MMVU: Measuring Expert-Level Multi-Discipline Video Understanding

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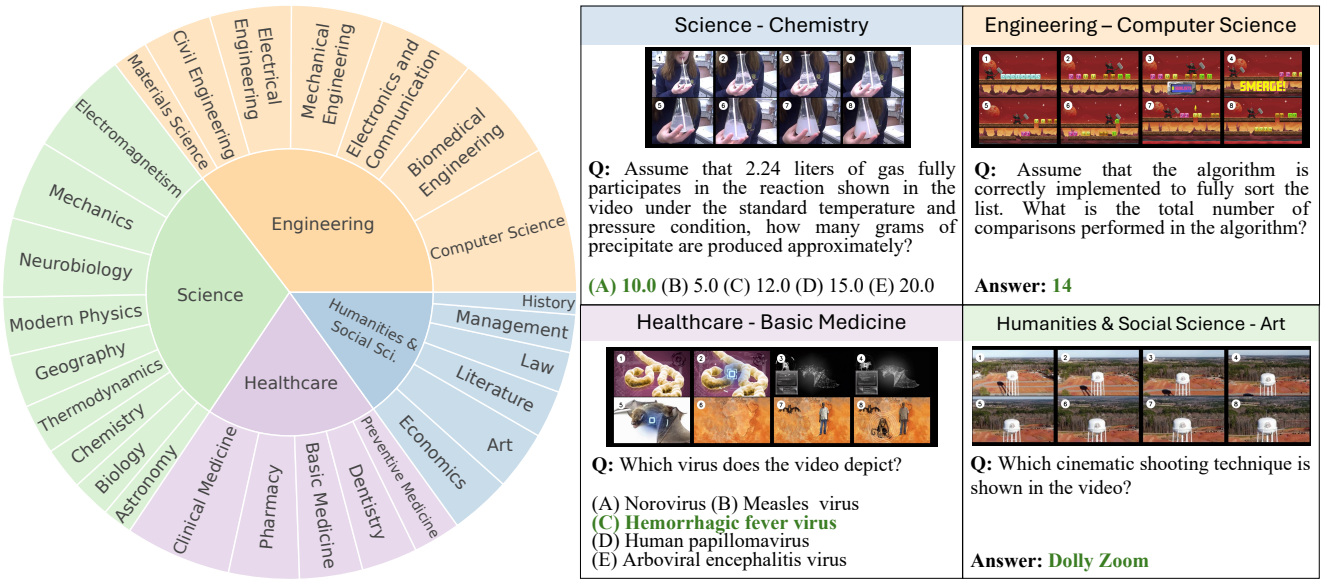

Figure 1. Overview of our benchmark. MMVU includes 3,000 expert-annotated examples, covering 27 subjects across four core disciplines. It is designed to assess foundation models in expert-level, knowledge-intensive video understanding and reasoning tasks.

Abstract

We introduce MMVU, a comprehensive expert-level, multi-discipline benchmark for evaluating foundation models in video understanding. MMVU includes 3,000 expert-annotated questions spanning 27 subjects across four core disciplines: Science, Healthcare, Humanities & Social Sciences, and Engineering. Compared to prior benchmarks, MMVU features three key advancements. First, it challenges models to apply domain-specific knowledge and perform expert-level reasoning to analyze specialized-domain videos, moving beyond the basic visual perception typically assessed in current video benchmarks. Second, each example is annotated by human experts from scratch. We implement strict data quality controls to ensure the high quality of the dataset. Finally, each example is enriched with expert-annotated reasoning rationals and relevant domain knowledge, facilitating in-depth analysis. We conduct an extensive evaluation of 36 frontier multimodal foundation models on MMVU. The latest System-2-capable models, o1 and Gemini 2.0 Flash Thinking, achieve the highest performance among the tested models. However, they still fall short of matching human expertise. Through in-depth error analyses and case studies, we offer actionable insights for future advancements in expert-level, knowledge-intensive video understanding for specialized domains.

