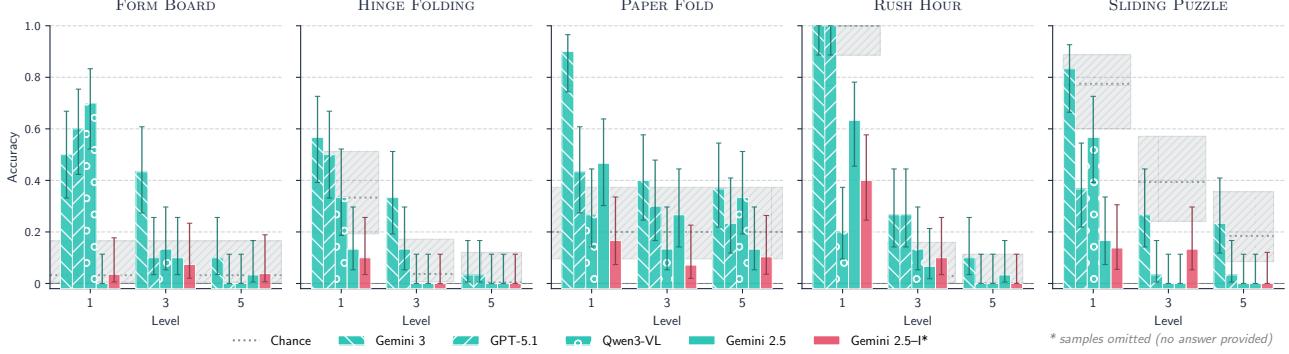


Figure 2. MLLMs and UMMs display similar failure patterns across tasks: Performance degrades noticeably with difficulty and falls below chance at Level 5, indicating that visual reasoning limitations are task-agnostic. Data for all levels in Figure 11.

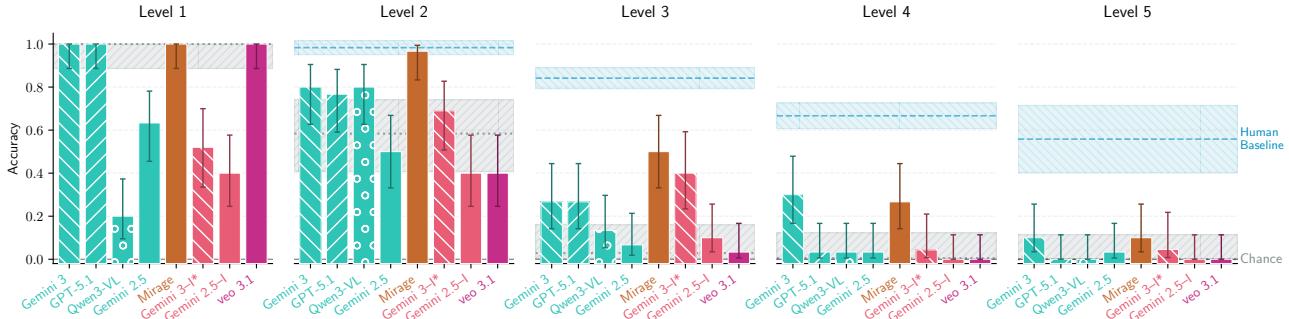


Figure 3. Different kinds of mental imagery do not greatly improve multi-step reasoning on RUSH HOUR: Compared to **MLLMs**, the **latent visual reasoning model Mirage** that is fine-tuned to generate interleaved visual latent tokens shows some improvement (especially considering its relatively weak base model), but with diminishing returns at harder levels. In contrast, **UMMs** that interleave generated images and texts generally perform below their MLLM counterparts. The **video model Veo 3.1** operates purely in pixel space and breaks down quickly as difficulty increases.

* samples omitted (no answer provided)

Across tasks, performance degrades noticeably as difficulty increases, validating our stratification. While accuracies vary, the relative ranking of models is largely consistent: **Gemini 3** performs best, followed by **GPT-5.1** and **Qwen3-VL**. **Gemini 2.5-I** often lags behind **Gemini 2.5**—we analyze this more closely in Sections 4.2 and 4.3.

With the exception of **Gemini 3**, models fail to reliably exceed chance even at Level 1 on all tasks except FORM BOARD. Thus, performance is often limited already at the level of extracting a single valid action from the visual state, rather than by long-horizon reasoning. As difficulty increases, this weakness compounds: by Level 5, all models operate at or below chance. Notably, even cases of sub-chance performance arise. This is mainly caused by early termination and under-utilization of the action budget, not incorrect state transitions.

Takeaway 1 MENTISOCULI is far from saturated. Below-chance performance at Level 5 highlights the limitations of SotA visual reasoning models (Figure 2).

4.2. Comparing model families on RUSH HOUR

Given the stability of relative performance across tasks, we focus on a single representative task in Figure 3 to compare the full spectrum of reasoning paradigms, from implicit text-only reasoning in **MLLMs** to explicit visual generation in **UMMs**. We select RUSH HOUR because it enables a unified, action-based evaluation across all model families while covering a broad range of difficulty levels, before analyzing failure modes across tasks in Section 4.3.

MLLMs vs. latent reasoning Fine-tuned on 200 samples per level, **Mirage** outperforms **MLLMs** on Levels 2–3, but this advantage is brittle: at higher levels it merely matches **Gemini 3** and drops to near-chance at Level 5. This suggests that latent visual tokens (and fine-tuning) offer only limited gains, particularly for longer action sequences.

MLLMs vs. UMMs Contrary to our intuition, we see no improvements moving from **Gemini 3** to **Gemini 3-I** or from **Gemini 2.5** to **Gemini 2.5-I**. In fact, text-only **MLLMs** frequently outperform **UMMs**. This implies that *explicit interleaved visualizations* currently provide no consistent benefit to *implicit multimodal reasoning*. A further

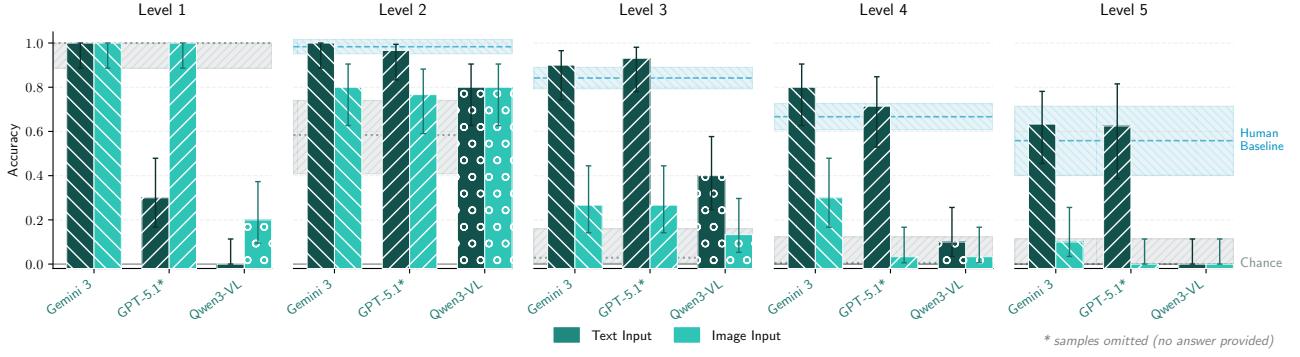


Figure 4. **MLLMs have the competence to solve RUSH HOUR** when prompted with a transcription of the task. **Gemini 3** and **GPT-5.1** even perform on par with humans, even though the text-only RUSH HOUR requires mathematically solving for possible collisions.

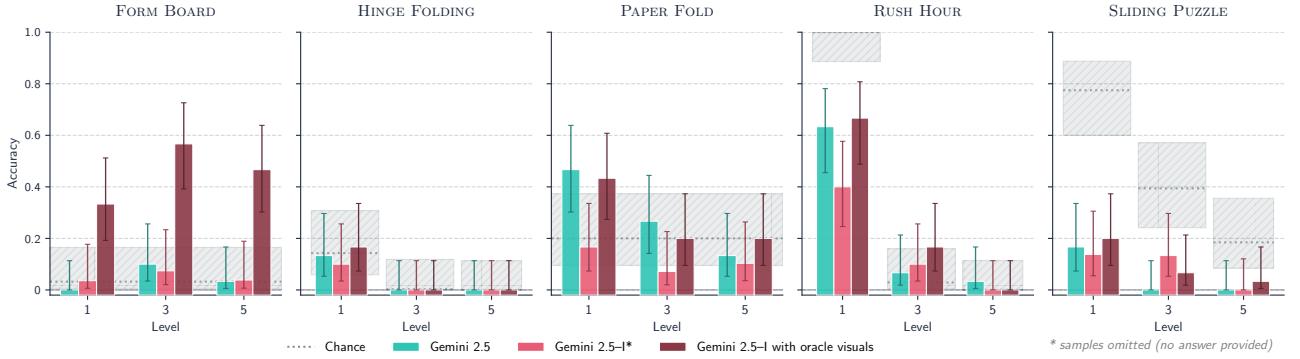


Figure 5. **UMM performance faces a dual issue:** Generation errors are ubiquitous—performance on all tasks increases with oracle visualizations. However, on most tasks, UMMs fail to utilize even correct visuals to aid their reasoning, which we term *interpretation errors*. Data for all levels in Figure 12.

analysis of this phenomenon follows in Section 4.3.

Video models Despite the lenient scoring policy (Section 3.2), **Veo 3.1** never exceeds chance performance. Yet, its ability to match or exceed **Gemini 2.5-I** on lower levels lends credence to the potential for *natively visual* reasoning.

Human-machine gap While **Mirage** comes close on Level 2, models generally fall far behind human performance. Human performance is consistent between subjects and drops with higher difficulty (see Figures 3 and 9). A detailed analysis follows in Section 4.5.

Takeaway 2 Explicit visual thought is currently ineffective. We find no evidence that self-generated imagery (latent, interleaved, or video-based) improves text-only reasoning in multi-step visual problems (Figure 3).

4.3. What is holding MLLMs and UMMs back?

Symbolic vs. sensory reasoning While our tasks are designed to be non-isomorphic to *low-token* text, we can still provide a lossless (if complex) transcription of RUSH HOUR:

We specify the parking lot size and the exit location, as well as each car’s center coordinates, spatial extent, orientation, and admissible motion axis (see Section G.1). For humans, reasoning about the problem in this formulation is exceedingly cumbersome compared to eyeballing a visual solution. But it allows us to shift the reasoning problem away from visual understanding and planning with mental imagery to mathematically solving geometrical constraints.

The comparison in Figure 4 shows that the task is not inherently beyond the reach of **MLLMs**: **Gemini 3** and **GPT-5.1** possess the reasoning capabilities to solve RUSH HOUR, even in this (from a human perspective) complex form.

This makes visual understanding and manipulation the main bottleneck. UMMs possess linguistic abilities mirroring those of corresponding MLLMs. They also understand and generate visuals with high precision (see Figures 14 and 15). So why do they not outperform corresponding MLLMs?

Reasoning with oracle visual chain-of-thought Where does the failure of UMMs to reason with interleaved images stem from? Is it an inability to generate correct visuals (*generation error*)? Or do UMMs fail to utilize generated visuals to aid reasoning (*interpretation error*)? To test this,

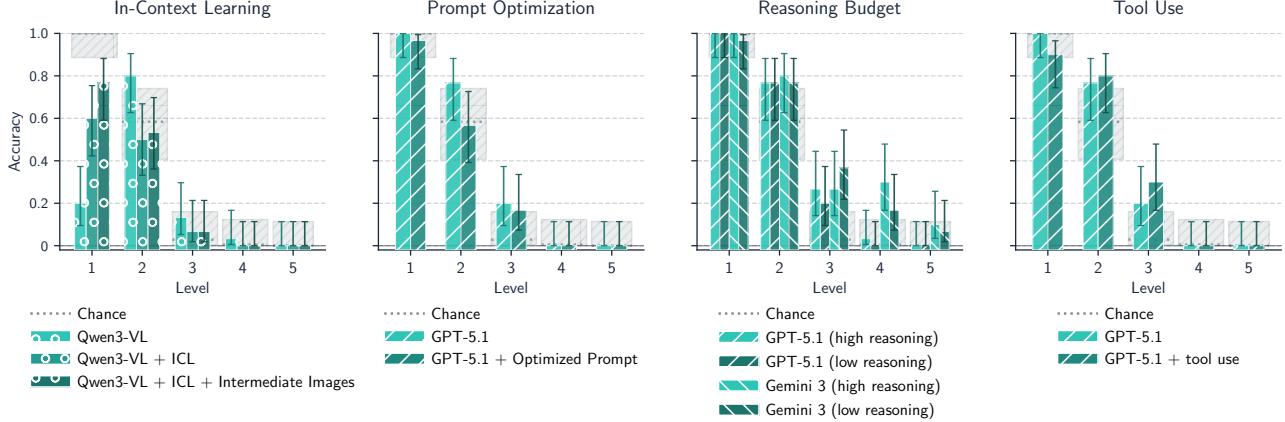


Figure 6. Techniques that improve language-based reasoning fail to benefit visual reasoning: In-context learning (ICL), prompt optimization, increased reasoning budget, and tool use yield no consistent gains, especially at higher levels. The tool use and prompt optimization experiments were conducted with low reasoning.

we replace self-generated imagery with oracle visuals (see Section G.2) in **Gemini 2.5-I**’s chain-of-thought (CoT).

