VISSCIENCE: AN EXTENSIVE BENCHMARK FOR EVAL UATING K12 EDUCATIONAL MULTI-MODAL SCIENTIFIC REASONING

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ABSTRACT

Multi-modal large language models (MLLMs) have shown promise in integrating textual and visual information to handle complex visual understanding tasks. However, most benchmarks evaluating MLLMs focus mainly on mathematics or general visual understanding, revealing a significant gap in assessing capabilities across other critical scientific disciplines like physics and chemistry. To bridge this gap, we meticulously construct a comprehensive benchmark, VisScience, to evaluate multi-modal scientific reasoning across mathematics, physics, and chemistry. This benchmark comprises 3,000 questions drawn from K12 education, from elementary to high school levels, evenly distributed with 1,000 questions per discipline. VisScience encompasses 21 distinct subjects, classified into five difficulty levels to cover a wide range of topics within each discipline. We utilize VisScience to conduct a detailed evaluation of 25 representative MLLMs in scientific reasoning. The experimental results show that closed-source MLLMs generally surpass open-source models, with standout performances including a 53.4% accuracy in mathematics by Claude3.5-Sonnet, 38.2% in physics by GPT-40, and 47.0% in chemistry by Gemini-1.5-Pro. These results underscore the strengths and limitations of MLLMs, suggesting areas for future improvement and highlighting the importance of developing models that can effectively handle the diverse demands of multi-modal scientific reasoning.

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1 INTRODUCTION

034 Recently, large language models (LLMs) OpenAI (2022); Achiam et al. (2023); GLM et al. (2024); Touvron et al. (2023a;b); Bai et al. (2023a); Brown et al. (2020); Chowdhery et al. (2023); Anil et al. (2023) have demonstrated remarkable capabilities across a wide range of tasks, including 036 natural language understanding, text generation, and complex problem solving. The success of LLMs 037 facilitates the development of multi-modal large language models (MLLMs) OpenAI (2023); Team et al. (2023); Anthropic (2024); Liu et al. (2024b;a); Ye et al. (2023; 2024), which extends these capabilities by integrating the ability to process and analyze both textual and visual information. 040 Evaluation is a significant component in assessing the ability of these MLLMs across various tasks, 041 which has attracted widespread attention and developed rapidly in recent years. For instance, several 042 benchmark datasets are proposed to evaluate the ability of MLLMs in general visual understanding, 043 including MME Fu et al. (2023), MMMU Yue et al. (2024), MMBench Liu et al. (2023), MMStar Chen 044 et al. (2024a), and SEED-Bench Li et al. (2023a).

As a primary evaluation domain, mathematical reasoning presents specific challenges, requiring 046 models to handle complex mathematical problems accompanied by visual information. Previous 047 works Chen et al. (2021; 2022); Cao & Xiao (2022) focus on geometric problems, resulting in 048 the emergence of various evaluation datasets such as GeoQA Chen et al. (2021), Geometry3K Lu 049 et al. (2021), and UniGeo Chen et al. (2022). Subsequently, several benchmark datasets Lu et al. (2023); Zhang et al. (2024b); Wang et al. (2024) extend the scope of mathematical reasoning beyond 051 geometry to encompass various branches such as arithmetic, algebraic, statistics, logic, and functions. Notably, MathVista also contains a portion of scientific datasets such as TQA Kembhavi et al. (2017), 052 SciBench Wang et al. (2023b), and ScienceQA Lu et al. (2022). However, despite these advancements, there remains some issues:

- Existing benchmarks often focus narrowly on specific mathematics, neglecting other crucial scientific disciplines like physics and chemistry.
- Existing benchmarks are often collected from limited sources, resulting in a lack of natural difficulty levels and leading to an incomplete evaluation of models' capabilities.
- Current benchmarks are predominantly available in a single language, limiting the evaluation of MLLMs' multilingual capabilities.

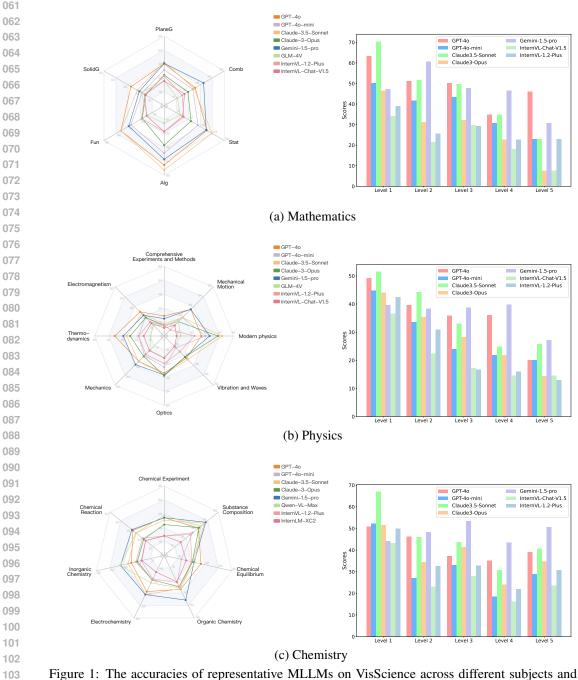


Figure 1: The accuracies of representative MLLMs on VisScience across different subjects and
 difficulty levels. (Left) The accuracies on different subjects. (Right) The accuracies on various
 difficulty levels.

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107 To address the limitations of existing benchmarks and provide a more comprehensive evaluation benchmark, we introduce a more expansive evaluation benchmark, named **VisScience**, integrating

both textual and visual information. This benchmark is designed to assess the performance of MLLMs in multi-modal scientific reasoning tasks across disciplines like physics and chemistry alongside mathematics. To construct this benchmark, we gather a total of 450,000 questions from K12 education and meticulously select 3,000 questions as the final dataset, with each discipline containing 1,000 questions. This benchmark spans a comprehensive range of knowledge points across different chapters, with difficulty levels ranging from 1 to 5, ensuring that models are assessed on both basic and challenging problems.

115 In order to better understand MLLMs' performance on more detailed subjects within three disciplines, 116 we categorize VisScience into several subjects across each discipline. Specifically, we divide the 117 mathematical part of VisScience into six subjects such as plane geometry, solid geometry, functions 118 and equations, algebraic operations, probability and statistics, and combinatorial mathematics. For physics, the dataset is categorized as eight subjects, including mechanics, thermodynamics, compre-119 hensive experiments and methods, mechanical motion, vibration and waves, optics, electromagnetism, 120 and modern physics. The chemistry section includes seven topics such as chemical experiments, 121 organic chemistry, material composition, electrochemistry, chemical reactions, inorganic chemistry, 122 and chemical equilibrium. In summary, VisScience contains 21 subjects across the three disciplines 123 of mathematics, physics, and chemistry. 124

We conduct extensive experiments on VisScience to evaluate the scientific reasoning abilities of 25 125 representative MLLMs. These models include close-source LLMs, close-source and open-source 126 MLLMs, offering a comprehensive analysis of their performance across various disciplines. As 127 illustrated in Figure 1, the best performance is observed in close-source MLLMs, with distinct models 128 excelling in different disciplines. In specific, Claude3.5-Sonnet achieves an accuracy of 53.4% in 129 mathematics, GPT-40 reaches a 38.2% accuracy in physics, and Gemini-1.5-Pro records an accuracy 130 of 47.0% in chemistry. Among open-source models, InternVL-1.2-Plus performs best with accuracies 131 of 30.1% in mathematics, 24.8% in physics, and 31.2% in chemistry. Lastly, we systematically 132 analyze the errors made by advanced models like GPT-40 on VisScience, which providing valuable 133 insights into the specific domains where these models excel and where they struggle.

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2 VISSCIENCE BENCHMARK

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In this section, we first illustrate the overview of our specially curated VisScience benchmark, designed to assess the capabilities of MLLMs in multi-modal scientific reasoning. Next, we introduce data generation process, which encompasses three core scientific disciplines: mathematics, physics, and chemistry. Lastly, we perform a comprehensive data analysis on the VisScience benchmark, including subject distributions and difficulty levels.

2.1 OVERVIEW

145 We introduce the VisScience benchmark, a meticulously curated collection aimed at evaluating the 146 capabilities of multi-modal large language models (MLLMs) in multi-modal scientific reasoning, with 147 a particular focus on bilingual tasks involving both English and Chinese. This dataset incorporates 148 textual and visual contexts as inputs and spans three scientific disciplines, including mathematics, 149 physics, and chemistry. Each discipline comprises 1,000 questions, meticulously gathered from 150 different chapters to ensure comprehensive coverage of topics and concepts. The core statistics of the 151 VisScience benchmark are presented in Table 1. The distributions of question length in VisScience 152 are provided in Appendix A.1. A detailed introduction of each subjects within the three disciplines is 153 available in Appendix A.2.

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2.2 DATA GENERATION

The goal of the VisScience benchmark is to establish a comprehensive, bilingual (Chinese and English) benchmark for evaluating the capabilities of MLLMs in processing and understanding complex, scientifically-oriented tasks across various disciplines. In order to achieve this goal, we present a two-stage data generation pipeline to meticulously construct a benchmark dataset comprising 3,000 questions, evenly distributed with 1,000 questions each in the fields of mathematics, physics, and chemistry. More cases in VisScience are provided in Appendix B.

162	Statistic	Number
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164	Total questions	3000
165	- multiple-choice questions	2,053 (68.4%)
166	- Free-form questions	947 (31.6%)
167	Number of categories of math questions	6
168	Number of categories of physics questions	8
169	Number of categories of chemistry questions	7
170	Number of difficulty levels	5
171	Unique number of images	3,000
172	Unique number of questions	3,000
173	Unique number of answers	1,427
174	Statistics with Chinese Languag	<i>ze</i>
175	Maximum question length	1297
176	Maximum answer length	112
177	Maximum choice number	5
178	Average question length	162.85
179	Average answer length	20.93
180		
181	Statistics with English Languag	<i>le</i>
182	Maximum question length	418
183	Maximum answer length	92
184	Maximum choice number	5
185	Average question length	80.93
186	Average answer length	12.30

Table 1: Key statistics of VISSCIENCE.

189 **Data Collection.** We gather a total of 450,000 questions from the disciplines of mathematics, 190 physics, and chemistry, each enriched with visual information sourced from K12 education. This 191 collection spans a comprehensive range of knowledge points across different chapters, with the 192 difficulty levels scaled based on education grade. Consequently, we cluster 150,000 questions per 193 discipline and carefully select 1,000 representative questions. These questions exemplify a range of difficulty levels and a variety of subjects, guided by the following principles: (1) Guaranteeing every 194 knowledge point is included in VisScience benchmark. (2) Prioritizing the selection of questions from 195 high-frequency knowledge points. (3) Ensuring a mixture of questions across various difficulty levels. 196

197 In the end, the VisScience benchmark is constructed with 3,000 questions, with each of the three disciplines - mathematics, physics, and chemistry - contributing 1,000 questions. This approach ensures that the benchmark comprehensively covers a wide array of topics within each discipline, 199 reflecting the breadth and depth required for a thorough assessment of MLLMs' capabilities. 200

Data Annotation. To improve the quality of the VisScience benchmark, we conduct multiple checks 202 using both manual reviews and LLM assessments to confirm the completeness of each question. For 203 textual content, we check for accuracy, coherence and relevance, ensuring that each question aligns 204 with the corresponding scientific discipline and is free of ambiguities. For associated visual content, 205 we rigorously screen out images that are incorrect, unclear, or lacking in detail, retaining only those 206 that are clear and richly informative. To maintain the volume of the VisScience benchmark, we 207 compensate for questions removed due to incomplete information by selecting new questions on 208 identical topics from the original dataset. This approach ensures that the overall number of questions 209 and the breadth of content coverage are consistently maintained. This verification process guarantees 210 that both the textual and visual components of the VisScience benchmark is a reliable and effective tool for evaluating the capabilities of MLLMs in scientific reasoning. 211

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- 213 2.3 DATA ANALYSIS
- We utilize statistical analysis to assess subject distributions and difficulty levels within the VisScience 215 benchmark. Figure 2 presents a visual representation of the categorization of question within the

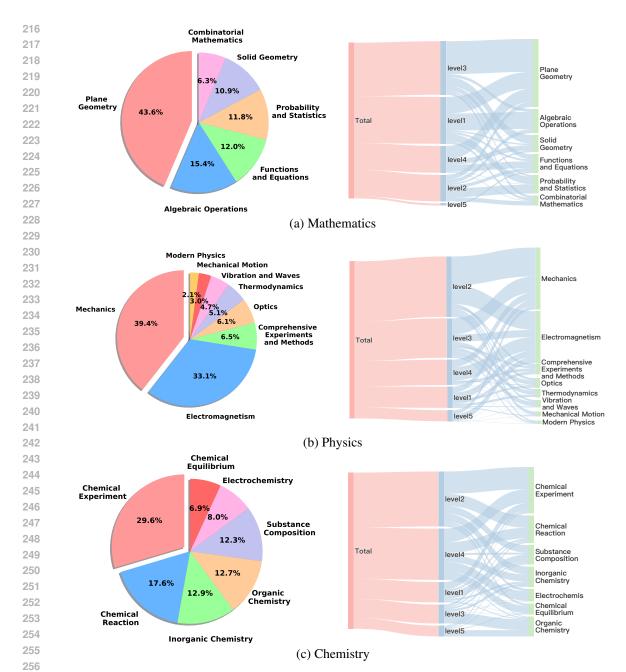


Figure 2: The distribution of detailed subjects and difficulty levels in the each discipline within the
VisScience benchmark. (Left) The distributions of various subjects. (Right) The distributions of
difficulty levels.

VisScience benchmark. This illustration shows the distribution of questions dedicated to each subject area – mathematics, physics, and chemistry – and details the distribution across various difficulty levels, ranging from 1 to 5. Besides, we discuss comparison among VisScience and other benchmarks in Appendix C.

Subject Distributions. To categorize each discipline into more detailed subjects, we first utilize LLM
 to segment the overall discipline into specific topics based on knowledge points and terminologies
 presented in the questions. Subsequently, we conduct a manual review of these categories to confirm
 its rationality and appropriateness, ensuring that each question is accurately categorized. As shown in
 Figure 2, the mathematical part of the VisScience benchmark is divided into six subjects, i.e., plane
 geometry (43.6%), algebraic operations (15.4%), functions and equations (12%), probability and

statistics (11.8%), solid geometry (10.9%), and combinatorial mathematics (6.3%). Furthermore, the distributions for physics and chemistry disciplines are presented in the figure, providing a comprehensive overview of the scope of the VisScience benchmark within these scientific fields.

274 Difficulty Levels. To classify the questions into distinct difficulty levels, we first utilize LLM for the initial sorting, and then conduct a manual verification. The questions within each discipline are 275 stratified into five difficulty levels ranging from 1 to 5, defined as follows: Basic, Easy, Intermediate, 276 Advanced, and Expert. Figure 2 shows the distribution of difficulty levels, providing a visual 277 representation of the distribution of questions across different difficulty levels. Each discipline 278 demonstrates a unique profile of topic distribution across the difficulty levels. For instance, in the 279 field of mathematics, *plane geometry* is classified at the intermediate level, *algebraic operations* 280 are positioned at the basic level, and *functions and equations* appears at the highest difficulty level, 281 reflecting their various placement within educational curricula. In physics, mechanics dominates the 282 introductory level, which belongs to a fundamental concept in physics education. Electromagnet is 283 positioned at the highest difficulty level, demanding the application of various advanced knowledge 284 points. In the discipline of chemistry, organic chemistry and chemical equilibrium represent the 285 pinnacle of K12 chemical education, requiring deep conceptual understanding and the ability to apply knowledge to complex scenarios. 286

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3 EXPERIMENTS

In this section, we conduct experiments to evaluate a variety of MLLMs using the VisScience benchmark. Besides, we provide a detailed error analysis of the advanced model GPT-40.

3.1 EXPERIMENTAL SETUP

Models. We conduct our evaluation across a diverse array of models, including close-source text-only LLMs, close-source MLLMs, and open-source MLLMs. This comprehensive assessment covers 25 models, which are listed below. The sources of models is reported in Appendix D.1.