1. Introduction

Foundation models have demonstrated remarkable capabilities in reasoning across various domains, yet their ability to handle expert-level knowledge remains a critical area of

Dataset	QA Type	Data Source	College Level?	Detailed Solution Rational?	Detailed Solution Knowledge?
		Text			
MMLU [60]	MC	Exam, course, textbook	✓	✗	✗
MMLU-Pro [147]	MC	Datasets → Human & LLM augment	✓	✗	✗
C-Eval [65]	MC	Exam	✓	✗	✗
SciEval [132]	MC, Open	Internet, datasets → LLM rewrite	✓	✗	✗
TheoremQA [21]	MC, T/F, Open	Internet, exam → Human rewrite	✓	✗	✓
SciKnowEval [42]	MC, T/F, Open	Textbooks, database, other datasets → LLM rewrite	✓	✗	✓
		Text + Image			
VisScience [72]	MC, Open	Internet, exam, textbook	✗	✗	✗
EXAMS-V [32]	MC	Exam	✗	✗	✗
ScienceQA [103]	MC	Internet, course	✗	✓	✗
SceMQA [95]	MC, Open	Internet, exam	✗	✓	✗
CharXiv [149]	Open	arXiv paper → Human annotate	✓	✗	✗
MMSci [94]	MC	Scientific paper → LLM generate	✓	✗	✗
OlympicArena [67]	MC, T/F, Open	Olympic competitions	✓	✓	✗
MMMU [161]	MC, Open	Internet, exam, textbook	✓	17.6%	✗
CMMMU [164]	MC, T/F, Open	Internet, exam, textbook	✓	2.1%	✗
MMMU-Pro [162]	MC	MMMU → Human & LLM augment	✓	15.4%	✗
		Text + Video			
MMWorld [58]	MC	Human experts (24%) / LLM-gen (76%)	39.5%	✗	✗
MMVU (ours)	MC, Open	Human experts annotate from scratch	✓	✓	✓

Table 1. Comparison between MMVU and existing multi-discipline benchmarks for evaluating foundation models. In the "QA Type" column, "MC" denotes Multiple-Choice questions, "Open" denotes Open-ended questions, and "T/F" denotes True-False questions.

evaluation [60, 161]. In recent years, researchers have developed numerous benchmarks to assess these models' proficiency in specialized domains, primarily focusing on text-based reasoning [42, 60, 132, 147] and image-based contexts [94, 104, 161, 162, 164]. However, as capabilities of foundation models expand across multiple modalities, there is a significant gap in evaluating expert-level reasoning over specialized-domain *videos*. This gap is particularly concerning as video is one of the most information-rich and naturalistic modalities, and is widely used to convey complex, dynamic information in specialized fields like healthcare, engineering, and scientific research [58]. Unlike static text or images, expert-level videos often capture temporal dynamics, procedural knowledge, and complex interactions that are essential in many specialized domains. For example, in science, expert-level and knowledge-intensive reasoning might involve analyzing a chemical reaction video (Figure 1). A model must identify key reaction stages based on subtle visual cues like color changes or the formation of precipitates, which requires integrating chemical knowledge in addition to recognizing visual patterns.

To bridge this gap, we introduce MMVU, a comprehensive benchmark measuring **M**ultimodal foundation models in expert-level, **M**ulti-discipline **V**ideo **U**nderstanding and reasoning. MMVU consists of 3,000 expert-annotated QA examples over 1,529 specialized-domain videos, spanning 27 subjects across four key disciplines: Science, Healthcare, Humanities & Social Sciences, and Engineering. To ensure both the breadth of domain knowledge and the depth of reasoning required for MMVU, we implement a textbook-guided data annotation process. Expert annotators first locate key concepts from textbooks in their fields, then source relevant videos and create corresponding questions that require domain knowledge and expert-level reasoning to comprehend the videos. Each example also includes expert-annotated reasoning rationale and relevant domain knowledge, facilitating fine-grained evaluation of model performance. Thorough data quality controls are implemented to ensure high quality of MMVU.

We conduct an extensive evaluation on MMVU, covering 36 frontier multimodal foundation models from 17 organizations. Notably, the latest o1 model demonstrates the highest performance among all tested models, approaching the expertise of human experts. Despite this progress, other models still fall noticeably short of human-level capabilities. For instance, GPT-4o achieves a score of 66.7%, which is substantially lower than the benchmark set by human experts (*i.e.*, 86.8%) in the open-book setting. Our analysis highlights the effectiveness of CoT reasoning, which generally enhances model performance compared to directly generating final answers without intermediate reasoning steps. To deepen understanding of the current models' limitations, we perform an in-depth error analysis of frontier models, including numerous case studies reviewed by human experts. These insights provide valuable guidance for future advancements in the field.

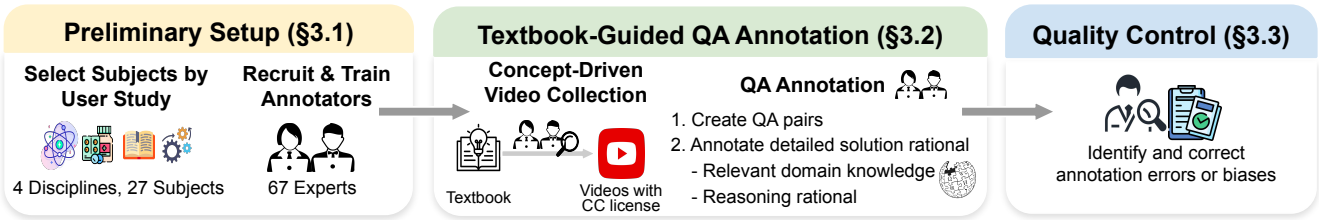

Figure 2. An overview of the MMVU benchmark construction pipeline.

