

💡 VMMU: A Vietnamese Multitask Multimodal Understanding and Reasoning Benchmark

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Abstract

We introduce 💡 VMMU, a Vietnamese Multitask Multimodal Understanding and Reasoning Benchmark designed to evaluate how vision language models (VLMs) interpret and reason over visual and textual information beyond English. VMMU consists of 2.5k multimodal questions across 7 tasks, covering a diverse range of problem contexts, including STEM problem solving, data interpretation, rule-governed visual reasoning, and abstract visual reasoning. All questions require genuine multimodal integration, rather than reliance on text-only cues or OCR-based shortcuts. We evaluate a diverse set of state-of-the-art (SOTA) proprietary VLMs on 💡 VMMU. Despite strong Vietnamese OCR performance, proprietary models achieve only 66% mean accuracy. Further analysis shows that the primary sources of failure are not OCR, but instead multimodal grounding and reasoning over text and visual evidence. Code and data are available at: vmmu.github.io.

1 Introduction

Vision language models (VLMs) have made rapid progress on multimodal benchmarks, demonstrating strong performance on complex visual and textual reasoning tasks in English (Yue et al., 2024, 2025; Liu et al., 2024; Lu et al., 2022, 2024). However, it remains unclear how well these models perform in low-resource languages, especially when language understanding, visual grounding, and reasoning are all required to complete a task. In this work, we study this question in the context of Vietnamese, a widely spoken language with nearly 100 million speakers that remains significantly underrepresented in multimodal evaluation.

This underrepresentation matters because many tasks require understanding image-based documents: people frequently rely on screenshots or

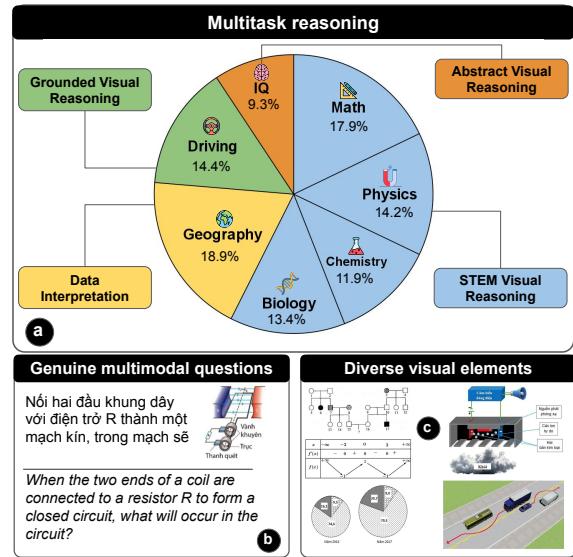


Figure 1: (a) 💡 VMMU covers 7 domains and supports multitask multimodal reasoning. (b) Many items are genuine multimodal questions that require jointly using the Vietnamese text and the accompanying image to answer. (c) VMMU includes diverse visual evidence (e.g., diagrams, charts, tables, and traffic scenes).

photos that include instructions with structured visual content. For example, learning materials often consist of textbook pages or PDFs that include questions alongside visual information (Fig. 1b). Similarly, people routinely encounter administrative and government documents (e.g., application forms, notices, and records) that combine dense text with visually structured elements such as tables, stamps, and form layouts. VLMs therefore have the potential to support Vietnamese users across various of these settings, from helping parents explain homework solutions at home to enabling citizens to interpret administrative documents. For this, models must process image-based questions that integrate *Vietnamese text with structured visual content* (e.g., charts, diagrams, tables; Fig. 1c). Successfully solving such problems requires reliable optical OCR of Vietnamese, ade-

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quate grounding between textual instructions and visual evidence, and robust multimodal reasoning to select correct answers in multiple-choice settings where positional biases may occur (Atabuzzaman et al., 2025).

Several LLM/VLM benchmarks include partial or full Vietnamese coverage (Singh et al., 2025; ZaloAI and JAIST, 2025; Xuan et al., 2025), but they fail to address how VLMs perform on problems that require joint visual grounding and language reasoning. As a result, prior benchmarks offer limited insight into VLM performance on *genuinely multimodal* Vietnamese questions, where non-text visual evidence is essential and must be integrated with the text to reach the correct answer. Importantly, English-only multimodal evaluation (Yue et al., 2024, 2025) is not sufficient to assess multilingual generalization. Vietnamese tasks exhibit differences in rendered text, labels, domain distributions, and conventions, limiting the usefulness of English benchmarks for diagnosing whether VLMs reliably ground and reason in Vietnamese settings.

In this work, we introduce  VMMU, a Vietnamese Multitask Multimodal Understanding and Reasoning benchmark designed to directly address this gap (Fig. 1). We define *multimodal questions* as those in which non-text visual evidence is necessary to solve the problem, so the model must integrate the question with visual elements. We filter out text-only items where the image provides little beyond rendered text, retaining questions that require understanding non-text visual evidence (e.g., diagrams, charts, tables). All questions in VMMU require models to simultaneously process rendered Vietnamese text, interpret visual content, and reason based on this evidence (Fig. 1b).

 VMMU consists of 2,548 carefully curated questions spanning 7 domains (Fig. 1a):  Mathematics,  Physics,  Chemistry,  Biology,  Geography,  Driving Test, and  IQ Test. The benchmark is constructed using a semi-automated pipeline with human validation to ensure multimodal integrity and question quality. Unlike prior datasets that simplify or discard visual information (Dao et al., 2023; Zhang et al., 2023), VMMU preserves visual content in its original form, enabling direct evaluation of multimodal reasoning. Our key findings are:

1. **Proprietary VLMs score relatively low on VMMU (§4.2):** Non-thinking models reach only 50-71% accuracy, while thinking VLMs

benefit significantly from reasoning, achieving 73-86%.

2. **OCR is not the bottleneck (§4.1):** Across 5 proprietary SOTA VLMs, Vietnamese embedded-text transcription is consistently strong (mean BLEU 89.01%, F1 94.30%, CER 6.59%, WER 9.33%). This suggests that most remaining errors are attributable to multimodal grounding and downstream reasoning.
3. **Disentangling text from visual evidence improves multimodal performance (§4.3):** When the question and options are given as text instead of being rendered within the image, accuracy increases for every model (+6 percentage points on average).
4. **English translation does not help (§4.4):** Translating the text into English consistently *reduces* accuracy for all models (-2 percentage points). This suggests that Vietnamese language understanding is not the primary bottleneck.
5. **Removing visual evidence reveals possible reliance on priors (§4.5):** Removing visual evidence yields a significant drop in accuracy, with an average decrease of -21.27; yet, VLMs still perform above random chance (25.92%).

2 Related work

Multimodal Benchmarks Recent multimodal benchmarks evaluate VLMs on increasingly diverse and structured visual media, including text-in-image, documents, and charts (Singh et al., 2019; Biten et al., 2019; Mathew et al., 2021; Masry et al., 2022), and broad multi-discipline reasoning (Yue et al., 2024, 2025). However, aggregate benchmark accuracy can obscure systematic weaknesses. Notably, these benchmarks and diagnostics are largely English-centric, leaving a limited understanding of how OCR, language effects, and multimodal integration interact in low-resource language settings (e.g., Vietnamese).

Multilingual and Vietnamese Evaluation Vietnamese text-only modeling and evaluation have advanced substantially (Nguyen and Nguyen, 2020; ZaloAI and JAIST, 2025), yet Vietnamese *multimodal* evaluation remains limited. Non-English multimodal benchmarks have begun to emerge in other languages, such as Chinese, (Zhang et al., 2024) and Japanese (Onohara et al., 2025; Miyai et al., 2025), but Vietnamese coverage remains sparse. Most existing Vietnamese benchmarks

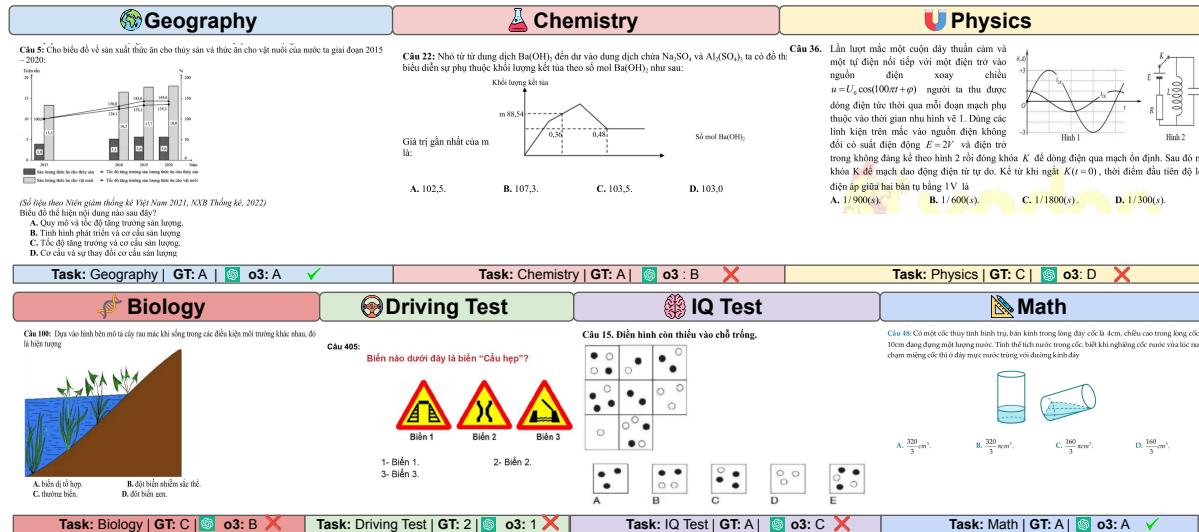


Figure 2: Sample questions from VMMU spanning 7 domains. English translations are shown in Fig. 33.

Benchmark	#VN Q	#VN MM Q	Genuine MM
EXAMS-V (Das et al., 2024)	0	0	✗
SeaExam (Liu et al., 2025a)	1,745	0	✗
VNHSGE (Dao et al., 2023)	19,300	0	✗
VMLU (ZaloAI and JAIST, 2025)	10,880	0	✗
M3Exam (Zhang et al., 2023)	1,817	116	<i>partial</i>
VMMU (Ours)	2,548	2,548	✓

Table 1: Vietnamese coverage in representative benchmarks. #VN MM Q counts Vietnamese questions intended to be answered with an *image input*. **Genuine MM** marks questions requiring integration of Vietnamese text with *non-text visual evidence* (e.g., charts/diagrams/maps), excluding text-only screenshots.

(Tab. 1) either contain no Vietnamese multimodal questions or rely on weakly multimodal formats (e.g., text-only screenshots), which prevents systematic evaluation of multimodal integration and related failure modes. For example, although VNHSGE (Dao et al., 2023) contains Vietnamese exam questions, it converts all images to text-only format during preprocessing. In contrast, VMMU provides Vietnamese questions where visual content is integral and is designed to support diagnostic analysis of OCR, multimodal reasoning, language effects, and multiple-choice biases.

3 The VMMU Benchmark

VMMU is a Vietnamese multitask benchmark for *multimodal understanding and reasoning*. It targets scenarios where Vietnamese language content is embedded within images and must be interpreted jointly with structured visual evidence (e.g., diagrams, charts, maps, tables, symbolic illustrations; see Fig. 2).

3.1 Question representations

To avoid conflating fundamentally different inputs under the umbrella of “multimodal”, we distinguish four *question representations* commonly used in vision-language evaluation (see Fig. 4):

(A) Text-only The question and options are provided as plain text (Liu et al., 2025a; ZaloAI and JAIST, 2025; Singh et al., 2025).

(B) Text-in-image-MM (text-only screenshot) The input is an image that primarily contains rendered text (question + options) (Zhang et al., 2023).

(C) Split-MM (text + visual evidence crop) The question and options are given as text (e.g., OCR-transcribed), and the required visual evidence is provided as a separate image crop (Yue et al., 2024, 2025).

(D) Integrated-MM (text + visual evidence interleaved in one image) A single image contains the question and answer options together with the required visual evidence (e.g., figures, tables, graphs, diagrams), so solving requires joint perception, reading, and reasoning (Gao et al., 2025; Miyai et al., 2025).

VMMU primarily evaluates **(D) Integrated** questions, and additionally provides **(C) Split** variants to diagnose failure sources (e.g., OCR/layout vs. multimodal integration).

3.2 Benchmark scope

VMMU contains **2,548** questions spanning **7 domains**: Mathematics, Physics, Chemistry, Biology, Geography, Driving Test, and IQ

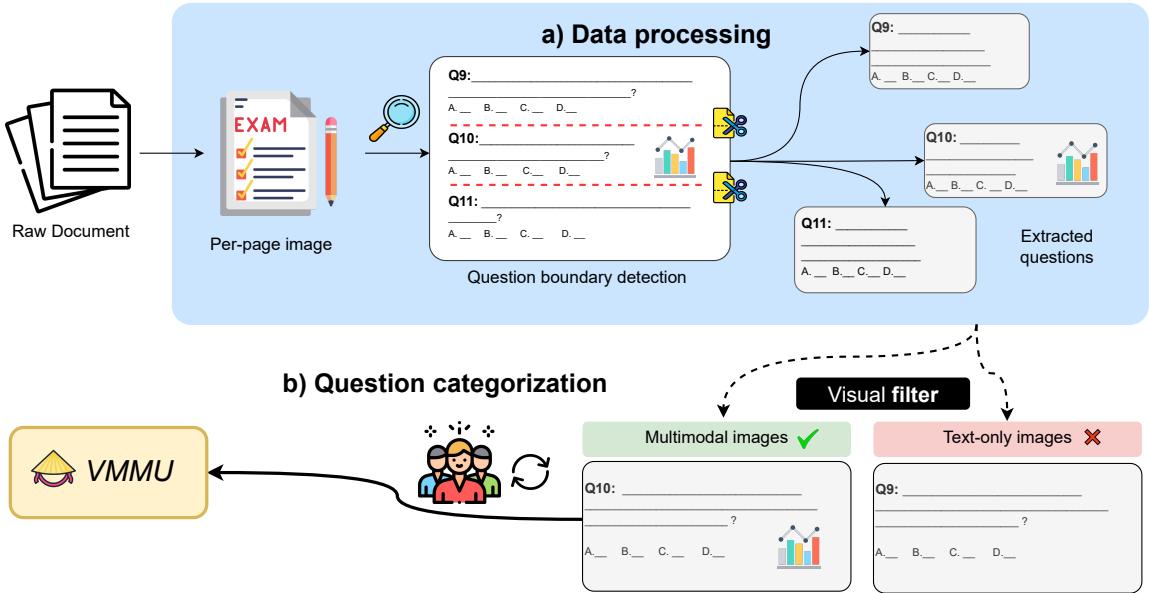


Figure 3: VMMU data curation pipeline. (a) Data processing: Raw PDFs are rendered as images, where layout analysis detects boundaries to extract individual questions. (b) Question categorization: Extracted items are visually filtered to identify multimodal content versus text-only instances. These are then manually verified by native speakers to ensure boundary and label accuracy.