As illustrated in Figure 5, oracle visuals enable the **UMM Gemini 2.5-I** to match or exceed the corresponding **MLLM Gemini 2.5** on all tasks. On FORM BOARD, which mostly requires understanding static spatial properties, oracle visuals even elevate performance far above chance. *Generation errors* are evidently a problem (see also Section E).

Yet, on other tasks, oracle visuals are still not sufficient to reliably meet or exceed chance performance. Thus, UMMs also suffer from *interpretation errors* as they fail to interpret visual states as actionable evidence for decision-making.

Takeaway 3 Frontier models possess the *competence* to solve RUSH HOUR (Figure 4). Yet, *performance* on the visual task suffers from generation errors and a deeper inability to utilize visual aids in planning (Figure 5).

4.4. Limits of common reasoning enhancements

Do techniques that improve language-based reasoning also elevate performance on visual reasoning tasks? We evaluate four such approaches on RUSH HOUR:

In-context learning Providing ICL examples yields no systematic improvement beyond Level 1. Moreover, we observe no difference between ICL examples that include images and those that do not (see Section H.7).

Prompt optimization Optimizing prompts (57 variants over 50 iterations) using OpenEvolve (38) does not improve performance over our default prompt. The optimized prompt can be found in Section H.8.

Reasoning budget Increasing reasoning effort does not improve accuracy. Although **GPT-5.1** and **Gemini 3** use substantially more tokens under high reasoning settings (on average 13 \times more for **GPT-5.1**), performance remains largely unchanged across difficulty levels. Results on all tasks can be found in Section D.2.

Tool use Enabling tool use yields no meaningful gains. The model primarily uses image preprocessing tools (cropping, resizing) without improving downstream accuracy.

Takeaway 4 Established techniques to improve text-based reasoning—including ICL, prompt optimization, increased reasoning budget, and tool use—fail to provide systematic gains for visual reasoning (Figure 6).

4.5. Comparing humans and machines

Mapping performance to response time To contextualize the best model performance, we compare **Gemini 3** to time-constrained humans in Figure 7. We artificially reduce the available time to an arbitrary threshold t by only considering trials with a correct response given in $< t$ seconds. Thus, we obtain time-constrained observers without re-testing with different limits. Evidently, humans are quite capable of solving the task, achieving more than 60% accuracy at Level 5 (Figure 9). **Gemini 3** then falls between humans limited to 5–10s.

Human vs. machine adaptive reasoning effort Beyond absolute performance, humans and models differ in how they allocate effort across difficulty levels. Humans reliably spend more time on higher-level puzzles, indicating a consistent internal difficulty assessment. In contrast, **Gemini 3** shows no increase in token usage from Level 3 to Level 5

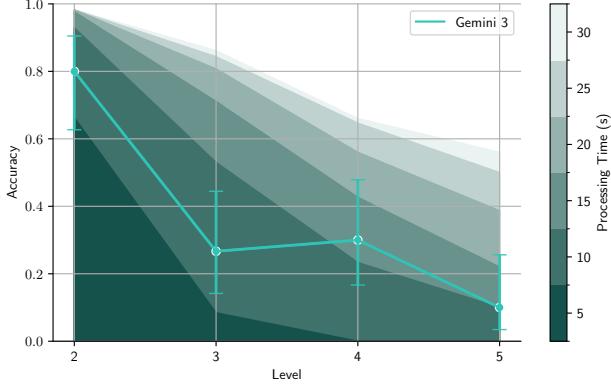


Figure 7. **Gemini 3 performs like humans at 5 – 10s.** We plot average human performance at each difficulty level, while simulating different thinking time cutoffs (5 – 30s).

(Figure 8). Unlike humans, it does not dynamically adjust its internal reasoning process in response to increasing complexity (see Section C for other models).

Takeaway 5 Unlike humans, models don’t increase their reasoning effort in response to visual–spatial complexity, meaning they lack adaptive reasoning depth (Figure 8).

5. Discussion & conclusion

Is explicit visual thought a dead end? We currently don’t observe UMMs or video models using self-generated mental imagery to outperform text-only reasoning (Section 4.2). Yet, our experiments also suggest that frontier models already possess the *competence* to solve our tasks (Figure 4). We also see that performance could increase on some tasks if *generation errors* were curbed (Figure 5), and we can speculate that fixing *interpretation errors* might yield further gains. Looking at related literature (e.g., 28), it is likely that getting models to ground their decisions in mental imagery will require dedicated training data and a greater focus on multi-step visual reasoning by model developers.

The fragility of visual thought Our observation that models often fail to benefit from ground-truth visual chains of thought (see Figure 5) affirms prior work. For example, Li et al. (23) report variable effects of visual traces, while Zhou et al. (50) observe average improvements that obscure task-level heterogeneity. We observe a similar pattern: Visual aids can be helpful in some settings, but their effectiveness is neither uniform nor reliable. This suggests that the key question is not whether mental imagery is beneficial in general, but which visual aids are useful for which tasks.

The high price of visualization Beyond accuracy, it remains to be seen whether machine mental imagery can

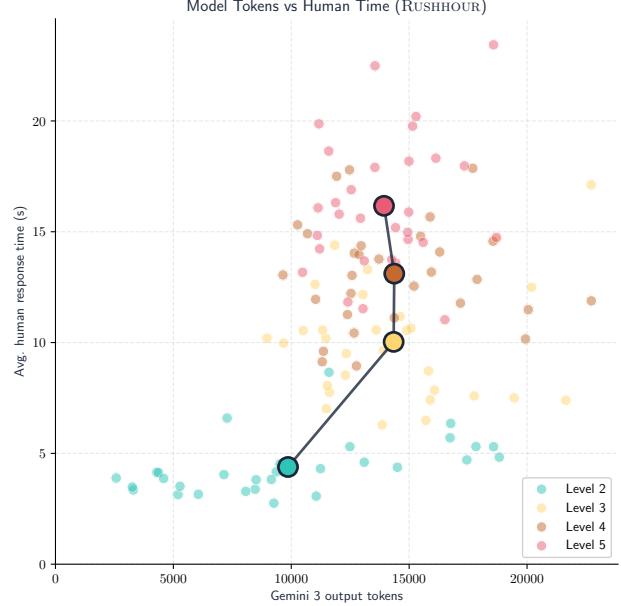


Figure 8. **Humans and machines allocate reasoning effort differently:** Humans spend more time on harder problems, but **Gemini 3** does not use more tokens. More models in Section C.

become economically viable. Generating a video reasoning trace with **Veo 3.1** costs \$3.2 per sample—over 21× more than **Gemini 2.5-I**, and over 60,000× more than **Gemini 2.5**—despite all three approaches yielding roughly similar performance. For UMMs or video models to replace text-centric MLLMs on specific tasks, they would have to justify this overhead through clear performance gains or qualitatively new capabilities.

Conclusion In this work, we consider visual reasoning *with* imagery rather than merely *about* images. Our results show that current models struggle to effectively use visual aids as actionable evidence, even when correct visualizations are given. MENTISOCULI provides a controlled, procedural testbed for isolating this failure mode and distinguishing reasoning capacity from representational alignment. We view MENTISOCULI as a step toward understanding when and why (explicit) visual representations support reasoning, and toward clearer criteria for progress in machine mental imagery.

Contribution Statement

The project was led by JZ and TW. The initial idea was pitched by TW and refined with the help of JZ, PM, WB, TK, and RC. The tasks were designed and implemented by JZ with inputs from TW, PM, TK, WB, MB. FL implemented the video auto-rater and tested different video models. All other training, inference, and evaluation were run by JZ, with help on the evaluation design by TW, RC, PM, and WB.

Human experiments were designed and analyzed by TK with input from FW and conducted by JZ. The manuscript was written by JZ and TW, with help from FL for sections on the video models and from TK for sections on human experiments, and general comments from RC and WB.

Impact Statement

This paper presents work aimed at advancing the evaluation of multimodal reasoning systems. We introduce a benchmark to better understand the limits of current models in reasoning with visual representations and to support more rigorous analysis of their capabilities and failure modes. We do not anticipate significant negative societal impacts arising directly from this work. As with most advances in machine learning research, there may be broader downstream applications, but we believe these are well understood and do not warrant specific discussion here.

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A. Automatic Puzzle Generation

To construct MENTISOCULI, we implement five task-specific auto-generators that can produce infinitely many puzzle instances with controllable difficulty. For each instance, the generator produces a single question image specifying the full problem state and a ground-truth visual chain of thought capturing the sequence of intermediate states required to reach the solution. Restricting task input to a single image ensures that the same instance format can be used across models that allow for multiple image inputs (**UMMs**, **MLLMs**, **latent visual reasoning models**) and models that only allow one initial image input (**video models**), and our human study.

FORM BOARD We build on the FORM BOARD implementation of Huang et al. (20). Each instance is generated by cutting an initial shape into a set of target pieces that together form the ground-truth solution. To avoid trivial matching, all target pieces are constrained to be pairwise distinct. The distractor pieces are generated by subdividing the target pieces so that their areas differ sufficiently from all the correct solution pieces, this ensure that the false candidate shapes are indeed false. The visual CoT depicts the progressive reconstruction of the target shape, adding one piece at a time in the correct location.

HINGE FOLDING Instances consist of rigid shapes connected by hinges. We generate either chains of identical shapes or chains with varying shapes. Hinge rotation angles are sampled in 45° increments; 180° rotations are excluded when identical shapes are connected, as overlapping configurations are visually ambiguous. The visual CoT shows the sequential application of hinge rotations corresponding to each folding step.

PAPER FOLD We build on the generator of Huang et al. (20). Each instance is created by randomly sampling a sequence of folds and a hole-punch location, while tracking the resulting hole pattern through the folding process. Negative answer options are generated by sampling hole configurations that are globally similar, i.e. similar amount and placement of holes, but guaranteed to differ by at least one hole beyond a fixed minimum spatial threshold. We additionally generate a visual CoT that explicitly visualizes the unfolding process step by step. Both the minimal-difference constraint between answer options and the generation of the unfolding visual CoT are novel relative to prior work.

RUSH HOUR We generate RUSH HOUR instances by first sampling an exit location and placing the red car on the opposite side of the board. Depending on the difficulty level, we then sample zero to two primary blocking cars aligned with the red car’s movement axis. Additional cars and obstacles are placed randomly, with a bias toward blocking the movement of these primary blockers to induce secondary dependencies. Each instance is solved using breadth-first search to ensure solvability and minimal solution length. To avoid visually ambiguous near-collisions, we re-evaluate the solution using slightly enlarged car sizes and discard instances where the red car no longer reaches the exit.

SLIDING PUZZLE We build on the SLIDING PUZZLE generator of de Oliveira et al. (7). Each instance is constructed by sampling an image from ImageNet-1k (9), randomly selecting a tile to replace with the blank tile, and applying a sequence of valid moves to scramble the puzzle. This avoids permutation parity constraints and produces reachable states. To ensure correct difficulty classification and a minimal visual CoT, we subsequently solve the scrambled puzzle and record the shortest solution trajectory. Unlike the original implementation, the blank tile is sampled at arbitrary positions rather than being fixed in the bottom-right corner, which would otherwise enable shortcut strategies. All difficulty levels share the same underlying images.

B. Psychophysics Experiment

To collect human reference data, we implement a minimalist web application, which displays a puzzle instance and lets participants respond via keyboard input. Experiments were conducted in a quiet environment on standard MacBook screens. We employ a block design, where 10 instances are sequentially presented for a maximum of 30 seconds each, with breaks of arbitrary length between blocks, so that participants can rest their eyes. At the beginning of each experiment, instructions (see Section H.4) are presented that closely resemble those given to the models. Then, seven practice trials are presented, which only serve the purpose of familiarizing participants with the interface. For the first two practice trials, we show the correct response, so that participants can learn the correct response format. Each car in the RUSH HOUR instance has a letter and can go forward or backward, so to indicate that car A should go forward and car B should go backward, participants would respond *AFBB*. Each block contains trials of varying difficulty, thus keeping the difficulty of blocks balanced, which aids in motivation. We provide positive and negative feedback after a response was given, but reveal the default solution

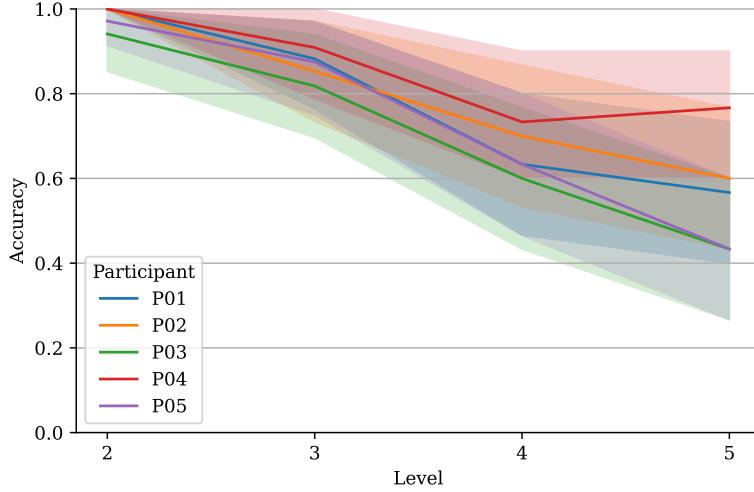


Figure 9. Human subjects perform similarly We plot the difficulty levels against performance for all our human subjects. Evidently, differences between humans present themselves only at the hardest difficulty level. Overall, our subjects perform similarly and, crucially, on par with the authors, demonstrating that we successfully investigated subjects close to the performance ceiling.

only during the practice phase. All participants gave informed consent, and we obtained IRB approval for the human study.