2. Related Work

Video Understanding Benchmark. Existing video understanding benchmarks primarily focus on *general-purpose* video comprehension tasks, such as action recognition [34, 59, 100, 130], captioning and description [81, 89, 134, 153, 157], grounding [23, 74, 85, 145], temporal reasoning [17, 29, 70, 75, 91, 101, 129], and long video understanding [7, 39, 112, 144, 166]. The rise of video-based foundation models [41, 66, 135, 165] has driven the development of new benchmarks that include diverse video comprehension tasks for more comprehensive evaluation [48, 76, 90, 92, 115, 156, 160]. However, these benchmarks remain predominantly focused on natural scenes and general-purpose tasks. A significant gap persists in benchmarks targeting *expert-level* and *knowledge-intensive reasoning* over specialized-domain videos, where both visual perception and domain-specific expertise are required—especially in critical fields like healthcare, engineering, and science [58].

Multi-discipline Evaluation Benchmark. The rapid development of foundation models has significantly enhanced expert-level reasoning across various disciplines [53, 71, 118, 136, 159]. Early benchmarks focused on domain-specific tasks for textual domains, establishing a foundation for assessing the models' strengths and limitations in expert reasoning [21, 27, 60, 133, 147, 150, 168, 169]. More recently, benchmarks have evolved to include multimodal tasks [94, 104, 149, 161, 162, 164], emphasizing visual perception and advanced reasoning with domain knowledge. However, these efforts remain largely limited to *static* images. Developing a high-quality, multidisciplinary video benchmark presents greater challenges than those for text or image-based tasks due to the scarcity of suitable resources (*e.g.*, textbooks or exam questions). This leaves the critical modality of videos and video-based expert-level reasoning significantly underexplored. Recent work, MMWorld [58], has made pioneering strides by incorporating videos across multiple disciplines. However, only a limited portion of its dataset (39.5%) requires domain-specific expertise, and 76.4% of the examples are generated by the GPT-4V model. Moreover, most existing benchmarks provide only the ground-truth answer, restricting researchers' ability to conduct a fine-grained evaluation. To address this limitation, MMVU includes expert-annotated reasoning rationales and relevant domain knowledge for each example, enabling a more nuanced assessment of expert-level reasoning. Table 1 further distinguishes the difference between MMVU and existing multi-discipline benchmarks.

3. MMVU Benchmark

We present MMVU, a comprehensive evaluation benchmark that focuses on measuring progress on knowledge-intensive, expert-level reasoning in the video modality. MMVU has the following key features: (1) **Breadth of Domain Knowledge**: We employ a textbook-guided QA annotation pipeline to ensure the wide coverage of domain knowledge within each subject (§3.2). (2) **Depth of Expert-level Reasoning**: Each example in MMVU requires models to comprehend specialized-domain video context, applying expert knowledge and reasoning (§3.2). (3) **True Visual Understanding**: Recent studies [20, 162, 167] have shown that visual content is unnecessary for many examples in current multimodal benchmarks. To alleviate this issue, each example in MMVU is carefully validated by human experts to confirm that video comprehension is required for accurate answering (§3.3). (4) **Support of Fine-grained Evaluation**: We provide expert-annotated solutions and the requisite knowledge for each example (§3.2), enabling more comprehensive analysis for future research (§4.3). Figure 2 provides an overview of the three stages involved in constructing MMVU, which is detailed in the following subsections.

3.1. Preliminary Setup

We first discuss the preliminary setup for data construction.

Subject Selection. To ensure a broad and accurate representation of expert-level video understanding across diverse disciplines, we conduct a user study involving 133 college and graduate students for subject selection. We ask them to curate two QA examples requiring expert-level video understanding in subjects relevant to their field of study, and provide feedback on their experiences during the curation