- Close-source text-only LLMs: ChatGPT OpenAI (2022), GPT-4 Achiam et al. (2023), Claude2 Anthropic (2023a).
- Close-source MLLMs: Gemini-1.0-Pro Team et al. (2023), Gemini-1.5-Pro Team et al. (2023), GPT-40 OpenAI (2024), Qwen-VL-Max Bai et al. (2023b), Qwen-VL-Plus Bai et al. (2023b), Claude3.5-Sonnet Anthropic (2023b), Claude3-Opus Anthropic (2024), GLM-4V AI (2023), and Step-1V StepFun (2024).
- Open-source MLLMs: mPLUG-Owl Ye et al. (2024), LLaMA-Adapter-V2 Gao et al. (2023), MiniCPM-Llama3-V2.5 Hu et al. (2024), LLaVA-1.5 Liu et al., DeepSeek-VL Lu et al. (2024), ShareGPT4V Chen et al. (2023a), SPHINX-Plus Gao et al. (2024), InternLM-XC2 Dong et al. (2024), InternVL-1.2-Plus Chen et al. (2023b), InternVL-Chat-V1.5 Chen et al. (2024c), CogVLM Wang et al. (2023a), CogVLM2 Wang et al. (2023a), and GLM-4V-9B GLM et al. (2024).
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311 **Evaluation Details.** The evaluation process is conducted through two steps: generation and 312 judgment. During the generation phase, the models are tasked with producing responses based on a 313 set of questions. For zero-shot setting, we directly prompt the models with these questions without 314 any examples. For 2-shot Chain-of-Thought (CoT) setting, we provide the models with two relevant 315 examples before they are prompted with the questions. For MLLMs, we supply the models with the textual questions and the corresponding image to obtain their responses. During the judgment phase, 316 we utilize GPT-40 to evaluate the models' responses by comparing them with the standard answers to 317 assess consistency. This phase involves calculating the accuracy across different subjects and levels. 318 The prompts used in two phases is defined in Appendix D.2. 319

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- 3.2 EXPERIMENTAL RESULTS
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- **Overall Results.** Table 2 demonstrates the performance of several models on VisScience within the version of the Chinese language. Experimental results show that the close-source models achieves

324 best performance on VisScience. Specifically, Claude3.5-Sonnet achieves an accuracy of 53.4% 325 in mathematics, GPT-40 attains a 38.2% accuracy in physics, and Gemini-1.5-Pro accomplishes 326 an accuracy of 47.0% in chemistry. Among open-source models, InternVL-1.2-Plus stands out, 327 demonstrating robust capabilities across various scientific disciplines with accuracies of 30.1% in 328 mathematics, 24.8% in physics, and 31.2% in chemistry. Despite this, there is a notable disparity in performance between close-source and open-source models, with close-source models generally 329 exhibiting superior performance. The performance of InternVL-1.2-Plus, although trailing behind 330 the advanced close-source models such as GPT-40, Claude3.5-Sonnet, and Gemini-1.5-Pro, showing 331 significant potential for improvement. Notably, the performance in physics underscores unique 332 challenges that necessitate targeted improvements in model training. This discipline often involves 333 the interpretation of conceptual and numerical data, challenging the reasoning and computational 334 abilities of MLLMs. As evidenced in Table 2, even advanced models like GPT-40 achieve relatively 335 lower accuracies in physics compared to other disciplines. Results on VisScience with the version of 336 the English language are provided in Appendix E.1. 337

338 **Results on Mathematics Across Different Subjects.** The mathematical part of VisScience 339 encompasses a wide range of subjects, including plane geometry, solid geometry, functions and equations, algebraic operations, probability and statistics, and combinatorial mathematics. Table 3 340 reports the comprehensive results across different mathematical subjects. It is evident that models like 341 Claude3.5-Sonnet and GPT-40 in close-source MLLMs excel across multiple subjects, particularly in 342 functions and equations, probability and statistics, and algebraic operations. Conversely, open-source 343 models show a more varied performance with notable strengths in certain areas but generally lower 344 scores compared to close-source models. For instance, InternVL-1.2-Plus and InternVL-Chat-V1.5 345 perform relatively well in *plane geometry*, and *functions and equations*. These detailed performance 346 on different subjects provide valuable insights into the specific strengths and weaknesses of various 347 MLLMs. Additionally, results on physics and chemistry across different subjects are presented in 348 Appendix E.2 and Appendix E.3, respectively. Case studies illustrating correct responses by MLLMs 349 can be found in Appendix F.

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3.3 Error Analysis

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353 To analyze the causes of errors in model responses, we meticulously review incorrect answers to identify common patterns. We specifically focus on GPT-40 to illustrate specific instances of errors 354 and their distributions across the disciplines of mathematics, physics, and chemistry. Figure 3 355 demonstrates the distributions of these errors, categorizing them into several types such as reasoning 356 error, knowledge error, calculation error, vision recognition error, and question misunderstood error. 357 Notably, across all disciplines, reasoning errors are the most prevalent, indicating a challenge in 358 model's ability to solve scientific problems that involve visual information. Specifically, reasoning 359 errors account for 56.5% of the total errors in mathematics, 50.1% in physics, and 40.6% in chemistry, 360 respectively. This is followed by knowledge error, which is particularly significant in chemistry, 361 constituting 33.2% of the errors in that discipline. Similarly, knowledge error also represent the 362 second most common error type in physics. However, knowledge error in mathematics is less 363 prevalent, making up only 8.8% of the total errors. This indicates that while the model struggle with conceptual and fundamental principles in chemistry and physics, it demonstrate a better grasp of 364 mathematical concepts. Vision recognition error is another significant type of error, accounting for 365 18.8% of the errors in mathematics, making it the second most prevalent error type in this discipline. 366 This error category is also significant in physics and chemistry, where it constitutes 17.8% and 367 15.3% of the errors, respectively. This type of error highlights the challenges faced by the model in 368 processing and understanding visual information. Furthermore, calculation error accounts for a small 369 portion of the errors, especially in chemistry, indicating that the model excels particularly in handling 370 numerical computations. More detailed examples of these errors can be found in Appendix G.

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4 RELATED WORKS

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Multi-modal Reasoning Benchmarks. Recently, the evaluation of multi-modal large language models (MLLMs) OpenAI (2023); Team et al. (2023); Anthropic (2024); Bai et al. (2023b); Wang et al. (2023a); Liu et al. (2024a;b) in various reasoning tasks has become increasingly crucial. So many benchmark datasets for these tasks span several categories are proposed like MME Fu et al.

Model	LLM	Input	Mathematics	Physics	Chemistry
	Close Source Mod	els (APIs	;)		
Text-only LLMs					
Zero-shot ChatGPT	-	Q	22.4	22.7	18.6
Zero-shot GPT-4	-	\tilde{Q}	25.9	30.4	33.1
Zero-shot Claude-2	-	$\tilde{\varrho}$	27.3	22.0	24.4
Zero-shot Claude3-Opus	-	\tilde{Q}	29.3	30.8	32.5
Zero-shot Claude3.5-Sonnet	-	\tilde{Q}	29.7	35.3	36.9
Zero-shot GPT-40	-	Q	31.1	38.0	39.6
2-shot CoT Claude2	-	Q	27.8	21.7	23.9
2-shot CoT ChatGPT	-	\tilde{Q}	20.2	18.6	21.3
2-shot CoT GPT-4	-	\tilde{Q}	32.1	31.5	32.4
Multi-modal LLMs		-			
Gemini-1.0-Pro	-	Q, I	26.6	23.70	27.8
Gemini-1.5-Pro	-	Q, I	49.4	38.1	47.0
GPT-40	-	Q, I	51.7	38.2	41.6
GPT-40-mini	-	Q, I	42.6	29.8	28.4
Qwen-VL-Max	-	Q, I	35.5	30.70	42.5
Qwen-VL-Plus	_	Q, I	27.6	26.5	37.7
Claude3.5-Sonnet	-	Q, I	53.4	38.0	43.1
Claude-3 opus	-	\tilde{Q}, I	34.4	31.1	34.1
GLM-4V	-	\tilde{Q}, I	24.2	19.2	25.0
Step-1V	-	\tilde{Q}, I	28.1	23.5	25.0
	Open Source Models				
General Multi-modal LLMs					
mPLUG-Owl	LLaMA-7B	Q, I	7.6	8.3	9.5
LLaMA-Adapter-V2	LLaMA-7B	\tilde{Q}, I	9.6	10.3	10.8
MiniCPM-Llama3-V2.5	LLaMA3-8B	\tilde{Q}, I	15.4	17.9	19.5
LLaVA-1.5	Vicuna-13B	\tilde{Q}, I	15.5	15.2	18.8
LLaVA-1.5	Vicuna-7B	\tilde{O} , I	13.0	13.5	16.0
DeepSeek-VL	DeepSeek-LLM-7B	\tilde{Q}, I	8.3	16.8	21.0
ShareGPT4V	Vicuna-7B	\tilde{Q}, I	15.7	14.0	19.0
ShareGPT4V	Vicuna-13B	\tilde{Q}, I	16.4	14.9	18.4
SPHINX-Plus	LLaMA2-13B	\tilde{Q}, I	17.0	15.3	20.4
InternLM-XC2	InternLM2-7B	\tilde{Q}, I	24.9	18.3	25.6
InternVL-1.2-Plus	Nous-Hermes-2-Yi-34B	\tilde{Q}, I	30.1	24.8	31.2
InternVL-Chat-V1.5	Mixtral 8*7B	\tilde{Q}, I	26.9	20.8	23.7
CogVLM	Vicuna-7B	\tilde{Q}, I	16.7	14.5	17.0
CogVLM2	LLaMA-3-8B	\tilde{Q}, I	23.2	14.4	21.0
GLM-4V-9B	GLM-4-9B	\tilde{O}, I	24.7	19.3	22.5

Table 2: Results on VisScience within the version of the Chinese language across the disciplines of mathematics, physics, and chemistry. For input, Q represents for question, I represents for image. The highest scores among close-source and open-source models are highlighted in red and blue, respectively.

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423 (2023), MMMU Yue et al. (2024), MMBench Liu et al. (2023), MMStar Chen et al. (2024a), SEED-424 Bench Li et al. (2023a), and CMMMU Zhang et al. (2024a), which evaluate models' capabilities to 425 apply logic and inference; mathematical reasoning; scientific reasoning, and agent-based reasoning. 426 These benchmark datasets provide comprehensive measurements of MLLMs' capabilities in applying 427 specialized knowledge and decision-making in simulated environments. For instance, MMMU 428 covers university-level questions from six domains, which is utilized to assess MLLMs' advanced perception and reasoning abilities. CMMMU Zhang et al. (2024a) evaluates models' reasoning 429 abilities across various disciplines through bilingual multi-modal questions in Chinese and English. 430 Existing benchmark like ScienceQA Lu et al. (2022) is a specialized dataset designed to evaluate 431 the capabilities of MLLMs, particularly in the domain of scientific reasoning. Furthermore, several

Madal			Mathem	atics			
Model	ALL	PlaneG	SolidG	Fun	Alg	Stat	Com
	Close	Source M	odels (API	s)			
Text-only LLMs							
Zero-shot ChatGPT	22.40	20.18	11.93	18.33	13.63	15.25	26.98
Zero-shot GPT-4	25.90	30.73	18.35	28.33	17.53	24.58	33.3
Zero-shot Claude-2	27.30	27.06	25.69	25.83	31.17	31.36	25.4
Zero-shot Claude3-Opus	29.30	30.28	21.10	32.50	27.27	34.75	31.7
Zero-shot Claude3.5-Sonnet	29.70	33.94	15.60	33.33	27.27	27.12	34.9
Zero-shot GPT-40	31.10	36.24	24.77	35.83	25.32	24.58	31.7
2-shot CoT Claude2	27.80	30.05	26.61	25.00	28.57	27.97	26.9
2-shot CoT ChatGPT	20.20	23.17	20.18	19.17	17.53	22.88	14.29
2-shot CoT GPT-4	32.10	37.16	31.19	28.33	22.08	30.51	38.1
Multi-modal LLMs							
Gemini-1.0-Pro	26.60	24.08	22.02	23.73	35.71	29.66	34.9
Gemini-1.5-Pro	49.40	48.74	33.03	47.06	61.69	55.93	52.3
GPT-4o	51.70	48.17	44.04	57.50	68.18	56.78	41.2
GPT-4o-mini	42.60	41.28	29.36	44.17	54.55	44.92	38.1
Qwen-VL-Max	35.50	34.86	27.52	35.83	50.00	33.05	26.9
Qwen-VL-Plus	27.60	27.98	18.35	29.17	31.17	35.59	20.6
Claude3.5-Sonnet	53.4	50.23	35.78	57.50	74.03	63.56	39.6
Claude3-Opus	34.40	35.31	24.77	29.17	45.45	35.59	31.7
GLM-4V	24.20	28.57	30.28	22.50	20.26	21.37	17.4
Step-1V	28.10	31.68	24.71	23.15	48.85	40.57	22.6
	0	pen Source	Models				
General Multi-modal LLMs							
mPLUG-Owl	7.60	6.19	10.09	5.00	12.34	7.63	7.94
LLaMA-Adapter-V2	9.60	10.78	10.09	7.50	9.09	13.56	4.76
MiniCPM-Llama3-V2.5	15.40	23.62	19.27	15.83	26.62	26.27	15.8
LLaVA-1.5-13B	15.50	15.83	15.60	12.50	18.83	14.41	14.2
LLaVA-1.5-7B	13.00	12.84	12.84	15.83	14.29	11.86	11.1
DeepSeek-VL	8.30	13.99	8.26	10.00	11.04	10.17	7.94
ShareGPT4V-7B	15.70	16.06	16.51	13.33	14.29	17.80	17.4
ShareGPT4V-13B	16.40	15.60	11.93	19.17	17.53	22.03	14.2
SPHINX-Plus	17.00	21.79	19.27	15.83	20.13	22.88	7.94
InternLM-XC2	24.90	25.92	22.02	22.50	27.92	27.97	20.6
InternVL-1.2-Plus	30.10	34.40	25.69	30.00	29.87	26.27	23.8
InternVL-Chat-V1.5	26.90	28.44	25.69	23.33	29.87	24.58	26.9
CogVLM	16.70	16.06	23.85	17.50	17.53	13.56	19.0
CogVLM2	23.20	21.56	22.02	29.17	22.73	26.27	20.6
GLM-4V-9B	14.70	25.23	20.18	19.17	27.27	33.05	19.0

Table 3: **Results on the mathematical part of VisScience across different subjects.** Subjects: PlaneG: plane geometry, SolidG: solid geometry, Fun: functions and equations, Alg: algebraic operations, Stat: probability and statistics, Comb: combinatorial mathematics. The highest scores among close-source and open-source models are highlighted in red and blue, respectively.

benchmarks such as MathVista Lu et al. (2023), MathVerse Zhang et al. (2024b), and MATH-Vision (MATH-V) Wang et al. (2024) are specially designed to evaluate the mathematical reasoning capabilities of MLLMs. While these benchmarks are valuable, they present limitations such as an overemphasis on mathematics and a broad array of topics that often lack depth in science-related questions and exhibit uneven difficulty levels. Our dataset addresses these shortcomings by

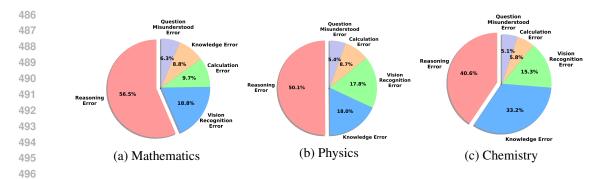


Figure 3: Error distributions of GPT-40 on VisScience across the disciplines of mathematics, physics, and chemistry.

providing 3,000 scientific reasoning questions across mathematics, physics, and chemistry, which is
 collected from K12 education. Additionally, it includes bilingual questions in Chinese and English,
 enriching the knowledge base and offering a more extensive range of difficulty levels to create a more
 comprehensive evaluation platform.

504 Multi-modal Large Language Models. Recently, the success of large language models (LLMs) Du 505 et al. (2021); Zeng et al. (2022); Achiam et al. (2023); Gao et al. (2023); GLM et al. (2024); Bai et al. 506 (2023a) has spurred the ongoing development of multi-modal large language models (MLLMs). These 507 MLLMs Liu et al. (2024b); Liu et al.; Wang et al. (2023a); Li et al. (2023b); Dai et al. (2024); Bai et al. 508 (2023a) expand upon traditional LLM capabilities by integrating the ability to process and analyze 509 both text and images. For instance, models like miniGPT Zhu et al. (2023) and InstructBLIP Dai et al. (2024) attempt to utilize a trainable Q-Former or a linear layer to connect a frozen pretrained vision 510 encoder and language model. Subsequently, LLaVA Liu et al. (2024b); Liu et al. presents visual 511 instruction tuning, which achieves a end-to-end fine-tuning on a large multi-modal model (LMM) 512 comprising visual encoder and language model. Currently, close-source MLLMs like Gemini Team 513 et al. (2023), GPT-4v OpenAI (2023), Qwen-VL Bai et al. (2023b), and Claude3 Anthropic (2024) 514 demonstrate impressive capabilities in general image understanding and scientific reasoning. Besides, 515 the development of open-source multi-modal large language models (MLLMs) continues to expand, 516 providing an important complement to their closed-source models. These open-source MLLMs, 517 such as mPLUG-Owl Ye et al. (2023; 2024), LLaMA-Adapter-V2 Gao et al. (2023), MiniCPM Hu 518 et al. (2024), LLaVA-1.5 Liu et al. (2024a), LLaVA-NeXT Liu et al., DeepSeek-VL Lu et al. (2024), 519 ShareGPT4V Chen et al. (2023a), SPHINX Gao et al. (2024), InternVL Chen et al. (2023b), InternVL 520 1.5 Chen et al. (2024b), InternLM-XComposer2 Dong et al. (2024), and CogVLM Wang et al. (2023a), also achieves advance performance, further enriching the landscape of MLLM domain. Here, 521 we utilize our specially curated benchmark VisScience to evaluate these MLLMs across tasks in 522 mathematics, physics, and chemistry. This comprehensive evaluation aims to assess their capabilities 523 in scientific reasoning. 524

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5 CONCLUSION

528 In this paper, we introduce a comprehensive benchmark, VisScience, designed to evaluate the capabilities of multi-modal large language models (MLLMs) in scientific reasoning across mathematics, 529 physics, and chemistry. VisScience consists of 3,000 questions, evenly distributed across these three 530 disciplines, spanning 21 subjects and categorized into five difficulty levels. We conduct evaluations 531 using VisScience on 25 prominent models, including both closed-source and open-source variants. 532 The experimental results reveal that closed-source MLLMs generally excel over open-source models, 533 particularly in complex problem-solving and analytical reasoning. Notable performances include 534 Claude3.5-Sonnet with a 53.4% accuracy in mathematics, GPT-40 achieving 38.2% in physics, and 535 Gemini-1.5-Pro securing 30.1% in chemistry. Despite the performance gap between open-source 536 models and closed-source models, some open-source models, such as InternVL-1.2-Plus, demonstrate 537 competitive strengths, outperforming others like Gemini-1.0-Pro in all three disciplines. By offering 538 a challenging set of questions across varied scientific fields, VisScience provides a robust benchmark for assessing the scientific reasoning abilities of MLLMs.