The results validate our experiment design: The performance of tested humans is closely aligned, even though two of them are authors and thus intimately familiar with the tasks (see Figure 9). Therefore, we are confident that our small- N design is adequate and sufficient for the purposes of this study (see also 39).

C. Reasoning Budget Correlation on More Models

Our analysis reveals that access to visual reasoning traces effectively aligns model compute with human difficulty metrics. As shown in Figure 10, providing models with visual CoT (i.e., **Gemini 2.5-I** with oracle visual CoT and **Qwen3-VL** with in-context-learning examples containing visual CoT) induces a highly linear relationship ($R^2 \geq 0.98$) between the number of tokens spent on a problem and the time the average human requires to solve it. This suggests that these visual CoT-guided models mirror human cognitive scaling when navigating the puzzle’s state space.

However, we find that such alignment is not a definitive predictor of task success. While the oracle-guided models are the most aligned, **Gemini 3** demonstrates superior downstream performance—particularly on the most challenging Level 5 puzzles—despite having a lower alignment score ($R^2 = 0.68$) also compared to other **MLLMs**.

D. Results Across All Difficulties & Tasks

D.1. Performance Across All Difficulty Levels

Figures 11 and 12 report results for all five difficulty levels of each task. We observe smooth and largely monotonic accuracy degradation as difficulty increases, with no qualitative regime changes between adjacent levels. Crucially, the relative ordering of model families and the effect of interleaved visual reasoning are stable across levels. Interleaved visual chains of thought yield consistent but task-specific effects across difficulty, benefiting static spatial tasks while providing little to no improvement for planning-dominated tasks.

D.2. Reasoning Budget Comparison on All Tasks

We compare *low* vs. *high* reasoning-budget settings across all MENTISOCULI tasks. Overall, increasing the budget yields negligible and inconsistent changes in accuracy, with differences typically within 95% confidence intervals. Figure 13 reports accuracy by task and difficulty level under both budgets.

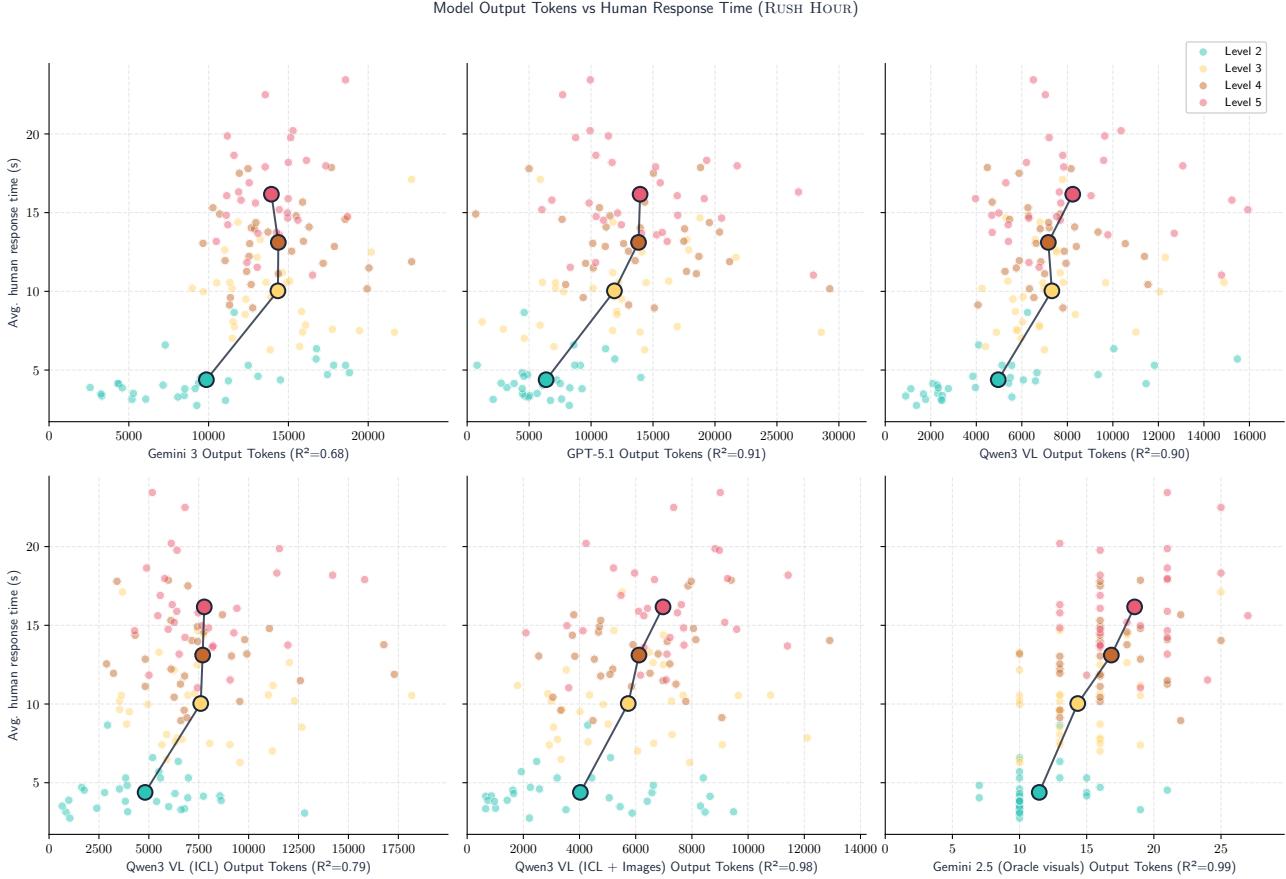


Figure 10. Visual CoT induces linear scaling between model compute and human response time, yet alignment is not a proxy for performance We find that **Gemini 2.5-I** equipped with oracle visual CoT ($R^2 = 0.99$) and **Qwen3-VL** with in context learning examples containing a visual CoT ($R = 0.98$)—exhibit near-perfect linear scaling, where token expenditure is directly proportional to human cognitive load. However, this alignment is not a silver bullet for accuracy: **Gemini 3** achieves the highest downstream performance on complex tasks (Levels 4–5) despite displaying significantly lower scaling alignment ($R^2 = 0.68$) compared to the other **MLLMs**.

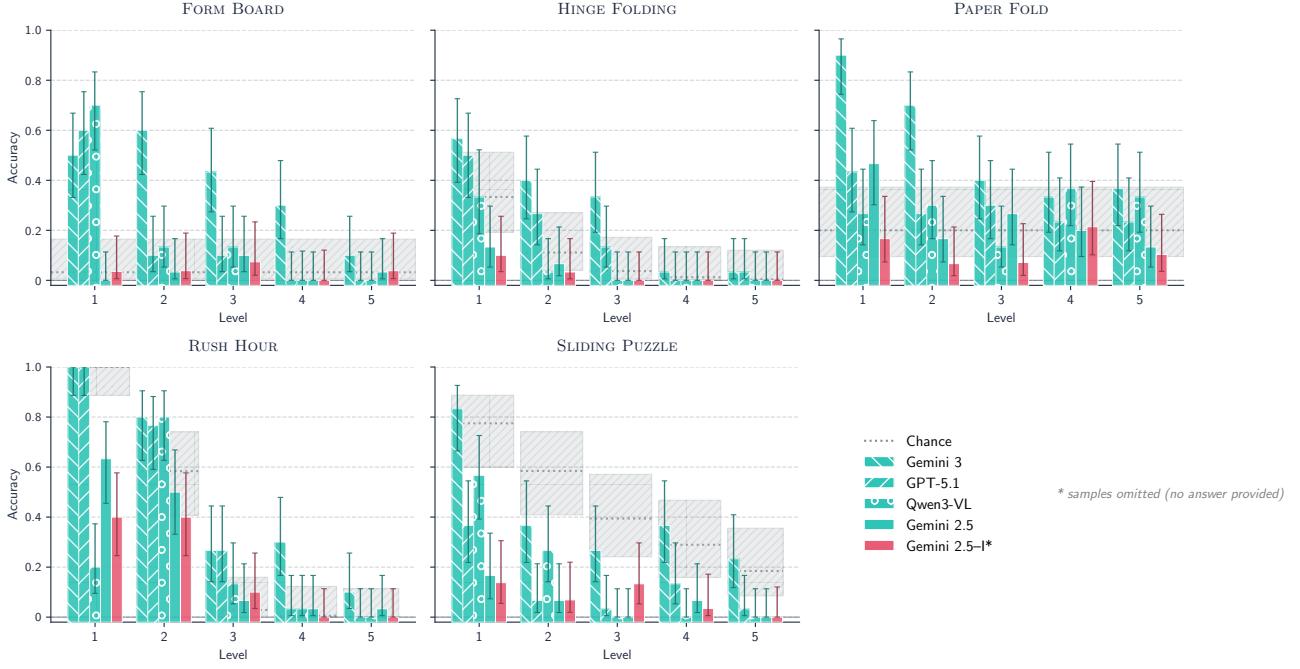


Figure 11. Performance across all difficulty levels for MLLMs and UMMs While Figure 2 reports results for representative difficulty levels (1, 3, and 5) for clarity, the full set of levels exhibits consistent qualitative trends: performance degrades monotonically with difficulty, and relative differences between model families are stable across adjacent levels.

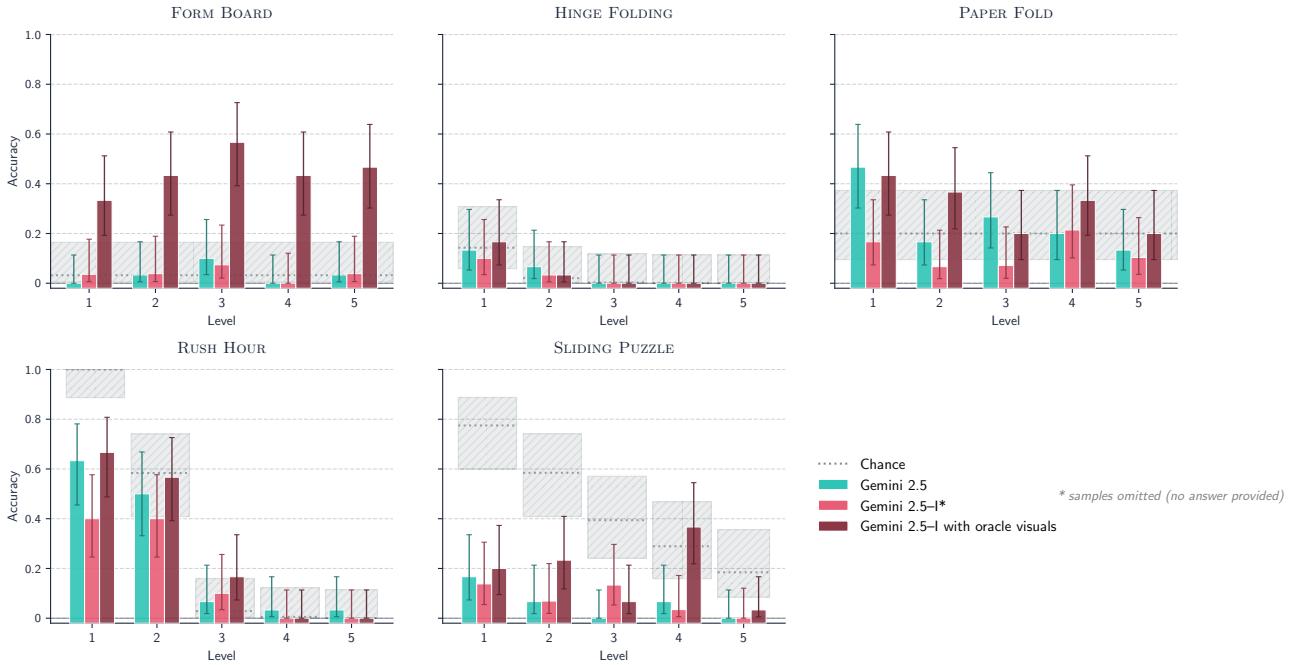


Figure 12. Performance across all difficulty levels of Gemini 2.5 and Gemini 2.5-I While Figure 5 reports results for representative difficulty levels (1, 3, and 5) for clarity, the full set of levels exhibits consistent benefits from visual intermediates are highly task-dependent and remain consistent across difficulty levels.