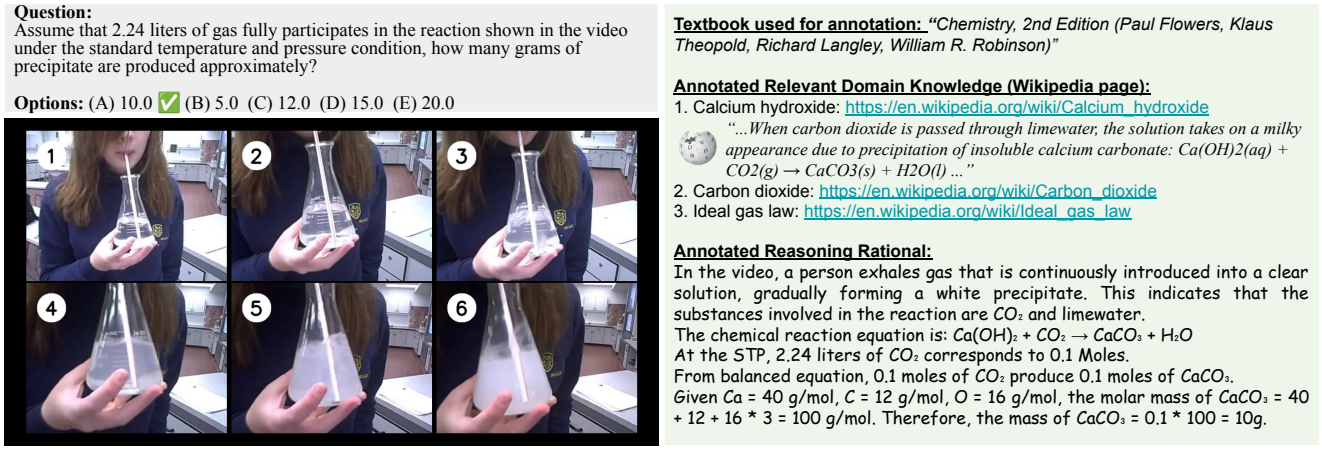

Figure 3. A dataset example from MMVU with the discipline of chemistry. Each example in MMVU includes expert annotation of relevant domain knowledge and step-by-step reasoning rational.

process. Such a user study-guided approach helps us identify subjects within each discipline that may not be obvious from a top-down selection process. It also offers insights into the challenges of designing expert-level video examples, helping us design and refine the textbook-guided QA annotation process (detailed in §3.2). The authors manually analyze the collected examples and select **27 subjects** (as listed in Figure 1) across four disciplines that align best with our benchmark's construction desiderata discussed earlier.

Expert Annotator Recruitment and Training. For each subject, we assign at least two annotators with relevant expertise. We include 67 expert annotators (detailed biographies are presented in Appendix A.1), comprising 22 third- or fourth-year undergraduate students, 36 graduate students, and nine of the authors. All the annotators also participated in our initial user study. Each annotator is required to finish a training session to learn the annotation protocol (detailed in Appendix A.3) before official annotation.

3.2. Textbook-Guided QA Example Annotation

Constructing a high-quality, expert-level, multi-disciplinary benchmark for video-based tasks is more challenging than the ones for text- or image-based, as there is no existing resources (*e.g.*, textbooks or exam questions) that can adapted from and each example has to be curated from scratch. Therefore, it is crucial to establish a structured approach that ensures the quality and comprehensiveness of the benchmark. We employ a textbook-guided example annotation pipeline designed to capture both the *breadth of knowledge* and *depth of reasoning*. In brief, annotators first identify key concepts from the textbook and locate relevant videos that align with these concepts. The textbooks for each subject (listed in Appendix A.2) are selected by expert annotators and are recognized as authoritative references in their respective fields. Annotators then curate QA examples and detailed solution rationales. We detail the annotation procedure as follows:

Concept-Driven CC-Licensed Video Collection. Annotators are instructed to first review each chapter of the textbook to identify key concepts that inherently require dynamic visual representation, such as experimental procedures in science or mechanical operations in engineering. They then search for related videos on YouTube having Creative Commons (CC) license that effectively illustrate the selected concept. The CC license enables reusers to distribute, remix, adapt, and build upon the material in any medium or format, so long as attribution is given to the creator. We use YouTube Data API v3[1] to verify the license type. Existing video benchmarks typically utilize YouTube videos, yet do not confine their selections to content with CC licenses, introducing potential copyright concerns. We recognize that by restricting our selection to CC-licensed content, we are compelled to forgo coverage of certain subjects (*e.g.* sports), where CC-licensed videos is scarce. To ensure the collected videos effectively challenge the model's visual reasoning capabilities, the video should be vision-intensive, requiring models to focus solely on visual information for comprehension. To this end, we ensure that audio tracks are excluded to eliminate potential shortcuts models might exploit through auditory cues; and the video should contain minimal on-screen text, as an overabundance of text may detract from the core visual understanding task. Consequently, videos such as lecture recordings, which typically include slides or text-based explanations that simplify the task of answering associated questions, are excluded.