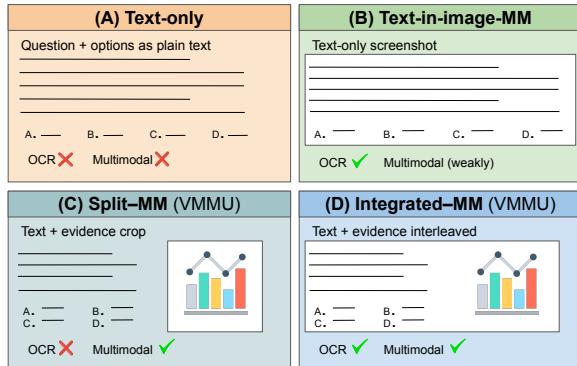


Figure 4: VMMU covers (C) Split-MM, where the question/options are provided as text and the required visual evidence is given as a separate crop, and (D) Integrated-MM, where question text, options, and visual evidence are interleaved within a single image. In our evaluation, **the content placed on the white canvas is passed to VLMs as the image input**, while the remaining components are provided as plain text.

Test. We view these 7 tasks as *broad, representative problem settings* that collectively probe four multimodal reasoning skills: (i) STEM visual reasoning (e.g., equations, diagrams): , , , , (ii) data & chart interpretation (tables, plots): , (iii) rule-governed grounded reasoning (traffic signs and situation): , and (iv) abstract visual reasoning (pattern completion and spatial logic): . All questions are multiple-choice. A very small fraction ($\approx 1\%$) requires selecting multiple answers, as they

contain more than one question within the same image.

Tasks 1-5: STEM & data interpretation (Math, Physics, Chemistry, Biology, Geography) Vietnamese academic assessments require integrated visual–textual reasoning across multiple disciplines. Our questions are collected from Vietnam’s *High School Graduation Examination*, a nationwide standardized test used for graduation eligibility and university/college admission. These subjects involve complex diagrams, equations, scientific illustrations, and geographical maps. Samples are in Appendices E.1 to E.5.

Task 6: Rule-governed grounded reasoning (Driving Test) Vietnamese driving license examinations are standardized safety-critical assessments. These questions test traffic-rule knowledge and situational judgment from scenario-based images that require visual understanding and application of Vietnamese traffic regulations. Samples are in Appendix E.6.

Task 7: Abstract visual reasoning (IQ Test) Intelligence quotient (IQ) assessment through visual reasoning provides evaluation of pattern recognition and logical thinking capabilities. Samples are in Appendix E.7.

3.3 Data sources and curation pipeline

To ensure question quality, we collect question-answer pairs from official government sources (e.g., the Ministry of Education and Training and the Ministry of Transportation), official national academic tests, and curated public repositories (Tab. 11). All questions are used under Article 25 of Vietnam’s IP Law, which permits non-commercial research use (see Ethical Considerations). We implement a systematic collection and filtering pipeline, which initially downloads exams in PDF format and renders each page into PNG images.

The key challenge is separating image-rich questions from text-only items. We use Tesseract OCR (Smith, 2007) to locate question boundaries by detecting Vietnamese markers (e.g., “Câu”; Question). We then detect image-containing regions using: (1) contour-area analysis to capture non-textual shapes above a minimum threshold, (2) geometric filtering to distinguish text-like rectangles from graphical elements by aspect ratio and size, and (3) morphological operations to identify complex visual structures. Finally, all automatically extracted items undergo manual review in a web-based interface, where three Vietnamese native speakers (i.e., co-authors) perform triple verification with binary accept/reject decisions to ensure correctness of crops, modality labels, and answers. Details are provided in Appendix D.

4 Evaluations

4.1 OCR is not the bottleneck

A frequent problem when interpreting in text-in-image evaluations is whether low accuracy reflects poor reasoning or simply failures in reading text. We begin by verifying the reliability of OCR in our tested models before attributing errors to multimodal grounding and reasoning.

Experiments We construct OCR ground truth via human-AI collaboration on a 210-question subset. We first ask o3 to transcribe all embedded text, including the prompt and answer options (see Figs. 12 and 13), then a human annotator verifies and edits the transcription to correct residual errors. We evaluate 5 proprietary VLMs: ♦⚡ Gemini-2.5-Flash (Comanici et al., 2025), ⚡ Sonnet-4.0 (Anthropic, 2025), and ⚡ GPT-4.1 (OpenAI, 2025), ⚡ o3 (OpenAI, 2025), ♦ Gemini-3.0-Pro (DeepMind, 2025). We also evaluated OCR on open-source VLMs, but observed that they

perform poorly for this task (see Appendix A.7). Since this makes it difficult to disentangle OCR errors from other multimodal reasoning failures, we focus the remaining analyses on proprietary models.

Model	BLEU (%) ↑	F1 (%) ↑	CER (%) ↓	WER (%) ↓
♦⚡ Gemini-2.5-Flash	82.58	89.88	14.46	17.57
⚡ Sonnet-4.0	88.77	94.58	4.24	7.52
⚡ GPT-4.1	90.28	95.29	4.10	7.04
⚡ o3	94.28	97.25	4.09	5.25
♦ Gemini-3.0-Pro	89.13	94.50	6.04	9.27
Mean	89.01	94.30	6.59	9.33

Table 2: Across 5 SOTA VLMs, Vietnamese embedded-text recognition is consistently high (mean BLEU 89.01%, mean F1 94.30%), with low error rates (mean CER 6.59%, mean WER 9.33%).

Results Across VLMs, OCR is consistently strong (mean BLEU 89.01%, F1 94.30%, CER 6.59%, WER 9.33%; Tab. 2). This indicates that reading Vietnamese text embedded in images is largely reliable in our setting, so downstream errors are more plausibly driven by multimodal grounding. That is, locating and using the right visual evidence and the subsequent reasoning over that evidence, rather than by OCR failures.

4.2 Integrated multimodal performance on VMMU highlights the role of reasoning

After confirming that embedded-text reading is largely reliable (Sec. 4.1), we next measure end-to-end performance on the core setting of VMMU (Integrated-MM (D); see Sec. 3.1 and Fig. 4). In this integrated setting, the question text, answer options, and required visual evidence are rendered into a single image, requiring joint reading, grounding, and reasoning.

Experiments We evaluate 5 SOTA proprietary VLMs on the full VMMU benchmark using the original Integrated-MM images with the prompt as in Figs. 10 and 11. We group models into non-thinking VLMs (♦⚡ Gemini-2.5-Flash, ⚡ Sonnet-4.0, ⚡ GPT-4.1) and thinking VLMs (⚡ o3, ♦ Gemini-3.0-Pro).

Results Overall, VLMs achieve only 66.76% mean accuracy in the Integrated-MM setting (Tab. 3), revealing substantial headroom for improvement. For reference, a random-choice baseline reaches only 25.92% mean accuracy, while humans average 66.54% and the best-performing test-takers reach 99.60% (Tab. 3). Across VLMs, performance varies substantially by category: Puzzle and Traffic situation is consistently the hard-

Model	Math	Physics	Chemistry	Biology	Geography	Driving	IQ	Task Mean
Human & Random baseline								
Human (Average)	64.50	66.70	66.80	62.80	71.90	–	–	66.54
Human (Best)	98.00	100.0	100.0	100.0	100.0	–	–	99.60
Random baseline	25.00	24.66	24.38	24.67	25.00	33.24	24.46	25.92
Non-thinking VLMs								
◆ GEMINI-2.5-FLASH	82.46	67.04	78.15	63.05	85.24	71.39	52.08	71.34
✳ SONNET-4.0	64.25	41.08	53.31	44.87	48.44	58.04	44.17	50.58
⚡ GPT-4.1	46.27	43.21	44.37	44.87	69.85	66.21	46.25	51.58
Thinking VLMs								
⌚ o3	84.87	68.98	82.78	67.16	88.98	74.66	50.42	73.98
◆ GEMINI-3.0-PRO	92.54	81.16	91.72	80.94	94.59	91.28	72.08	86.33
Model Mean	74.08	60.28	70.07	60.18	77.42	72.32	53.00	66.76

Table 3: Thinking VLMs are substantially stronger than non-thinking VLMs across all 7 domains of VMMU. ◆ Gemini-3.0-Pro leads overall with 86.33% mean accuracy. Overall accuracy across VLMs is 66.76%, and performance varies widely by subject, with ⚪ IQ being the most challenging category for VLMs. Humans achieve 66.54% on average, while the best-performing test-takers reach 99.60%. These human numbers are estimated from the official score distributions of the Vietnamese national high school graduation exam (VnExpress, 2024).

est, while Table, Traffic sign are comparatively easier (Fig. 5). We also observe a clear gap between non-thinking and thinking VLMs on the **Integrated-MM** setting. Non-thinking VLMs (◆, ✳, ⚪) achieve only 50.58%-71.34% mean accuracy (Tab. 3), whereas thinking VLMs perform substantially better (⌚: 73.98%, ◆: 86.33%; Tab. 3). This advantage holds across all domains, with ◆ Gemini-3.0-Pro leading in every domain. Meanwhile, ⚪ IQ remains the hardest overall (53.00% mean accuracy across models; Tab. 3).

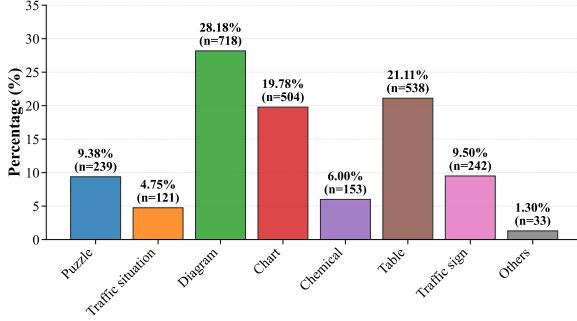
Together with strong OCR in Sec. 4.1, these results indicate that failures are dominated by multimodal grounding and, in particular, reasoning, as enabling reasoning mode yields large gains in the Integrated-MM setting. Our conclusions are also robust to decoding stochasticity, as repeating the evaluation across 5 runs preserves model ranking and the same qualitative trends (Appendix A.3). Moreover, evaluation artifacts are unlikely to explain the performance gap, because SOTA VLMs follow the required answer format reliably with near-perfect extraction rates (Appendix A.5). We also note that non-thinking VLMs remain substantially more overconfident and miscalibrated than thinking VLMs (Appendix A.4). Finally, open-source VLMs substantially underperform proprietary models in Integrated-MM (Appendix A.6), with their failures largely driven by weak OCR (Appendix A.7).

4.3 Separating text from visual evidence improves multimodal performance

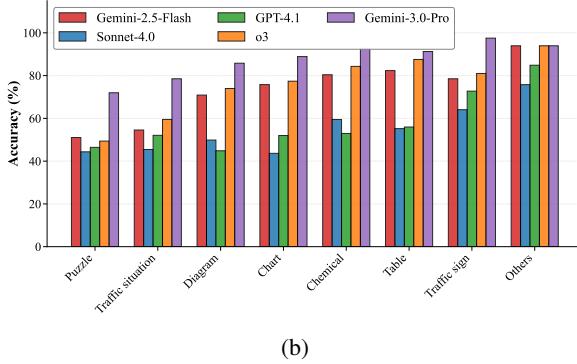
Integrated question images require VLMs to simultaneously (i) read dense rendered text and (ii) locate and interpret the relevant visual evidence (e.g., charts, tables, maps, diagrams) within the same canvas. This can introduce distraction from text-heavy regions and make it harder to attend to the correct evidence, even when models are capable of reading the text (Yue et al., 2025). We test whether separating the textual prompt from the visual evidence improves reliability by making both components easier to process.

Experiments We create a Split-MM variant (see Fig. 4) for the *full* VMMU dataset by separating the textual questions/options from the visual evidence. Following Sec. 4.1, we obtain high-quality text transcriptions through ⚪ o3 to OCR-transcribe the textual elements for all questions, and then manually crop the required visual evidence region into a separate image. We then re-evaluate the same 5 SOTA VLMs (Fig. 14) as in Sec. 4.1.

Results Split-MM improves performance for every model (+5.98%; Fig. 6). The gains are concentrated among non-thinking VLMs (+8.56% for ◆, ⚪, ⚪ on average; Fig. 6), while thinking VLMs improve only modestly (+2.10% for ⚪, ◆ on average; Fig. 6). The benefit of Split-MM is a cleaner reasoning setup where the non-thinking VLMs no longer have to locate and transcribe text while simultaneously grounding the visual evidence. Thinking VLMs seem more robust



(a)



(b)

Figure 5: Although most questions in VMMU are Diagram (28.2%), Table (9.4%), Chart (19.8%) (a), VLMs consistently perform worst on Puzzle (IQ Test) and Traffic situation questions, while Table and Traffic sign are comparatively easier (b).

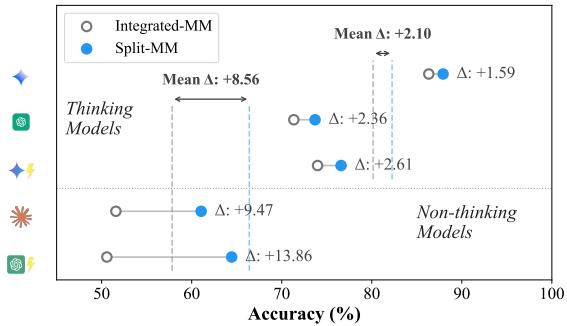


Figure 6: Separating the question text from the visual evidence (Split-MM) improves accuracy for every model compared to placing the question text, answer options, and visual evidence in a single image (Integrated-MM). The mean gain across 5 SOTA VLMs is **+5.98** points. Improvements are larger for non-thinking VLMs (than for thinking VLMs () because thinking models already perform strongly in the Integrated MM setting (**+8.56%** vs. **+2.10%**).

to the complexity of integrated-inputs, so we observe smaller gains consistent with partial saturation. Overall, separating the textual questions and options from the visual evidence reduces text-in-image interference and makes grounded reasoning more reliable, especially for non-thinking models.