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A DATASET DETAILS

A.1 QUESTION LENGTH DISTRIBUTION

We provide both Chinese and English versions of the VisScience benchmark. The Chinese version
features an average of 162.85 words per question, with the longest question comprising 1,297 words.
Answers in this version average 20.93 words, with the longest reaching 112 words. Conversely, the
English version shows an average of 80.93 words per question, with the longest question spanning 418
words. Answers here average 12.3 words, with the most detailed answer containing 92 words. Figure 4
depicts the distribution of word counts, highlighting the diversity and complexity of questions.

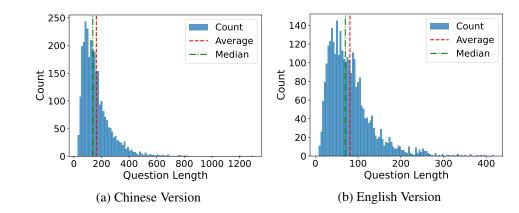


Figure 4: The distributions of word counts per question in the Chinese and English versions of VisScience.

A.2 DETAILED DESCRIPTION OF SUBJECTS

VisScience consists of three disciplines: mathematics, physics, and chemistry. The mathematics sec-tion includes six subjects: algebraic operations, combinatorial mathematics, functions and equations, probability and statistics, plane geometry, and solid geometry. The physics section is composed of eight subjects: mechanics, optics, modern physics, mechanical motion, electromagnetism, vibrations and waves, comprehensive experiments and methods, and thermodynamics. The chemistry section includes seven subjects: chemical experiments, chemical reactions, inorganic chemistry, organic chemistry, electrochemistry, substance composition, and chemical equilibrium. A more detailed introduction of the above subjects is presented as follows:

793 A.2.1 MATHEMATICS

Algebraic Operations. Algebraic operations include the manipulation of algebraic expressions,
 such as addition, subtraction, multiplication, and division. They are fundamental for solving algebraic
 equations and inequalities and are widely applied across various fields of mathematics.

Combinatorial Mathematics. Combinatorial mathematics studies the counting, arrangement, and combination of discrete structures, involving graph theory, number theory, and coding theory. It has significant applications in computer science, optimization, and probability theory.

Functions and Equations. Functions and equations are core parts of mathematics, dealing with
 relationships between variables and their representations. Functions are mappings between inputs
 and outputs, while equations are equalities concerning these mappings. Mastering knowledge of
 functions and equations is fundamental for solving many practical problems and is widely applied in
 engineering, physics, and economics.

Probability and Statistics. Probability and statistics study the laws of random events and methods
 of data analysis, including probability distributions, statistical inference, and data analysis techniques.
 They have broad applications in scientific research, engineering, and economics.

Plane Geometry. Plane geometry studies the shapes and figures in two-dimensional space, including points, lines, angles, and polygons. It is a fundamental part of mathematics education.

813 Solid Geometry. Solid geometry involves the study of geometric shapes in three-dimensional space,
 814 including points, lines, surfaces, and polyhedra. It examines the properties, volumes, and surface
 815 areas of these geometric bodies and is foundational for architecture, physics, and engineering.

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A.2.2 PHYSICS

Mechanics. Mechanics studies the motion of objects and the forces acting upon them, including classical mechanics, quantum mechanics, and relativistic mechanics. It is the foundation of physics and is widely applied in engineering, astronomy, and materials science.

Optics. Optics studies the properties of light and its interactions with matter, including reflection, refraction, interference, and diffraction. Optical technologies have broad applications in imaging, communication, and laser technology.

Modern Physics. Modern physics includes theories developed since the 20th century, such as
 quantum mechanics, relativity, and particle physics. These theories have expanded our understanding
 of the fundamental laws of nature.

Mechanical Motion. Mechanical motion studies the movement of objects under the influence of forces, including linear motion, rotational motion, and vibration. Understanding mechanical motion is fundamental for the design and analysis of mechanical systems.

834 Electromagnetism. Electromagnetism studies the interactions between electric and magnetic fields, including electrostatics, magnetic fields, and electromagnetic waves. It is the basis of modern physics and electrical engineering.
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Vibration and Waves. Vibration and waves study vibrating systems and wave phenomena,
 including sound waves, light waves, and electromagnetic waves. They have broad applications
 in communication, acoustics, and optical technologies.

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Comprehensive Experiments and Methods. Comprehensive experiments and methods involve using various experimental techniques and methods in physics teaching and research. They include designing and conducting experiments to observe and analyze the effects of specific variables on outcomes. Through comprehensive experiments, students can grasp the complexities of scientific research, cultivate scientific reasoning abilities, and understand the meticulousness and uncertainties of experimental work.

Thermodynamics. Thermodynamics studies the processes of energy transformation and transfer,
 including the laws of thermodynamics, thermodynamic systems, phase transitions, and heat engines.
 Thermodynamics is a fundamental aspect of both physics and engineering, with broad applications
 in energy, environmental science, and materials science. By investigating the relationship between
 internal and external energy of objects, thermodynamics reveals the basic principles of energy
 conversion and transfer in nature, providing theoretical support for the development of modern
 industrial technology.

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A.2.3 CHEMISTRY

Chemical Experiment. Chemical experiments involve studying the properties and changes of
 substances through experimental methods. Students learn to design experiments, observe chemical
 reactions, collect and analyze data, and draw conclusions in chemical experiments. Chemical
 experiments play a crucial role in understanding chemical theories and applying chemical knowledge.

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- **Chemical Reaction.** Chemical reactions study the chemical changes between substances, including reaction types, mechanisms, and rates. Understanding chemical reactions is essential for predicting

and controlling chemical processes, which have wide applications in pharmaceutical manufacturing,
 materials science, and environmental engineering.

867 Inorganic Chemistry. Inorganic chemistry studies the properties and reactions of non-carbon
 868 elements and their compounds. It covers a wide range of topics from metals and non-metals to
 869 transition metals and coordination compounds and is key to understanding the periodic table of
 870 elements and chemical reaction mechanisms.

 Organic Chemistry. Organic chemistry studies the structure, properties, and reactions of carboncontaining compounds. It has significant applications in pharmaceutical chemistry, materials science, and biochemistry.

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879 Substance Composition. Substance composition studies the chemical composition and structure of
 880 substances, including the arrangement of molecules, atoms, and ions. It has important applications in
 881 chemistry, materials science, and biology.

Chemical Equilibrium. Chemical equilibrium studies the behavior of chemical reactions when
 they reach a dynamic equilibrium state, including equilibrium constants, Le Chatelier's principle,
 and solubility equilibrium. Understanding chemical equilibrium is essential for predicting reaction
 directions and optimizing chemical processes.

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B DATASET CASE

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890 The VisScience dataset consists of 3,000 carefully selected high-quality questions, evenly distributed 891 across three disciplines: mathematics, physics, and chemistry, with each comprising 1,000 questions. 892 Each discipline within VisScience encompasses several subjects: mathematics includes six subjects, 893 physics contains eight subjects, and chemistry comprises seven subjects. To illustrate the diversity and depth of VisScience, we provide more examples sampled from each discipline. In mathematics, six 894 subjects include algebraic operations, combinatorial mathematics, functions and equations, probability 895 and statistics, plane geometry, and solid geometry are illustrated in Figure 5 to Figure 10. Figure 11 to 896 Figure 18 demonstrate eight subjects within the physics section of VisScience, comprising mechanics, 897 optics, modern physics, mechanical motion, electromagnetism, vibrations and waves, comprehensive 898 experiments and methods, and thermodynamics. The chemistry section includes seven subjects: 899 chemical experiments, chemical reactions, inorganic chemistry, organic chemistry, electrochemistry, 900 substance composition, and chemical equilibrium, which are illustrated in Figure 19 to Figure 25.

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C COMPARISON WITH OTHER BENCHMARKS

We compare the VisScience benchmark with 5 existing benchmarks, including MathVista Lu et al. (2023), Math-Vision Wang et al. (2024), CMMMU Zhang et al. (2024a), ScienceQA Lu et al. (2022), and SciBench Wang et al. (2023b).

908 VisScience vs MathVista. MathVista is a comprehensive multi-modal benchmark for mathematical 909 reasoning, comprising data from 28 existing datasets and 3 newly collected datasets. In MathVista, 910 the majority of questions are annotated after collecting images, which results in a certain homogeneity 911 within the data. In contrast, VisScience directly collects its questions from K12 education, featuring 912 an average question length of 80.93 words. Such questions provide more contextual information, 913 which facilitate a more thorough evaluation of the models' reasoning capabilities. Unlike MathVista 914 that encompasses only seven subjects within mathematics, VisScience offers a far broader scope, 915 including 22 distinct subjects across mathematics, physics, and chemistry. Furthermore, VisScience distinguishes itself by being a bilingual benchmark, including both Chinese and English versions of 916 questions. This feature is particularly advantageous as it assesses MLLMs' capabilities in scientific 917 reasoning across different languages.

VisScience vs Math-Vision. Math-Vision is a mathematics benchmark derived from 19 competitions, covering 16 topics across 5 levels of difficulty. Different from Math-Vision that collected from competitions, VisScience spans a broader educational spectrum, incorporating a natural gradient of difficulty from elementary school to high school. Furthermore, VisScience extends beyond mathematics to include questions from physics and chemistry, significantly broadening its scope and applicability. While Math-Vision primarily focuses on the unique challenges of competitive environments, VisScience is grounded in real-world educational settings.

925 VisScience vs CMMMU. CMMMU comprises 12,000 manually collected multi-modal questions 926 from university exams, quizzes, and textbooks, which covers 6 core subjects and 30 specific fields. 927 Similar to VisScience, CMMMU is a bilingual benchmark, offering questions in both Chinese and 928 English. Within this dataset, only 1,601 questions are dedicated to the disciplines of mathematics, 929 physics, and chemistry, accounting for only 13.34% of the total dataset. VisScience features a total 930 of 3,000 questions, significantly outnumbering those in CMMMU dedicated to the same subjects. 931 The questions in CMMMU are set at the university level, characterized by high difficulty, demanding 932 that the model possesses substantial professional domain knowledge and expert-level reasoning 933 abilities. In contrast, VisScience comes from K12 education, with a broader range of difficulty. This range allows VisScience to more comprehensively evaluate MLLMs' capabilities across different 934 educational stages. 935

VisScience vs ScienceQA. ScienceQA is a newly developed benchmark featuring approximately 937 21,000 multimodal multiple-choice questions across a variety of science topics. In the ScienceQA 938 dataset, 30.8% of questions incorporate both image and text contexts, providing a multimodal 939 benchmark to test MLLMs in scientific reasoning. The questions in ScienceQA have an average 940 length of only 12.11 words. In contrast, VisScience also serves as a benchmark for evaluating 941 the scientific reasoning abilities of MLLMs, but it typically features longer and more textually 942 detailed questions. Specifically, the Chinese version of VisScience has an average question length 943 of 162.85 words, providing a more comprehensive and intricate testing ground for evaluating the 944 depth of detailed reasoning in MLLMs. Additionally, VisScience contains mathematical problems, further enriching the benchmark's scope by testing MLLMs on their mathematical problem solving 945 capabilities alongside their scientific reasoning. 946

947 VisScience vs SciBench. SciBench is a benchmark developed to evaluate the reasoning capabilities 948 of LLMs in solving collegiate-level scientific problems within the domains of mathematics, chemistry, 949 and physics. The majority of the data in SciBench focuses on assessing the scientific reasoning of 950 LLMs, it only includes 177 problems that incorporate visual elements to evaluate the performance of 951 MLLMs. In contrast, VisScience is primarily focused on multimodal scientific reasoning, covering 952 similar subjects such as mathematics, chemistry, and physics. VisScience differentiates itself by 953 offering a more comprehensive range of difficulty levels and subjects, making it a broader benchmark 954 for assessing the capabilities of MLLMs in scientific reasoning.

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D EVALUATION DETAILS

D.1 THE SOURCES OF MODELS

⁹⁶⁰ In Table 4, we present the sources of the models tested on VisScience.

D.2 PROMPTS

We introduce the prompts used to guide models in generating responses in Chain-of-Thought (CoT) settings and judging the LLMs' answers. The specific prompts can be found in Table 5.

- E MORE EXPERIMENTAL RESULTS
- E.1 RESULTS ON VISSCIENCE IN ENGLISH VERSION
- Table 6 reports a comprehensive comparison of various models on the VisScience benchmark in the English version. The benchmark evaluates performance across three disciplines: mathematics,

Madal	Innut	LIMSing	Source
Model	Input	LLM Size	Source
	Close	ed Source Mod	dels
Text-only LLMs			
ChatGPT	Q	-	gpt-3.5-turbo
GPT-4	Q	-	gpt-4
Claude-2	Q	-	claude-2
Multi-modal LLMs			
Gemini-1.0-Pro	Q, I	-	gemini-pro
Gemini-1.5-Pro	\tilde{Q}, I	-	gemini-1.5-pro
GPT-40	\tilde{Q}, I	-	gpt-40
Claude3-Opus	\tilde{Q}, I	-	claude-3-opus-2024022
Claude3.5-Sonnet	\tilde{Q}, I	-	claude-3-5-sonnet-20246
Qwen-VL-Plus	\tilde{Q}, I	-	qwen-vl-plus
Qwen-VL-Max	\tilde{Q}, I	_	qwen-vl-max
GLM-4V	\tilde{Q}, I	_	glm-4v
Step-1V	\tilde{Q}, I	-	step-1v
	Ope	n Source Mod	els
General Multi-modal LLMs	-		
mPLUG-Owl	, Q, I	7B	mPLUG-Owl
DeepSeek-VL	Q, I Q, I	7B 7B	deepseek-vl-7b-base
LLaMA-Adapter-V2	Q, I Q, I	7B 7B	LLaMA-Adapter V2
LLaVA-1.5	Q, I Q, I	7B 7B	LLaVA-v1.5-7B
LLaVA-1.5	Q, I Q, I	13B	LLaVA-v1.5-13B
ShareGPT-4V	Q, I Q, I	7B	ShareGPT4V-7B
ShareGPT-4V	Q, I Q, I	13B	ShareGPT4V-13B
GLM-4v-9B	Q, I Q, I	7B	GLM-4v-9B
SPHINX-Plus	Q, I Q, I	13B	SPHINX-Plus
InternVL-Chat-V1.5	Q, I Q, I	20B	InternVL 1.5
InternVL-1.2-Plus	Q, I Q, I	20B 34B	InternVL-Chat-V1-2-Plu
InternLM-XC2	Q, I	7B 17B	InternLM-XComposer2-VI CogVLM-17B
CogVLM CogVLM2	Q, I	17B 19B	cogvlm2-llama3-chat-19
	Q, I	17D	•
MiniCPM-Llama3-V-2_5	Q, I	19B	MiniCPM-Llama3-V 2.