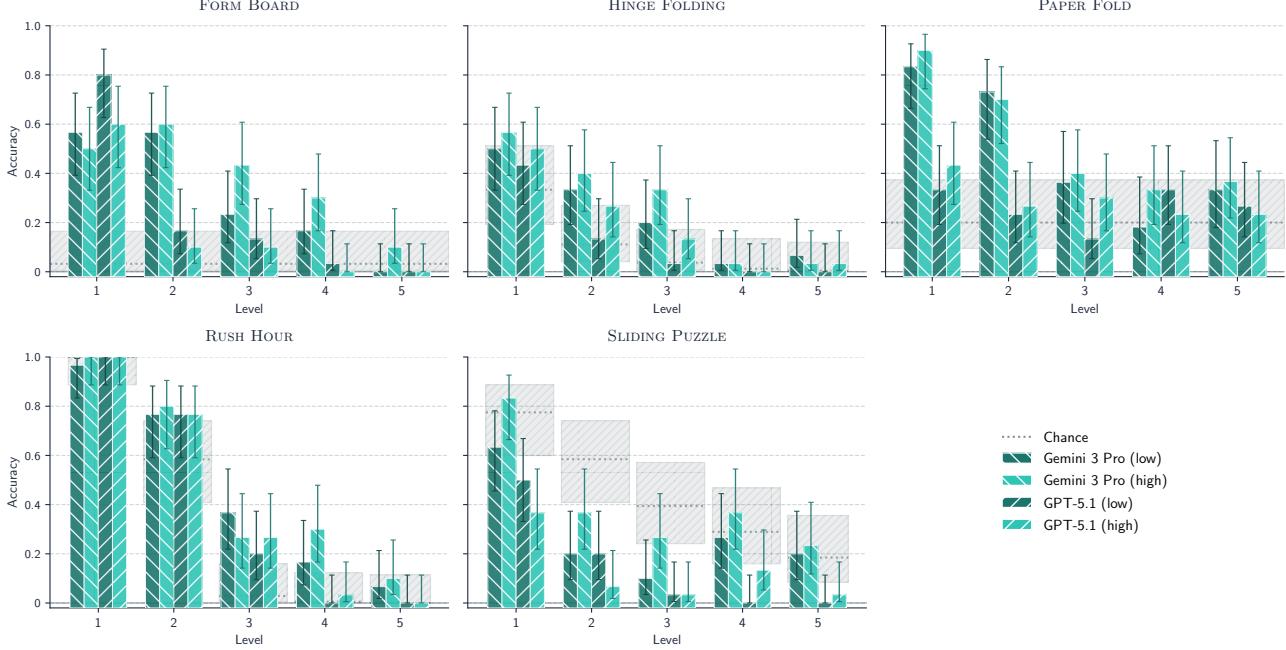


Figure 13. Higher reasoning budget does not reliably improve accuracy. Low vs. high budget results for Gemini 3 and GPT-5.1 across all tasks and levels in MENTISOCULI; any gains are small, inconsistent, and largely disappear at higher difficulty.

E. Generated Images & Videos

E.1. Unified Multimodal Models

Qualitative Results Qualitative inspection of the visual rollouts from **Gemini 2.5-I** reveals a pervasive lack of state consistency across all tested domains (Figure 14). Regardless of the task, the model struggles to maintain the identity and geometry of objects between frames. In spatial tasks like PAPER FOLD and HINGE FOLDING, the generated sequences fail to produce a coherent physical history, often introducing nonsensical geometry or extraneous symbols. While rollouts for RUSH HOUR or SLIDING PUZZLE may occasionally show objects moving toward a goal, these sequences are fundamentally undermined by the hallucination of new pieces, the disappearance of others, or illegal changes to the board layout. These errors are not isolated; they compound rapidly, causing the visual state to drift into impossible configurations rather than self-correcting.

Across the two models, **Gemini 3-I** generally produces visually cleaner and more temporally consistent rollouts than **Gemini 2.5-I** (Figures 14 and 15). For example, on easier RUSH HOUR levels the generated frames often track the ground-truth state updates closely (see Figure 22), whereas on harder instances the model increasingly hallucinates additional exits, introduces invalid motion directions, or adds/removes cars, with mistakes accumulating over steps. This qualitative trend is consistent with the quantitative improvement from **Gemini 2.5-I** to **Gemini 3-I** (Figure 3) and suggests that the gain may partially reflect improved state-update image generation (in addition to a stronger base model).

Quantitative Results We analyze two complementary diagnostics. First, we compare the number of generated images to the number of proposed actions (an $x = y$ relationship would indicate one explicit state-update image per action). Second, we compare the number of generated images to the number of *expected* images (i.e., the number of intermediate states implied by the ground-truth visual CoT), as a proxy for whether the model adjusts rollout length to instance difficulty.

For **Gemini 2.5-I**, the alignment between generated images and proposed actions is high for RUSH HOUR, but substantially noisier for other tasks (see Figure 17). For example, in FORM BOARD the model often proposes the same number of moves (3) but produces a wide range of image counts (between 1 and 9), indicating that image generation is not consistently used as a faithful step-by-step state tracker. The expected-vs-actual comparison shows moderate alignment for some tasks (notably RUSH HOUR, and to a lesser extent PAPER FOLD and HINGE FOLDING), but weak behavior for SLIDING PUZZLE and FORM BOARD (see Figure 16). This suggests that difficulty estimation from the prompt is unreliable and, on its own, does

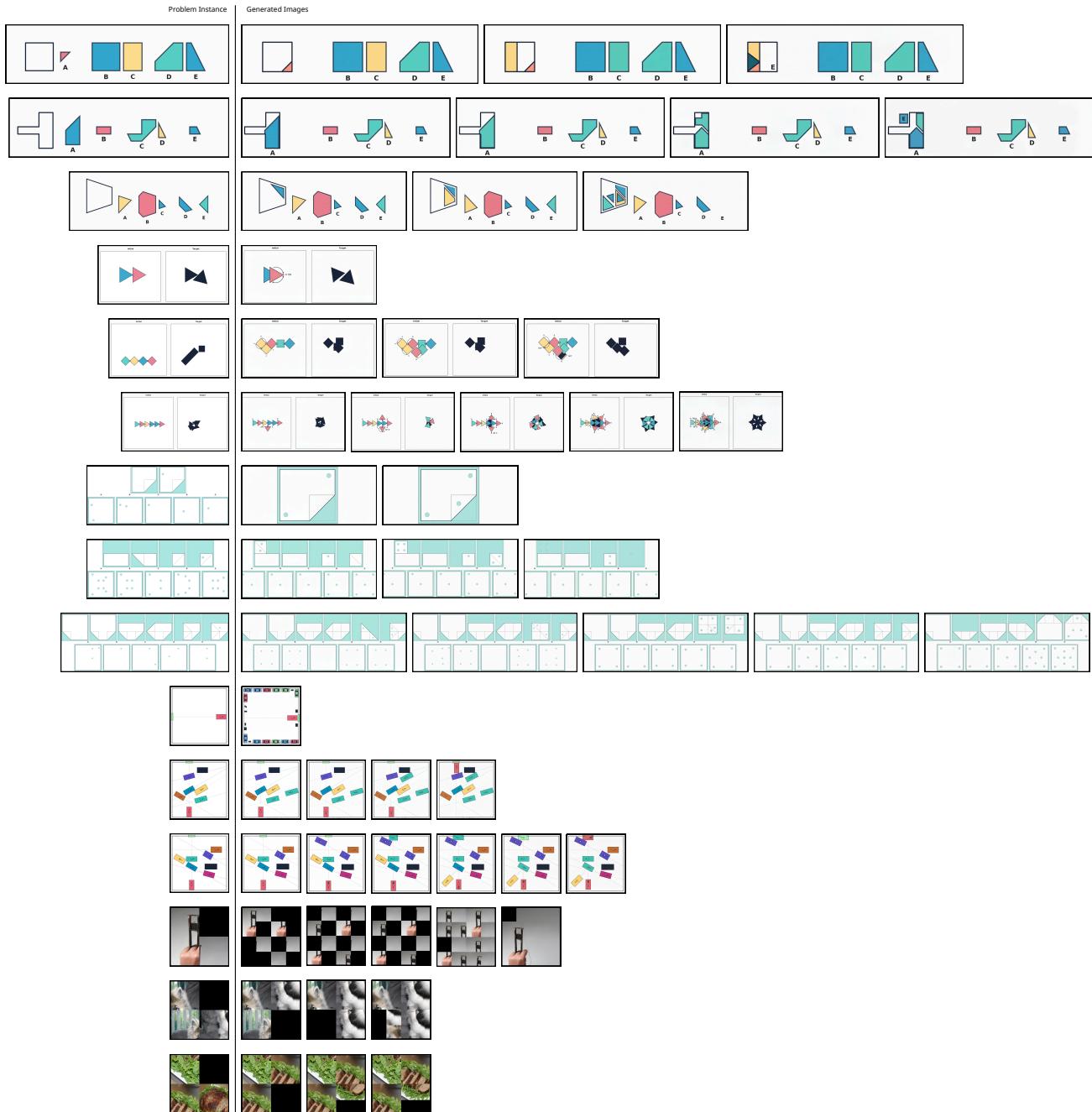


Figure 14. **Gemini 2.5-I** image rollouts are strongly task-dependent and often drift from valid state updates Random qualitative samples from instances where the model generated intermediate images (levels 1, 3, and 5), illustrating frequent rule violations and hallucinated state changes in several tasks.

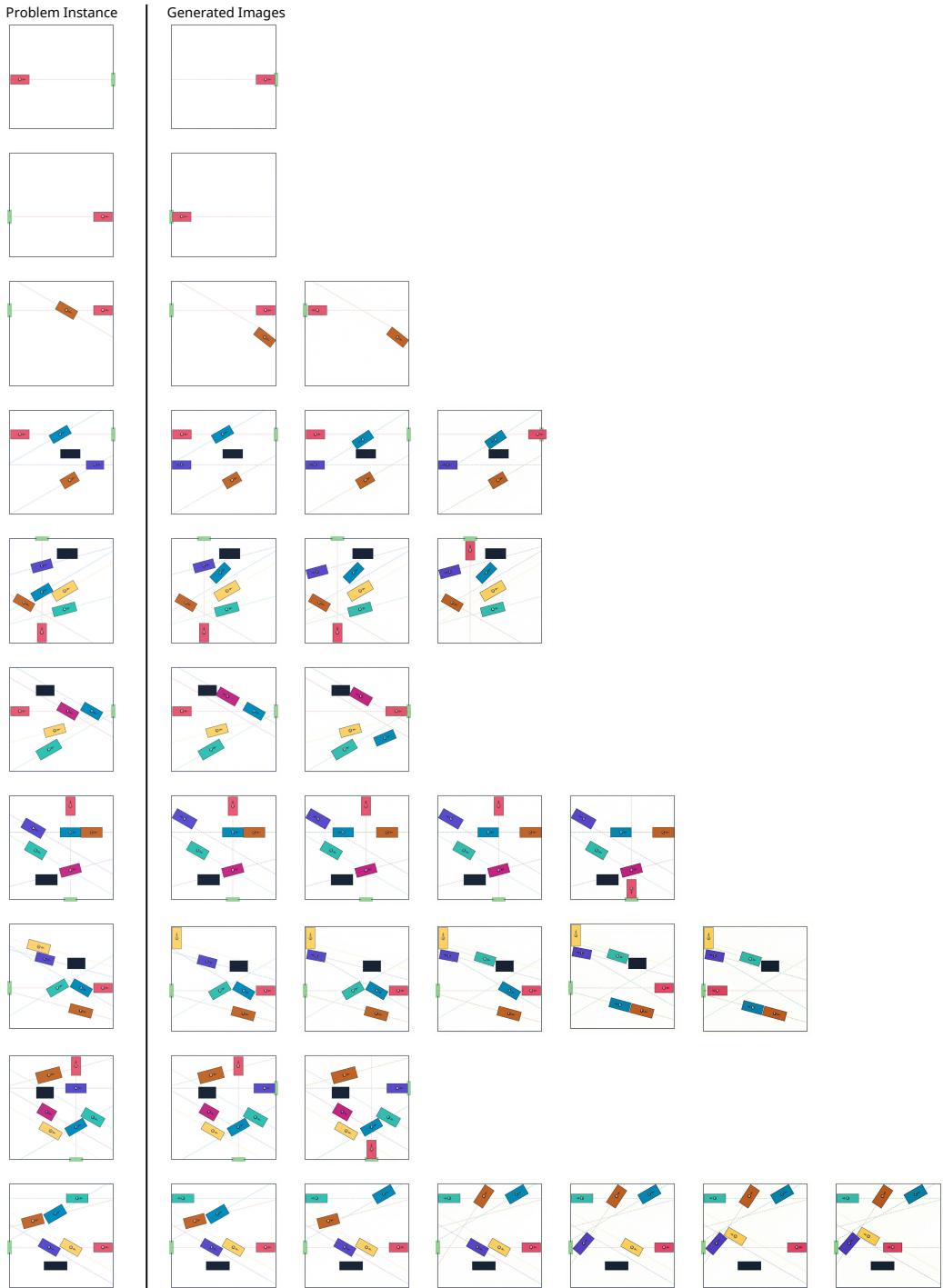


Figure 15. Gemini 3-I produces clean, coherent intermediate states in lower levels, but still hallucinates at higher difficulty Random qualitative samples from instances with generated intermediate images; two samples per RUSH HOUR level, highlighting improved visual consistency on easier levels and compounding errors on harder ones.