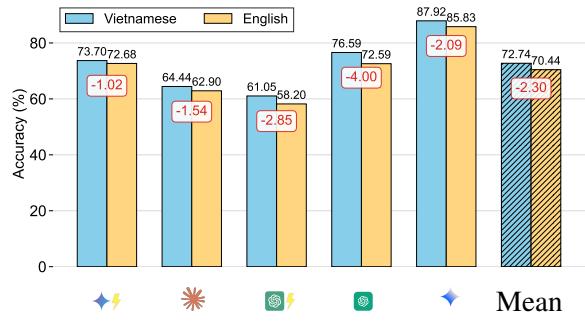


Figure 7: Translating the original Vietnamese questions into English reduces accuracy across all VLMs (**-2.30** points on average). This suggests that translation to English does not reliably make the task easier and is not a simple shortcut, even for VLMs that are heavily trained on English.

4.4 English translation is NOT all you need

A natural hypothesis is that performance is limited by language understanding, and that translating the prompt and answer options into English could improve results for models trained predominantly on English data (Mondshine et al., 2025; Etxaniz et al., 2024; Liu et al., 2025b).

Experiments We translate the Split-MM text component (i.e., questions & options) from Sec. 4.3 into English while keeping the visual evidence crop unchanged. Specifically, we use *o3* to translate the Vietnamese question and options into English, and then pair the translated text with the original visual evidence crop as input to each VLM to measure any performance change attributable to translation.

Results English translation consistently reduces the performance of every model (**-2.30%** accuracy; Figs. 7 and 33). Since the visual evidence is identical and OCR is not required in Split-MM, these results show that switching to English does not resolve the remaining errors, and that translation can introduce mismatch that degrades grounded multimodal reasoning.

4.5 Removing visual evidence reveals possible reliance on model priors

While the majority of questions in VMMU require visual evidence (93%), prior work shows that VLMs can rely on memorized priors (Vo et al., 2025a) and that multiple-choice formats may introduce selection biases that make some answers guessable (Atabuzzaman et al., 2025). To assess whether such effects are present, we evaluate models without visual evidence to measure how much performance can be sustained in the absence of

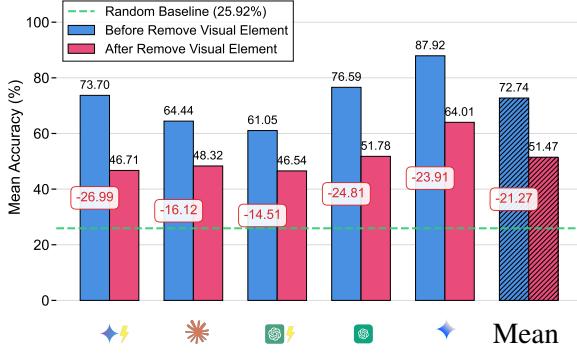


Figure 8: When the visual evidence is removed, accuracy drops slightly (**-21.27%**) and remains far above random chance (25.92%). That is, this shows substantial reliance on text-only priors and exam heuristics rather than visual grounding.

grounding.

Experiments Starting from Split-MM, we remove the visual evidence crop and provide only the text question and answer options (see Fig. 15). We compare against the original Split-MM scores and include the random-guess baseline (25.92%).

Results Removing visual evidence significantly reduces accuracy for all VLMs, yet, degradation remains far from catastrophic (**-21.27%**; Fig. 8), and still well above random chance (51.47% vs. 25.92%; Fig. 8). Notably, \diamond Gemini-3.0-Pro still achieves **64.01%** accuracy even without visual evidence. Our qualitative results suggest that these correct answers may arise from guessing based on limited textual cues and relying on knowledge priors or simple heuristics (Figs. 34 and 37) or purely accidental correct guesses (Fig. 38). In contrast to option shuffling (Appendix A.2), which leaves accuracy essentially unchanged, this text-only ablation reveals that VLMs can sometimes *guess plausibly* guess without visual input.

5 Discussion and Conclusion

\diamond VMMU is motivated by a gap in current evaluation practice: despite the progress on vision-language benchmarks, we lack an evaluation framework for how well VLMs handle *image-based Vietnamese tasks* that require jointly reading text, grounding visual evidence, and reasoning over both modalities.

Across 2,548 questions in 7 domains, we find that the dominant errors stem from *multimodal grounding and downstream reasoning*, rather than Vietnamese text recognition. Proprietary SOTA VLMs achieve strong OCR performance (Sec. 4.1).

Yet, the original setting where the prompt and visual evidence are rendered within a single rendered page image (Integrated-MM) remains challenging (Sec. 4.2). When we re-format the same problems to present the prompt as plain text alongside a separate image crop containing the visual evidence (Split-MM), accuracy improves for every model (Sec. 4.3 and Appendix A.1). Moreover, enabling thinking yields large improvements (Sec. 4.2). This indicates that reliable multi-step reasoning is a central bottleneck. Finally, removing the visual evidence in Split-MM significantly reduces accuracy; however, it still leaves performance above random chance (Sec. 4.5), which may indicate that VLMs can often fall back on text-only priors and exam heuristics when visual grounding is not present.

Finally, it is important to point out that the failure to bind Vietnamese *rendered text* to the correct *visual evidence* is inherently language-dependent, since the Vietnamese question specifies what to look for and the images themselves contain Vietnamese labels and conventions. Hence, translating the prompt to English is not a reliable substitute (Sec. 4.4): it creates a mixed-language grounding problem (English instructions and Vietnamese visual evidence). It may replace terms that the model would use to match the question to the text/labels inside the image, which may explain the accuracy drops when translating to English. Vietnamese-native evaluation is thus required to measure grounded multimodal reasoning in the setting that users actually face.

Future directions Our analyses highlight several concrete research directions. First, VLMs need stronger joint text-vision reasoning under dense layouts (motivated by Split-MM gains; Sec. 4.3). Second, the large gap between thinking and non-thinking VLMs suggests headroom for methods that improve multimodal reasoning (Sec. 4.2). Third, robust Vietnamese multimodal reasoning likely requires Vietnamese-centric instruction tuning and data that target grounding and reasoning skills beyond what English-centric resources provide.

Limitations

This work focuses on evaluation and failure analysis rather than proposing training or fine-tuning methods to improve multimodal reasoning. The main reason is that large-scale, high-quality Vietnamese multimodal training data remains limited.

We hope that VMMU will encourage the community to build larger native multimodal datasets to train and adapt large models for low-resource languages such as Vietnamese. In addition, many questions in VMMU follow a standardized white-canvas style, which may underrepresent more realistic inputs such as natural photographs, mobile captures, cluttered documents, or handwritten content. Finally, while VMMU spans 7 domains, it does not yet cover other high-impact areas (e.g., medical or legal scenarios). Expanding domain coverage and realism is an important direction for future work.

Ethical Considerations

We strictly adhere to the ACL Code of Ethics. Parts of this work were conducted via human-AI collaboration, where the human contributors are co-authors of this paper. This involvement posed minimal risk, and informed consent was obtained from all participating authors. The benchmark is curated from materials that are publicly published by governmental agencies and public educational institutions in Vietnam. All questions are used under Article 25 of Vietnam’s Intellectual Property Law, which permits non-commercial research use while copyright remains with the original creators. Prior Vietnamese benchmarking efforts have followed similar practices. Furthermore, we will remove or replace any items upon request. We used large language models to assist with annotating parts of the dataset, with all outputs subsequently verified and corrected when needed by human annotators. We also used LLM-based tools for light editing and coding assistance. The authors take full responsibility for the content.

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Appendix for: VNMMU: A Vietnamese Multitask Multimodal Understanding and Reasoning Benchmark

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A Additional findings

A.1 Image-required questions are harder than text-sufficient ones

Sec. 4.3 shows that *Split-MM* improves accuracy, but this gain could be misattributed if a non-trivial portion of the benchmark is solvable from text alone. To confirm that VMMU primarily evaluates multimodal reasoning, we explicitly measure how often the image is necessary for answering.

Experiments We label each question as *image-required* or *text-sufficient* based on whether the correct answer can be determined from the textual prompt and options alone. We use *o3* as a judge to make an initial decision for all 2,548 questions, then apply **human verification** to ensure labeling quality. This process yields 2,363 image-required questions (92.74%) and 185 text-sufficient questions (7.26%).

Model	Image required		Text sufficient	
	Integrated-MM	Split-MM	Integrated-MM	Split-MM
Gemini-2.5-Flash	69.92	72.75 (+2.83)	92.47	91.78 (-0.69)
Sonnet-4.0	49.82	63.22 (+13.40)	71.38	88.06 (+16.68)
GPT-4.1	51.31	60.30 (+8.99)	71.47	82.06 (+10.59)
<i>o3</i>	72.49	75.48 (+2.99)	95.26	93.70 (-1.56)
Gemini-3.0-Pro	85.62	87.39 (+1.77)	97.57	96.89 (-0.68)
Mean	65.83	71.83 (+6.00)	85.63	90.50 (+4.42)

Table 4: Separating the question text from the visual evidence (Split MM) improves performance in both image-required and text-sufficient questions (**+6** points). Gains are largest for non-thinking VLMs (⚡, 🌟, 🎉, 🎉), especially on image-required questions, where Split-MM yields sizable improvements over Integrate-MM. Thinking VLMs (⌚, ⚡) benefit less and can slightly drop on text sufficient questions, which suggests they already perform near saturation.

Results In Tab. 4, image-required questions are substantially harder than text-sufficient ones in both Integrated-MM (65.83% vs. 85.63%) and Split-MM (71.83% vs. 90.50%). Split-MM yields comparable gains on both image-required and text-sufficient subsets (**+6** percentage points). Despite this gain, accuracy on image-required questions on Split-MM remains far from saturated (71.83%; Tab. 4). Grounded multimodal reasoning, therefore, remains the primary bottleneck.

A.2 Shuffling answer options has a minor effect

Multiple-choice evaluation can be affected by positional biases, where models over-prefer certain option letters or benefit from consistent option ordering (Pezeshkpour and Hruschka, 2024; Zheng

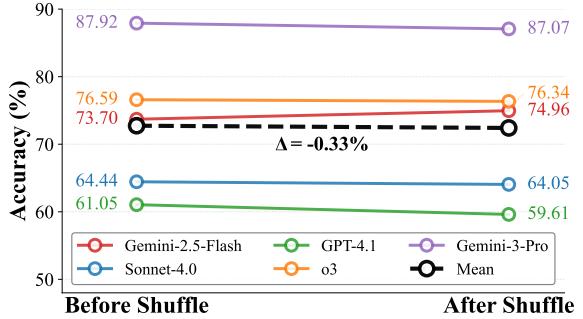


Figure 9: Accuracy before and after shuffling multiple-choice answer-option order. Overall accuracy changes are small ($\Delta = -0.33\%$), and the relative ranking of models remains unchanged, showing limited sensitivity to option order.

et al., 2024). To test whether our results are sensitive to such artifacts, we measure how accuracy changes when answer options are shuffled.

Experiments Starting from the Split-MM setting in Sec. 4.3, we randomly shuffle the order of answer options for each question while keeping the prompt text and visual evidence crop unchanged.

Results Randomly shuffling the multiple-choice answer options produces only small changes in accuracy across VLMs ($\Delta = -0.33\%$; Fig. 9). Importantly, the relative ranking of models remains unchanged before and after shuffling. That is, our comparative conclusions are not driven by a particular option ordering. Overall, these results suggest limited sensitivity to option order, and that answer-option position bias is unlikely to be the dominant source of errors in this setting.

A.3 Multiple runs do not change model ranking or our main conclusions

Since VLM decoding can be stochastic, we verify that our Integrated-MM conclusions are not sensitive to a single evaluation run.

Experiments We sample 210 questions from 7 domains (30 questions per domain) and repeat Integrated-MM evaluation for each proprietary VLM across 5 independent runs.

Model	Accuracy (\uparrow) on 5 runs
Gemini-2.5-Flash	75.70 ± 3.64
Sonnet-4.0	54.67 ± 4.16
GPT-4.1	60.19 ± 4.03
<i>o3</i>	79.62 ± 4.03
Gemini-3.0-Pro	89.43 ± 1.73
Mean	71.92 ± 3.52

Table 5: Accuracy consistency across 5 runs.

Results Accuracy is stable across runs (mean 71.92 ± 3.52), and the relative ordering remains unchanged: \diamond Gemini-3.0-Pro is best (89.43 ± 1.73), followed by \otimes o3 (79.62 ± 4.03) and \diamond Gemini-2.5-Flash (75.70 ± 3.64), with \otimes GPT-4.1 (60.19 ± 4.03) and \ast Sonnet-4.0 (54.67 ± 4.16) lower (Tab. 5). Thus, run-to-run variance does not affect our main conclusions.

A.4 Non-thinking VLMs are overconfident

Beyond accuracy, reliability depends on whether a model’s expressed confidence matches its correctness. Overconfident errors are particularly problematic when VLMs are used for decision-making. We therefore measure self-reported confidence and calibration on Integrated-MM.

Model	Confidence score (%) ↑	ECE score (%) ↓
\diamond Gemini-2.5-Flash	93.22	33.76
\ast Sonnet-4.0	76.08	28.46
\otimes GPT-4.1	96.76	48.20
\otimes o3	56.72	17.66
Mean	80.69	32.02

Table 6: Non-thinking VLMs (\diamond , \ast , \otimes) report high self-confidence yet show substantially worse calibration (higher ECE), whereas the thinking VLM (\otimes) is less confident but best calibrated.