Task	Prompt
Response Generation	You are an exceptionally talented mathematics (physics/chemistry) in- structor. Kindly furnish an elaborate, step-by-step solution to the ques- tion.
Answer Judgment	You are a highly skilled mathematics (physics/chemistry) teacher. I will provide you with a mathematics (physics/chemistry) problem, along with its ground answer and the model response from the model. Please deter- mine whether the ground answer and the model response are consistent. Note that you do not need to judge the correctness of either answer, only whether they are consistent. If it is a multiple-choice question, both an- swers must choose the exact same option to be considered consistent. If it is a calculation problem, the relative error between the model response and the ground answer must be less than 0.05 to be considered consistent. If the problem has multiple sub-questions, each sub-question's answer must be identical for consistency. If you find them consistent, please add [Consistent] at the end of your response. If you find them inconsistent, please add [Inconsistent] at the end of your response.
Table	5: Prompts for response generation and answer judgment.
across two disciplines, However, Claude3.5-Son source models generally InternVL-1.2-Plus displ in physics, and 27.8% in	Among close-source models, GPT-40 demonstrates the highest performance achieving an accuracy of 53.6% in mathematics and 42.7% in physics. anet surpasses GPT-40 in chemistry with a higher accuracy of 43.6%. Open- y show lower performance compared to close-source counterparts. Notably, ays competitive performance, reaching up to 26.0% in mathematics, 23.6% a chemistry. The English version of VisScience is designed to facilitate the hat specialize in English, assessing their capabilities in scientific reasoning.
E.2 RESULTS ON PHY	SICS ACROSS DIFFERENT SUBJECTS
the physics section, which experiments and method table highlights that which the best performance in specifically in modern phy models in this area. This of different models. Mo	ed analysis of various models on VisScience across different subjects within ch includes mechanics, electromagnetism, thermodynamics, comprehensive s, optics, vibration and waves, modern physics, and mechanical motion. The ile GPT-40 exhibits the top performance on the entire physics discipline, individual subjects varies notably. For instances, Claude3.5-Sonnet excels sysics with an accuracy of 66.67%, significantly surpassing other close-source ovariation in performance by subject underscores the specialized capabilities reover, this detailed analysis provides more insights, emphasizing the need hts to achieve balanced performance across all physics subjects.
E.3 RESULTS ON CHI	EMISTRY ACROSS DIFFERENT SUBJECTS
within the chemistry di- chemical experiment, cl chemical equilibrium, ar source models, excelling in organic chemistry an 61.16%, respectively. A chemistry, achieving th models demonstrate a ra the highest open-source performances within th	aced view of the performance of various models across different subjects scipline of the VisScience benchmark. The chemistry discipline includes nemical reaction, inorganic chemistry, electrochemistry, organic chemistry, ad substance composition. Notably, Gemini-1.5-Pro stands out among close- g across the entire chemistry discipline. It demonstrates particular prowess d substance composition, achieving impressive accuracies of 57.02% and Additionally, Qwen-VL-Max leads in chemical experiment and inorganic e highest accuracies of 46.28% and 51.94%, respectively. Open-source nge of performances, with InternVL-1.2-Plus leading this group. It achieves e accuracy in nearly all subjects. This comprehensive review of model e chemistry section of the VisScience benchmark highlights the need to ilities in scientific domains, ensuring models are both accurate and adaptable

across various disciplines.

Model	LLM	Input	Mathematics	Physics	Chemistry
	Close Source Mod	els (APIs	3)		
Text-only LLMs					
Zero-shot ChatGPT	-	Q	17.4	20.7	25.2
Zero-shot GPT-4	-	Q	29.9	37.7	38.7
Zero-shot Claude-2	-	Q	24.6	22.7	25.6
Zero-shot Claude3-Opus	-	Q	21.7	15.8	29.4
Zero-shot Claude3.5-Sonnet	-	Q	27.2	35.7	35.2
Zero-shot GPT-40	-	Q	35.2	40.3	42.5
2-shot CoT Claude2	-	Q	25.7	21.9	24.1
2-shot CoT ChatGPT	-	Q	24.4	20.1	22.1
2-shot CoT GPT-4	-	Q	36.5	39.0	38.1
Multi-modal LLMs					
Gemini-1.0-Pro	-	Q, I	26.4	39.1	27.9
Gemini-1.5-Pro	-	Q, I	47.8	35.1	39.1
GPT-4o	-	Q, I	53.6	42.7	43.3
GPT-4o-mini	-	Q, I	43.2	33.7	34.9
Qwen-VL-Max	-	Q, I	30.7	26.4	36.3
Qwen-VL-Plus	-	Q, I	21.9	20.9	29.7
Claude3.5-Sonnet	-	Q, I	50.8	36.6	43.6
Claude3-Opus	-	Q, I	34.4	29.4	34.7
GLM-4V	-	Q, I	23.1	18.5	23.4
Step-1V	7B	Q, I	32.0	19.5	27.6
	Open Source Models				
General Multi-modal LLMs					
mPLUG-Owl	LLaMA-7B	Q, I	7.4	12.3	12.3
LLaMA-Adapter-V2	LLaMA-7B	\tilde{Q}, I	12.6	11.4	16.2
MiniCPM-Llama3-V2.5	LLaMA3-8B	Q, I	24.4	20.6	24.4
LLaVA-1.5	Vicuna-13B	Q, I	15.0	17.4	21.1
LLaVA-1.5	Vicuna-7B	Q, I	17.4	16.6	18.9
DeepSeek-VL	DeepSeek-LLM-7B	Q, I	16.0	16.9	17.8
ShareGPT-4V	Vicuna-7B	Q, I	14.7	17.7	21.3
ShareGPT-4V	Vicuna-13B	Q, I	14.5	16.0	20.2
SPHINX-Plus	LLaMA2-13B	Q, I	17.9	15.7	22.4
InternLM-XC2	InternLM2-7B	Q, I	20.7	20.5	25.0
InternVL-1.2-Plus	Nous-Hermes-2-Yi-34B	Q, I	26.0	23.6	27.8
InternVL-Chat-V1.5	Mixtral 8*7B	Q, I	24.9	23.0	25.9
CogVLM	Vicuna-7B	\tilde{Q}, I	18.5	15.9	23.1
CogVLM2	LLaMA-3-8B	Q, I	24.2	16.6	24.9
GLM-4V-9B	GLM-4-9B	\tilde{Q}, I	24.7	19.2	23.9

Table 6: Results on VisScience within the version of the English language across the disciplines
 of mathematics, physics, and chemistry. The highest scores among close-source and open-source
 models are highlighted in red and blue, respectively.

Model	ALL	Mech	Ele	Therm	Comp	Physics Opt	Vib & Waves	Mod Phys	Mech Motion
			Close	Source M	lodels (Al			5	
Text-only LLMs									
Zero-shot ChatGPT	22.70	22.08	19.94	23.53	4.62	40.98	29.79	19.05	23.33
Zero-shot GPT-4	30.40	34.26	30.21	33.33	15.38	40.98	34.04	42.86	20.00
Zero-shot Claude-2	22.00	24.62	23.56	25.49	12.31	27.87	21.28	28.57	23.33
Zero-shot Claude3-Opus	30.80	34.26	32.02	33.33	10.77	39.34	31.91	42.86	10.00
Zero-shot Claude3.5-Sonnet	35.30	40.36	35.95	35.29	15.38	40.98	34.04	47.62	26.67
Zero-shot GPT-40	38.00	43.91	38.67	45.10	9.23	49.18	38.30	52.38	23.33
2-shot CoT Claude2	21.70	24.87	22.96	25.49	10.77	18.03	23.40	28.57	10.00
2-shot CoT ChatGPT	18.60	20.30	20.54	13.73	12.31	22.95	23.40	23.81	13.33
2-shot CoT GPT-4	31.50	35.03	32.02	37.25	12.31	44.26	29.79	47.62	23.33
Multi-modal LLMs									
Gemini-1.0-Pro	23.70	26.97	23.03	17.65	6.15	31.15	34.04	19.05	10.00
Gemini-1.5-Pro	38.10	46.56	33.74	47.06	20.00	45.00	34.04	52.38	43.33
GPT-40	38.20	41.37	39.27	56.86	23.08	42.62	36.17	42.86	43.33
GPT-4o-mini	29.80	31.73	30.51	29.41	10.70	36.07	19.15	47.62	30.00
Qwen-VL-Max	30.70	36.13	26.59	39.22	9.23	34.43	31.91	28.57	30.00
Qwen-VL-Plus	26.50	31.04	24.77	33.33	6.15	36.07	36.17	23.81	16.67
Claude3.5-Sonnet	38.00	41.62	36.56	43.14	13.85	44.26	38.30	66.67	30.00
Claude3-Opus	31.10	33.25	29.91	39.22	12.31	45.90	34.04	61.90	23.33
GLM-4V	19.20	23.16	17.82	15.69	12.31	25.00	17.02	19.05	23.33
Step-1V	23.50	21.55	24.35	28.57	7.84	12.82	25.00	31.25	39.13
			0	pen Sourc	e Models				
General Multi-modal LLMs									
mPLUG-Owl	8.30	11.93	8.46	1.96	4.62	8.20	10.64	4.76	10.00
LLaMA-Adapter-V2	10.30	10.41	10.88	8.00	4.84	13.11	25.53	14.29	3.33
MiniCPM-Llama3-V2.5	17.90	21.57	19.64	15.69	6.15	26.23	19.15	9.52	23.33
LLaVA-1.5-13B	15.20	17.26	14.80	7.84	7.69	21.31	17.02	9.52	16.67
LLaVA-1.5-7B	13.50	15.28	15.12	11.76	3.12	15.25	15.56	5.26	17.24
DeepSeek-VL	16.80	18.77	19.33	13.73	7.69	16.67	13.04	19.05	3.45
ShareGPT4V-7B	14.00	13.71	15.41	9.80	3.08	19.67	19.15	28.57	6.67
ShareGPT4V-13B	14.90	15.23	16.92	9.80	6.15	14.75	19.15	19.05	16.67
SPHINX-Plus	15.30	16.50	18.43	17.65	4.62	11.48	12.77	19.05	13.33
InternLM-XC2	18.30	20.81	17.82	13.73	10.77	26.23	21.28	14.29	6.67
InternVL-1.2-Plus	24.80	29.69	22.94	29.41	12.31	31.67	25.53	35.00	10.00
InternVL-Chat-V1.5	20.80	23.97	20.87	23.53	9.23	25.42	17.02	14.29	17.24
CogVLM	14.50	18.02	13.29	7.84	6.15	14.75	19.15	19.05	6.67
CogVLM2	14.40	16.75	16.00	12.00	6.15	13.11	19.15	4.76	10.00
GLM-4V-9B	19.30	21.78	21.12	24.00	4.62	25.42	15.91	15.00	13.33

1169 Table 7: Results on the physics part of VisScience across different subjects. Subjects: Mech: 1170 mechanics, Ele: electromagnetism, Threm: thermodynamics, Comp: comprehensive experiments and 1171 methods, Opt: optics, Vib & Waves: vibration and waves, Mod Phys: modern physics, Mech Motion: 1172 mechanical motion. The highest scores among close-source and open-source models are highlighted 1173 in red and blue, respectively.

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1178 The VisScience dataset includes three disciplines: mathematics, physics, and chemistry. The math-1179 ematical section comprises 6 subjects, the chemistry section contains 7 subjects, and the physics 1180 section includes 8 subjects, culminating in a total of 21 distinct subjects across the VisScience 1181 benchmark. Here, we present one question from each subject, along with its standard answer and the 1182 correct response provided by GPT-40. Figure 26 to Figure 28 demonstrate cases of the mathematical 1183 part of VisScience. Figure 29 to Figure 32 illustrate sampled questions from the physics section of 1184 the VisScience benchmark. Each figure provides insight into the diverse range of topics covered, showing GPT-4o's capabilities to handle complex physical principles and calculations. Figure 33 to 1185 Figure 36 display examples from the chemistry section. These examples not only demonstrate the 1186 diversity of the VisScience benchmark within chemistry but also illustrate how effectively GPT-40 1187 can generate accurate responses across different scientific subjects.

Model	ALL	Chem Exp	Chem React	Cł Inorg Chem	nemistry Electrochem	Org Chem	Chem Equil	Sub Com
		enem Exp		e Models (APIs		oig chem	enem Equi	bub com
T , 1 11M			Close sourc	e mouers (Al Is	5)			
Text-only LLMs Zero-shot ChatGPT	18.60	26.35	23.86	23.26	23.75	35.43	24.64	30.89
Zero-shot GPT-4	33.10	20.55 40.54	30.68	38.76	23.73 32.50	36.22	30.43	30.89
Zero-shot Claude-2	24.40	24.32	26.36	31.71	23.86	20.22	0.30	25.98
Zero-shot Claude3-Opus	32.50	24.32 37.16	20.50	31.71	25.80 31.25	36.22	30.43	23.98 39.84
Zero-shot Claude3.5-Sonnet	36.90	34.80	36.93	39.53	46.25	45.67	23.19	47.15
Zero-shot GPT-40	39.60	42.57	40.34	44.96	35.00	43.07	26.09	47.13 54.47
2-shot CoT Claude2	23.90	23.99	26.70	22.48	30.00	26.77	27.54	27.64
2-shot CoT ChatGPT	23.90	19.93	23.30	20.93	22.50	20.77	26.09	30.08
2-shot CoT GPT-4	32.40	29.05	32.39	32.56	32.50	42.52	28.99	53.66
	52.40	29.05	32.39	52.50	52.50	42.32	20.99	55.00
Multi-modal LLMs		24.02	26.70	26.26	21.25		21.02	
Gemini-1.0-Pro	27.80	24.03	26.70	26.36	31.25	35.54	31.82	37.19
Gemini-1.5-Pro	47.00	43.46	47.43	51.59	50.00	57.02	35.29	61.16
GPT-40	41.60	43.58	46.02	38.76	46.25	43.31	43.48	50.41
GPT-40-mini	28.40	22.30	27.27	27.13	30.00	34.65	20.29	42.09
Qwen-VL-Max	42.50	46.28	41.48	51.94	35.00	41.73	36.23	53.66
Qwen-VL-Plus Claude3.5-Sonnet	37.70 43.10	33.78 40.54	40.34 41.48	44.19 42.64	41.25 50.00	48.03 42.52	33.33 33.33	41.80 59.35
Claude3-Opus	45.10 34.10	40.34 35.47	30.11	42.04 31.78	31.25	42.32	33.33	51.22
GLM-4V	25.00	23.65	25.86		28.75	27.78	31.88	31.22
Step-1V	25.00	23.63 32.51	23.80	21.71 25.26	28.75	17.72	13.33	21.95
Step-1 v	23.00	32.51	27.40	23.20	25.45	17.72	15.55	21.93
			Open Sc	ource Models				
General Multi-modal LLMs								
mPLUG-Owl	9.50	7.77	11.36	7.75	12.50	12.60	13.04	9.76
LLaMA-Adapter-V2	10.80	7.77	13.64	8.53	12.66	12.80	17.65	17.07
MiniCPM-Llama3-V2.5	19.50	20.96	26.29	26.61	18.18	24.00	28.79	30.83
LLaVA-1.5-13B	18.80	15.54	16.48	24.03	20.00	22.05	23.19	19.51
LLaVA-1.5-7B	16.00	13.49	17.14	19.20	16.25	20.49	26.09	10.74
DeepSeek-VL	21.00	18.84	20.57	20.16	21.25	23.62	36.76	20.66
ShareGPT4V-7B	19.00	13.85	19.32	26.36	18.75	23.62	28.99	15.45
ShareGPT4V-13B	18.40	13.51	21.02	19.38	23.75	22.83	13.04	19.51
SPHINX-Plus	20.40	20.27	21.02	24.03	22.50	22.83	27.54	21.95
InternLM-XC2	25.60	22.64	27.27	26.36	21.25	33.86	26.09	24.39
InternVL-1.2-Plus	31.20	22.29	31.82	33.58	31.46	39.57	32.47	38.84
InternVL-Chat-V1.5	23.70	20.07	25.00	25.20	22.37	28.80	25.00	28.46
CogVLM	17.00	15.54	20.45	10.85	16.25	22.05	20.29	17.07
CogVLM2	21.00	13.10	21.39	25.78	20.51	31.45	22.73	30.17
GLM-4V-9B	22.50	21.00	25.44	26.23	23.08	26.83	17.39	25.83

Table 8: Results on the chemistry part of VisScience across different subjects. Subjects: Chem
Exp: chemical experiment, Chem React: chemical reaction, Inorg Chem: inorganic chemistry,
Electrochem: Electrochemistry, Org Chem: organic chemistry, Chem Equil: chemical equilibrium,
and Sub Comp: substance composition. The highest scores among close-source and open-source
models are highlighted in red and blue, respectively.

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G ERROR CASE

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1229 We conduct rigorous tests on a series of open-source and close-source models on VisScience and 1230 perform a detailed analysis of the models' responses. These errors in the models' answers can be 1231 classified into five categories: reasoning error, vision recognition error, knowledge error, calculation 1232 error, and question misunderstood error. We present examples of these five error types across the 1233 disciplines of mathematics, physics, and chemistry, with a specific focus on errors made by GPT-40. Additionally, we demonstrate error examples from other representative close-source models such as 1234 GLM-4V, Qwen-VL-max, and Claude 3.5, as well as open-source models like LLAVA-1.5, GLM-4V-1235 9B and InternVL-Chat-1.5. Notably, it should be noted that the types of errors made by these models 1236 in response to the same questions can differ from those made by GPT-40. This analysis helps to 1237 underline the varied challenges faced by different models in processing complex scientific questions, 1238 providing insight into their respective strengths and limitations. Figure 37 to Figure 46 demonstrate 1239 cases of errors from representative models in the mathematical part of VisScience. Figure 47 to 1240 Figure 59 show the incorrect answers in the physics section. Figure 60 to Figure 68 demonstrate the 1241 errors in the chemistry section.