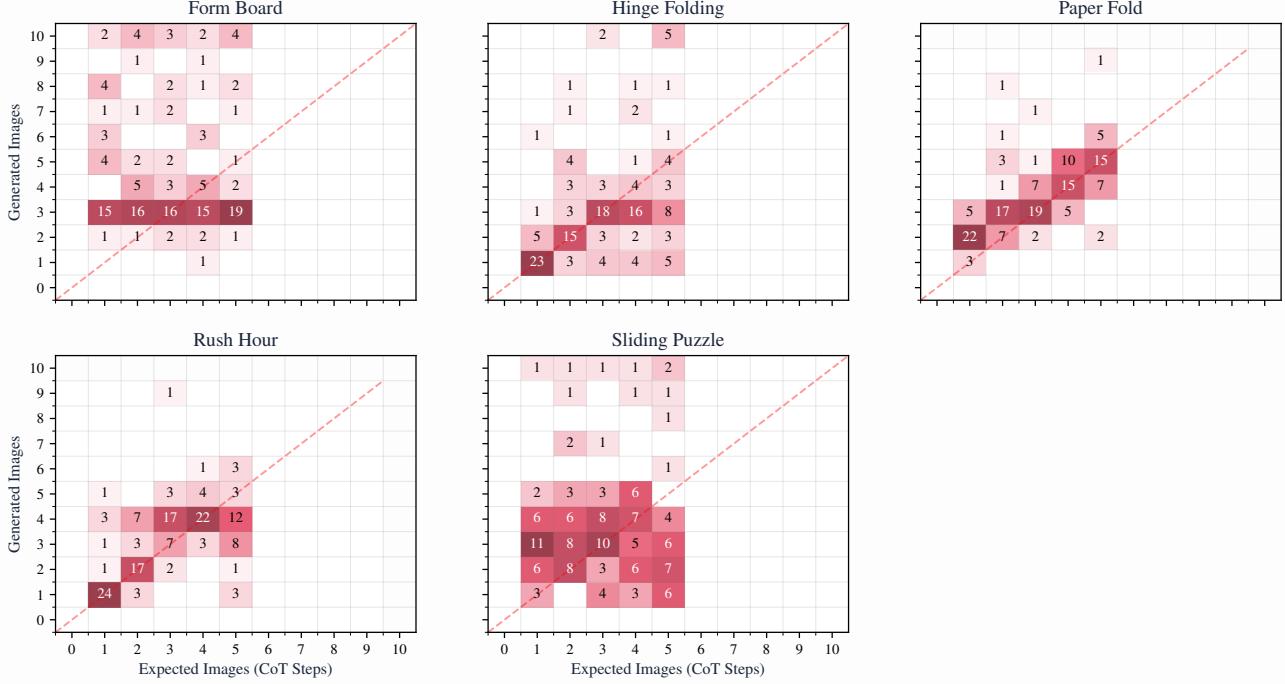


Figure 16. Gemini 2.5-I does not reliably match rollout length to the expected number of visual CoT steps Joint distributions of expected intermediate images (x-axis; implied by ground-truth CoT steps) vs. images generated by the model (y-axis). The dashed line indicates $x = y$ (perfect alignment).

not explain downstream performance; in addition, even when image counts align, the qualitative analysis shows that the intermediate states can still violate task rules.

For **Gemini 3-I**, we observe the tightest expected-vs-actual alignment on easier instances, which is also where performance is highest. As difficulty increases, the distribution broadens, consistent with the model under- or over-estimating required rollout length (see Figure 18). In contrast, the generated-images vs. proposed-actions relationship remains comparatively tight, indicating that when **Gemini 3-I** commits to a rollout, it more consistently produces an explicit image update per action than **Gemini 2.5-I**.

E.2. Qualitative Evaluation of Video Models

We conduct an initial qualitative comparison across multiple open-weight and closed-source video models. The open-weight models include **Hunyuan Video** (21), while the closed-source models include **Veo 3.1** (13), **Seedance** (36), **LTX-2** (17), and **Sora** (25). Based on the initial comparison as illustrated in Figure 19, we report results primarily for **Veo 3.1**, which consistently produced the most coherent and task-relevant outputs among the tested models.

Model Selection We begin by testing each model on RUSH HOUR, which is chosen as a representative tasks. For many models, performance on RUSH HOUR was already substantially suboptimal, and we did not proceed to additional tasks. After initial screening, **Veo 3.1** and **Hunyuan** showed partial attempts at solving RUSH HOUR. We therefore evaluated these models further on all visual reasoning tasks, primarily at Level 2 difficulty. Hunyuan, however, struggled on most tasks beyond RUSH HOUR, whereas Veo 3.1 demonstrated more consistent engagement with the task structure. We include qualitative results from Veo 3.1 on the RUSH HOUR task across five difficulty levels (Figure 20).

Task-Specific Observations For SLIDING PUZZLE, RUSH HOUR, and FORM BOARD, **Veo 3.1** appears to readily infer the task setup and produces videos that reflect meaningful attempts at solution execution. However, these attempts remain brittle and cue-driven, and do not translate into consistent task-solving behavior. Performance is sensitive to prompt design: adding stricter constraints and more explicit descriptions of scene structure, such as specifying grid size, improves adherence

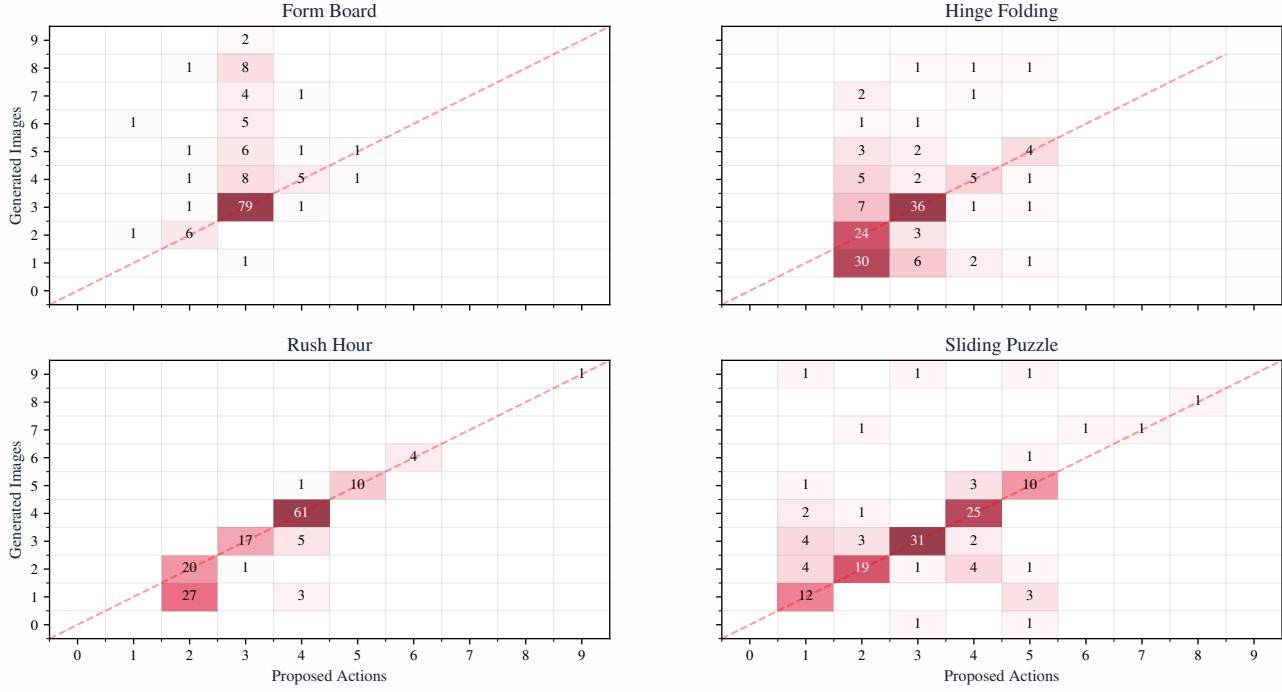
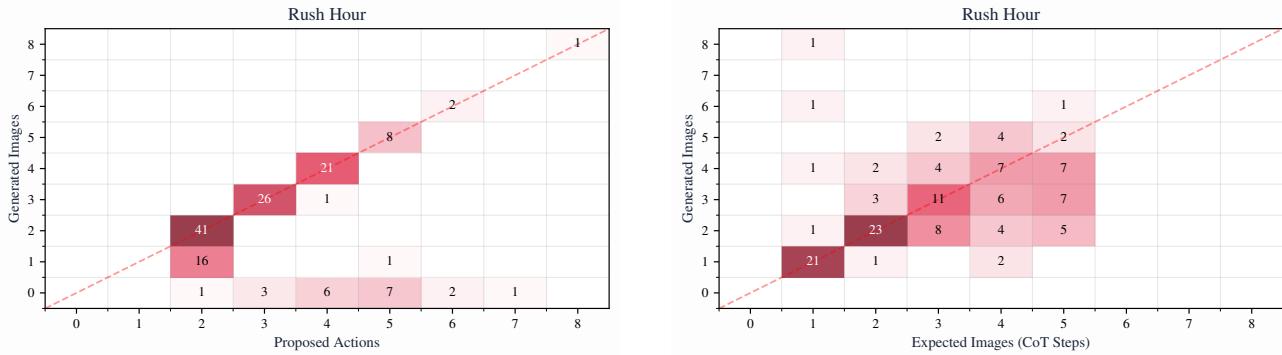


Figure 17. **Gemini 2.5-I** shows uneven coupling between action proposals and explicit visual state updates across tasks. Joint distributions of proposed actions (x-axis) vs. generated images (y-axis). The dashed line indicates $x = y$; values above the diagonal suggest extra images (e.g., backtracking), while off-diagonal spread indicates inconsistent per-action state tracking.



(a) **Per-action image updates for Gemini 3-I on RUSH HOUR are tighter than for Gemini 2.5-I** Proposed actions vs. generated images; dashed line indicates $x = y$ (perfect alignment).

Figure 18. **Gemini 3-I** more consistently generates one image per action, but still struggles to predict how many images a problem will require Same diagnostics as Figures 16 and 17.

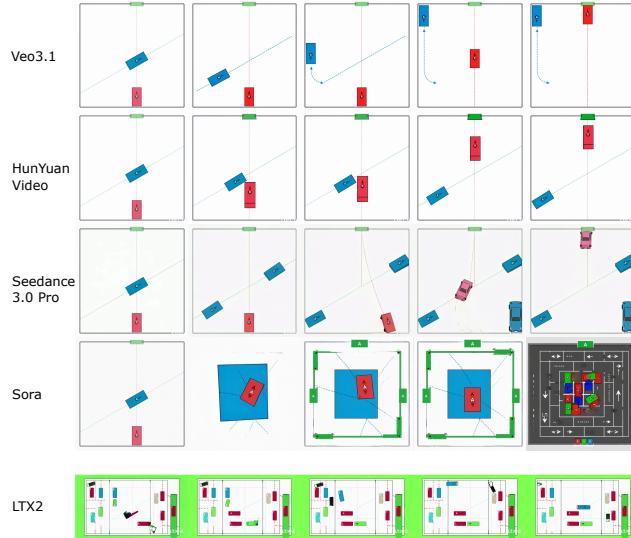


Figure 19. Video frames generated by multiple video models from the same prompt and initial image Following an initial qualitative comparison, we zoom in on results from Veo-3.1 for more detailed analysis.

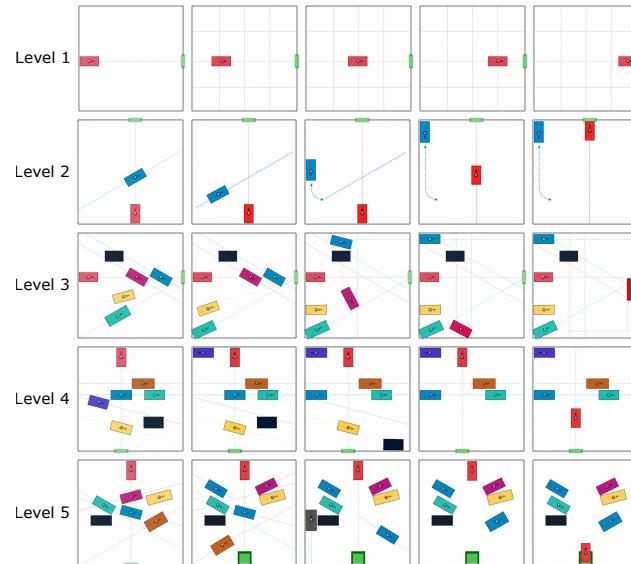


Figure 20. Qualitative results from Veo 3.1 on RUSH HOUR across five difficulty levels.

to task rules. This suggests that the model may rely heavily on textual cues to infer latent spatial structure, rather than robustly integrating visual generation with multi-step reasoning. In contrast, PAPER FOLD proves substantially more challenging. Despite detailed instructions, the model often fails to correctly interpret the spatial relationships in the input image, for example, by treating the entire image as a single sheet of paper or confusing relative spatial references. A plausible explanation is that tasks such as SLIDING PUZZLE, RUSH HOUR, and FORM BOARD are easier because all relevant entities are explicitly visible and can be directly manipulated. PAPER FOLD, by contrast, requires tracking latent spatial structure that is not fully represented in the image, a hypothesis we leave to future work to validate.