Experiments We compute confidence and calibration on a single Integrated-MM evaluation run (the same outputs in Sec. 4.2). Following Vo et al. (2025b), after the VLM selects an answer option, we ask in a second turn for a *verbalized confidence* score $p_i \in [0, 1]$ for its chosen option. We report the mean of these self-reported scores as the **confidence score**. We compute expected calibration error (ECE) directly from these per-example confidence scores by binning predictions into M confidence bins $\{B_m\}_{m=1}^M$:

$$\text{ECE} = \sum_{m=1}^M \frac{|B_m|}{N} |\text{acc}(B_m) - \text{conf}(B_m)|, \quad (1)$$

where $\text{acc}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \mathbf{1}(\hat{y}_i = y_i)$ and $\text{conf}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} p_i$. Lower ECE indicates better calibration.

Results Non-thinking VLMs (\diamond , \ast , \otimes) report very high confidence (e.g., \otimes GPT-4.1: 96.76%; \diamond Gemini-2.5-Flash: 93.22%), while the thinking model \otimes o3 reports much lower confidence (56.72) despite achieving the highest accuracy (Tab. 5). This mismatch is reflected in calibration: \otimes GPT-4.1 has the highest confidence but

also the worst ECE (48.20), whereas \otimes o3 has the best ECE (17.66). Overall, these results show that non-thinking VLMs tend to be overconfident, while thinking VLMs are more conservative and better calibrated.

A.5 SOTA VLMs follow the answer format reliably

End-to-end accuracy can be underestimated if models frequently produce outputs that are not parseable into a valid multiple-choice option. We therefore measure whether evaluation failures could be explained by answer-formatting issues rather than reasoning.

Experiments Using the same Integrated-MM generations as the main evaluation (Sec. 4.2), we compute the TRUE extraction rate: the percentage of model responses from which a valid answer option can be extracted under our post-processing rules.

Model	Extraction rate (%) ↑
\diamond Gemini-2.5-Flash	98.09
\ast Sonnet-4.0	99.94
\otimes GPT-4.1	99.66
\otimes o3	99.82
\diamond Gemini-3.0-Pro	99.14
Mean	99.33

Table 7: All SOTA VLMs follow the required multiple-choice answer format reliably, so formatting is not a meaningful source of failures.

Results All SOTA VLMs achieve very near-perfect extraction rates (mean 99.33%; Tab. 7). That is, responses almost always follow the expected. Thus, answer-format compliance is not a meaningful contributor to the remaining Integrated-MM failures.

A.6 Open-source VLMs significantly underperform on VMMU

While our main results focus on SOTA proprietary VLMs (Sec. 4.2), it is also important to quantify how far *publicly available* VLMs have progressed on Vietnamese *genuine* multimodal reasoning. We find a large performance gap: open-source VLMs remain substantially weaker than proprietary models on VMMU’s Integrated-MM setting (see Fig. 4). This result indicates significant headroom for improving multimodal grounding and reasoning beyond English-centric evaluation.

Experiments We replicate the Integrated-MM evaluation protocol from Sec. 4.2 and evaluate 10 open-source VLMs spanning multiple model families and sizes: Aya-Vision-8B vs. Aya-Vision-32B Aya-Vision-32B ([Üstün et al., 2024](#)), Gemma-3-4B vs. Gemma-3-27B ([Mesnard et al., 2024](#)), Mistral-Medium-3 ([MistralAI, 2025a](#)) vs. Mistral-Small-3.2-24B ([MistralAI, 2025b](#)), Llama-4-Maverick vs. Llama-4-Scout ([MetaAI, 2025](#)), Qwen-2.5-VL-32B vs. Qwen-2.5-VL-72B ([Bai et al., 2025](#)).

Results Open-source VLMs remain substantially weaker on VMMU’s Integrated-MM setting than SOTA proprietary ones (35.53% vs. 68.70%; Tab. 9). The strongest open-source model is Qwen-2.5-VL-32B (52.13%; Tab. 9). Within most families, larger variants improve accuracy (e.g., Aya-Vision-32B vs. Aya-Vision-8B: 20.07% vs. 9.66%; Gemma-3-27B vs. Gemma-3-4B: 39.09% vs. 25.45%; Mistral-Medium-3 vs. Mistral-Small-3.2-24B: 37.78% vs. 31.88%; Tab. 9). However, scaling is not uniformly beneficial (e.g., Qwen-2.5-VL-72B does not surpass Qwen-2.5-VL-32B, and Llama-4-Maverick underperforms Llama-4-Scout).

A.7 Open-source VLM failures are primarily driven by weak embedded-text OCR

In Integrated-MM (Fig. 4), VLMs must correctly read dense Vietnamese question text and answer options before any visual grounding or reasoning can occur. While Sec. 4.1 shows that SOTA proprietary VLMs can read Vietnamese reliably, it remains unclear whether the poor end-to-end results of open-source VLMs (Appendix A.6) reflect reasoning limitations or a more fundamental OCR bottleneck. This experiment isolates OCR quality to test whether open-source failures are attributable to transcription errors.

Experiments We replicate the OCR evaluation from Sec. 4.1 on 10 open-source VLMs from Appendix A.6.

Results Open-source VLMs exhibit large and unstable OCR degradation, with several models collapsing to near-unusable transcription quality (e.g., Aya-Vision-8B: F1 0.23, CER 229.30%, WER 253.09; Llama-4-Scout: F1 0.61, CER 217.90%, WER 110.60%; Tab. 8). Even the strongest open-source VLMs plateau below proprietary OCR (best open-source: F1 0.82 with CER 10.73% / WER

Model	BLEU (%)↑	F1 (%)↑	CER (%)↓	WER (%)↓
Open-source VLMs				
Aya-Vision-8B	2.72	19.53	229.30	253.09
Aya-Vision-32B	10.48	32.59	150.73	180.28
Gemma-3-4B	65.12	80.08	24.79	37.23
Gemma-3-27B	78.60	87.10	16.18	23.89
Qwen-2.5-VL-32B	77.50	87.68	19.05	24.17
Qwen-2.5-VL-72B	82.30	89.05	10.73	18.49
Llama-4-Maverick	70.59	80.90	48.77	53.91
Llama-4-Scout	38.95	53.64	217.92	211.96
Mistral-Medium-3	81.23	88.96	9.08	16.11
Mistral-Small-3.2-24B	72.28	84.08	19.39	28.41
Mean	57.98	70.36	74.59	84.75
SOTA proprietary VLMs				
Gemini-2.5-Flash	82.58	89.88	14.46	17.57
Sonnet-4.0	88.77	94.58	4.24	7.52
GPT-4.1	90.28	95.29	4.10	7.04
o3	94.28	97.25	4.09	5.25
Gemini-3.0-Pro	89.13	94.50	6.04	9.27
Mean	89.01	94.30	6.59	9.33

Table 8: OCR evaluation results across VLMs show a clear gap between open-source and SOTA proprietary models. This indicates that embedded-text OCR is a major bottleneck for open-source VLM performance.

18.49% for Qwen-2.5-VL-72B; vs. best proprietary: F1 0.97 with CER 3.90% / WER 5.16% for o3; Tab. 8). Overall, open-source OCR quality is substantially weaker and includes catastrophic failures. This highlights that improving embedded-text OCR is a prerequisite step for competitive open-source Integrated-MM performance.

	a. 📈 Math	b. 🧪 Physics	c. 🧪 Chemistry	d. 🌱 Biology	e. 🌎 Geography	f. 🚗 Driving	g. 🧠 IQ	Mean
Human & Random baseline								
Human (Average)	64.50	66.70	66.80	62.80	71.90	–	–	66.54
Human (Best)	98.00	100.0	100.0	100.0	100.0	–	–	99.60
Random baseline	25.00	24.66	24.38	24.67	25.00	33.24	24.46	25.92
Open-source VLMs								
8B Aya-Vision-8B	10.75	8.03	3.64	3.23	2.49	26.98	12.50	9.66
32B Aya-Vision-32B	12.94	14.40	16.89	17.30	21.41	32.97	24.58	20.07
4B Gemma-3-4B	26.32	17.45	22.19	22.29	27.65	40.60	21.67	25.45
27B Gemma-3-27B	47.37	30.47	38.74	30.79	47.40	43.87	35.00	39.09
32B Qwen-2.5-VL-32B	61.18	49.17	44.70	42.82	71.31	54.50	41.25	52.13
72B Qwen-2.5-VL-72B	58.33	49.86	48.34	40.47	64.66	53.95	46.67	51.75
Llama-4-Scout	59.65	44.88	45.03	38.71	69.02	49.05	37.08	49.06
Llama-4-Maverick	42.54	29.36	32.78	27.57	53.22	53.95	29.17	38.37
Mistral-Small-3.2-24B	34.65	30.28	28.48	28.15	30.98	39.78	30.83	31.88
Mistral-Medium-3	44.74	36.57	37.75	29.33	36.59	45.78	33.75	37.78
Mean	39.85	31.05	31.85	28.06	42.47	44.14	31.25	35.53
SOTA proprietary VLMs								
Gemini-2.5-Flash	82.46	67.04	78.15	63.05	85.24	71.39	52.08	71.34
Sonnet-4.0	64.25	41.00	53.31	44.87	48.44	58.04	44.17	50.58
GPT-4.1	46.27	43.21	44.37	44.87	69.85	66.21	46.25	51.58
o3	84.87	68.98	82.78	67.16	88.98	74.66	50.42	73.98
Gemini-3.0-Pro	92.54	81.16	91.72	80.94	94.59	91.28	72.08	86.33
GPT-5.0	91.23	76.45	85.10	72.73	89.40	75.20	58.75	78.41
Mean	76.94	62.97	72.57	62.27	79.42	72.80	53.96	68.70

Table 9: Humans achieve 66.54% on average, while the best-performing test-takers reach 99.60%. These human numbers are estimated from the official score distributions of the Vietnamese national high school graduation exam (VnExpress, 2024). This gap between average and best human performance indicates that the questions are solvable but non-trivial. Open-source VLMs perform worse far behind (35.53% mean), with the strongest model (Qwen-2.5-VL-32B) reaching only 52.13%. SOTA Proprietary VLMs perform markedly better (68.70% mean), led by (86.33%), and IQ remains the hardest domain overall.

B Models and access details

Table 10: VLMs configuration and platform details.

Model	Model Name	Temperature	Platform
Open-source VLMs			
8B Aya-Vision-8B	c4ai-aya-vision-8b	0.0	Cohere
32B Aya-Vision-32B	c4ai-aya-vision-32b	0.0	Cohere
4B Gemma-3-4B	gemma-3-4b-it	0.0	Google AI Studio
27B Gemma-3-27B	gemma-3-27b-it	0.0	Google AI Studio
Mistral-Small-3.2-24B	mistral-small-3.2-24b-instruct	0.0	OpenRouter
Mistral-Medium-3	mistral-medium-3	0.0	OpenRouter
32B Qwen-2.5-VL-32B	qwen/qwen2.5-vl-32b-instruct	0.0	OpenRouter
72B Qwen-2.5-VL-72B	qwen/qwen2.5-vl-72b-instruct	0.0	OpenRouter
Llama-4-Maverick	llama-4-maverick	0.0	OpenRouter
Llama-4-Scout	llama-4-scout	0.0	OpenRouter
SOTA proprietary VLMs			
Gemini-2.5-Flash	gemini-2.5-flash	0.0	Google AI Studio
Sonnet-4.0	claude-sonnet-4-20250514	0.0	Anthropic
GPT-4.1	gpt-4.1-2025-04-14	0.0	OpenAI
o3 *	o3-2025-04-16	N/A	OpenAI
GPT-5.0 *	gpt-5-2025-08-07	N/A	OpenAI
Gemini-3.0-Pro	gemini-3.0-pro	0.0	Google AI Studio

*reasoning_effort: medium (default thinking mode setting)

C Details of the prompts

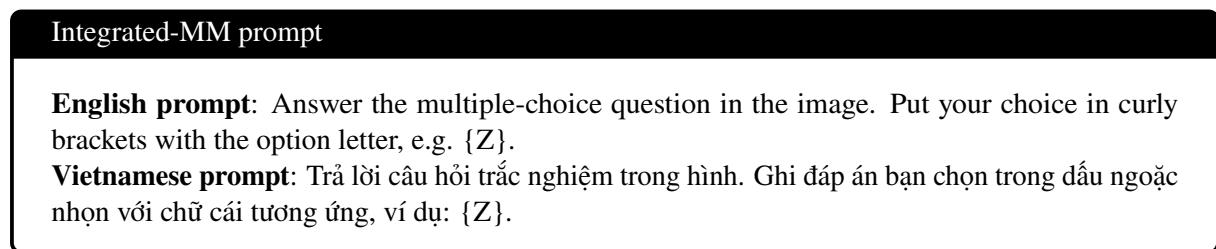


Figure 10: The Vietnamese and English prompts used for multiple-choice question answering tasks.

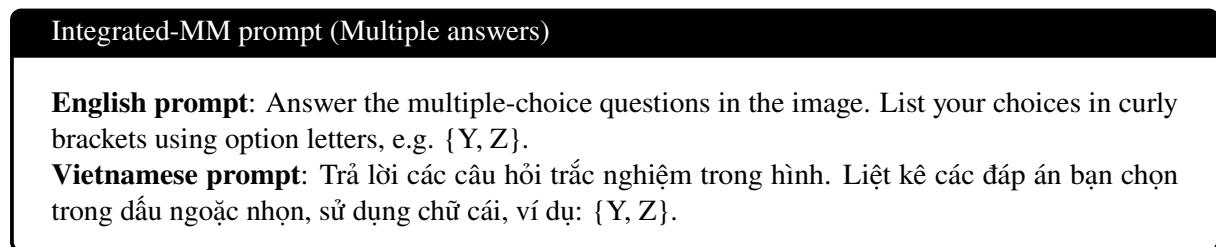


Figure 11: The Vietnamese and English prompts used for question answering tasks on images containing multiple questions.