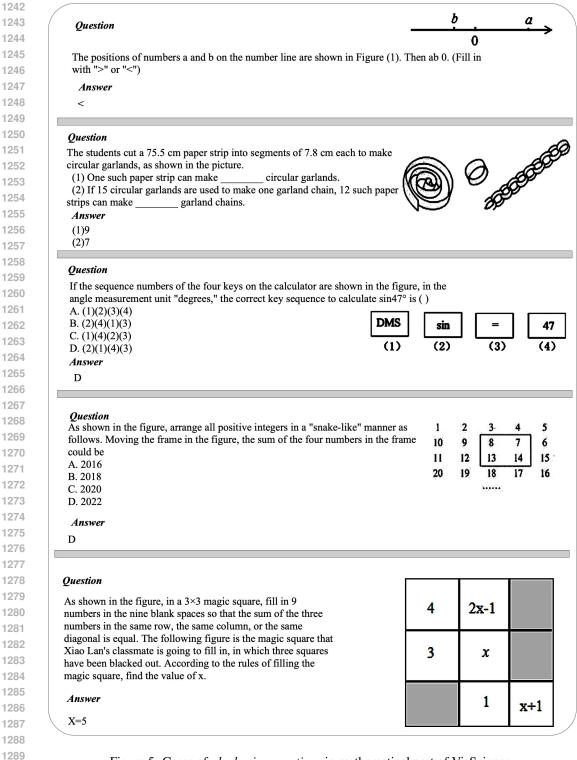


Figure 5: Cases of algebraic operations in mathematical part of VisScience.

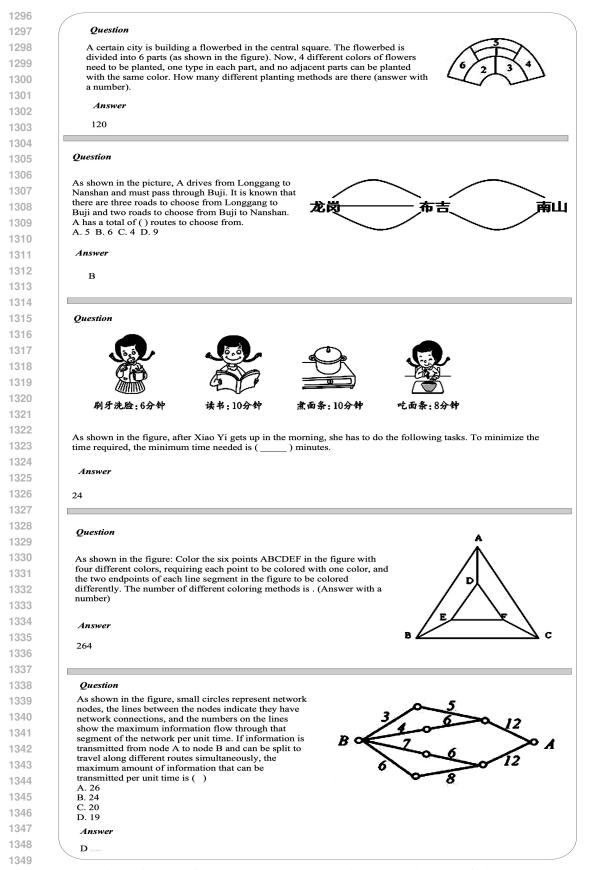


Figure 6: Cases of combinatorial mathematics in mathematical part of VisScience.

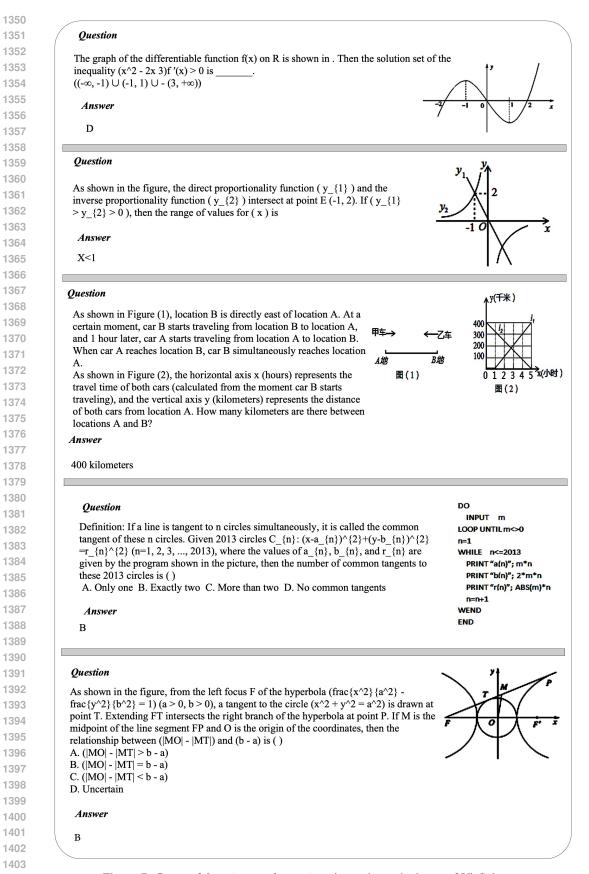


Figure 7: Cases of *functions and equations* in mathematical part of VisScience.

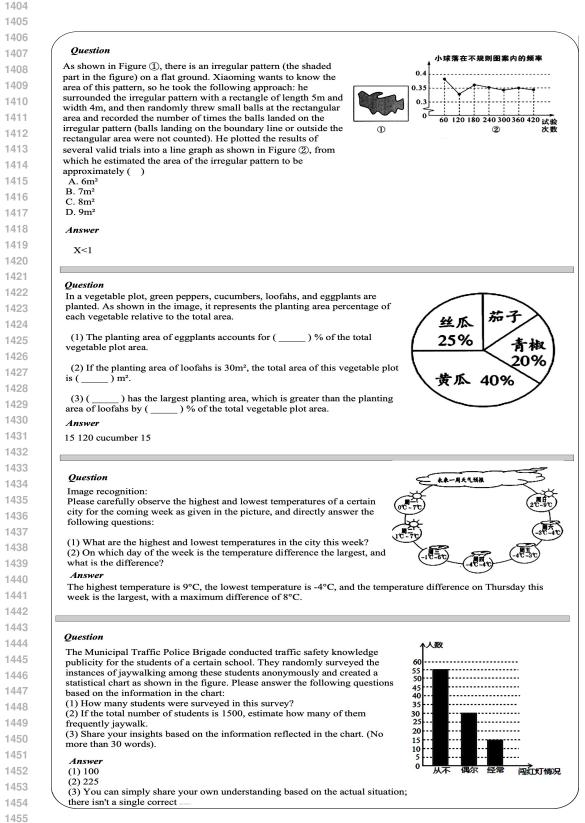


Figure 8: Cases of probability and statistics in mathematical part of VisScience.

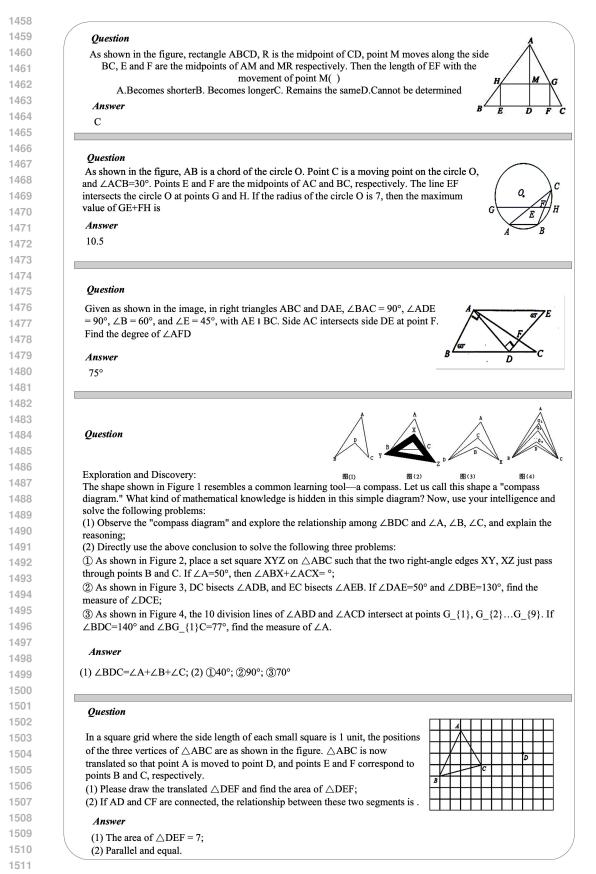
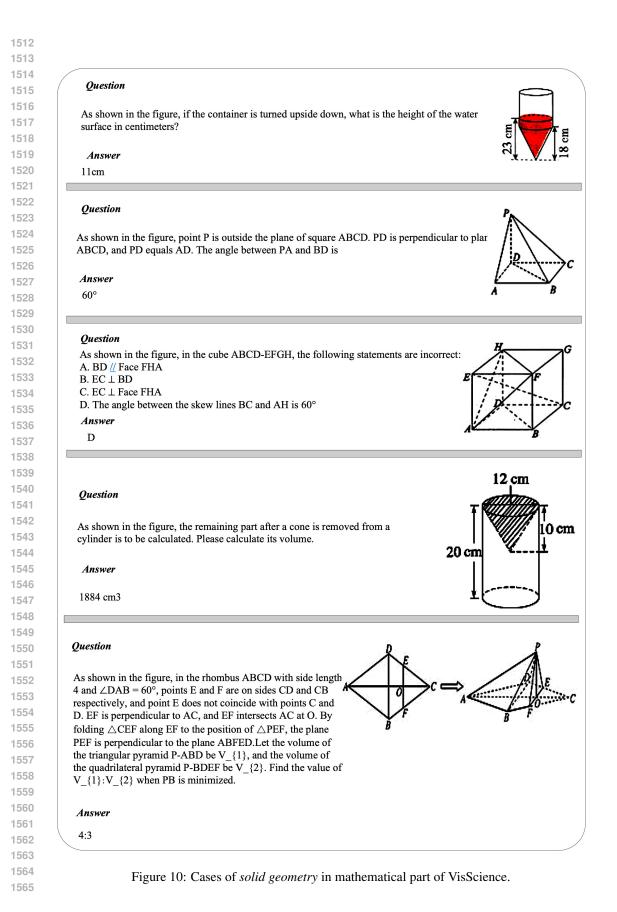


Figure 9: Cases of *plane geometry* in mathematical part of VisScience.



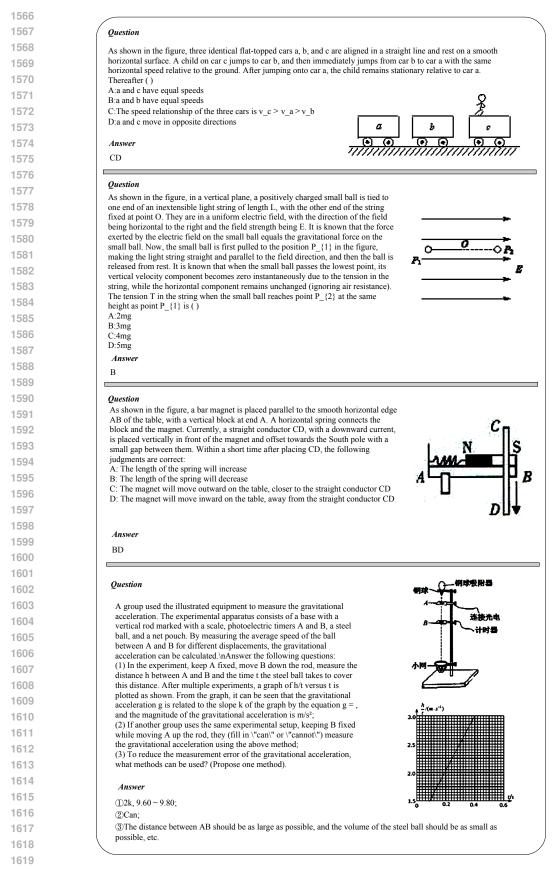


Figure 11: Cases of mechanics in physics part of VisScience.

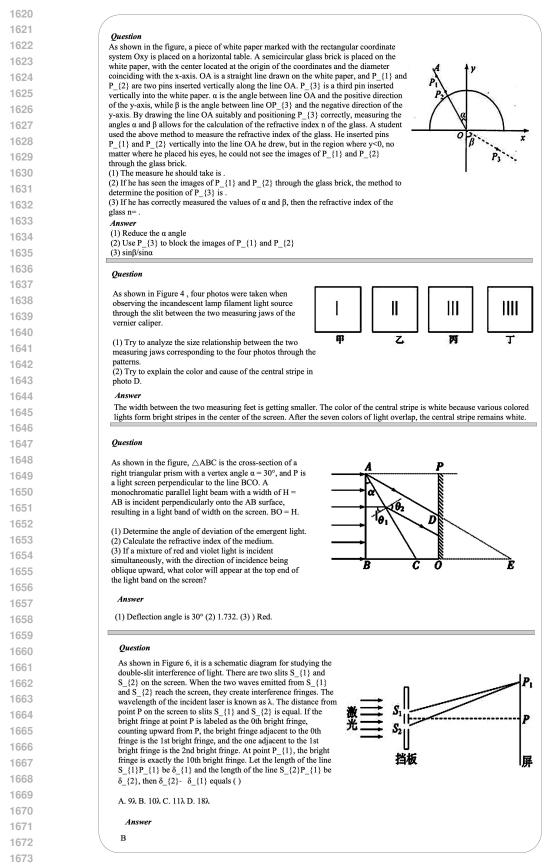


Figure 12: Cases of optics in physics part of VisScience.

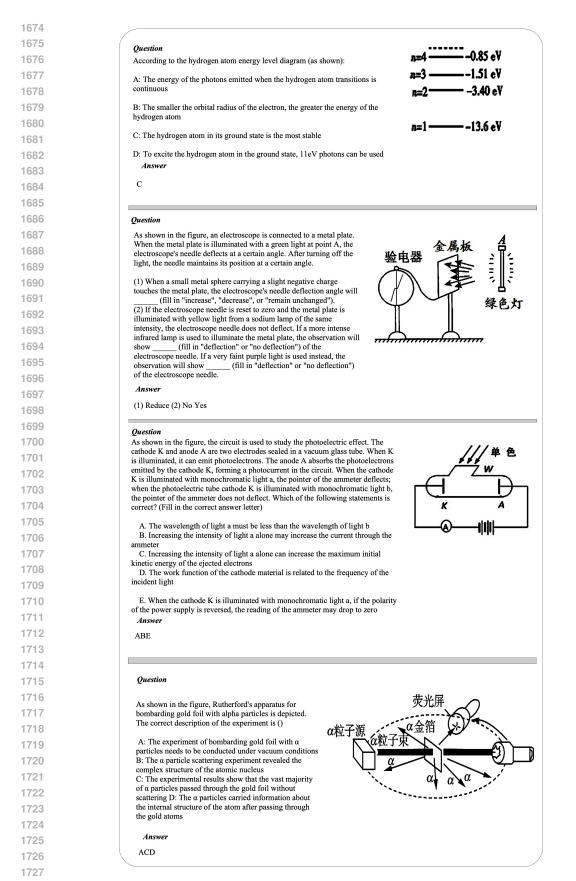


Figure 13: Cases of modern physics in physics part of VisScience.

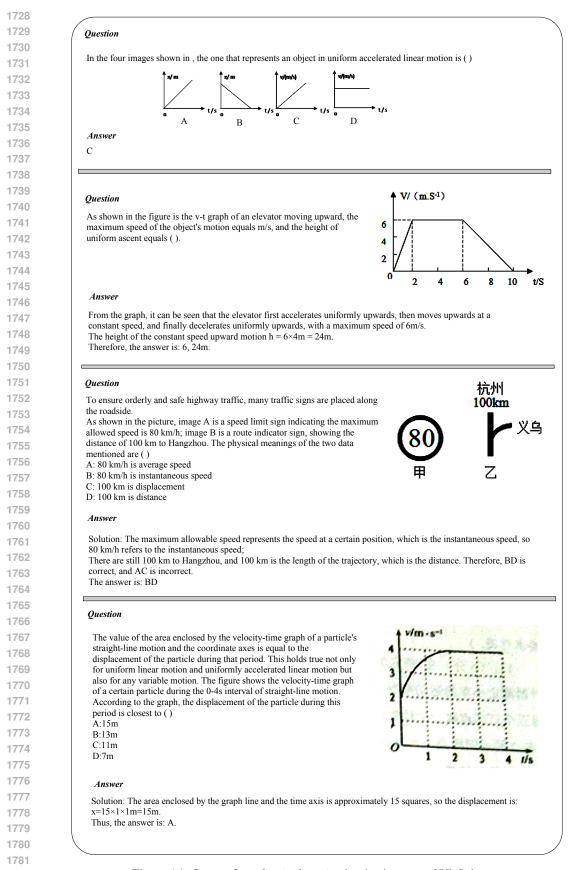


Figure 14: Cases of mechanical motion in physics part of VisScience.