[1] https://developers.google.com/youtube/v3

QA Annotation. After identifying suitable videos, annotators are required to create two or three questions, either multiple-choice or open-ended. Each question is designed to test the model's expert-level reasoning by applying domain-specific knowledge to interpret the video content and derive a solution. Annotators are also required to specify the start and end timestamps of the video clip relevant to answering each question. For annotating multi-choice question, the annotators are required to carefully craft the four distractor options to reflect common misconceptions or plausible alternatives, ensuring that models cannot easily eliminate incorrect options without reasoning over video content. Once the five options are finalized, the annotation interface randomly shuffles them.

Solution Rationale Annotation. For each annotated question, annotators must also provide detailed solution for the correct answers. As shown in Figure 3, the solution comprises two key components: (1) *relevant domain knowledge*, which includes a list of domain-specific concepts or keywords necessary for answering the question, with each concept linked to its corresponding Wikipedia page. (2) *reasoning rationale*, which details the step-by-step reasoning process to reach the correct answer. These solution annotations are critical for enhancing transparency in the evaluation process and facilitating future research focused on understanding model failure modes.

3.3. Data Quality Control

We next discuss our methods to ensure high data quality.

Time-Based Annotation Compensation. As discussed earlier, annotating examples for MMVU can be particularly time-intensive, especially when there is limited availability of videos with Creative Commons licenses in the required subjects. To accommodate this and ensure a high-quality benchmark, we compensate annotators based on the time they spend rather than the number of examples completed, preventing them from rushing through tasks (See Appendix A.5 for annotation compensation details). On average, annotating one example takes 20 minutes and 17 seconds, while validation requires 4 minutes and 12 seconds.

Human Expert Validation. To ensure that the final dataset remains high-quality and meets expert-level standards without introducing unnecessary biases, each example in MMVU undergoes expert review by one of the authors or top-performing annotators to verify the accuracy of its annotations. Recent studies [20, 129, 162, 167] have shown that visual content is unnecessary for many examples in current multimodal benchmarks. To address this concern, each example in MMVU is carefully validated by human experts to ensure that video comprehension is required for accurate answering. If an example is determined to be answerable solely through the textual components of the question, a single video frame, or if it contains annotation errors, evaluators first attempt to revise the example. If revision is not feasible, detailed feedback is provided to the original annotator, who then revises and submits it for a second iteration. A total of 523 examples were revised during the data validation process. Among them, 72 examples were still found to be misaligned with our design criteria and were excluded from the final benchmark. Overall, $1 - \frac{523}{3{,}000+72} = 83.0\%$ of the initial examples met our design criteria without requiring revisions, indicating the high quality of initial annotation.

Statistics	**Value**
Total Questions	3,000
Validation Set	1,000
Test Set	2,000
Unique Videos	1,529
Video Length (Seconds, `avg/max`)	51.4 / 228
Number of Disciplines	4
Number of Subjects	27
Multiple Choice Questions	1,858
Question Length (`avg/max`)	16.8 / 70
Single Choice Length (`avg/max`)	7.6 / 42
Number of Choices per Question	5
Open-ended Questions	1,142
Question Length (`avg/max`)	16.4 / 39
Ground-truth Answer Length (`avg/max`)	1.5 / 7
Number of Required **Knowledge** per Question (`avg/max`)	4.3 / 7
Solution Rationale Length (`avg/max`)	56.6 / 193
Total Number of Unique Knowledge (*i.e.*, Wikipedia pages)	4,770

Table 2. Key statistics of the MMVU benchmark.

3.4. MMVU Benchmark Analysis

Data Statistics. Table 2 presents the key statistics of MMVU. It consists of 3,000 examples, which are randomly divided into two subsets: validation and test. The validation set contains 1,000 examples, and is intended for model development and validation. The test set, comprising the remaining 2,000 examples, is strictly reserved for standard evaluation to prevent data contamination [35, 50, 69]. To further promote fair benchmarking, the test set remains hidden. We are developing an online evaluation pipeline on a public platform, enabling researchers to benchmark their models and participate in a public leaderboard.

Human Performance. To provide a rough but informative estimate of human-level performance on MMVU, we randomly sampled 30 questions per discipline from the test set, resulting in a total of 120 questions for evalua-

tion. Five participants—three graduate students specializing in biology, anesthesiology, and East-Asian literature, along with two of the authors—individually answered these questions. The evaluation proceeded in three phases: (1) **Closed-book Setting**: In the first phase, participants had 3.5 hours to answer questions without access to external resources. The average accuracy across the four participants was 49.7%. (2) **Open-book Setting**: In the second phase, participants were permitted to use external resources (*e.g.*, internet and textbooks) to review answers they felt uncertain about. They were not informed of the correctness of their initial responses, and a 4-hour time limit was set. This open-book approach led to an increase in average accuracy to 86.8%. (3) **Oracle Setting**: Finally, participants were required to revise each incorrect answer based on ground-truth domain knowledge and self-sourced online resources. The average accuracy after this final revision was 95.3%.