F. Models and Inference details

We query **GPT-5.1** (gpt-5.1-2025-11-13) via the OpenAI API, using sampling parameters `temperature = 1.0` and `top_p = 1.0`. For experiments that allow tool use, we enable the `code_interpreter` tool.

We query **Qwen3-VL** (qwen/qwen3-vl-235b-a22b-thinking) via OpenRouter (provider: Nova). The model was used in its non-quantized form.

We query **Gemini 2.5** (gemini-2.5-flash-image), **Gemini 3** (gemini-3-pro-preview), **Gemini 2.5-I** (gemini-2.5-flash-image), **Gemini 3-I** (gemini-3-pro-image-preview), **Veo 3.1** (veo-3.1-generate-preview) both via OpenRouter and directly via the Gemini API. Note that for both **Gemini 2.5** and **Gemini 2.5-I** we query `gemini-2.5-flash-image` but we only respect answers with or without generated images for the respective model.

For **Mirage** we use the same hyperparameters like the paper, i.e. a latent size of 4, training each stage for 15 epochs, a datasetsize of 1,000 samples distributed uniformly across difficulty levels. For the target image we utilize the last frame of the ground truth visual chain-of-thought.

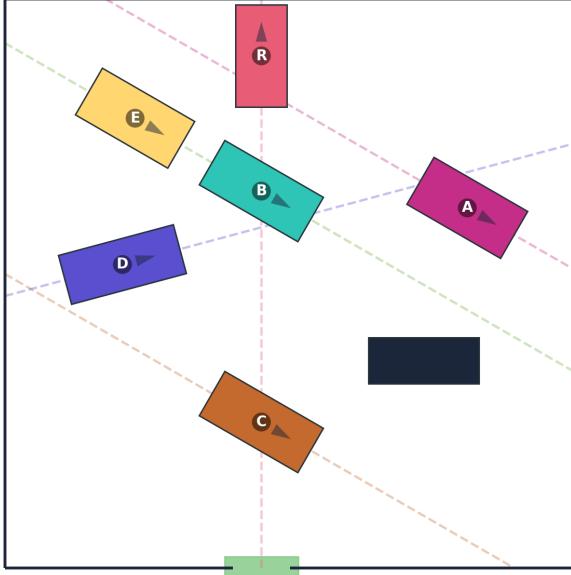
G. More Examples from MENTISOCULI

G.1. Example Text Description

The text-only setting uses a simulator-derived *state specification* rather than a human-style natural-language description. Importantly, this representation is *not* isomorphic to a short, low-token text prompt: it is substantially longer, uses continuous-valued attributes (positions, sizes, rotations), and encodes motion constraints explicitly. As a result, solving from text requires models (and humans) to reason over an unusual, high-precision format. See an example of the text description in Figure 21.

G.2. Example Visual CoT

In addition to the initial rendered instance, MENTISOCULI provides an *ground truth visual chain-of-thought* for each example: a sequence of images meant to aid the visual reasoning process by showing intermediate states. These rollouts serve two purposes in our experiments: they define the *expected* number of intermediate images for an instance and enable direct diagnostics of image-generation-based reasoning by comparing model-generated intermediate states to the ground-truth trajectory (see Figure 22).



Text Description

The parking lot has a size of 10×10 .

There is an exit on the bottom ($y = 0$) edge, from $x = 4.01$ to $x = 5.01$.

There is a red car (R) at center $(4.51, 9.00)$ with length 1.80 and width 0.90, rotated by 90.0° , i.e. the car can move forwards along the $(0.00, 1.00)$ axis and backwards along $(-0.00, -1.00)$.

There is a car (A) at center $(8.12, 6.33)$ with length 1.90 and width 0.95, rotated by -30.0° , i.e. the car can move forwards along the $(0.87, -0.50)$ axis and backwards along $(-0.87, 0.50)$.

There is a car (B) at center $(4.51, 6.62)$ with length 2.00 and width 0.90, rotated by -30.0° , i.e. the car can move forwards along the $(0.87, -0.50)$ axis and backwards along $(-0.87, 0.50)$.

There is a car (C) at center $(4.51, 2.57)$ with length 2.00 and width 0.90, rotated by -30.0° , i.e. the car can move forwards along the $(0.87, -0.50)$ axis and backwards along $(-0.87, 0.50)$.

There is a car (D) at center $(2.06, 5.33)$ with length 2.09 and width 0.89, rotated by 15.0° , i.e. the car can move forwards along the $(0.97, 0.26)$ axis and backwards along $(-0.97, -0.26)$.

There is a car (E) at center $(2.29, 7.90)$ with length 1.87 and width 0.95, rotated by -30.0° , i.e. the car can move forwards along the $(0.87, -0.50)$ axis and backwards along $(-0.87, 0.50)$.

There is a static, immovable object at $((6.38, 3.24), (8.33, 4.05))$.

Figure 21. Text descriptions are verbose simulator states, not compact natural-language prompts Example RUSH HOUR instance (left) and its deterministic state specification (right), which uses continuous-valued geometry and explicit motion axes.

H. Prompts & Instructions

H.1. MLLM Standard Prompts

FORM BOARD

Look at the image:

It is showing from left to right, a target shape outlined in black and five pieces labeled A through E in various colors:
<image combined.png>

Rules:

1. The target shape can be assembled using 1 to 5 of the given pieces.
2. Pieces must fit together perfectly with no gaps or overlaps.
3. Some pieces are distractors and are not needed.
4. Pieces are shown in their correct orientation and size (no rotation or scaling needed).

Task:

Determine the subset of pieces from $\{A, B, C, D, E\}$ necessary to assemble the target shape.

Output: Respond in JSON format as follows:
`{"answer": "A C E"}`

List only the letter labels of the pieces needed, separated by space.

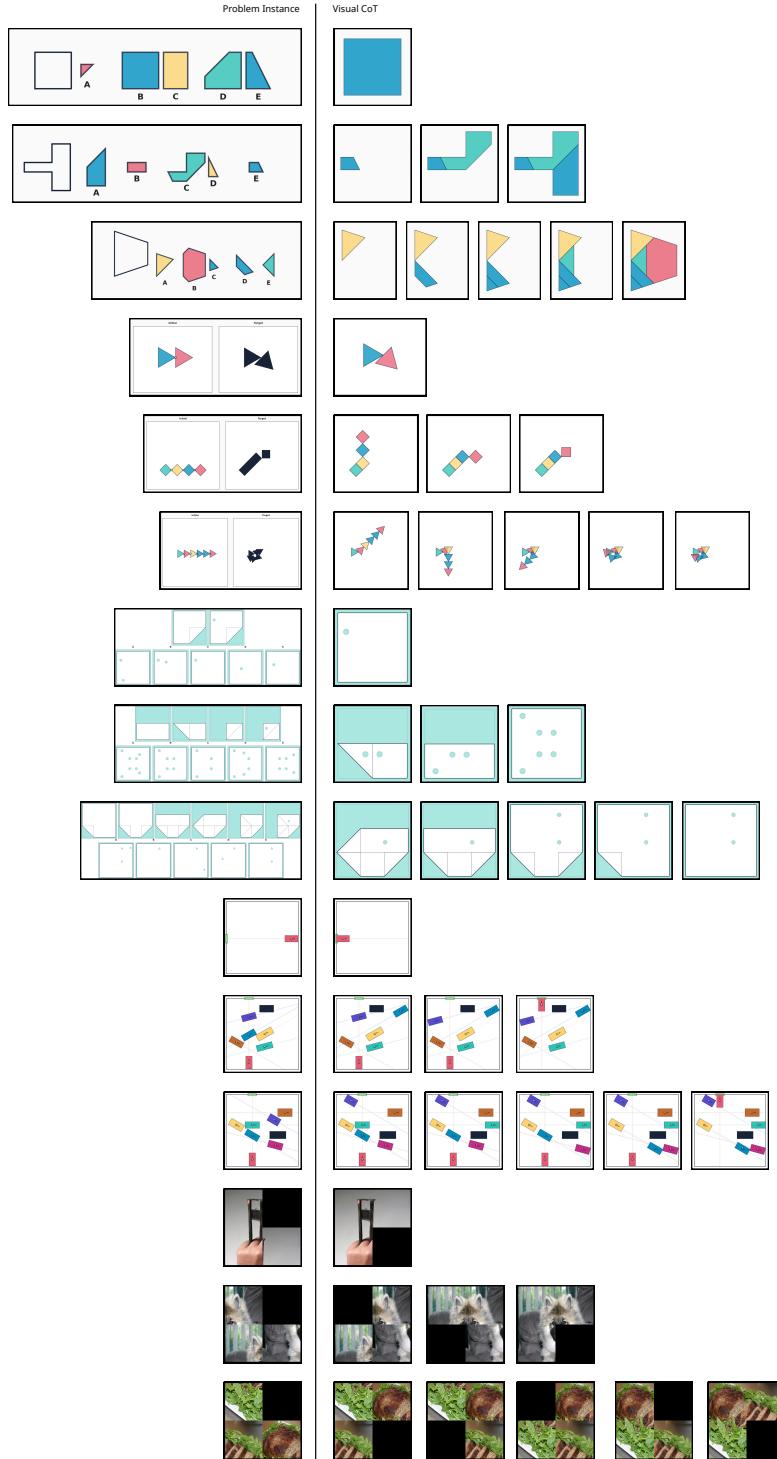


Figure 22. Ground-truth visual CoTs render the simulator state after every action, providing step-aligned supervision for multi-step imagery Random samples from levels 1, 3, and 5 across tasks; each example shows the initial instance (left) and the corresponding sequence of intermediate rendered states along the reference solution trajectory (right).

HINGE FOLDING

Look at the image:

The left side shows several rigid shapes connected by labeled hinges (A, B, C, ...).
On the right side is a target folded configuration:
<image combined.png>

Rules:

1. Shapes are connected in a kinematic chain; each hinge connects two adjacent shapes.
2. Rotating hinge N causes the shape on the right side of the hinge in the original configuration to rotate anti-clockwise.
All shapes are connected; all shapes to the right of the rotated shape rotate with it.
All shapes to the left of the hinge remain fixed.
3. Rotations must be multiples of 45° (i.e., $45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ$).
4. Shapes maintain their connections throughout all rotations.
5. The goal is to find the sequence of hinge rotations that transforms the initial configuration into the target.

Task:

Determine the rotation angle (in degrees) for each numbered hinge to achieve the target configuration.

Output: Respond in JSON format as follows:

```
{"answer": "A 90, B 90, C 180"}
```

Each pair specifies the hinge label and its rotation angle in degrees.

If multiple solutions exist, output any valid sequence that produces the target configuration.

PAPER FOLD

Look at the image:

In the first row, it shows a sequence of folds performed on a square paper. The final image in the sequence shows one or more holes being punched into the folded paper.
The second row shows five unfolded square papers with different hole patterns labeled A through E:
<image combined.png>

Rules:

1. The paper starts as a flat square.
2. Each step shows the paper being folded along a line (horizontal, vertical, or diagonal).
3. After all folds are complete, one hole is punched through all layers at the marked positions.
4. When the paper is unfolded completely, holes appear at multiple positions due to the layering.
5. One of the five options (A, B, C, D, E) shows the correct hole pattern.

Task:

1. Mentally follow each fold in sequence as shown in the first row.
2. Track where the hole is punched through all folded layers.
3. Mentally unfold the paper with the punched hole step-by-step in reverse order.
4. Determine which unfolded pattern (A, B, C, D, or E) matches your mental result.

Output: Respond in JSON format as follows:

```
{"answer": "C"}
```

RUSH HOUR

Look at the image:

It shows the initial configuration of a congested parking lot. Each colored rectangle with a letter and arrow represents a vehicle. Black rectangles without a letter represent immovable obstacles. The light green area at the border indicates the exit. The goal is to move the red vehicle (marked with an R) to the exit:
<image initial.state.png>

Rules:

1. Each vehicle can only move forward or backward along its own axis (indicated in the image as a dashed line) — no rotation is allowed. The arrow on each vehicle indicates the forward direction.
2. A vehicle continues to move in the chosen direction until it touches another vehicle, an immovable object, or the image's boundary (marked with a light black line).
3. Only one vehicle moves per action.
4. The red vehicle must reach the exit on the edge of the grid.

Task:

Plan the minimal sequence of moves needed to free the red car and allow it to exit the parking lot.
Each move should specify which vehicle moves and in which direction (forward or backward).

Output: Respond in JSON format as follows:

```
{"answer": "A forward, C backward, E forward, R forward"}
```

Each pair specifies the vehicle label and the direction of its move.

If multiple sequences lead to a valid solution, output any one valid sequence that allows the red car to exit.

SLIDING PUZZLE

Look at the image:

Below is a scrambled sliding tile puzzle where a natural image has been cut into an $n \times n$ grid with one blank (black) tile:
<image initial.png>

Rules:

1. The puzzle consists of an $n \times n$ grid with one blank tile and $n^2 - 1$ image tiles.
2. You can move the blank tile in four directions: up, down, left, right.
3. Each action swaps the blank with the adjacent tile in the specified direction.
4. Only valid moves are allowed (the blank cannot move outside the grid boundaries).
5. The goal is to reconstruct the original, coherent image by rearranging the scrambled tiles.

Task:

Determine the shortest sequence of moves needed to solve the puzzle and restore the original image.