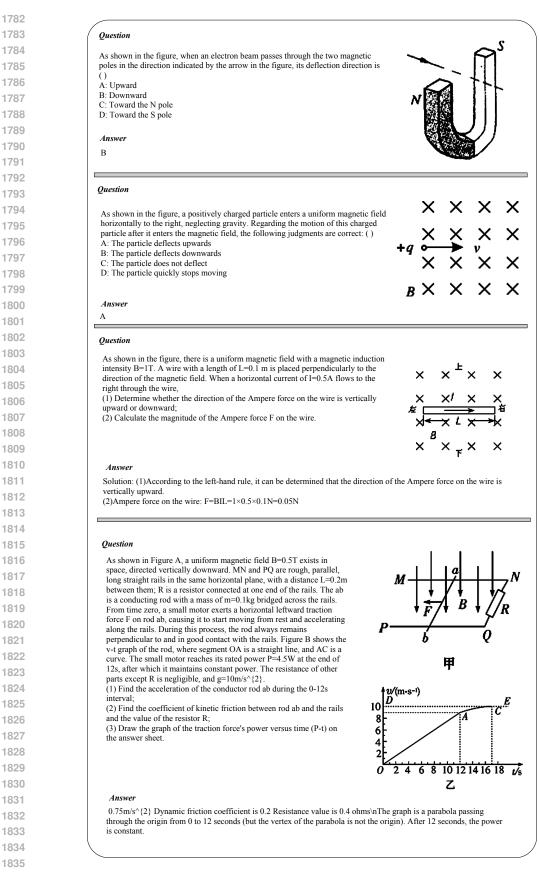


Figure 15: Cases of *electromagnetism* in physics part of VisScience.

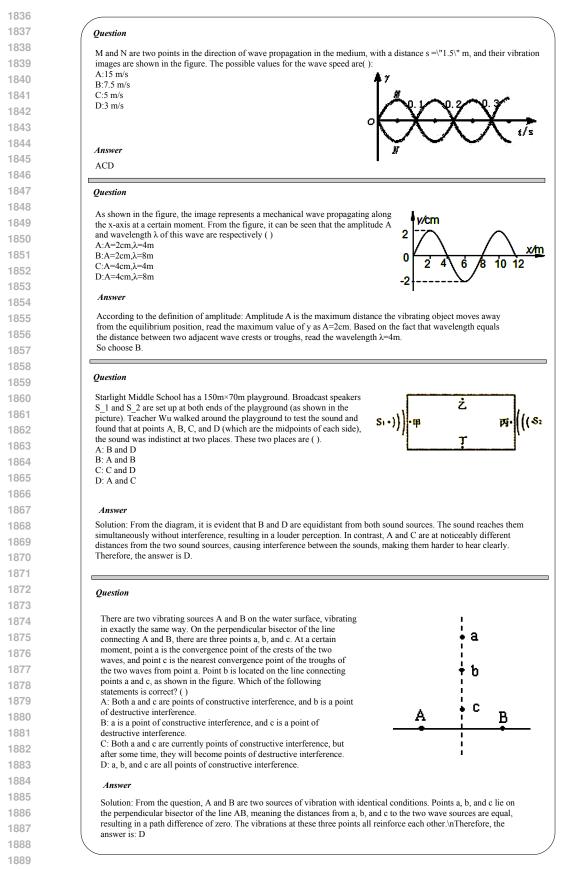


Figure 16: Cases of vibration and waves in physics part of VisScience.

Question



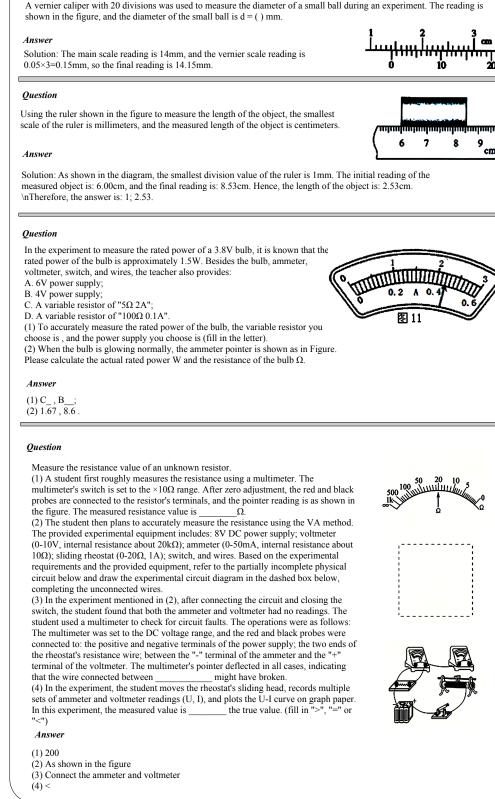


Figure 17: Cases of *comprehensive experiments and methods* in physics part of VisScience.

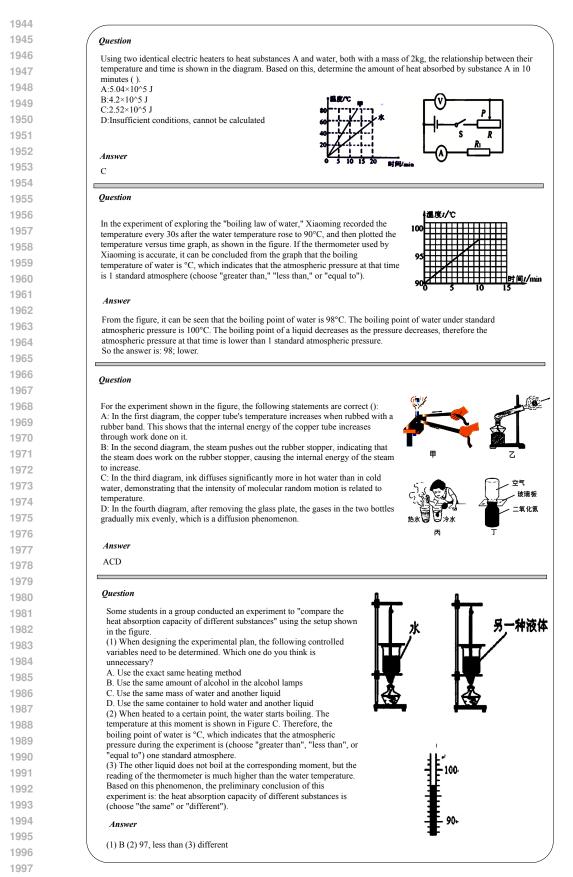


Figure 18: Cases of thermodynamics in physics part of VisScience.

1998	Question
1999	Duestion The apparatus designed by an extracurricular group for synthesizing ethyl acetate in the laboratory
2000	is shown in the figure. Concentrated sulfuric acid is placed in A, ethanol and anhydrous sodium acetate are placed in B, and a saturated sodium carbonate solution is placed in D.
2001	Throw information: (1) Anhydrous calcium chloride can form insoluble CaCl2-6C2H5OH with ethanol.
2002	2 Boiling points of related organic compounds: Reagent Ether Ethanol Acetic acid Ethyl acetate
2003	Boiling point/°C 34.7 78.5 118 77.1 Please answer:
2004	(1) The role of concentrated sulfuric acid is; if isotope 180 tracing method is used to determine the provider of oxygen atoms in the water molecules produced, write the chemical
2005	equation indicating the position of 180: (2) The role of spherical drying tube C is If a few drops of
2006	phenolphthalein are added to D before the reaction, the solution appears red; the reason for this phenomenon (expressed in ionic equation) is; the phenomenon in D after the reaction is
2007	
2008	Answer
2009	(1) Catalyst, dehydrating agent CH3COOH + C2H518OH CH3CO18OC2H5 + H2O
2010	(2) Prevent backflow, condensation CO + H2O == HCO + OH− The solution layers, with the upper layer being a colorless oily liquid and the lower layer solution becoming lighter in color
2011	apper myer oning a contract only input a molecular input to union occoming righter in contract
2012	Question
2013	The equipment shown in the figure can be used in the laboratory to separate and dry a
2013	mixed gas of CO and CO2. It is known that a is a water stopper, b is the stopcock of the separating funnel C. The available reagents are NaHCO3 solution, NaOH solution, NaOH solution, NaHS solution, concentrated sulfuric acid, anhydrous calcium chloride, and dilute
2015	sulfuric acid. Please fill in the blanks with the answers:
2016	(1) The reagent to be put in wide-mouth bottle A is, the reagent to be put in wide-mouth bottle B is, and the reagent to be put in separating funnel C is
2017	(2) In the first step,should be separated out first. During the separation,
	should be closed first. Open, and the ionic equation of the reaction that occurs is
2018	(3) In the second step, when separating, first close, and open The
2019	ionic equation of the reaction that occurs is
2020	Answer
2021	(1) NaOH solution concentrated sulfuric acid dilute sulfuric acid
2022	(2) CO b a CO2 + 2OH- =CO32- + H2O
2023	(3) CO2 a b CO32- +2H +=H2O + CO2↑
2024	Question
2025	You are provided with pure zinc, pure copper sheets, 500mL of 0.2 mol·L^{- }^{1}
2026	H_{2}SO_{4} solution, wires, and a 1000mL measuring cylinder. Using the dev shown in the figure, try to determine the amount of electrons passing through the
2027	when zinc reacts with dilute sulfuric acid over a certain period of time.
2028	cylinder is filled with water. At the beginning of the experiment, the first thing to 0.2mol L
2029	(2) The material of electrode a is, and its electrode reaction equation
2030	The material of electrode b is, and its electrode reaction equation
2031	· · · · · · · · · · · · · · · · · · ·
2032	(3) When 672mL of gas is collected in the measuring cylinder (converted to standard conditions), the amount of electrons passing through the wire is
2033	Answer
2034	(1) Use a wire to connect the electrodes a and b
2035	(2) Pure zinc sheet Zh- $2e^{-} = Zn^{2}^{+} $ Pure copper sheet $2H^{+} + 2e^{-} $
2036	(3) 0.06mol
2037	Question
2038	To purify solid potassium nitrate containing a small amount of potassium chloride, a student
2039	conducts the experiment shown in the figure. Answer the following questions: (1) Place the sample in a beaker and add an appropriate amount of water to dissolve it, while
2040	stirring with a glass rod. The purpose of stirring is
2041	(2) Add an appropriate amount of solution to the solution to convert potassium chloride into a precipitate.
2042	(3) Filter the mixture using the filtration apparatus and operations shown in the figure, and
2043	identify two errors in the figure:
2044	(4) To obtain potassium nitrate crystals from the filtrate, two methods that can be selected are:
2045	
2046	Answer
2047	(1) Speed up the dissolution of a solid (2) Silver nitrate
2048	 (3) ① The liquid was not guided by a glass rod ② The lower end of the funnel was not close to the inner wall of the beaker
2049	(4) ① Cool the hot saturated solution ② Evaporate the solvent
2050	
2051	

Figure 19: Cases of *chemical experiment* in chemistry part of VisScience.

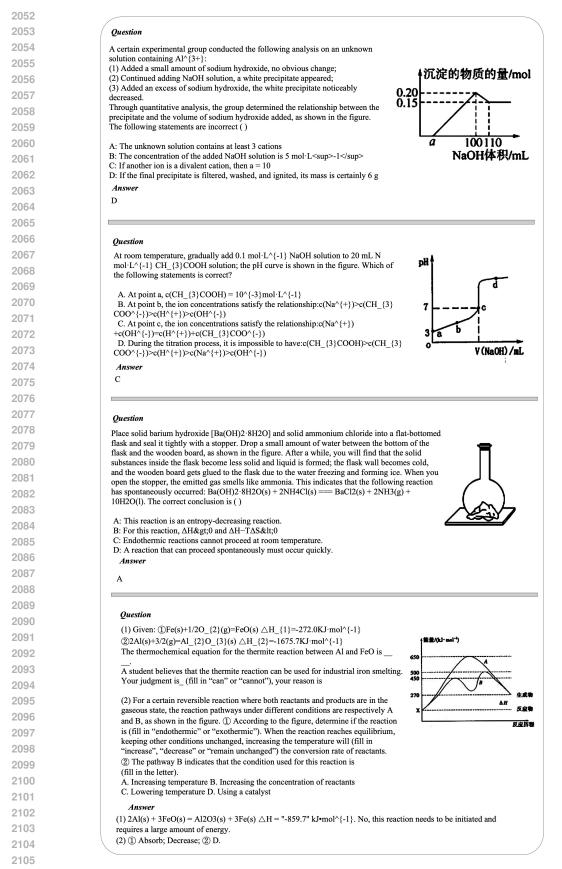


Figure 20: Cases of *chemical reaction* in chemistry part of VisScience.

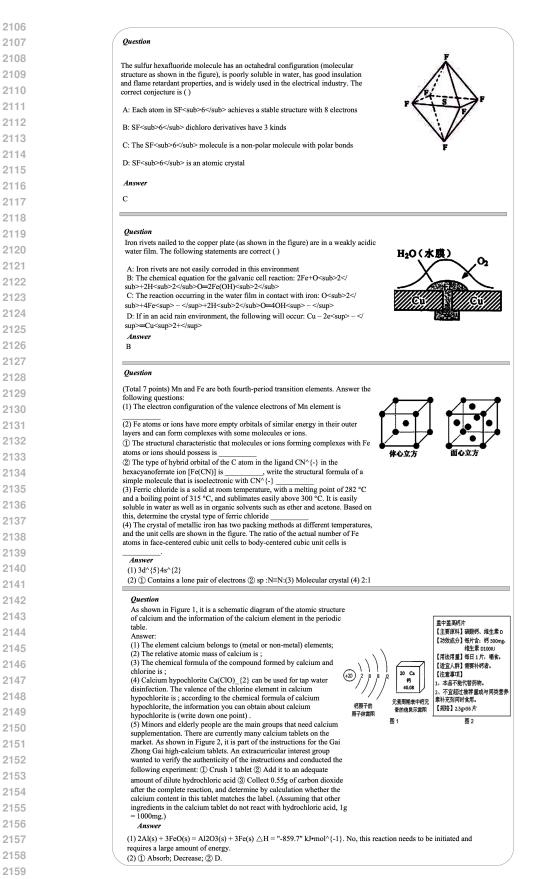


Figure 21: Cases of inorganic chemistry in chemistry part of VisScience.

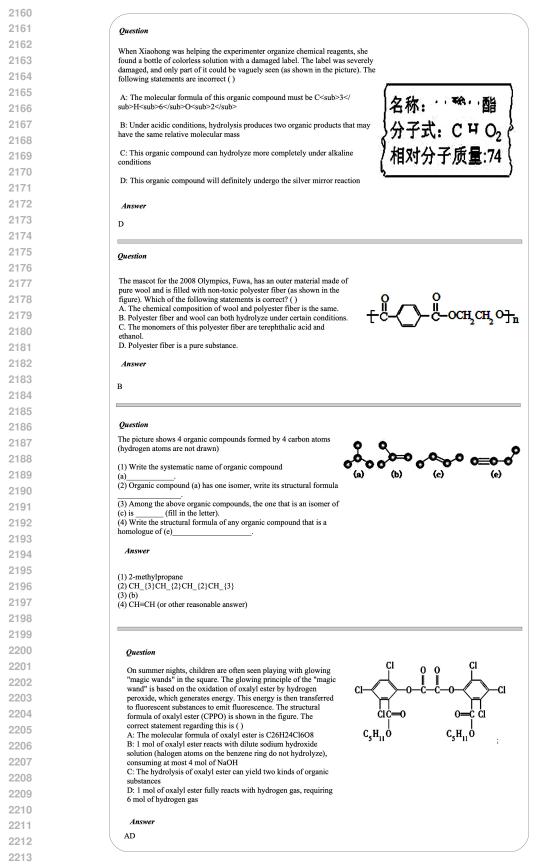


Figure 22: Cases of organic chemistry in chemistry part of VisScience.

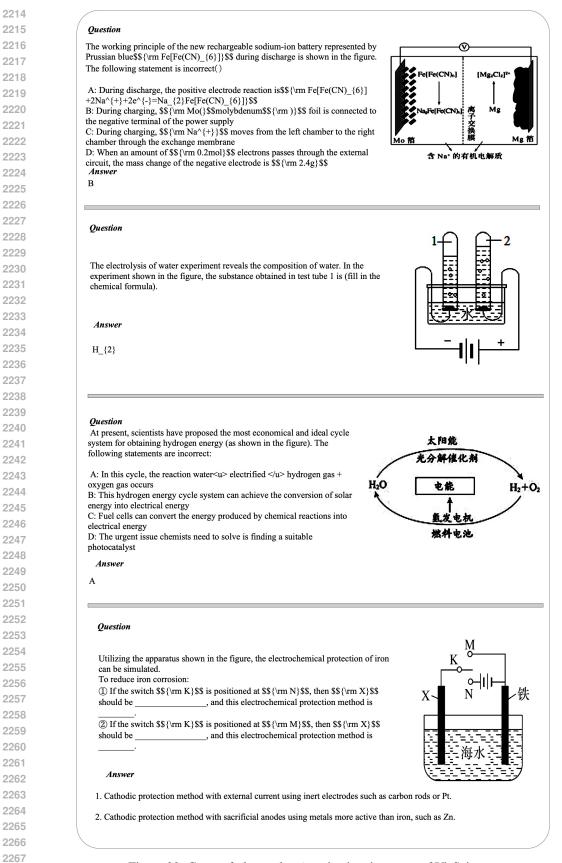


Figure 23: Cases of *electrochemistry* in chemistry part of VisScience.