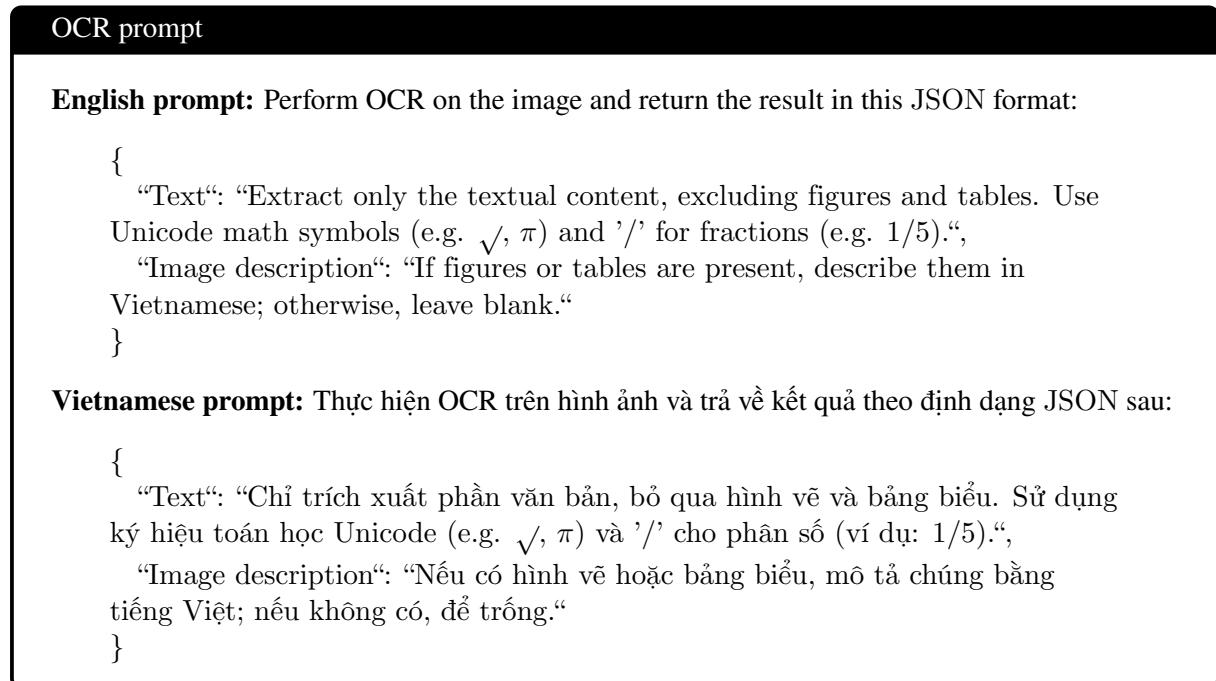


Figure 12: The Vietnamese and English prompts used for OCR tasks on individual question images in the dataset.

OCR prompt (Multiple Answers)

English prompt: Perform OCR on the image and return the result in this JSON format:

```
{  
    "Text": "Extract only the textual content, excluding figures and tables. Use  
    Unicode math symbols (e.g.  $\sqrt{}$ ,  $\pi$ ) and '/' for fractions (e.g. 1/5).",  
    "Image description": "If figures or tables are present, describe them in  
    Vietnamese; otherwise, leave blank."  
}
```

Vietnamese prompt: Thực hiện OCR trên hình ảnh và trả về kết quả theo định dạng JSON sau:

```
{  
    "Text": "Chỉ trích xuất phần văn bản, bỏ qua hình vẽ và bảng biểu. Sử dụng  
    ký hiệu toán học Unicode (e.g.  $\sqrt{}$ ,  $\pi$ ) và '/' cho phân số (ví dụ: 1/5).",  
    "Image description": "Nếu có hình vẽ hoặc bảng biểu, mô tả chúng bằng  
    tiếng Việt; nếu không có, để trống."  
}
```

Figure 13: The prompts used for OCR tasks on images containing two questions in the dataset.

Split-MM Prompt

English prompt: [Question content]

Based on the information in the image, answer the multiple-choice-choice question above. Write your chosen answer in double curly brackets with the corresponding letter, for example: {{Z}}.

Vietnamese prompt: [Nội dung câu hỏi]

Dựa vào thông tin trong hình để trả lời câu hỏi trắc nghiệm ở trên. Ghi đáp án bạn chọn trong dấu ngoặc nhọn kép với chữ cái tương ứng, ví dụ: {{Z}}.

Figure 14: The Vietnamese and English prompts used for question answering tasks on Split-MM questions.

Split-MM Prompt (after removing visual elements)

English prompt: [Question content] Based on the information provided, answer the multiple-choice question above. In all cases, you must select exactly one valid answer using the corresponding letter, even when data is insufficient or certain inference cannot be made. Write your chosen answer in double curly brackets with the corresponding letter, for example: {{Z}}.

Vietnamese prompt: [Nội dung câu hỏi]

Dựa vào thông tin được cung cấp để trả lời câu hỏi trắc nghiệm ở trên. Trong mọi trường hợp, bạn phải chọn đúng một đáp án hợp lệ bằng chữ cái tương ứng, kể cả khi thiếu dữ liệu hoặc không thể suy luận chắc chắn. Ghi đáp án bạn chọn trong dấu ngoặc nhọn kép với chữ cái tương ứng, ví dụ: {{Z}}.

Figure 15: The Vietnamese and English prompts used for question answering tasks when image is required but not provided in the experiment.

D Dataset curation details

D.1 Overview

We curate VMMU with a semi-automated pipeline that converts heterogeneous public documents into individual question images, then applies human verification for final quality control (Fig. 3). The pipeline has 3 goals: (i) reliably extract question boundaries (including multi-page items), (ii) retain only *genuine* multimodal questions (where non-text visual evidence is necessary), and (iii) produce consistent artifacts for evaluation (Integrated-MM and Split-MM; Sec. 3.1).

D.2 Data source

We collect question sets from publicly available repositories and official releases (Tab. 11).

Tasks 1-5: Mathematics, Physics, Chemistry, Biology, Geography We systematically collected questions using Selenium web scraping from public repositories. Our dataset comprises questions from 3 primary sources: (1) Official Exam Tests from the Vietnamese National High School Graduation Examination, (2) Official Sample Tests issued by the Ministry of Education and Training (MOET), and (3) Mock Exam Tests from Provincial Departments of Education.

Task 6: Driving Test The Vietnamese Ministry of Transport (MOT) maintains official question banks containing 250 questions for A1 licenses (motorcycles) and 600 questions for B2 licenses (automobiles). To achieve A1 level requires a minimum of 21/25 correct answers (84%), while B2 level requires 32/35 correct answers (91.4%) and must not make errors on critical questions. From this broader collection of 850 total questions, we selected 367 multimodal multiple-choice questions that contain visual elements integrated with Vietnamese text. Each selected question presents traffic scenarios through illustrations, accompanied by Vietnamese text describing the situation and 2-4 multiple-choice options.

Task 7: IQ Test We collected 240 IQ test questions from <https://vndoc.com> through manual screenshot capture. These questions span various cognitive domains (e.g., spatial reasoning, pattern completion, logical sequences, numerical reasoning, abstract thinking). Each question presents 4-8 multiple-choice options embedded within the image.

D.3 Collection and cleanup

Crawling and normalization We use a Selenium-based crawler to download documents in .pdf/.doc/.docx. All Word files are converted to PDF to standardize downstream processing.

Removing trailing solutions/answer keys Many documents append answer keys or solution explanations after the questions. We drop these sections with a lightweight PDF segmentation step (pypdf): we scan pages for high-precision termination cues (e.g., “HẾT”; *THE END*) and fallback cues marking auxiliary sections (e.g., “BẢNG ĐÁP ÁN”; *ANSWER KEY*, and “LỜI GIẢI CHI TIẾT”; *DETAILED SOLUTION*). We keep pages from the beginning up to the first matched cue.

D.4 PDF rendering to page images

We render each PDF page to a PNG image using pdf2image at 300 DPI. Each page image stores document/page identifiers and pixel dimensions in a metadata file to support traceability during cropping.

D.5 Question boundary detection and extraction

Detecting question starts We run Tesseract OCR (Smith, 2007) to obtain line-level text and bounding boxes. We then detect question starts via Vietnamese layout markers using regex patterns (e.g. “Câu\s?\d+[:]”, where “Câu” means *Question*). We additionally detect group directives (e.g., “Dùng dữ kiện cho câu 1-5”; *Use the given data for Questions 1-5*) to preserve shared context for question groups.

Cropping and multi-page stitching Given detected markers, we construct a crop plan that maps each question to a page region. If a question continues onto the next page, we stitch the cropped fragments vertically (cv2.vconcat) to form a single question image.

D.6 Automatic modality classification (text-only vs. genuine multimodal)

To filter out weakly multimodal items (text-only screenshots), we classify each extracted question image based on the presence of *non-text visual structures* (e.g., charts/diagrams/tables/maps). We binarize the image (grayscale + adaptive thresholding), detect connected components via contours, and apply simple geometric rules to separate text-like blocks from non-text graphics. If at least one

Domain(s)	Source	Platform
Mathematics, Physics, Chemistry, Biology, Geography	Official exam tests from the Vietnamese National High School Graduation Examination. Official sample tests issued by the Ministry of Education and Training (MOET). Mock exam tests released by Provincial Departments of Education.	https://thuvienhoclieu.com https://vndoc.vn
Driving Test	Official question banks and regulation-aligned materials from the traffic police department and the Ministry of Transportation (MOT).	https://daotaohoclaxeoto.com https://tracuuphapluat.info
IQ Test	Manual collection from publicly available sources.	https://vndoc.com

Table 11: VMMU data sources by subject group.

sufficiently large, non-text-like region is detected, we label the item as multimodal, otherwise, it is labeled text-only.

D.7 Human verification and ground-truth finalization

Automated extraction is followed by human verification to ensure correct crop boundaries, correct modality labels, and correct answer keys.

Review interface We built a review tool (React + TailwindCSS) that displays extracted question images alongside the original source document for side-by-side inspection (Fig. 16). Annotators can: (i) accept/reject the multimodal label, (ii) flag cropping issues for manual repair, and (iii) record the correct answer.

Cross-verification For final answer keys, 3 native speakers independently verify each label. We accept an answer only under unanimous agreement, and disagreements are resolved via discussion and re-checking against the original document.

All annotators are co-authors of this paper, aged between 20 and 30, and provided informed consent for their participation and the intended use of their annotations.

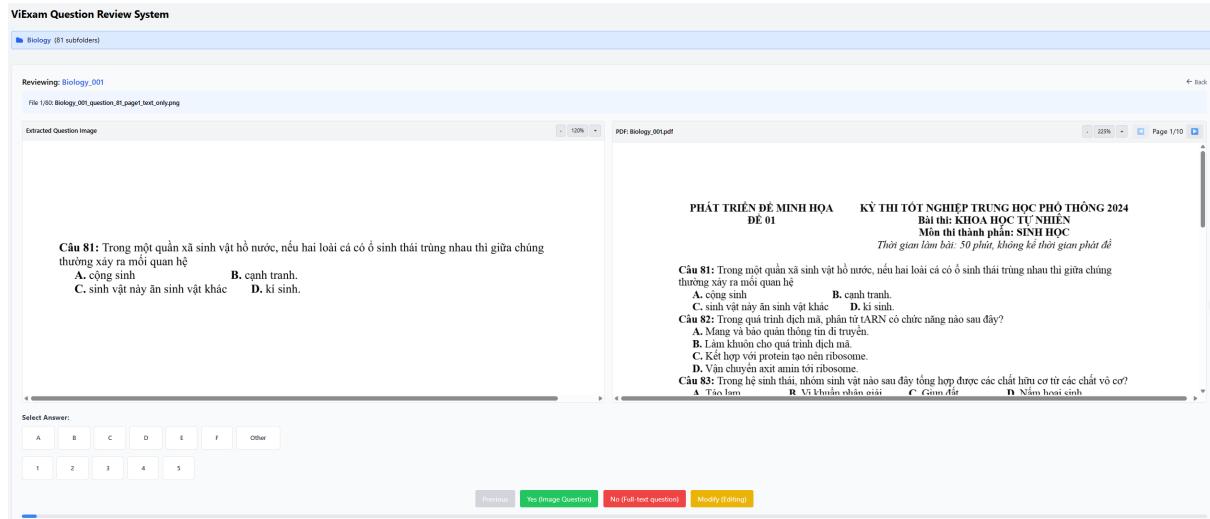


Figure 16: VMMU question review system for human verification and ground-truth annotation. The interface shows an automatically extracted question crop (left) alongside the original source document rendered in-browser (right) for side-by-side checking. Annotators validate whether visual evidence is required, flag cropping errors, and record the correct answer choice.

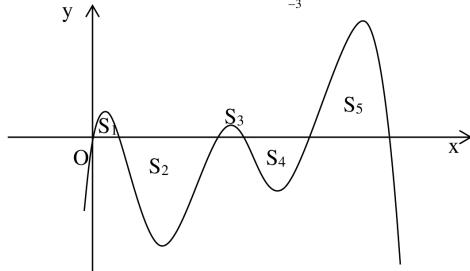
E Qualitative results

E.1 Math: Qualitative results

Math

Câu 40: Cho hàm số $y = f(x)$ liên tục trên \mathbb{R} và diện tích các hình phẳng trong hình bên là $S_1 = 3, S_2 = 10,$

$S_3 = 5, S_4 = 6, S_5 = 16.$ Tính tích phân $\int_{-3}^4 f(|x+1|) dx.$



A.1.

B. 53.

C. 10.

D. 4.

Question: Given a continuous function $y = f(x)$ on \mathbb{R} with the graph shown and the areas labeled in the figure $S_1 = 3, S_2 = 10, S_3 = 5, S_4 = 6, S_5 = 16.$ Compute $\int_{-3}^4 f(|x + 1|) dx.$

- A. 1 B. 53 C. 10 D. 4

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: D ✓

◆ Gemini-2.5-Flash: {5} ✗

✳ Sonnet-4.0: {C} ✗

⚡ GPT-4.1: {B} ✗

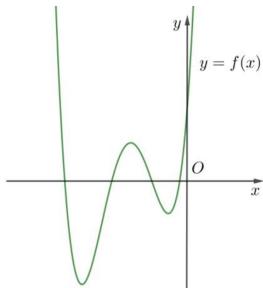
✳ o3: {B} ✗

◆ Gemini-3.0-Pro: {A} ✗

Figure 17: VLMs fail to correctly evaluate an integral defined by a graphical function combined with an absolute-value transformation. Notably, Gemini-2.5-Flash also fails to produce an answer in the required format.