Output: Respond in JSON format as follows:

```
{"answer": "up right down left up"}
```

Each word specifies a direction to move the blank tile.

You may guess the most plausible move even if uncertain. Small mistakes are acceptable.

H.2. Interleaved Image and Text Generation

HINGE FOLDING

Look at the image:

It shows, from left to right, a target shape outlined in black and five pieces labeled A through E in various colors:
<image combined.png>

Rules:

1. The target shape can be assembled using 1 to 5 of the given pieces.
2. Pieces must fit together perfectly with no gaps or overlaps.
3. Some pieces are distractors and are not needed.
4. Pieces are shown in their correct orientation and size (no rotation or scaling needed).

Task:

Move one piece at a time of {A, B, C, D, E} from the right into the outlined target shape on the left. Generate a new image for each move.

If you notice a mistake, you may also return a piece from the outlined target shape back to the candidate shapes. Also generate a new image in this case.
Finally, using your intermediate images, determine the subset of pieces from {A, B, C, D, E} necessary to assemble the target shape.

Output:

First, reason through the moves and generate images with the updated puzzle states. Make sure that these updated images are generated by the rules specified above. Generate one image after each move.
Finally, respond in JSON format as follows:

```
{"answer": "A C E"}
```

List only the letter labels of the pieces needed, separated by spaces.

Revealing the Limits of Reasoning with Mental Imagery

HINGE FOLDING

Look at the image:

The left side shows several rigid shapes connected by labeled hinges (A, B, C, ...).

On the right side is a target folded configuration:

<image combined.png>

Rules:

1. Shapes are connected in a kinematic chain — each hinge connects two adjacent shapes.
2. Rotating hinge N causes the shape on the right side of the hinge in the original configuration to rotate anti-clockwise.
All shapes are connected; all shapes to the right of the rotated shape rotate with it.
All shapes to the left of the hinge remain fixed.
3. Rotations must be multiples of 45° (i.e., $45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ$).
4. Shapes maintain their connections throughout all rotations.
5. The goal is to find the sequence of hinge rotations that transforms the initial configuration into the target.

Task:

Determine the rotation angle (in degrees) for each numbered hinge to achieve the target configuration.

After each move, generate a new image in which you update the left side of the image to reflect your proposed hinge rotation.

Once the outlines of the left and right side of the image match, output your rotation sequence.

Output:

First, reason through the moves and generate images with the updated puzzle states. Make sure that these updated images are generated by following the rules specified above. Generate one image after each rotated hinge.

Respond in JSON format as follows:

```
{"answer": "A 90, B 90, C 180"}
```

Each pair specifies the hinge label and its rotation angle in degrees.

If multiple solutions exist, output any valid sequence that produces the target configuration.

PAPER FOLD

Look at the image:

In the first row, it shows a sequence of folds performed on a square paper. The final image in the sequence shows one or more holes being punched into the folded paper.

The second row shows five unfolded square papers with different hole patterns labeled A through E:

<image combined.png>

Rules:

1. The paper starts as a flat square.
2. Each step shows the paper being folded along a line (horizontal, vertical, or diagonal).
3. After all folds are complete, one hole is punched through all layers at the marked positions.
4. When the paper is unfolded completely, holes appear at multiple positions due to the layering.
5. One of the five options (A, B, C, D, E) shows the correct hole pattern.

Task:

1. Mentally follow each fold in sequence as shown in the first row.
2. Track where holes are punched through all folded layers.
3. Unfold the paper with the punched hole step-by-step in reverse order.
4. After each unfolding move, generate an image of the (partially) unfolded paper with hole(s) in the correct positions.
5. Determine which unfolded pattern (A, B, C, D, or E) matches your generated result.

Output:

First, reason through the moves and generate images with the progressively more unfolded paper sheet. Make sure that these updated images are generated by following the rules specified above.

Generate one image after each unfold.

Finally, respond in JSON format as follows:

```
{"answer": "C"}
```

RUSH HOUR

Look at the image:

It shows the initial configuration of a congested parking lot. Each colored rectangle with a letter and arrow represents a vehicle. Black rectangles without a letter represent immovable obstacles. The light green area at the border indicates the exit. The goal is to move the red vehicle (marked with an R) to the exit:
<image initial_state.png>

Rules:

1. Each vehicle can only move forward or backward along its own axis (indicated in the image as a dashed line) — no rotation is allowed. The arrow on each vehicle indicates the forward direction.
2. A vehicle continues to move in the chosen direction until it touches another vehicle, an immovable object, or the image's boundary (marked with a light black line).
3. Only one vehicle moves per action.
4. The red vehicle must reach the exit on the edge of the grid.

Task:

Plan the minimal sequence of moves needed to free the red car and allow it to exit the parking lot.

Each move should specify which vehicle moves and in which direction (forward or backward).

After each move, generate an image showing the updated puzzle state.

Output:

First, reason through the moves and generate images with the updated puzzle states. Make sure that these updated images are generated by following the rules specified above.

Generate one image after each move.

Finally, respond in JSON format as follows:

```
{"answer": "A forward, C backward, E forward, R forward"}
```

Each pair specifies the vehicle label and the direction of its move.

If multiple sequences lead to a valid solution, output any one valid sequence that allows the red car to exit.

SLIDING PUZZLE

Look at the image:

Below is a scrambled sliding tile puzzle where a natural image has been cut into an $n \times n$ grid with one blank (black) tile:

<image initial.png>

Rules:

1. The puzzle consists of an $n \times n$ grid with one blank tile and $n^2 - 1$ image tiles.
2. You can move the blank tile in four directions: up, down, left, right.
3. Each action swaps the blank with the adjacent tile in the specified direction.
4. Only valid moves are allowed (the blank cannot move outside the grid boundaries).
5. The goal is to reconstruct the original, coherent image by rearranging the scrambled tiles.

Task:

Determine the shortest sequence of moves needed to solve the puzzle and restore the original image.

After each move, generate an image of how the puzzle state looks, i.e., showing the swap of the blank tile and the adjacent image tile.

Output:

First, reason through the moves and generate images with the updated puzzle states. Make sure that these updated images are generated by following the rules specified above. Generate one image after each proposed move.

Finally, respond in JSON format as follows:

```
{"answer": "up right down left up"}
```

Each word specifies a direction to move the blank tile.

You may guess the most plausible move even if uncertain. Small mistakes are acceptable.

H.3. Video Models

RUSH HOUR

Look at the image:

Below is the first image, showing the initial configuration of a congested parking lot. Each colored rectangle represents a vehicle, and the red car is the one that must reach the exit. The exit is marked with a green area at the border:

Rules:

1. Each vehicle can only move forward or backward with straight sliding motion along its own axis.
2. No rotation is allowed at any time.
3. A vehicle continues to move in the chosen direction until it touches another vehicle or a boundary.
4. Only one vehicle moves per action.
5. The goal is for the red car to reach the exit located on the edge of the grid.
6. Vehicle shapes, colors, exit, and outlines must not change throughout the solution.
7. No camera motion: no zoom, no pan, no rotate, no tilt, no dolly.
8. Do not add or remove anything: no new objects, labels, lights, shadows, reflections, textures, markings, or UI elements.
9. The background, grid, exit, and all pieces remain perfectly static, except for the piece currently sliding.

Task:

Plan the minimal sequence of moves needed to free the red car and allow it to exit the parking lot.

Output:

A video demonstrating the full solution to the puzzle, one move at a time.

<image initial.state.png>

H.4. Human Instructions

For the human psychophysics experiment we used the following set of instructions:

Human Instructions

Look at the image:

You are shown the initial configuration of a congested parking lot.

Each colored rectangle with a letter and arrow represents a vehicle. Black rectangles without a letter represent immovable obstacles. The light green area at the border indicates the exit. The goal is to move the red vehicle (marked with an R) to the exit.

<image initial.state.png>

Rules:

1. Each vehicle can only move forward or backward along its own axis (indicated in the image as a dashed line) — no rotation is allowed. The arrow on each vehicle indicates the forward direction.
2. A vehicle continues to move in the chosen direction until it touches another vehicle, an immovable object, or the image's boundary (marked with a light black line).
3. Only one vehicle moves per action.
4. The red vehicle must reach the exit on the edge of the grid.

Task:

Plan the minimal sequence of moves needed to free the red vehicle and allow it to exit the parking lot.

Each move should specify which vehicle moves and in which direction (forward or backward).

Output:

Respond by first specifying the label of the vehicle, then specifying whether it should move forwards or backwards, for example:

AF CB RF

to indicate that first A should move forward, then C should move backward, and then the red vehicle should move forward, i.e. each pair specifies the vehicle label and the direction of its move.

Once you are done, press ENTER.

If multiple sequences lead to a valid solution, output any one valid sequence that allows the red car to exit.

Press ENTER to begin the experiment.

H.5. Ground Truth Visual Chain of Thought

We append the prompt from Section H.1 with

GT Visual CoT

The following images correspond to intermediate images in the reasoning process.

You must use them to obtain your answer:

<images visual_cot>

H.6. Tool Use

We append the prompt from Section H.1 with

Tool Use

Use your python tool to solve this question.

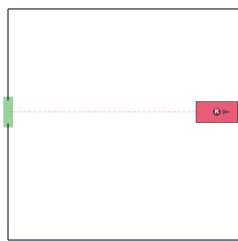
H.7. In-Context Learning

We append the prompt from Section H.1 with one example from each level. We use the same examples for all queried models across in-context learning (ICL) with intermediate images and no intermediate images.

In-Context Learning Prompt (no intermediate visuals). Shortened to fit on one page

Examples:

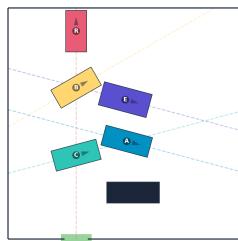
1. This is the initial parking lot:



The correct solution for this sample would be:
`{"answer": "R backward"}`

2. [omitted]

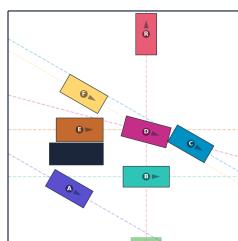
3. This is the initial parking lot:



The correct solution for this sample would be:
`{"answer": "B backward, C backward, R backward"}`

4. [omitted]

5. This is the initial parking lot:



The correct solution for this sample would be:

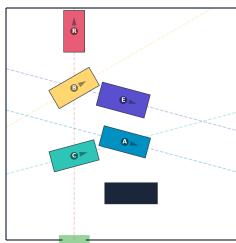
`{"answer": "B backward, F backward, E backward, D backward, R backward"}`

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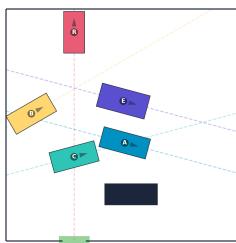
In-Context Learning Prompt (intermediate visuals). Shorten to fit on a page

Examples:

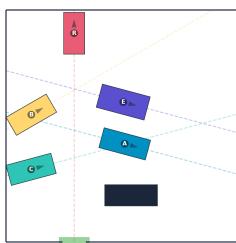
1. [omitted]
2. [omitted]
3. This is the initial parking lot:



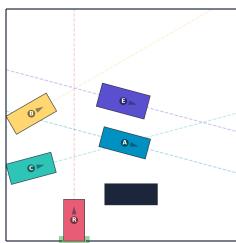
After moving B backward the parking lot would look like:



After moving C backward the parking lot would look like:



After moving R backward the parking lot would look like:



The correct solution for this sample would be:

```
{"answer": "B backward, C backward, R backward"}
```

4. [omitted]

5. [omitted]

H.8. Optimized Prompt

Optimized Prompt

Look at the image:

You are given an image of a RUSH HOUR-style sliding block puzzle. Each colored rectangle with a capital letter and an arrow is a movable vehicle. Black rectangles with no letters are fixed obstacles (walls). A light green opening on the border is the exit. The goal is to move the red vehicle labeled "R" so it can slide out through the exit:

<image initial.state.png>

Rules:

1. Each vehicle is either horizontal or vertical (shown by its arrow direction). Vehicles never rotate or move diagonally.
2. A vehicle may move only along its own axis:
 - "forward" = exactly in the direction the arrow points,
 - "backward" = exactly opposite that direction.
3. When a vehicle moves, it must slide in the chosen direction until its front edge first touches:
 - another vehicle, or
 - a fixed black obstacle, or
 - the outer boundary of the grid.

It cannot stop earlier and cannot pass through anything.
4. Only one vehicle moves per action.
5. The puzzle is solved when R can make a single legal slide through the green exit area.

Task:

1. From the image, internally identify every vehicle by:
 - its letter (a single uppercase letter),
 - its arrow direction (which defines forward vs. backward),
 - its orientation (horizontal or vertical).
2. Internally reason step-by-step to find a legal sequence of moves that:
 - clears a path for R to the exit, and then
 - moves R out through the exit in a final legal move.

Focus first on vehicles directly blocking R, then on vehicles blocking those blockers, and so on. Avoid pointless back-and-forth moves; prefer short, efficient solutions.
3. Check that every planned move obeys the rules: the chosen vehicle moves only along its axis and slides as far as possible in that direction until contact.