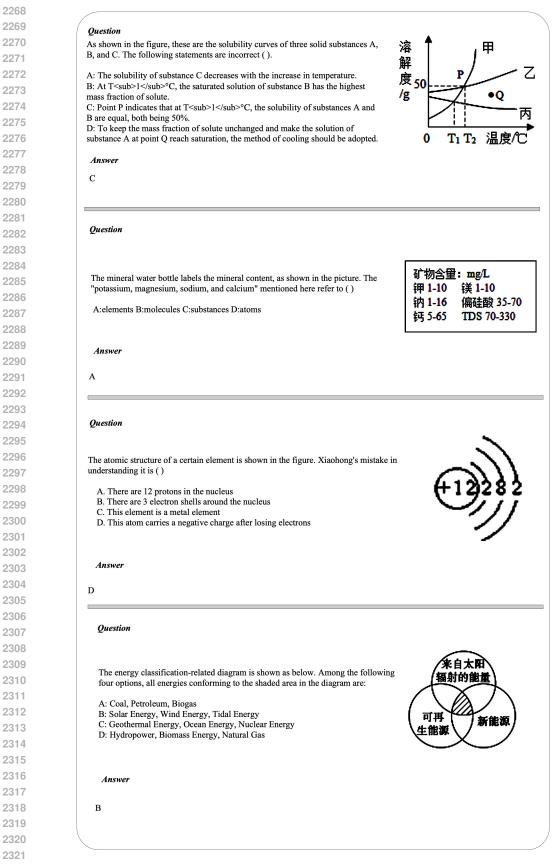


Figure 24: Cases of substance composition in chemistry part of VisScience.

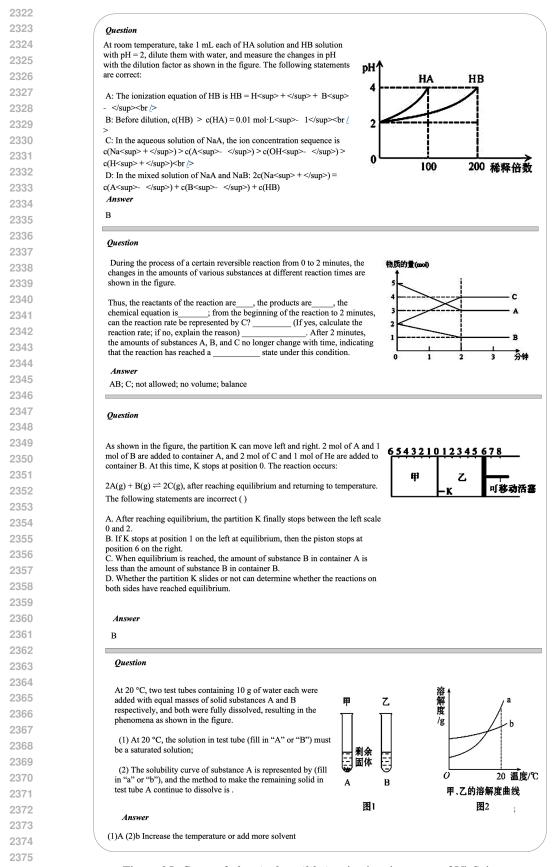
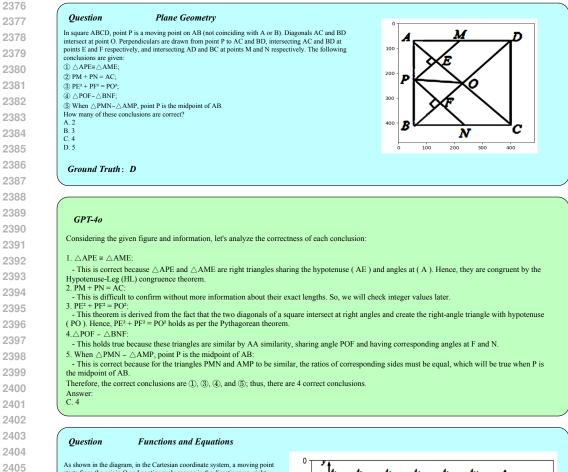
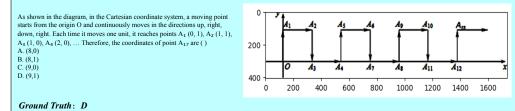


Figure 25: Cases of *chemical equilibrium* in chemistry part of VisScience.





2412	
2413	GPT-40
2414	Let's analyze the movement pattern of the point:
2415	1. A ₁ (0, 1) 2. A ₂ (1, 1)
2416	3. A ₃ (1, 0)
2417	4. A ₄ (2, 0) Based on these four steps, it repeats as a cycle:
2417	- Moving up: y increases by 1. - Moving right: x increases by 1.
	- Moving down: y decreases by 1.
2419	- Moving right: x increases by 1. So every 4 moves, the point completes one cycle. Each cycle results in an increase of the x-coordinate by 2 and leaves the y-coordinate either at 0 or 1
2420	depending on the position within the cycle.
2421	Since we need to find A ₁₇ , we first determine which part of the cycle the 17th move falls into: - Cycle length: 4 moves
2422	- Number of completed cycles in 16 moves: floor(16 / 4) = 4 - Residual moves after 4 cycles: 17 - 16 = 1
2423	Each complete cycle increases x by 2:
2424	- After 4 complete cycles: 4 * 2 = 8 The 17th move is the first move in the 5th cycle:
2425	- The point moves up from (8, 0) to (8, 1) Thus, the coordinates of A ₁₇ are (8, 1).
2426	The correct answer is:
2427	B. (8, 1)

Figure 26: A question, the standard answer, and GPT-4o's correct response from the mathematical part in VisScience.

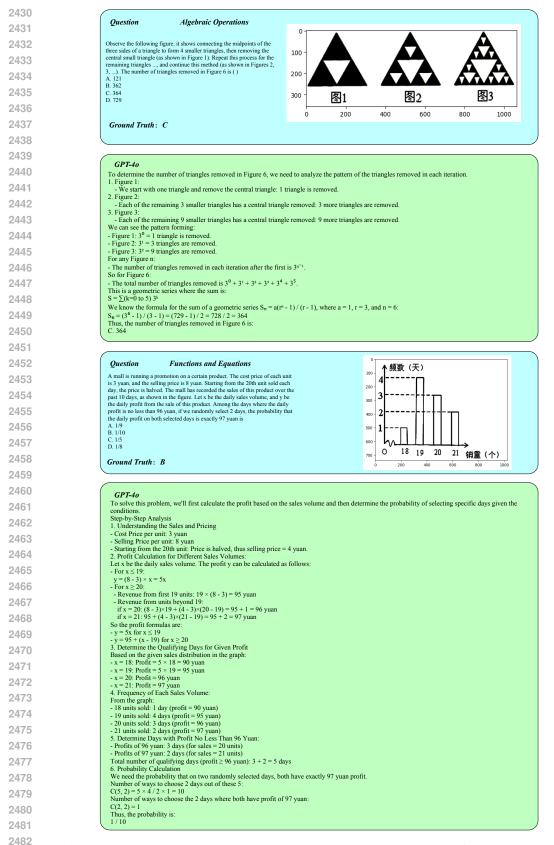


Figure 27: A question, the standard answer, and GPT-4o's correct response from the mathematical part in VisScience.

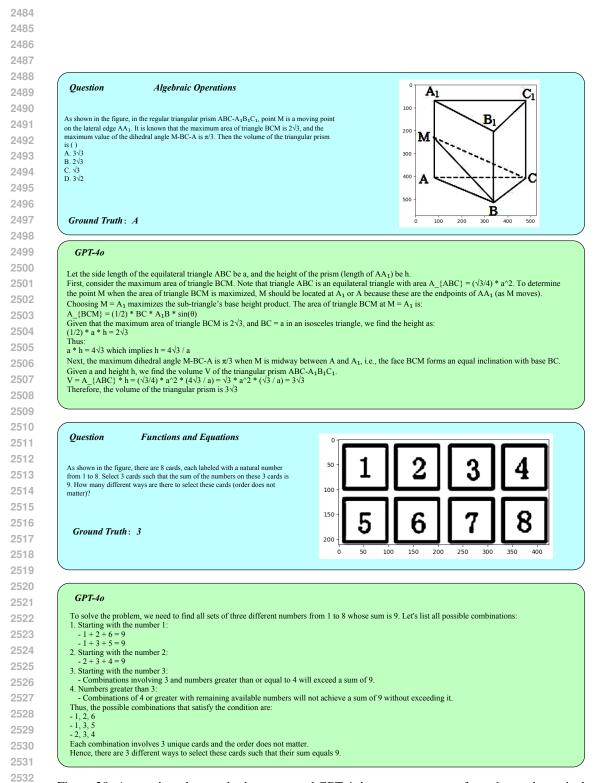


Figure 28: A question, the standard answer, and GPT-4o's correct response from the mathematical part in VisScience.

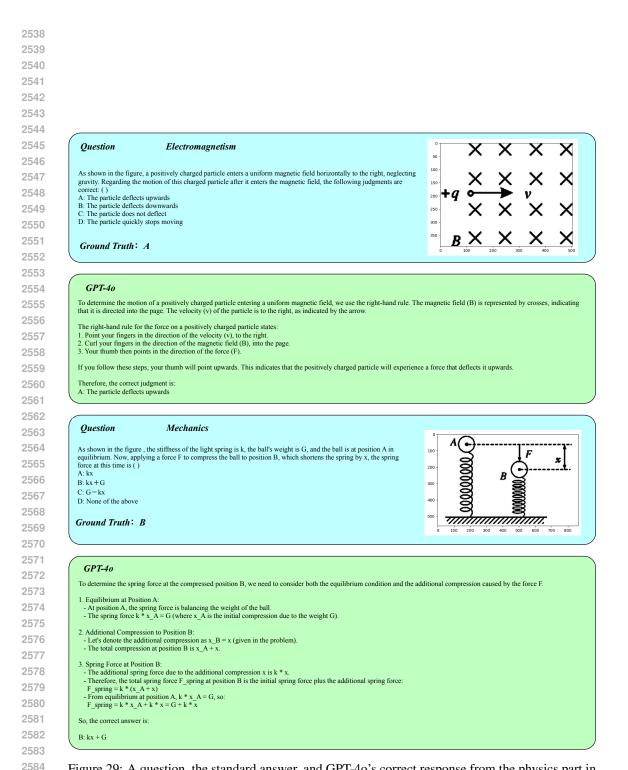


Figure 29: A question, the standard answer, and GPT-4o's correct response from the physics part in VisScience.

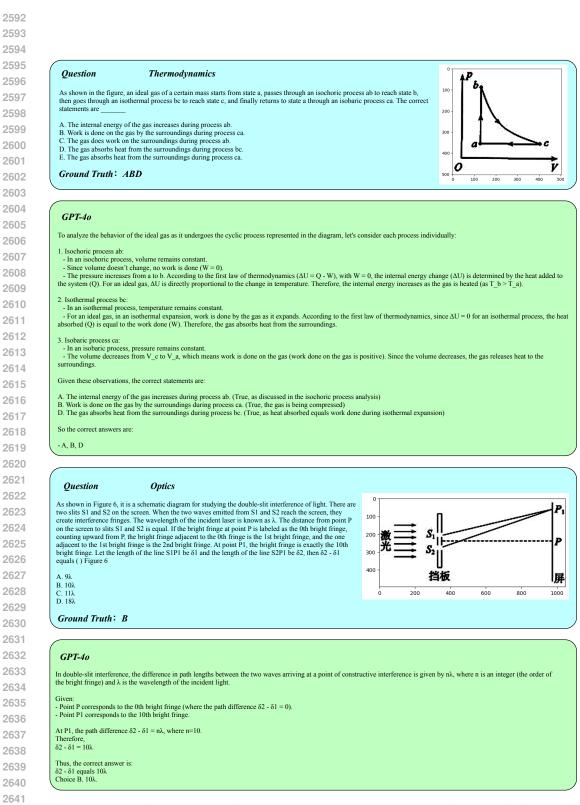
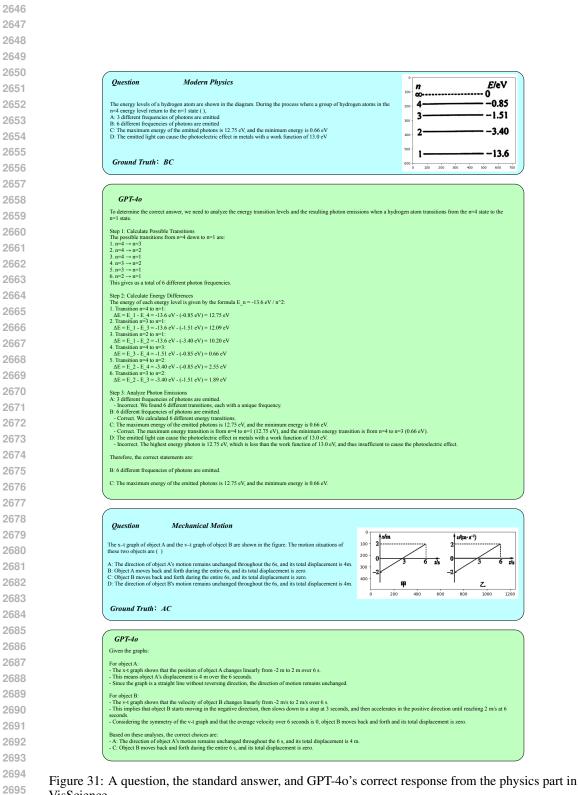


Figure 30: A question, the standard answer, and GPT-4o's correct response from the physics part in VisScience.



VisScience.

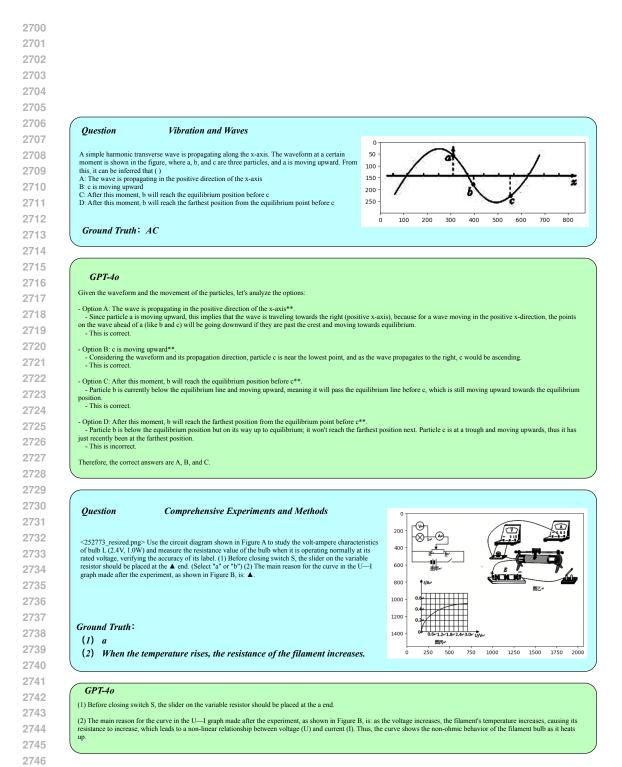
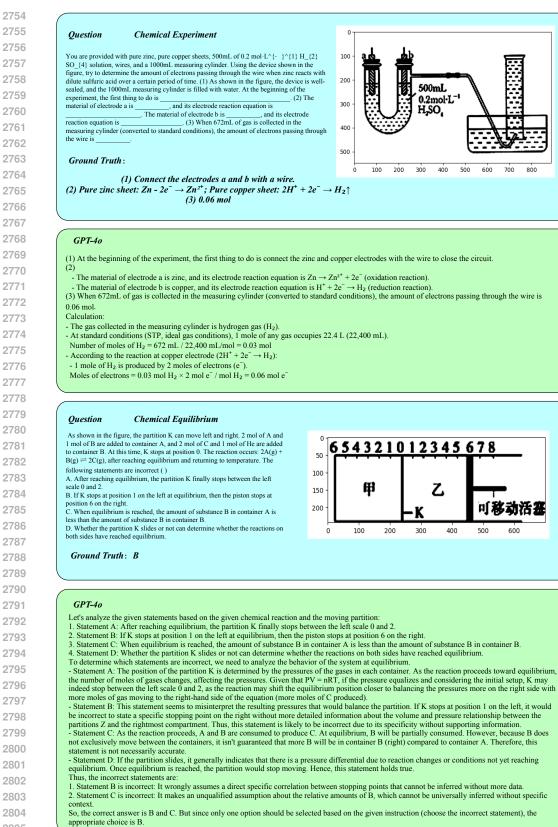


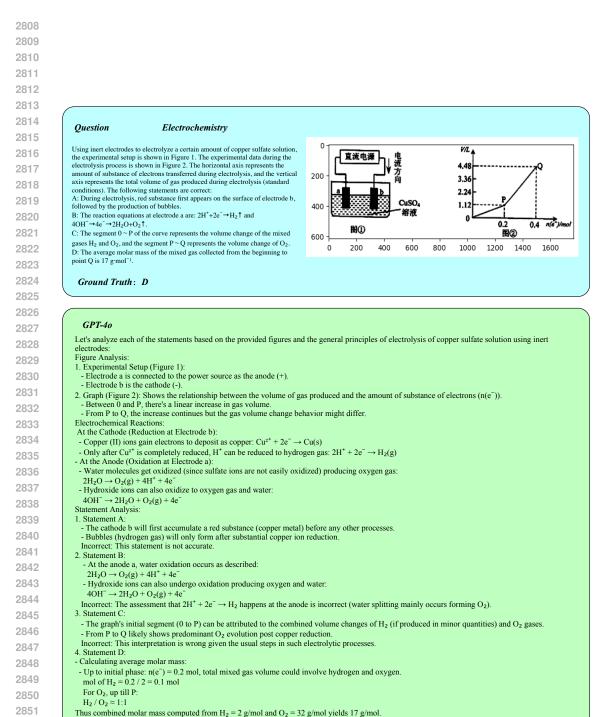
Figure 32: A question, the standard answer, and GPT-4o's correct response from the physics part in VisScience.