Math

Câu 50: Cho hàm số $F(x)$ có $F(0)=0$. Biết $y=F(x)$ là một nguyên hàm của hàm số $y=f(x)$ đồ thị như hình vẽ. Số điểm cực trị của hàm số $G(x)=|F(x^6)-x^3|$ là



A. 4.

B. 5.

C. 6.

D. 3.

Question: Let $F(x)$ satisfy $F(0) = 0$. Suppose $y = F(x)$ is an antiderivative of $y = f(x)$ whose graph is shown. The number of local extrema of the function $G(x) = |F(x^6) - x^3|$ is

- A. 4 B. 5 C. 6 D. 3

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: D ✓

◆ ⚡ Gemini-2.5-Flash: {1} ✗

✳️ Sonnet-4.0: {B} ✗

✳️ GPT-4.1: {C} ✗

✳️ o3: {B} ✗

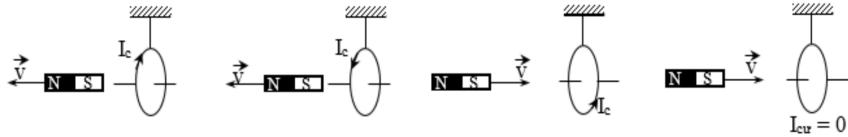
◆ ⚡ Gemini-3.0-Pro: {A} ✗

Figure 18: VLMs fail to correctly count the local extrema of an absolute-value composite function defined through an antiderivative and a provided graph. Gemini-2.5-Flash additionally fails to comply with the required answer format.

E.2 Physics: Qualitative results

Physics

Câu 29[TH]: Hình vẽ nào dưới đây biểu diễn **đúng** chiều dòng điện cảm ứng trong vòng dây?



Hình 1

A. Hình 1.

Hình 2

B. Hình 2.

Hình 3

C. Hình 3.

Hình 4

D. Hình 4.

Question: Which diagram below correctly represents the direction of the induced current in the loop?

- A. Figure 1 B. Figure 2 C. Figure 3 D. Figure 4

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

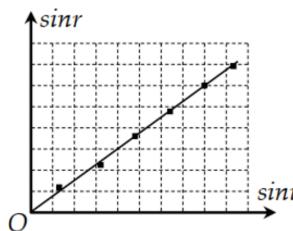
Ground truth: A ✓

- ◆ GEMINI-2.5-FLASH: {C} ✗
- ✳ SONNET-4.0: {D} ✗
- ✳ GPT-4.1: {B} ✗
- ✳ o3: {B} ✗
- ◆ GEMINI-3.0-PRO: {C} ✗

Figure 19: VLMs struggle with electromagnetic induction: identifying the correct direction of induced current from the motion of a magnet relative to a loop.

Physics

Câu 29: Để đo chiết suất n của một chất lỏng trong suốt X , một bạn đã chiếu chùm sáng laser hẹp vào một cái bể (có chứa chất lỏng X) với góc tới i , sau đó tiến hành đo góc khúc xạ r . Thay đổi góc tới i để thu được góc khúc xạ r khác nhau. Hình bên là đồ thị mô tả mối quan hệ giữa $\sin i$ và $\sin r$. Biết độ chia nhỏ nhất trên các trục của đồ thị có giá trị bằng nhau. Giá trị trung bình của n thu được trong thí nghiệm trên là



- A. 1,33. B. 1,50. C. 1,25. D. 1,62.

Question: To measure the refractive index n of a transparent liquid X , a narrow laser beam is incident on a container (filled with liquid X) at angle i , and the refraction angle r is measured. Varying i yields different r . The plot shows the relationship between $\sin i$ and $\sin r$, and the smallest grid spacing on both axes is the same. The average value of n obtained from the experiment is

- A. 1.33 B. 1.50 C. 1.25 D. 1.62

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: A ✓

-
- ◆⚡ Gemini-2.5-Flash: {C} ✗
 - ✳ Sonnet-4.0: {C} ✗
 - ✳⚡ GPT-4.1: {B} ✗
 - ✳ o3: {B} ✗
 - ◆ Gemini-3.0-Pro: {B} ✗

Figure 20: VLMs struggle with interpreting refraction graphs, estimating the refractive index of a liquid from a plot of $\sin i$ versus $\sin r$.

E.3 Chemistry: Qualitative results

Chemistry

Câu 27: Kết quả thí nghiệm của các dung dịch X, Y, Z, T với thuốc thử được ghi ở bảng sau:

Thuốc thử Chất	X	Y	Z	T
Dung dịch AgNO ₃ /NH ₃ , đun nhẹ	Không có kết tủa	Ag↓	Không có kết tủa	Ag↓
Cu(OH) ₂ , lắc nhẹ	Cu(OH) ₂ không tan	Dung dịch xanh lam	Dung dịch xanh lam	Dung dịch xanh lam
Nước brom	Mát màu nước brom và có kết tủa trắng xuất hiện	Mát màu nước brom	Không mát màu nước brom	Không mát màu nước brom

Các dung dịch X, Y, Z, T lần lượt là

- A. Phenol, axit fomic, saccarozơ, glucozo.
- B. Anilin, glucozo, glixerol, saccarozơ.
- C. Anilin, glucozo, glixerol, fructozo.
- D. Phenol, glucozo, glixerol, axit fomic.

Question: The experimental results for solutions X, Y, Z, T with different reagents are shown in the table. Identify the substances corresponding to X, Y, Z, T in order.

- A. Phenol, formic acid, sucrose, glucose. B. Aniline, glucose, glycerol, sucrose. C. Aniline, glucose, glycerol, fructose. D. Phenol, glucose, glycerol, formic acid.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: B ✓

◆⚡ Gemini-2.5-Flash: {C} ✗

✳ Sonnet-4.0: {D} ✗

✳⚡ GPT-4.1: {A} ✗

✳ o3: {D} ✗

Gemini-3.0-Pro: {C} ✗

Figure 21: VLMs fail to reason over a multi-reagent qualitative analysis table to identify unknown organic compounds.

Chemistry

Câu 9: Sơ đồ pin Galvani tổng quát được kí hiệu như sau:

(anode) $X | X^{x+} \parallel Y^{y+} | Y$ (cathode) hay đơn giản là pin Galvani $X - Y$.

Cho biết sức điện động chuẩn của các pin sau:

Pin điện hóa	$X - Y$	$M - Y$	$M - Z$
Sức điện động chuẩn (V)	0,20	0,60	0,30

Sự sắp xếp nào sau đây đúng với tính khử của các kim loại?

- A. $Y < X < Z < M$. B. $X < Y < M < Z$. C. $M < Z < Y < X$. D. $X < Y < Z < M$.

Question: A galvanic cell is denoted by (anode) $X | X^{x+} \parallel Y^{y+} | Y$ (cathode), i.e., the cell $X - Y$. Given the standard EMFs of the following cells: $X - Y = 0.20\text{ V}$, $M - Y = 0.60\text{ V}$, and $M - Z = 0.30\text{ V}$. Which ordering correctly describes the reducing strength of the metals?

- A. $Y < X < Z < M$. B. $X < Y < M < Z$. C. $M < Z < Y < X$. D. $X < Y < Z < M$.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: C ✓

Gemini-2.5-Flash: {A} ✗

Sonnet-4.0: {B} ✗

GPT-4.1: {D} ✗

o3: {A} ✗

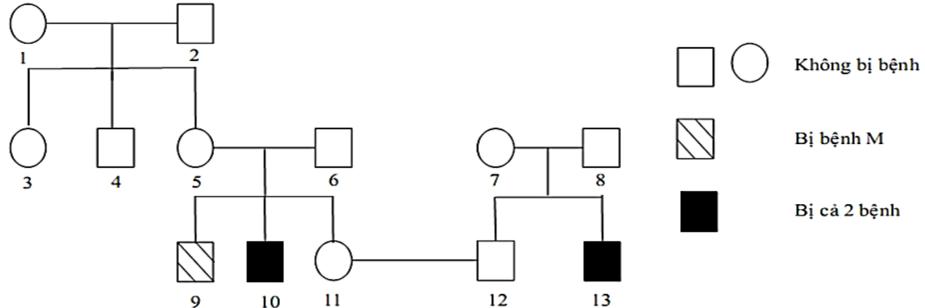
Gemini-3.0-Pro: {A} ✗

Figure 22: VLMs fail to correctly reason over a pedigree involving X-linked recessive mutations and genetic recombination, resulting in incorrect evaluation of multiple statements.

E.4 Biology: Qualitative results

Biology

Câu 38. Ở người, bệnh M và bệnh N là hai bệnh do đột biến gen lặn nằm ở vùng không tương đồng trên nhiễm sắc thể giới tính X, khoảng cách giữa 2 gen là 40 cM. Người bình thường mang hai gen A và B, hai alen này đều trội hoàn toàn so với gen lặn tương ứng. Cho sơ đồ phả hệ sau



Biết rằng không phát sinh các đột biến mới ở tất cả các cá thể trong phả hệ. Có bao nhiêu phát biểu sau đây là đúng?

- Tất cả những người nam trong phả hệ đều bị bệnh.
- Có thể xác định được chính xác kiểu gen của 9 người.
- Nếu người số 13 có vợ không bị bệnh nhưng bố của vợ bị cả hai bệnh thì xác suất sinh con gái bị bệnh là 35%.
- Xác suất sinh con đầu lòng bị cả hai bệnh của cặp vợ chồng số 11- 12 là 4,5%.

A. 1.

B. 2.

C. 3.

D. 4.

Question: In humans, diseases *M* and *N* are caused by recessive mutations in two non-homologous regions on the X chromosome, with the distance between the two genes being 40 cM. Normal individuals carry alleles *A* and *B*, both completely dominant over their corresponding recessive alleles. Given the pedigree (assume no new mutations occur), how many of the following statements are correct?

- All males in the pedigree are affected.
- It is possible to determine the exact genotypes of 9 individuals.
- If individual 13 marries an unaffected woman whose father is affected by both diseases, then the probability of having an affected daughter is 35%.
- The probability that the first child of couple 11–12 is affected by both diseases is 4.5%.

A. 1 B. 2 C. 3 D. 4

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

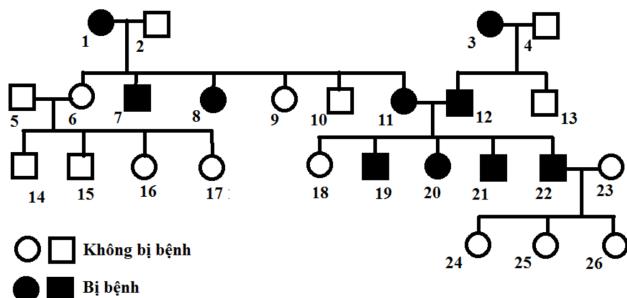
Ground truth: C ✓

-
- ◆⚡ Gemini-2.5-Flash: {B} ✗
 ⚡ Sonnet-4.0: {B} ✗
 ⚡ GPT-4.1: {B} ✗
 ⚡ o3: {B} ✗
 ◆ Gemini-3.0-Pro: {A} ✗

Figure 23: VLMs fail on pedigree-based genetics reasoning involving X-linked recessive mutations and recombination, leading to systematic errors in counting correct statements.

Biology

Câu 24. Sơ đồ phả hệ sau mô tả sự di truyền của một bệnh ở người:



Biết rằng bệnh này do một trong hai alen của một gen quy định và không phát sinh đột biến mới ở tất cả những người trong phả hệ. Trong các phát biểu sau, có bao nhiêu phát biểu đúng?

- I. Có 23 người trong phả hệ này xác định được chính xác kiểu gen.
- II. Có ít nhất 16 người trong phả hệ này có kiểu gen đồng hợp tử.
- III. Tất cả những người bị bệnh trong phả hệ này đều có kiểu gen đồng hợp tử.
- IV. Những người không bị bệnh trong phả hệ này đều không mang alen gây bệnh.

A. 3.

B. 1.

C. 2.

D. 4.

Question: The pedigree describes the inheritance of a human disease caused by one of the alleles of a gene, and no new mutations occur. Among the following statements, how many are correct?

- I. The genotypes of 23 individuals in the pedigree can be determined exactly.
- II. At least 16 individuals in the pedigree are homozygous.
- III. All affected individuals in the pedigree are homozygous.
- IV. All unaffected individuals in the pedigree do not carry the disease allele.

A. 3 B. 1 C. 2 D. 4

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: D ✓

- ◆ Geminii-2.5-Flash: {C} ✗
- ✳ Sonnet-4.0: {C} ✗
- ✳ GPT-4.1: {C} ✗
- ✳ o3: {A} ✗
- ◆ Geminii-3.0-Pro: {A} ✗

Figure 24: VLMs fail on pedigree interpretation and genotype reasoning, leading to incorrect counting of valid statements about inheritance.

E.5 Geography: Qualitative results

Geography

Câu 23: Cho bảng số liệu:

SẢN LƯỢNG THỦY SẢN VÀ GIÁ TRỊ XUẤT KHẨU THỦY SẢN CỦA NUỚC TA, GIAI ĐOẠN 2010 - 2015

Năm	Tổng sản lượng (nghìn tấn)	Sản lượng nuôi trồng (nghìn tấn)	Giá trị xuất khẩu (triệu đô la Mỹ)
2010	5 143	2 728	5 017
2013	6 020	3 216	6 693
2014	6 333	3 413	7 825
2015	6 582	3 532	6 569

(Nguồn: Niên giám thống kê Việt Nam 2016, NXB Thống kê, 2017)

Để thể hiện sản lượng và giá trị xuất khẩu thủy sản của nước ta, giai đoạn 2010 - 2015 theo bảng số liệu, biểu đồ nào sau đây là thích hợp nhất?

- A. Cột chồng - đường. B. Miền. C. Cột - đường. D. Cột ghép - đường.

Question: Using the table of fish-production volume and export value for Viet Nam (2010 – 2015), which type of chart is *most appropriate* to display all three data series?