Output format:

- Do all visual analysis and reasoning internally. Do NOT display your intermediate reasoning or any text other than the JSON object.
- Respond with a single JSON object and no extra text before or after it.
- Use exactly this format: one string listing the moves in order, separated by commas:

```
{"answer": "A forward, C backward, E forward, R forward"}
```

Each item in the string must be:

- a single uppercase vehicle letter from the image,
 - a space,
 - the word "forward" or "backward".
- Return only this JSON object as your final answer.

I. Datasheet for MENTISOCULI

We here include a Datasheet for MENTISOCULI following the template proposed by Gebru et al. (12).

Motivation

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

MENTISOCULI was created to evaluate and probe whether modern multimodal foundation models can form, maintain, and manipulate high-fidelity visual representations in a goal-directed manner (i.e., “mental imagery” as a computational strategy). The benchmark targets multi-step visual reasoning problems that are naturally amenable to visual solution and are tuned to challenge frontier models, including models capable of interleaved generation and video models. The design emphasizes procedural generation, stratified difficulty, and the availability of ground-truth solution trajectories (including oracle visualizations) to enable detailed diagnosis and future extensibility.

Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

The dataset was created by the (currently anonymous) authors of the accompanying paper. The specific entity/affiliation will be filled in for the final de-anonymized version.

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

To be filled in with funding/grant information in the final de-anonymized version.

Any other comments?

Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

Instances are five procedurally generated visual puzzle problems: FORM BOARD, HINGE FOLDING, PAPER FOLD, RUSH HOUR, and SLIDING PUZZLE. Each instance is associated with a discrete difficulty level (1–5) corresponding

to the minimum number of operations required (moves/folds/placements/etc.). For each instance, the generators produce (i) a single question image specifying the full problem state, and (ii) a ground-truth solution that includes a ground-truth visual chain-of-thought (a sequence of intermediate states/images) capturing the step-by-step trajectory to reach the solution.

How many instances are there in total (of each type, if appropriate)?

The initial release contains 30 instances per difficulty level for each task. Since there are 5 tasks and 5 difficulty levels, this corresponds to $5 \times 5 \times 30 = 750$ total puzzle instances in the initial benchmark release.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

The dataset is a finite sample from an effectively unbounded set of instances produced by the task auto-generators (which can generate infinitely many instances with controllable difficulty). The initial release samples 30 instances per level per task from the generators’ sampling procedures (randomized instance construction subject to task-specific constraints). Representativeness in a geographic or demographic sense is not applicable because the benchmark is primarily synthetic/procedural; diversity is instead governed by generator parameters and constraint checks. For SLIDING PUZZLE specifically, each instance is constructed by sampling a natural image from ImageNet-1k (9); the same underlying images are shared across difficulty levels, while difficulty is varied by solution length.

What data does each instance consist of? “Raw” data (e.g., unprocessed text or images) or features? In either case, please provide a description.

Each instance consists primarily of raw rendered image data plus structured metadata:

- A single rendered question image containing the full initial state of the puzzle.

- A difficulty level label (1–5), defined by the minimum number of operations required to solve the instance.
- A ground-truth solution specification (task-dependent; e.g., subset selection, hinge angles, unfolded option, action sequence).
- A ground-truth visual chain-of-thought: a sequence of intermediate rendered states/images corresponding to the step-by-step solution trajectory.
- (Task-dependent) additional metadata such as the source-image identity for SLIDING PUZZLE (which is derived from ImageNet-1k).

Some analyses in the paper also use a deterministic simulator-state specification (e.g., for RUSH HOUR) as a non-natural-language textual description; this is optional and primarily intended for controlled ablations rather than as the main dataset modality.

Is there a label or target associated with each instance? If so, please provide a description.

Yes. Each instance has a task-specific target:

- FORM BOARD: the subset of pieces (from A–E) that exactly tiles the target silhouette.
- HINGE FOLDING: the discrete rotation angles (in 45-degree increments) for each hinge to match the target configuration.
- PAPER FOLD: the correct unfolded hole pattern (one of A–E).
- RUSH HOUR: a valid (minimal, per generator) sequence of discrete forward/backward moves that moves the red car to the exit.
- SLIDING PUZZLE: the shortest sequence of moves (up/down/left/right) that restores the coherent original image.

The dataset also provides ground-truth intermediate states (visual CoT) aligned with the reference solution trajectory.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

No systematic missing information is expected: instances are procedurally generated and include both the initial question image and ground-truth solution information (including

intermediate visual states). A practical consideration is that SLIDING PUZZLE relies on ImageNet-1k as an upstream image source; users may need to ensure they have appropriate access/rights to ImageNet-1k-derived imagery.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.

Instances are intended to be independent puzzle problems and do not contain explicit relational structure (no graphs, links, or cross-instance annotations). One notable dependency is that SLIDING PUZZLE shares the same underlying sampled images across difficulty levels (i.e., the image source is reused while scramble difficulty differs), which can be treated as a mild grouping factor if users perform per-image stratified analysis.

Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.

MENTISOCULI is primarily introduced as an evaluation benchmark rather than a training dataset. For users who want to train on MENTISOCULI-like data, the recommended approach is to use the released generators to create new, non-overlapping instances (e.g., by using new random seeds and/or holding out ImageNet source images for SLIDING PUZZLE) and reserve the released 750-instance set as a held-out test benchmark.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

Labels are generated automatically and verified by construction/solving, which reduces annotation noise relative to human-labeled datasets. The generators also include task-specific filtering to remove ambiguous or invalid instances (e.g., RUSH HOUR instances are solved via breadth-first search to ensure solvability and minimal solution length, and visually ambiguous near-collisions are discarded; SLIDING PUZZLE instances are solved to record the shortest solution and ensure correct difficulty classification). Potential residual noise is primarily graphical/rendering-related (e.g., minor aliasing or small visual artifacts), and redundancy may arise from shared image sources in SLIDING PUZZLE across difficulty levels.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are

there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

Most tasks are fully procedural and self-contained (synthetic rendering of geometric configurations). However, SLIDING PUZZLE relies on sampling natural images from ImageNet-1k as the source imagery. Users should ensure they comply with the ImageNet terms of access and any downstream licensing constraints associated with ImageNet-derived images.

Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals non-public communications)? If so, please provide a description.

No. The benchmark consists of procedurally generated puzzles and (for SLIDING PUZZLE) images sampled from a standard public research dataset; it does not include private communications or privileged records.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.

The procedural puzzle renderings are not designed to include offensive content. However, SLIDING PUZZLE uses natural images sampled from ImageNet-1k, which may contain a wide range of real-world visual content. While ImageNet-1k is widely used in research, users should be aware that some images could potentially be unsettling or culturally sensitive depending on the sampled image content.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

Not directly. MENTISOCULI is not a dataset about individuals or human attributes; it is a dataset of puzzle instances. That said, SLIDING PUZZLE may include natural images that depict people, as it samples from ImageNet-1k.

Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

No.

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

Any other comments?

Collection Process

How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

Puzzle data is acquired primarily via procedural generation: task-specific software generators render each puzzle instance and simultaneously produce the corresponding ground-truth solution and intermediate visual trajectory. For SLIDING PUZZLE, the only external acquisition step is sampling a source image from ImageNet-1k before tiling/scrambling it. Ground-truth labels/trajectories are validated by construction and automated solving (e.g., solving trajectories are computed to ensure solvability and to record shortest/minimal solutions used for difficulty classification).

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?

Software programs (task auto-generators, renderers, and solvers) were used to create instances. Validation is performed via algorithmic checks and automated solving:

- Planning tasks use explicit solvers to ensure solvability

| | |
|---|--|
| and minimal/shortest solution trajectories and to avoid ambiguous states. | question directly, or obtain it via third parties or other sources (e.g., websites)? |
| <ul style="list-style-type: none"> Geometric tasks enforce construction constraints (e.g., distinct pieces, controlled distractors). | Not applicable for dataset construction. |
| If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)? | Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself. |
| The dataset is a sample from the generators' instance distributions. Instances are produced by randomized sampling of generator parameters subject to task-specific constraints, and the initial release selects 30 instances per difficulty level per task. | Not applicable for dataset construction. |
| Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)? | Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented. |
| No crowdworkers or contractors are required for puzzle generation; instances and labels are produced automatically by the generators. | Not applicable for dataset construction. |
| Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created. | If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate). |
| Instances were generated procedurally during benchmark development from October 2025 to January 2026. | Not applicable for dataset construction. |
| Were any ethical review processes conducted (e.g., by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation. | Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation. |
| The dataset itself is primarily synthetic/procedural and does not require human-subject review for instance creation. However, the paper's human reference experiment (RUSH HOUR) received IRB approval, and participants provided informed consent. | Because the benchmark is primarily synthetic/procedural and does not target personal data, a formal data-subject impact analysis is not necessary. |
| Does the dataset relate to people? If not, you may skip the remaining questions in this section. | Any other comments? |
| Not directly. The dataset contains puzzle instances; SLIDING PUZZLE uses natural images that may depict people, but no personal data is collected from subjects as part of dataset construction. | Preprocessing/cleaning/labeling |
| Did you collect the data from the individuals in | Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section. |

No.

Was the “raw” data saved in addition to the pre-processed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.

No.

Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.

Not applicable.

Any other comments?

Uses

Has the dataset been used for any tasks already?
If so, please provide a description.

Yes. The dataset is used in the accompanying paper to benchmark and analyze multiple model families (including MLLMs and unified multimodal models) on multi-step visual reasoning and planning, and to study whether interleaved visual generation (explicit “visual thoughts”) improves performance.

Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.

To be added when the dataset/code is released in the de-anonymized version.

What (other) tasks could the dataset be used for?

Potential uses include:

- Benchmarking step-by-step state tracking and intermediate visual reasoning traces.
- Training or fine-tuning models to produce faithful intermediate visual updates (if using freshly generated training instances and keeping the official benchmark set held out).
- Studying scaling behavior with respect to number of required operations (difficulty) and analyzing failure modes (e.g., compounding generation errors).
- Evaluating planning-from-vision and state representation learning (especially in SLIDING PUZZLE / RUSH HOUR).

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

Key considerations:

- SLIDING PUZZLE uses ImageNet-1k imagery; users should consider licensing/terms and potential incidental sensitive content in natural images.
- Difficulty levels are controlled by minimum operation counts; comparing models across levels is meaningful, but training on the released test instances may create contamination. Mitigation: train on newly generated instances (new seeds / held-out source images) and keep the official set for evaluation.
- Some optional text-only ablations use verbose simulator-state specifications rather than natural-language prompts; results from those settings should not be interpreted as evidence that the tasks are “easily textualizable.”

Are there tasks for which the dataset should not be used? If so, please provide a description.

Yes. The dataset is not intended for evaluating real-world perception, natural image understanding, or semantic visual recognition. All tasks are procedurally generated and abstract, and do not reflect the visual statistics, ambiguities, or noise present in natural images or videos.

The dataset should also not be used to draw conclusions about human-level general intelligence, real-world planning ability, or safety-critical decision making. Its purpose is narrowly scoped to analyzing models’ ability to form, maintain, and manipulate internal visual representations under controlled conditions.

Finally, the dataset is not suitable for training models intended for deployment in real-world environments, as it deliberately avoids real-world content, social context, or human-centered scenarios.

Any other comments?

Distribution

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.

The dataset is not intended for:

- Real-world perception benchmarking (it is puzzle-based and largely synthetic).
- Any form of biometric identification, profiling, or demographic inference (no such labels exist, and any incidental human depictions are not meant for this purpose).
- High-stakes deployment decisions (medical, legal, or safety-critical evaluation), since the tasks are stylized puzzles rather than operational environments.

How will the dataset will be distributed (e.g., tarball on website, API, GitHub) Does the dataset have a digital object identifier (DOI)?

In the de-anonymized release, we plan to provide (i) a public code repository containing the generators, solvers, and evaluation scripts, and (ii) a versioned archive of the fixed evaluation instances (e.g., a tarball/zip with images, metadata, and ground-truth solution traces).

When will the dataset be distributed?

The release timeline (e.g., upon publication / camera-ready) will be stated in the final de-anonymized version.

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

In the de-anonymized release, we will provide an explicit license for (a) the code (generators/solvers/evaluation) and (b) the dataset assets (rendered instances and annotations). We will additionally document any usage constraints inherited from external resources (notably ImageNet-1k for SLIDING PUZZLE). Any applicable Terms of Use and links will be added in the final version.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

Yes. The SLIDING PUZZLE task uses natural images sampled from ImageNet-1k as source imagery; therefore, ImageNet access terms and any downstream restrictions may apply to those ImageNet-derived assets. Links to the relevant third-party licensing/terms will be included in the final version.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

No.

Any other comments?

Maintenance

Who will be supporting/hosting/maintaining the dataset?

Intended maintainers are the paper authors via the dataset-/code release channel (GitHub).

How can the owner/curator/manager of the dataset be contacted (e.g., email address)?

An email and GitHub page will be added in the de-anonymized version.

Is there an erratum? If so, please provide a link or other access point.

Will be provided in the de-anonymized version.

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?

Yes, concrete communication channels will be added in the de-anonymized version.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.

Not applicable to the dataset instances (puzzle problems).

Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.

Versioned snapshots will be hosted and we will maintain an archive of prior versions with clear deprecation notes, if updates should be necessary

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description.

Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.

Contributors should refer to the GitHub repository to create issues and pull requests which upon inspection of the authors will be included into the benchmark.

Any other comments?