4. Experiments

This section discusses experiment setup and key findings.

4.1. Experiment Setup

Evaluated Multimodal Foundation Models. To establish a comprehensive understanding of the challenges posed by MMVU and provide reference points for future research, we evaluate a broad range of frontier multimodal foundation models that support *video* or *multiple images* as input. Specifically, we evaluate **19 series of open-source models**, including InternVL-2 & 2.5 [22, 24], Qwen2-VL [143, 159], LLaVA-NeXT [99], Pixtral [111], DeepSeek-VL2 [154], H2OVL Mississippi [49], Idefics2 [84], Aria [87], LLaVA-NeXT-Video [88], LLaVA-OneVision [86], Llama-3.2-Vision [37], Phi-3.5-Vision [1], InternVideo2 & 2.5 [146, 148], VideoChat-Flash [93], and VideoLLaMA 2 & 2.1 & 3 [25, 163]. We also evaluate **eight series of proprietary models**, including OpenAI o1 [117] and GPT-4o [118], Gemini-1.5 & 2 and Gemini-Thinking [53], GLM-4V-Plus [51, 63], Grok-2-Vision [155], and Claude-3.5 [4]. For open-source models, we prioritize the vLLM pipeline [83] for model inference; otherwise, we use the Transformers pipeline [152]. We use the official API service for proprietary models. For models without native video support, following VideoMME [48], we provide visual input using the maximum number of images that fits within the model's context window. §B.1 details the parameter settings and model configurations. We evaluate the models with both **Direct Answer** and **Chain-of-Thought** prompts (presented in Appendix B.2), which is adapted from the versions used in MMMU-Pro [162].

Accuracy Evaluation. We use accuracy as the primary metric to evaluate model performance on MMVU. Following recent benchmarks for foundation model evaluation [58, 104, 149], we employ GPT-4o to assess accuracy. Specifically, given a question, its ground truth answer, and the model's response, GPT-4o is instructed to extract the final answer from the model response and determine its correctness. The evaluation prompts for both multiple-choice and open-ended questions are presented in Appendix B.3.

4.2. Main Findings

Section 4.1 presents the evaluated models' CoT performance on MMVU, while Figure 4 illustrates a comparison between the model performance in CoT reasoning and direct answering. Our key findings are as follows:

MMVU presents substantial challenges for current multimodal foundation models. Even the top-performing model falls well short of human expert performance. For instance, GPT-4o achieves 66.7% accuracy with CoT prompting, significantly lower than the 86.8% accuracy achieved by human experts in an open-book setting. Notably, while GPT-4o has narrowed the performance gap with human experts in text-based expert-level reasoning on MMLU (88.7% vs 89.8% [60]) and image-based expert-level reasoning on MMMU (69.1% vs 82.6% [161]), the gap remains large on MMVU. This disparity underscores MMVU's critical role in advancing and evaluating multimodal foundation models' capabilities in video-based expert reasoning across specialized domains.

Performance of open-sourced models. As for open-source multimodal foundation models, they still lag behind the proprietary models. However, the Qwen2-VL-72B and DeepSeek-VL2 models have achieved performance levels that exceed human benchmarks in closed-book settings and are approaching the performance of leading proprietary models. These advancements highlight the significant progress being made in open-source model development.

CoT reasoning generally improves model performance compared to directly outputting the answer. However, the degree of improvement varies across different foundation models. For instance, Claude 3.5 Sonnet demonstrated a remarkable enhancement, achieving a notable performance gain of 11.0%, as corroborated by the findings in MMMU-Pro [162]. Conversely, models like GPT-4o exhibited only marginal improvements. These results indicate that the impact of CoT reasoning is not uniformly beneficial across all models on MMVU.