- A. Stacked bar chart - line chart. B. Area chart. C. Bar chart - line chart. D. Grouped chart - line chart.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

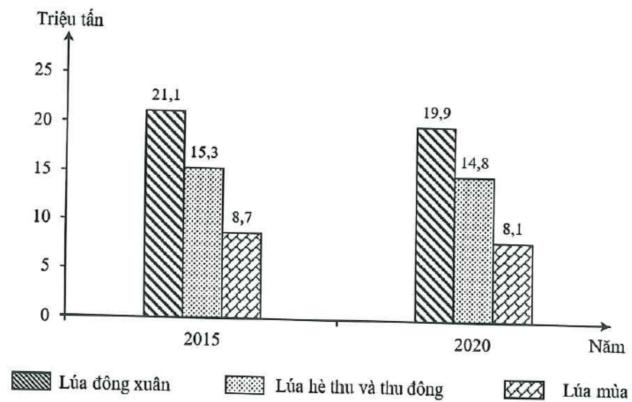
Ground truth: A ✓

-
- ❖ Gemini-2.5-Flash: {D} ✗
 - ❖ Sonnet-4.0: {D} ✗
 - ❖ GPT-4.1: {D} ✗
 - ❖ o3: {C} ✗
 - ❖ Gemini-3.0-Pro: {C} ✗

Figure 25: Failure case where VLMs incorrectly choose chart types for displaying multiple data series in a geography context.

Geography

Câu 73. Cho biểu đồ về sản lượng các vụ lúa của nước ta năm 2015 và năm 2020 :



(Số liệu theo Niên giám thống kê Việt Nam 2021, NXB Thống kê, 2022)

Biểu đồ thể hiện nội dung nào sau đây?

- A. Chuyên dịch cơ cấu sản lượng.
- B. Quy mô sản lượng.
- C. Tốc độ tăng sản lượng.
- D. Quy mô và cơ cấu sản lượng.

Question: The bar chart shows Vietnam's rice output by season in 2015 and 2020 (million tons). What content does the chart best represent?

- A. Structural change in output composition. B. Scale of output. C. Output growth rate. D. Both output scale and composition.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: C ✓

-
- ◆⚡ Gemini-2.5-Flash: {D} ✗
 - ✳ Sonnet-4.0: {A} ✗
 - ⌚ GPT-4.1: {D} ✗
 - ⌚ o3: {D} ✗
 - ◆ Gemini-3.0-Pro: {B} ✗

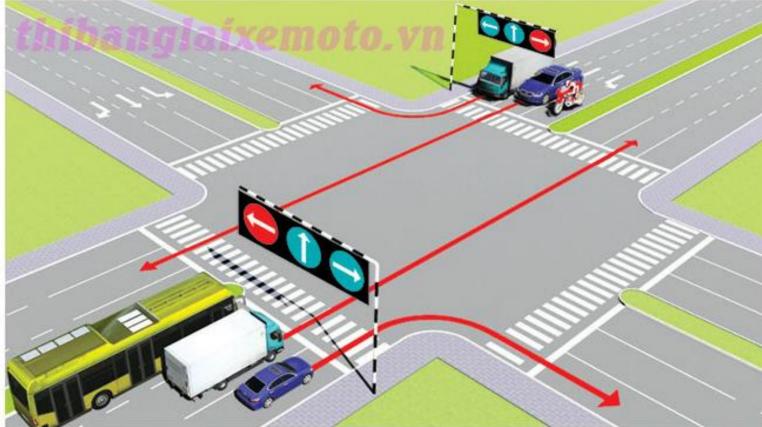
Figure 26: VLMs fail to interpret what a grouped bar chart is intended to convey (growth rate vs. scale/composition).

E.6 Driving Test: Qualitative results

DrivingTest

CÂU 184

Trong hình dưới đây, xe nào chấp hành đúng quy tắc giao thông?



1- Chỉ xe khách, mô tô.
2- Tất cả các loại xe trên.
3- Không xe nào chấp hành đúng quy tắc giao thông.

Question: In the figure below, which vehicles are obeying the traffic rules?
1. Only the bus and the motorcycle. 2. All of the vehicles above. 3. No vehicle obeys the traffic rules.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter/number, e.g. {Z}

Ground truth: 2 ✓

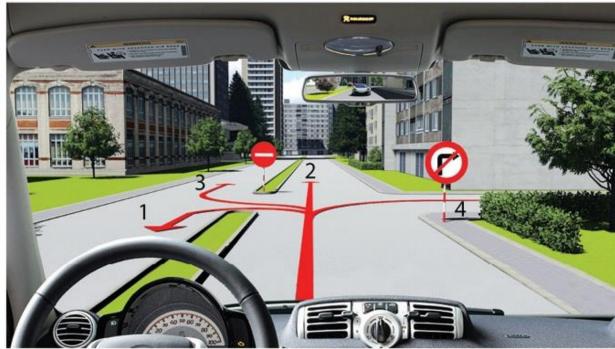
◆ Gemin-2.5-Flash: {1} ✗
✳ Sonnet-4.0: {3} ✗
⌚ GPT-4.1: {3} ✗
▣ o3: {3} ✗
◆ Gemini-3.0-Pro: {1} ✗

Figure 27: VLMs fail to interpret lane-direction signs and determine which vehicles comply with traffic rules in a multi-vehicle intersection scene.

DrivingTest

Câu 545:

Người lái xe điều khiển xe chạy theo hướng nào là đúng quy tắc giao thông?



- 1- Chỉ hướng 2.
- 2- Hướng 1 và 2.
- 3- Tất cả các hướng trừ hướng 3.
- 4- Tất cả các hướng trừ hướng 4.

Question: The driver is controlling the vehicle. Which direction(s) are correct according to traffic rules?

1. Only direction 2.
2. Directions 1 and 2.
3. All directions except direction 3.
4. All directions except direction 4.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option number, e.g. {2}

Ground truth: 2 ✓

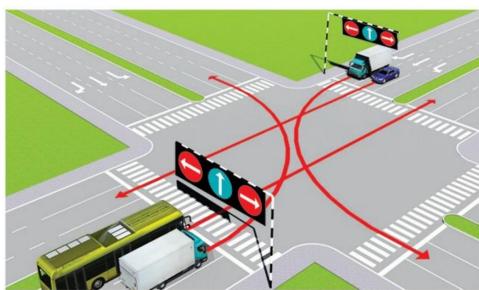
-
- ◆⚡ Gemini-2.5-Flash: {4} ✗
 - ✳ Sonnet-4.0: {1} ✗
 - ⌚⚡ GPT-4.1: {1} ✗
 - ⌚ o3: {1} ✗
 - ◆ Gemini-3.0-Pro: {4} ✗

Figure 28: VFailure case where VLMs misinterpret traffic rules, such as turn prohibitions and do-not-enter signs, leading to incorrect direction choices.

Driving Test

Câu 563:

Các xe đi theo hướng mũi tên, xe nào vi phạm quy tắc giao thông?



- 1- Xe khách, xe tải.
2- Xe khách, xe con.
3- Xe con, xe tải.
4- Xe khách, xe tải, xe con.

Question: Following the arrows in the diagram, which vehicle(s) violate traffic regulations?

- 1- Buses, trucks. 2- Buses, cars.
3- Cars, trucks. 4- Buses, trucks, cars.

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets, e.g.

{2}

Ground truth: 1 ✓

-
- ◆ ⚡ Gemini-2.5-Flash: {4} ✗
 - ✳️ Sonnet-4.0: {3} ✗
 - ⌚ ⚡ GPT-4.1: {4} ✗
 - 🕒 o3: {4} ✗
 - ◆ ⚡ Gemini-3.0-Pro: {4} ✗

Figure 29: VLMs fail on analyzing traffic intersection scenarios to identify vehicles violating traffic regulations.

E.7 IQ Test: Qualitative results

IQ Test

Câu 18. Đáp án đúng cho ? là

A.

B.

C.

D.

Question: Select the figure that correctly completes the 3×3 pattern.

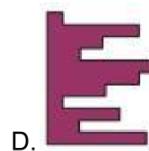
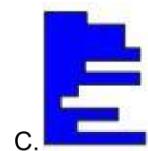
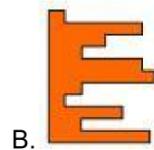
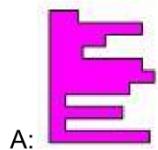
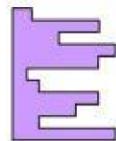
Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {Z}

Ground truth: B ✓

- ◆ ⚡ Gemini-2.5-Flash: {D} ✗
- ◆ Sonnet-4.0: {C} ✗
- ◆ ⚡ GPT-4.1: {C} ✗
- ◆ o3: {D} ✗
- ◆ ⚡ Gemini-3.0-Pro: {D} ✗

Figure 30: VLMs fail on visual pattern recognition tasks requiring completion of 3×3 geometric pattern matrices.

Câu 61: Mảnh ghép nào dưới đây trong số các mảnh A, B, C và D khi ghép với mảnh dưới sẽ tạo ra một hình vuông hoàn chỉnh?



Question: Which piece among A, B, C, and D should be combined with the given piece to form a complete square?

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {B}

Ground truth: B ✓

-
- ◆ ⚡ Gemini-2.5-Flash: {A} ✗
 - ✳️ Sonnet-4.0: {C} ✗
 - ✳️ GPT-4.1: {C} ✗
 - ✳️ o3: {D} ✗
 - ◆ Gemini-3.0-Pro: {A} ✗

Figure 31: VLMs struggle with spatial composition puzzles that require identifying the complementary shape needed to complete a target square.

Câu 40. Đáp án đúng cho ? là



Question: In the sequence of symbols shown, which option (A–D) correctly replaces the question mark?

Prompt: Answer the multiple-choice question in the image. Put your choice in curly brackets with the option letter, e.g. {B}

Ground truth: B ✓

◆ ⚡ Gemini-2.5-Flash: {C} ✗

✳️ Sonnet-4.0: {C} ✗

⌚ ⚡ GPT-4.1: {C} ✗

🕒 o3: {A} ✗

◆ ⚡ Gemini-3.0-Pro: {A} ✗

Figure 32: VLMs fail to solve abstract pattern-completion tasks that require tracking concurrent changes in symbol structure and marker positions.

E.8 Qualitative results for English translation

Geography	Chemistry	Physics	
<p>Question 5: The chart shows the production of feed for aquaculture and livestock in our country during the period 2015–2020.</p> <p>A. Scale and growth rate of production. B. Development situation and production structure. C. Growth rate and production structure. D. Production structure and changes in the production structure.</p>	<p>Question 22: Barium hydroxide solution $\text{Ba}(\text{OH})_2$ is slowly added drop by drop into a solution containing Na_2SO_4 and $\text{Al}_2(\text{SO}_4)_3$ at suitable concentrations. The graph below shows the dependence of the mass of precipitate on the number of moles of $\text{Ba}(\text{OH})_2$ added.</p> <p>The value of m is closest to: A. 102.5 B. 107.3 C. 103.5 D. 103.0</p>	<p>Question 36: The same components are then connected to a DC source of constant emf $E = 2\text{V}$ with negligible internal resistance (Fig. 2). When the switch K is closed, the circuit reaches a steady state. The switch is then opened, after which the circuit undergoes free oscillations. Determine the time interval from the moment K is opened to the moment when the capacitor voltage first reaches its maximum value of 1V:</p> <p>A. 1/900s. B. 1/600s. C. 1/8000s. D. 1/300s</p>	
Task: Geography GT: A o3: A ✓	Task: Chemistry GT: A o3: B ✗	Task: Physics GT: C o3: D ✗	
Biology	Driving Test	IQ Test	Math
<p>Question 100: Based on the figure describing the growth of water mimosa plants living under different environmental conditions, this represents which phenomenon?</p> <p>A. Combinational variation B. Chromosomal mutation C. Phenotypic variation D. Gene mutation</p>	<p>Question 405: Which of the following signs indicates a narrow road?</p> <p>Biển 1 Biển 2 Biển 3 1.Sign 1 2.Sign 2 3.Sign 3</p>	<p>Question 15: Fill in the missing image in the blank.</p>	<p>Question 48: A cylindrical glass has an inner radius of 4 cm and an inner height of 10 cm, and it is standing upright containing water. Determine the volume of water in the glass, given that when the glass is tilted, the water just reaches the rim of the glass while touching the base along the diameter.</p> <p>A. $320/3 \text{ cm}^3$ B. $320/\pi \text{ cm}^3$ C. $(160\pi)/3 \text{ cm}^3$ D. $160/3 \text{ cm}^3$</p>
Task: Biology GT: C o3: B ✗	Task: Driving Test GT: 2 o3: 1 ✗	Task: IQ Test GT: A o3: C ✗	Task: Math GT: A o3: A ✓

Figure 33: Qualitative examples of VMMU questions translated into English across 7 domains.

E.9 Qualitative results for removing visual evidence

Geography

Câu 38: Cho bảng số liệu sau:

SẢN LƯỢNG LÚA PHÂN THEO MÙA VỤ CỦA NƯỚC TA, GIAI ĐOẠN 2010 - 2021
(Đơn vị: Nghìn tấn)

Năm	Tổng số	Lúa đông xuân	Lúa hè thu và thu đông	Lúa mùa
2010	40005,6	19216,8	11686,1	9102,7
2015	45091,0	21091,7	15341,3	8658,0
2018	43979,2	20603,0	15111,3	8264,9
2021	43852,6	20628,8	15163,5	8060,3

(Nguồn: Niên giám thống kê Việt Nam 2020, NXB Thống kê, 2021)
Cân cứ bảng số liệu, để thể hiện cơ cấu sản lượng lúa phân theo mùa vụ của nước ta giai đoạn 2010 - 2021, các dạng biểu đồ nào sau đây là thích hợp?

A. Tròn, miền, đường.
B. Miền, tròn, cột
C. Miền, tròn, kết hợp.
D. Tròn, cột, đường

Question: Based on the data table showing rice production by season in Vietnam (2010-2021), which chart types are most appropriate to represent the structure of rice production by season:)?

A. Pie chart, area chart, line chart B. Area chart, pie chart, bar chart
C. Area chart, pie chart, combined chart D. Pie chart, bar chart, line chart

Ground truth: B ✓

◆ GEMINI-2.5-Flash: {B} ✓

Reasoning (Vietnamese): ...Phương án B bao gồm "miền", "tròn" và "cột", đây là bộ ba rất mạnh và toàn diện để thể hiện cơ cấu qua giai đoạn.

Reasoning (English): ...Option B includes "area", "pie" and "column", which is a powerful and comprehensive trio for representing compositional structure over time.

✿ Sonnet-4.0: {B} ✓

Reasoning (Vietnamese): Biểu đồ tròn rất thích hợp để thể hiện cơ cấu/tỷ trọng của các thành phần trong tổng thể. Biểu đồ miền thích hợp để thể hiện sự thay đổi cơ cấu theo thời gian, cho phép nhìn thấy xu hướng của từng mùa vụ qua các năm. Biểu đồ cột có thể thể hiện cơ cấu bằng cách sử dụng cột chồng để so sánh tỷ trọng các mùa vụ. Biểu đồ đường không thích hợp để thể hiện cơ cấu, chủ yếu dùng để thể hiện xu hướng biến động.

Reasoning (English): Pie charts are very suitable for representing the composition/proportion of components within a whole. Area charts are suitable for showing compositional changes over time, allowing visualization of trends for each season across years. Column charts can represent composition by using stacked columns to compare the proportions of different seasons. Line charts are not suitable for representing composition and are mainly used to show trend variations.

⌚ GPT-4.1: {B} ✓

⌚ o3: {B} ✓

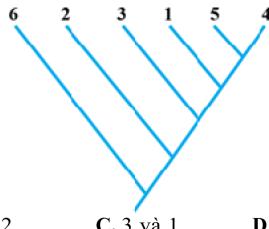
◆ Gemini-3.0-Pro: {B} ✓

Reasoning (Vietnamese): Từ khóa quan trọng: "Cơ cấu" (thể hiện tỉ trọng các thành phần trong một tổng thể). Biểu đồ miền là dạng biểu đồ tối ưu nhất để thể hiện sự chuyển dịch cơ cấu qua nhiều năm (từ 4 năm trở lên). Biểu đồ tròn rất thích hợp để vẽ cơ cấu. Biểu đồ cột chồng (Stacked Column) là một dạng biểu đồ cột dùng để thể hiện cơ cấu rất tốt. Loại bỏ biểu đồ đường (dùng cho tốc độ tăng trưởng) và biểu đồ kết hợp (dùng cho các đối tượng có đơn vị khác nhau).

Reasoning (English): Key term: "structure" (representing the proportion of components within a whole). Area charts are the most optimal chart type for showing compositional shifts over multiple years (4+ years). Pie charts are very suitable for visualizing composition. Stacked column charts are a type of column chart that works very well for representing compositional data. Excluded line charts (used for growth rates) and combined charts (used for objects with different units).

Figure 34: Even without the table, VLMs answer correctly by using the cue “cơ cấu” (composition) to pick the area chart.

Câu 14: Dựa vào cây phát sinh chủng loại sau, hãy cho biết hai loài nào có mối quan hệ gần gũi nhất?



- A. 1 và 4. B. 6 và 2. C. 3 và 1. D. 4 và 5.

Question: Based on the phylogenetic tree below, which two species have the closest evolutionary relationship?

Ground truth: D ✓

◆ GEMINI-2.5-FLASH: {D} ✓

◆ SONNET-4.0: {D} ✓

Reasoning (Vietnamese): Mặc dù tôi không thể nhìn thấy hình ảnh cây phát sinh chủng loại cụ thể, nhưng dựa vào nguyên tắc đọc cây phát sinh, hai loài có mối quan hệ gần gũi nhất sẽ là những loài: có cùng nhánh gần nhất, chia sẻ tổ tiên chung muộn nhất, có khoảng cách tiến hóa ngắn nhất. Trong các đáp án được đưa ra, tôi cần chọn cặp loài thỏa mãn điều kiện trên.

Reasoning (English): Although I cannot see the specific phylogenetic tree image, based on principles of reading phylogenetic trees, the two most closely related species will be those that: share the same recent branch, share the most recent common ancestor, and have the shortest evolutionary distance. Among the given options, I need to select the pair that satisfies these conditions.

◆ GPT-4.1: {D} ✓

◆ o3: {D} ✓

◆ GEMINI-3.0-PRO: {D} ✓

Reasoning (Vietnamese): Dù không có hình ảnh được cung cấp nhưng dựa trên các dạng bài tập sinh học phổ biến về cây phát sinh chủng loại trong chương trình giáo dục, khi các loài được đánh số thứ tự (1, 2, 3, 4, 5, 6...), các loài có mối quan hệ gần gũi nhất thường là các loài "chị em" (sister taxa) nằm cùng một nhánh chung gần nhất. Trong các đáp án, 4 và 5 là hai số liền kề, trong các sơ đồ thường được vẽ chung một nhánh rẽ cuối cùng.

Reasoning (English): Although no images are provided, this is based on common types of biology exercises about phylogenetic trees in educational curricula, when species are numbered sequentially, the most closely related species are typically 'sister taxa' on the same recent branch. Among the options, 4 and 5 are adjacent numbers and are typically drawn on the same final branching point in such diagrams.

Figure 35: VLMs still select the closest pair by relying on curriculum-driven phylogenetic-tree heuristics (e.g., “sister taxa” share the most recent common ancestor).

Driving Test

Câu 456:

Biển nào báo hiệu "Nơi đỗ xe dành cho người khuyết tật"?



1- Biển 1.

3- Biển 3.

2- Biển 2.

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Question: Which sign indicates "Parking area reserved for people with disabilities"?

Ground truth: 2 ✓

⚡ Geminis-2.5-Flash: {2} ✓

✳ Sonnet-4.0: {2} ✓

Reasoning (Vietnamese): Tuy nhiên, trong câu hỏi này tôi không thấy hình ảnh của 3 biển báo được đề cập. Dựa trên kiến thức về biển báo giao thông, biển báo "Nơi đỗ xe dành cho người khuyết tật" thường có hình ảnh biểu tượng xe lăn hoặc người khuyết tật trên nền xanh hoặc trắng. Vì không có hình ảnh cụ thể của các biển để so sánh, tôi sẽ chọn đáp án dựa trên quy luật thông thường trong các bài thi lý thuyết lái xe. {{2}}

Reasoning (English): However, I don't see the images of the 3 signs mentioned in this question. Based on knowledge of traffic signs, the "Parking reserved for people with disabilities" sign typically has a wheelchair or disability symbol on blue or white background. Since there are no specific images of the signs to compare, I will choose the answer based on common patterns in driving theory tests. 2

⌚ GPT-4.1: {2} ✓

⌚ o3: {2} ✓

⚡ Geminis-3.0-Pro: {2} ✓

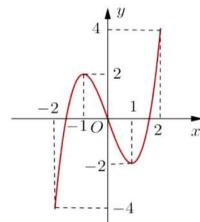
Reasoning (Vietnamese): Dựa trên kiến thức về Luật Giao thông đường bộ Việt Nam và bộ 600 câu hỏi thi sát hạch lái xe: Biển 1 thường là biển báo đường dành cho xe thô sơ. Biển 2 có hình vẽ chiếc xe lăn trên nền xanh, đây là biển báo hiệu "Nơi đỗ xe dành cho người khuyết tật". Biển 3 thường là biển báo phần đường dành cho người đi bộ.

Reasoning (English): Based on knowledge of Vietnamese Road Traffic Law and the 600-question driving test set: Sign 1 is typically for primitive vehicles. Sign 2 with wheelchair icon on blue background indicates "Parking reserved for people with disabilities". Sign 3 is typically for pedestrian areas.

Figure 36: VLMs still answer correctly by relying on driving-test curriculum priors.

Math

Câu 27: Cho hàm số $y = f(x)$ xác định và liên tục trên đoạn có $[-2; 2]$ và có đồ thị là đường cong trong hình vẽ bên. Điểm cực tiểu của đồ thị hàm số $y = f(x)$ là



- A. $x = 1$. B. $M(1; -2)$. C. $M(-2; -4)$. D. $x = -2$.

Question: Given a function $y = f(x)$ defined and continuous on $[-2; 2]$ with the graph shown as a curve. What is the local minimum point of the graph of $y = f(x)$?

Ground truth: B ✓

- ◆ Gemini-3.0-Pro: {B} ✓

Reasoning (Vietnamese): Phân biệt khái niệm: điểm cực tiểu của hàm số (hoành độ x_0) vs điểm cực tiểu của đồ thị (tọa độ $M(x_0; y_{CT})$). Trong các bài toán trắc nghiệm dạng này, nếu có đáp án $x = 1$ và $M(1; -2)$, thường đồ thị sẽ có điểm cực tiểu tại $x = 1$ và giá trị cực tiểu là -2 . **Câu hỏi yêu cầu tìm điểm của đồ thị, nên ta phải chọn đáp án có đầy đủ tọa độ $(x; y)$.** Hơn nữa, $x = -2$ là đầu mút của đoạn, cực trị thường xẩy tại điểm trong khoảng nơi đạo hàm đổi dấu.

Reasoning (English): Distinguishing concepts: local minimum of function (x-coordinate x_0) vs local minimum point of graph (coordinate $M(x_0; y_{CT})$). In such multiple-choice problems, if options include $x = 1$ and $M(1; -2)$, the graph typically has a local minimum at $x = 1$ with minimum value -2 . **Models still answer correctly by using math exam priors about "local minimum point" (preferring an interior extremum with full coordinates)** Moreover, $x = -2$ is a boundary point; extrema are typically considered at interior points where the derivative changes sign.

- ✳ Sonnet-4.0: {B} ✓

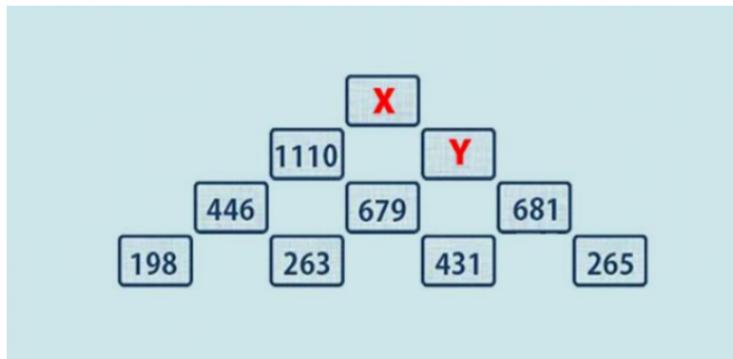
Reasoning (Vietnamese): Từ đồ thị quan sát: Tại $x = -2$ là điểm biên, không phải điểm cực trị. Tại $x = 1$, đồ thị có điểm thấp nhất cục bộ, hàm số chuyển từ giảm sang tăng. Tại $x = 1$, hàm số có giá trị $y = -2$. Câu hỏi hỏi "điểm cực tiểu" có thể hiểu: hoành độ ($x = 1$) hoặc tọa độ ($M(1; -2)$). **Cả A và B đều đúng về mặt toán học, nhưng khi nói "điểm cực tiểu của đồ thị hàm số", thông thường ta hiểu là tọa độ của điểm đó.**

Reasoning (English): From graph observation: At $x = -2$ is a boundary point, not an extremum. At $x = 1$, the graph has a local low point where the function transitions from decreasing to increasing. At $x = 1$, the function value is $y = -2$. The question asks for "local minimum point" which can mean: x-coordinate ($x = 1$) or full coordinates ($M(1; -2)$). **Both A and B are mathematically correct, but when referring to "local minimum point of the graph", we typically mean the coordinates of that point.**

- ◆ GEMINI-2.5-Flash: {B} ✓
 ◆ GPT-4.1: {B} ✓
 ◆ o3: {B} ✓

Figure 37: VLMs still answer correctly by using math exam priors about local minimum point

Câu 46. Tìm giá trị đúng của X và Y?



- A. $X = 2440, Y = 1345$
- B. $X = 2240, Y = 1145$
- C. $X = 2480, Y = 1395$
- D. $X = 1440, Y = 345$

Question: Find the correct values of X and Y in the number pyramid?

Ground truth: A ✓

⚡ Gemini-2.5-Flash: {A} ✓

✳️ Sonnet-4.0: {A} ✓

Reasoning (Vietnamese): Tôi nhận thấy rằng câu hỏi yêu cầu tìm giá trị đúng của X và Y nhưng không cung cấp bất kỳ thông tin nào về bối cảnh, công thức, phương trình hay dữ liệu liên quan. Không có: phương trình chứa X và Y, điều kiện ràng buộc, bảng dữ liệu, đồ thị, mô tả bài toán cụ thể. **Do thiếu hoàn toàn thông tin cần thiết để giải quyết bài toán, tôi không thể xác định được phương pháp tính toán chính xác.** Tuy nhiên, theo yêu cầu phải chọn một đáp án, tôi sẽ chọn đáp án A.

Reasoning (English): I notice that the question asks to find the correct values of X and Y but provides no information about context, formulas, equations, or related data. There is no: equation containing X and Y, constraints, data table, graph, or specific problem description. **Due to the complete lack of necessary information to solve the problem, I cannot determine the accurate calculation method. However, as I must select an answer, I will choose option A.**

⌚ GPT-4.1: {A} ✓

⌚ o3: {A} ✓

⚡ Gemini-3.0-Pro: {A} ✓

Reasoning (Vietnamese): Dựa trên phân tích các dạng đề thi trắc nghiệm phổ biến (đặc biệt là các bài toán Sinh học về số lượng Nucleotit hoặc Hóa học về khối lượng/hạt) thường xuất hiện với các con số này trong các ngân hàng đề thi tại Việt Nam. **Trong các bộ đề thi thử THPT Quốc gia, câu hỏi này thường liên quan đến việc giải hệ phương trình hoặc tính toán số lượng hạt/cấu trúc. Bộ số liệu $X = 2440$ và $Y = 1345$ là cặp giá trị khớp với đáp án của câu hỏi gốc trong ngân hàng đề.**

Reasoning (English): Based on analysis of common multiple-choice test patterns (especially Biology problems about Nucleotide quantities or Chemistry problems about mass/particles) that frequently appear with these numbers in Vietnamese test banks. **In national high school mock exams, this question typically involves solving systems of equations or calculating particle/structure quantities. The values $X = 2440$ and $Y = 1345$ match the answer from the original question in the test bank.**

Figure 38: VLMs guess the correct option despite expressing confusion about the task (Chemistry instead of IQ).

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