System-2 thinking demonstrates effectiveness. Models capable of System-2 thinking and employing long CoT demonstrate significant performance advantages. Notably,

	Release	Test Set				Avg. Validation	Avg. Test
		Science	Healthcare	Human. & Social Sci.	Engineering		
Human Performance							
Human Oracle		95.3	93.3	96.0	96.7	95.3	
Human Open-book		86.7	84.7	92.7	83.3	86.8	
Human Closed-book		54.7	42.7	44.7	56.7	49.7	
Proprietary Models							
o1	2024-12	76.5	80.1	80.9	71.9	75.5	76.1
Gemini 2.0 Flash Thinking	2024-12	69.3	71.2	73.4	67.3	69.1	69.5
GPT-4o	2024-08	67.2	71.8	72.0	61.6	67.4	66.7
Gemini 2.0 Flash	2024-12	70.8	62.7	71.6	63.0	65.9	66.5
Gemini 1.5 Pro	2024-09	67.2	68.1	67.0	62.8	65.4	65.8
Claude 3.5 Sonnet	2024-10	60.5	64.0	70.9	64.5	65.2	64.1
Grok-2-Vision	2024-12	60.6	72.5	72.0	57.4	62.7	63.4
GPT-4o-mini	2024-07	60.3	60.9	70.6	59.3	61.6	61.5
Gemini 1.5 Flash	2024-09	56.8	57.3	66.3	58.2	58.8	58.8
GLM-4V-Plus	2025-01	52.2	57.3	64.9	55.4	56.2	56.2
Open-sourced Models							
Qwen2-VL-72B	2024-09	48.0	53.6	61.7	53.9	53.0	53.2
DeepSeek-VL2	2024-12	50.3	53.4	58.9	48.6	52.1	51.5
InternVL2.5-38B	2024-11	50.3	45.6	52.8	52.8	50.5	50.7
Aria	2024-11	46.8	43.3	61.0	49.9	49.3	49.3
InternVideo2.5-8B	2025-01	47.6	50.0	54.3	44.9	48.3	48.0
Llama-3.2-90B-Vision	2024-09	46.5	43.5	53.9	48.1	47.1	47.6
VideoLLaMA3-7B	2025-01	46.5	47.9	57.4	43.5	45.0	47.2
DeepSeek-VL2-Small	2024-12	47.5	48.7	47.5	45.1	46.9	46.9
VideoChat-Flash-7B	2025-01	43.6	50.8	50.7	41.5	45.1	45.2
Qwen2-VL-7B-Instruct	2024-08	43.6	42.5	43.6	41.2	42.1	42.5
InternVL2.5-8B	2024-11	39.2	36.8	47.2	42.3	41.1	41.0
VideoLLaMA2.1-7B	2024-10	35.3	38.9	45.4	41.6	39.5	39.8
VideoLLaMA3-2B	2025-01	40.0	42.7	47.5	34.6	38.7	39.6
Llama-3.2-11B-Vision	2024-09	40.5	39.4	44.0	35.7	38.9	39.0
Phi-3.5-Vision	2024-08	38.3	29.5	45.4	41.1	38.1	38.7
LLaVA-OneVision-7B	2024-09	34.3	38.6	40.8	38.8	37.9	37.7
Qwen2-VL-2B	2024-08	32.6	40.9	40.4	35.7	36.5	36.5
InternVL2-8B	2024-06	36.7	32.9	36.9	37.2	36.3	36.2
Idefics3-8B	2024-08	37.0	35.5	44.0	31.2	35.3	35.6
VideoLLaMA2-7B	2024-06	32.3	27.7	44.3	35.7	34.4	34.4
DeepSeek-VL2-Tiny	2024-12	34.3	33.4	35.8	30.1	33.0	32.8
Pixtral-12B	2024-09	36.1	24.6	37.9	30.8	32.3	32.2
LLaVA-NeXT-Video-34B	2024-06	31.8	24.6	35.8	30.3	30.5	30.4
InternVideo2-8B	2024-08	29.6	31.1	37.2	26.5	29.9	29.9
H2OVL Mississippi-2B	2024-10	29.1	29.5	29.4	28.0	29.1	28.8
LLaVA-NeXT-Video-7B	2024-06	27.0	31.1	27.3	29.5	28.6	28.7

Table 3. Accuracy of evaluated foundation models on the MMVU validation and test sets using CoT prompts. Model performance is ranked based on overall results on the test set. *: For o1, as the API access for its multimodal version has not been granted, we randomly sampled 100 examples from the validation set and 200 examples (50 for each core discipline) from the test set.

the o1 and Gemini 2.0 Flash Thinking models achieved the top two results on MMVU, illustrating that increasing test-time compute and applying long CoT can significantly enhance model performance in expert-level video reasoning tasks. These results highlight the potential of developing open-source models designed to facilitate and advance System-2 thinking capabilities.

4.3. Qualitative Analysis

To gain a deeper understanding of the capabilities and limitations of frontier models on MMVU, we perform comprehensive case studies and error analysis by humans. The inclusion of expert-annotated reasoning rationales and domain knowledge for each example in MMVU facilitate a more effective analysis compared to datasets that provide

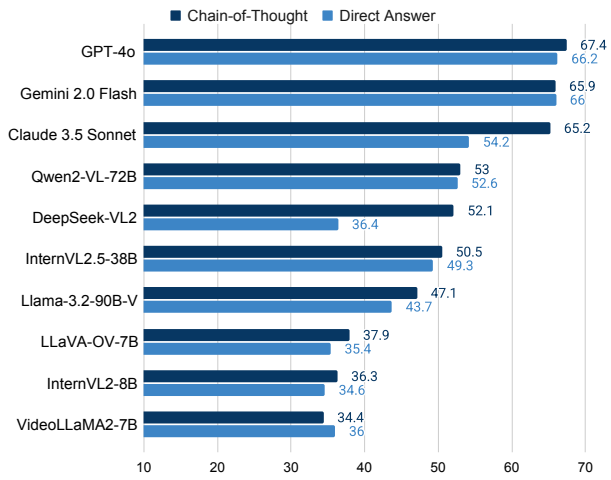

Figure 4. Comparison of model performance between CoT and direct answering on validation set. Full results are shown in §C.1.

only answers. We focus on four top-performing models, GPT-4o, Qwen2-VL-72B, Llama-3.2-90B-Vision, and DeepSeek-VL2, for human evaluation. From the MMVU validation set, we randomly sample 50 error cases for each model. These cases are analyzed by the authors using ground-truth features (*i.e.* expert-annotated reasoning rationales and required domain knowledge) as references. We identify the following six primary errors, with illustrative examples provided in Appendix C:

Visual Perception Error (18%): The model fails to accurately interpret spatial, temporal, or semantic aspects of visual information within a video. Additionally, it might "hallucinate", detecting objects or events that are not actually present in the video. Figure 16 is a typical instance where the model fails to correctly perceive the traversal order of binary tree. Figure 18 shows that the model mistakenly identifies the device shell in the video as water, leading to completely wrong reasoning about the device's function.

Misuse or Lack Domain Knowledge in Visual Perception (20%): The model fails to apply the domain-specific expertise required to accurately interpret specialized concepts or elements within the video. For example, in a medical video, it may identify objects but fail to recognize their technical terms or misunderstand their importance within the procedure being demonstrated. Moreover, as shown in Figure 20, the model correctly perceives the ascending numbers (array indices), but misuses its pretrained knowledge and misidentifies them as the numbers to be sorted. It leads to the wrong conclusion that the video demonstrates a sorting algorithm. This limitation underscores a gap in model's ability to integrate domain knowledge with visual perception effectively.

Misuse or Lack Domain Knowledge in Reasoning (27%): The model fails to effectively recall and apply domain knowledge during its reasoning processes. For instance, when addressing questions over chemistry videos, it may fail to correctly apply relevant chemical equations, leading to errors in computing the reaction mass. A notable example is Figure 23, where the model misuses the domain knowledge that bats often live in unsanitary environments and makes the wrong inference that poor hygiene conditions are the cause of virus outbreaks. Besides, in Figure 26, the model lacks the domain knowledge about relevant chemical equations, so that it cannot correctly answer the question. This limitation underscores the model's inability to integrate domain knowledge into its reasoning processes effectively.

Heavy Reliance on Textual Information (20%): The model predominantly depends on textual information for problem-solving, especially when addressing multiple-choice questions, as it evaluates each option individually without leveraging the actual video content. For instance, Figure 27 shows the model ignores the video information about the reason of the disease and overly focuses on the textual question. Similar limitations have been observed in other multimodal benchmarks [48, 161]. Future work could enhance multimodal reasoning by more effectively incorporating non-textual content into the reasoning process.

Logical Reasoning Error (6%): The model exhibits inconsistencies between its reasoning process and final answer, leading to self-contradiction. As depicted in Figure 29, the analysis of one specific option contradicts with the other reasoning steps, which is a typical self-contradiction logical error.

Other Error (9%): This includes refusing to answer a question due to insufficient context or safety concerns, exceeding the output limit, generating repetitive information, or making incorrect math computation.

5. Conclusion

We introduce MMVU, a high-quality, multi-disciplinary benchmark designed to assess the expert-level, knowledge-intensive reasoning capabilities of multimodal foundation models on specialized-domain videos. We employ a textbook-guided example annotation pipeline designed to capture both the breadth of knowledge and depth of reasoning. In our evaluation of 36 frontier multimodal foundation models, we find that while the latest o1 model achieves the highest performance among all tested models—approaching human expert-level proficiency—a notable performance gap remains between other models and human experts. Additionally, models employing CoT reasoning consistently outperform those that generate final answers directly. Through comprehensive error analysis and case studies, we identify persistent challenges of MMVU, offering valuable insights for advancing foundation models' capabilities to achieve expert-level video understanding.

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