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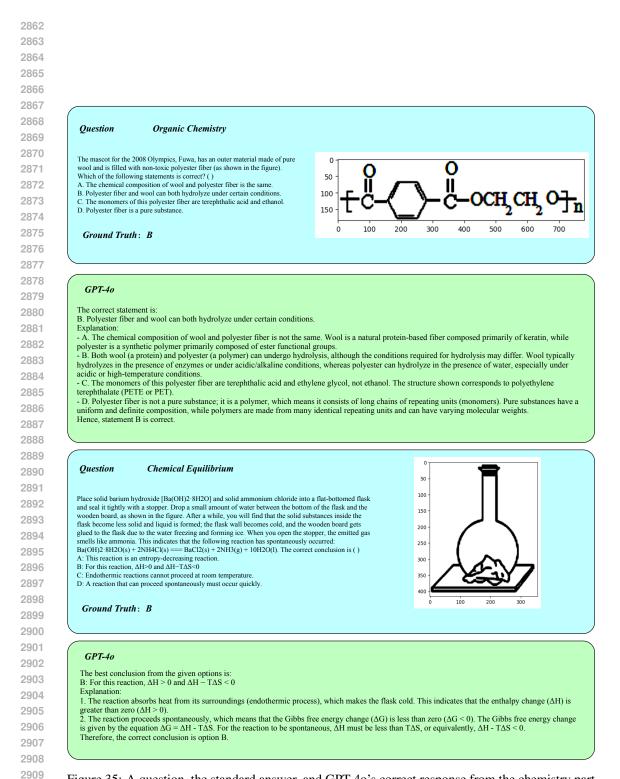
Figure 33: A question, the standard answer, and GPT-4o's correct response from the chemistry part in VisScience.

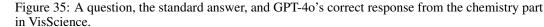


Conclusion: - Correct Statements: D

Figure 34: A question, the standard answer, and GPT-4o's correct response from the chemistry part in VisScience.

Correct: This matches the derived amounts from mixed gas estimations





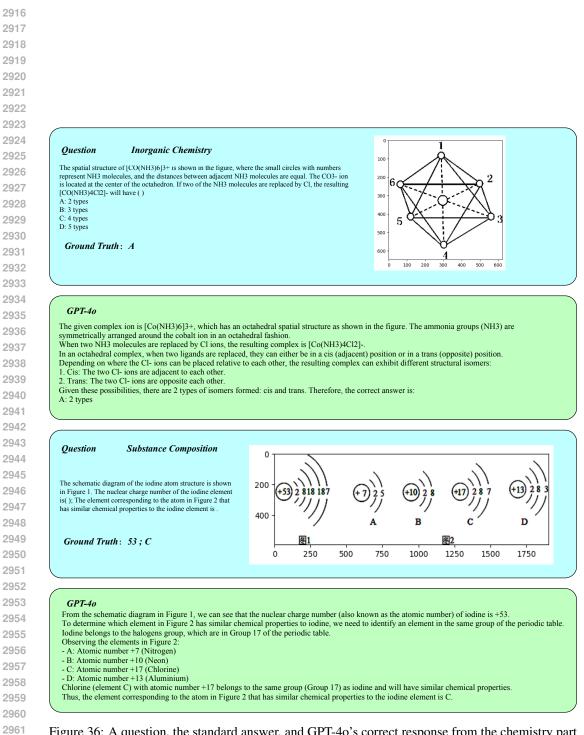


Figure 36: A question, the standard answer, and GPT-4o's correct response from the chemistry part in VisScience.

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3014 3015 3016

3017 3018

Question 0 Given a tetrahedron ABCD whose four vertices are the vertices of a cuboid (the cuboid is an 200 imaginary figure used as an auxiliary), which of the following sequences represents the front view, left view, and top view of the tetrahedron ABCD (using 123456 to represent the diagrams)? 400 A. 126 B. 123 600 C. (4)(5)(6) D. 345 800 400 600

Ground Truth: B

GPT-40 Vision Recognition Error

Based on the tetrahedron (ABCD) in the image and considering the auxiliary structure of the cuboid to determine the front view, left view, and top view:

200

800 1000 1200 1400 1600

1. Front view: When viewed from the front, vertex (C) is at the top, and vertices (A) and (D) are at the bottom (this should be diagram (3)).

2. Left view: When viewed from the left, vertex (C) is at the top, vertex (B) is on the left, and vertex (D) is on the right (this should be diagram (1)).

3. Top view: When viewed from above, vertex (C) is on one side, and vertices (A) and (B) are on the lower side (this should be diagram (5)).

Therefore, the answer is D. 345.

Claude3.5 Vision Recognition Error

To answer this question, we need to analyze the given tetrahedron ABCD within the rectangular prism and determine which views correspond to the front, left, and top views.Looking at the tetrahedron ABCD:

The front view would be the projection onto the plane perpendicular to the 5-unit edge of the prism.

The left view would be the projection onto the plane perpendicular to the 3-unit edge of the prism.
 The top view would be the projection onto the plane perpendicular to the 4-unit edge of the prism.

Now, let's examine the given projections

① (labeled 4) shows a 4x3 rectangle with both diagonals.② (labeled 5) shows a 5x4 rectangle with both diagonals.③ (labeled 3) shows a 5x3 rectangle with one diagonal. (4) (labeled 5) shows a 5x4 rectangle with one diagonal. (5) (labeled 3) shows a 4x3 rectangle with one diagonal. (6) (labeled 3) shows a 5x3 rectangle with both diagonals.

Based on this analysis: - The front view corresponds to ④ (5x4 rectangle)

- The left view corresponds to (5) (4x3 rectangle)

- The top view corresponds to (6) (5x3 rectangle)

Therefore, the correct answer is D. 345

Qwen-VL-Max Vision Recognition Error

The answer is D. (3)(4)(5)

To find the front view, left view, and top view of the tetrahedron ABCD, we need to look at how the faces of the tetrahedron intersect with each other when viewed from different angles.

- Front view: When looking directly at the face ABDC, we see that it intersects with the face ADCB to form a rectangle. This is represented by ③. - Left view: When looking at the side face ADCB, we see that it intersects with the face ADDB to form a rectangle. This is represented by ④.

- Top view: When looking down on the top face ABDC, we see that it intersects with the face ADDB to form a triangle. This is represented by (5).

Therefore, the correct answer is D. (3)(4)(5)

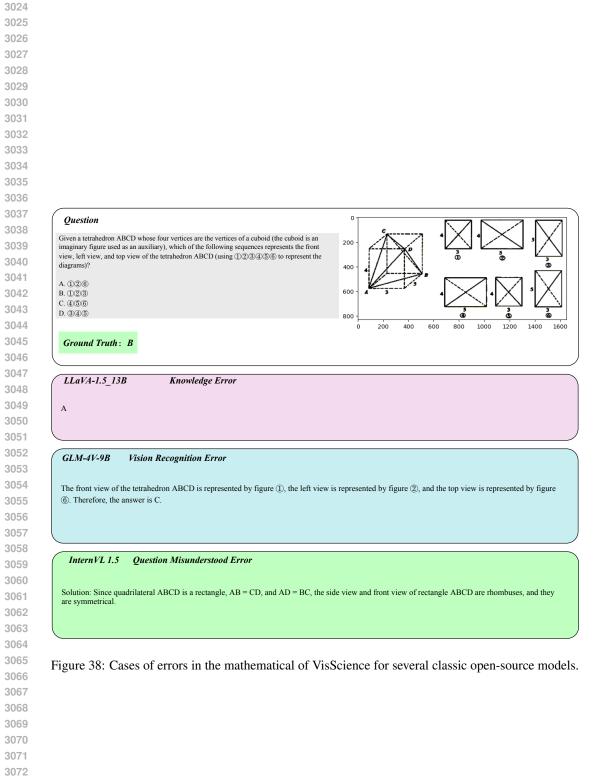
GLM-4V Vision Recognition Error

The front view of the tetrahedron ABCD is represented by figure ①, the left view is represented by figure ②, and the top view is represented by figure (6). Therefore, the answer is C.

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3022

Figure 37: Cases of errors in the mathematical of VisScience for several classic close-source models. 3023



B. The number of people taking the bus accounts for 50% of the total.

- Combined statement not provided, based on the available statements.

Calculation Error

1. The first bar (步行, which means "walking" or pedestrians) shows 60 people.

3. The third bar (乘公共汽车, which means "taking the bus") shows 150 people.

Vision Recognition Error

Ouestion Misundetstood Error

2. The second bar (骑自行车, which means "cycling") shows 90 people.

Therefore, the best answer among the given options is D.

Based on the bar graph shown in the image, the correct statement is:

- False. The number of pedestrians is 60. D. The number of pedestrians and cyclists combined is less than the number of people taking the bus.

D. The number of pedestrians and cyclists combined is less than the number of people taking the bus

- True. Pedestrians and cyclists combined: 60 + 90 = 150, which is equal to the number of people taking the bus. Not less.

C. The number of pedestrians is 50 people

Let's analyze the data from the graph:

E.

Claude3.5

riders.

Qwen-VL-Max

GLM-4V

The correct answer is A

Therefore, the correct statement is A

The number of pedestrians is at least 90 people

3128 3129

3130 3131

Figure 39: Cases of errors in the mathematical of VisScience for several classic close-source models.

Question 사람 100 As shown in the figure, the correct statement is () 150 200 120 A. The minimum number of people walking is only 90. 300 B. The number of people taking the bus accounts for 50% of the total 90 C. The number of people walking is 50. D. The combined number of people walking and cycling is less than the number of people taking the bus 40 60 500 30 60 **\$1**i 骑自行车 未公共汽车 Ground Truth: B 100 200 300 400 500 600 700 GPT-40 **Ouestion Misunderstood Error** Let's analyze the bar chart. - The first bar (步行, which translates to 'walking' or 'pedestrians') is at 60. - The second bar (骑自行车, which translates to 'cycling' or 'cyclists') is at 90. - The third bar (乘公共汽车, which translates to 'taking the bus') is at 150 Now, let's evaluate each statement: A. The number of pedestrians is at least 90 people. - False. The number of pedestrians is 60.

- False. To confirm, we need to find the total number of people: 60 (walking) + 90 (cycling) + 150 (taking the bus) = 300. 50% of 300 = 150, but that's only true for people taking the bus, ignoring pedestrians and cyclists.

None of the options from A to D are correct based on careful evaluation. Hence, the correct typical choice should be reviewed for consistency

When we add the number of pedestrians (60) and cyclists (90), we get 150. This is equal to, not less than, the number of people taking the bus (150). However, the question asks for the correct statement, and option D is the closest to being correct, as the combined number is not greater than the bus

Based on the information provided in the image, we can see that the number of pedestrians is represented by the first bar graph, which has a value

greater than or equal to 60 but less than or equal to 90. Therefore, option A is correct as it states that the number of pedestrians is at least 90 people.

Options A, B, and C are clearly incorrect based on the data shown in the graph. Option E is empty, so it cannot be the correct answer

Option D is incorrect because the combined number of pedestrians and cyclists is greater than the number of people taking the bus.

Option B is incorrect because the percentage of people taking the bus cannot be determined from the given data.

Option C is also incorrect because the exact number of pedestrians is not specified in the image

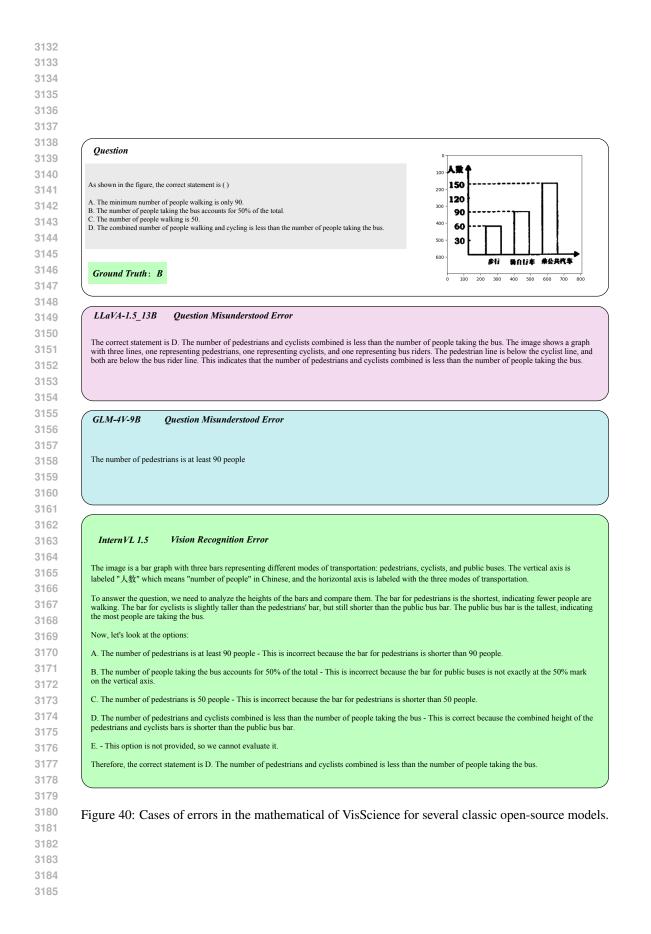
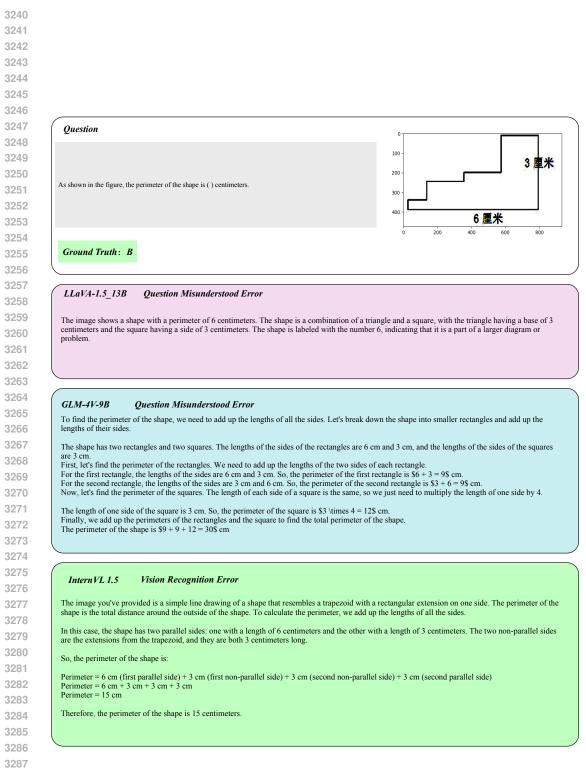
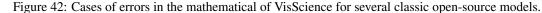




Figure 41: Cases of errors in the mathematical of VisScience for several classic close-source models.





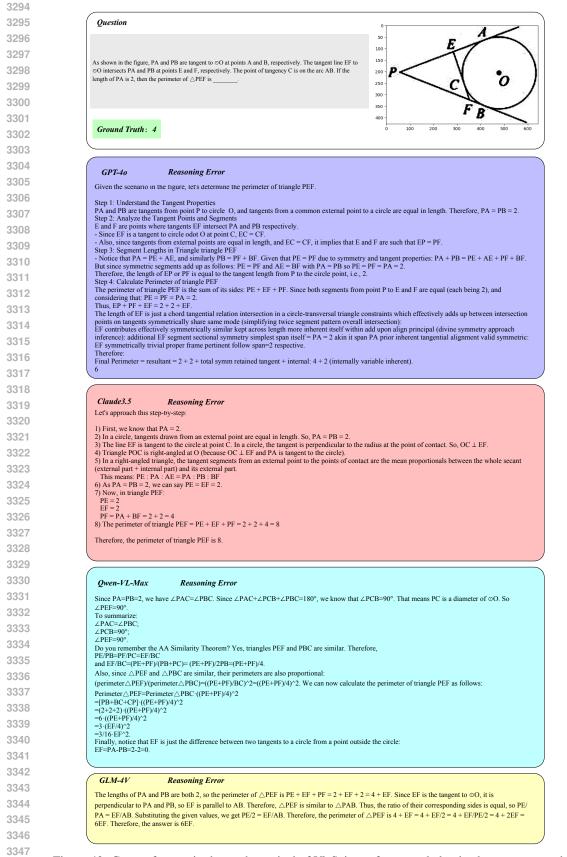
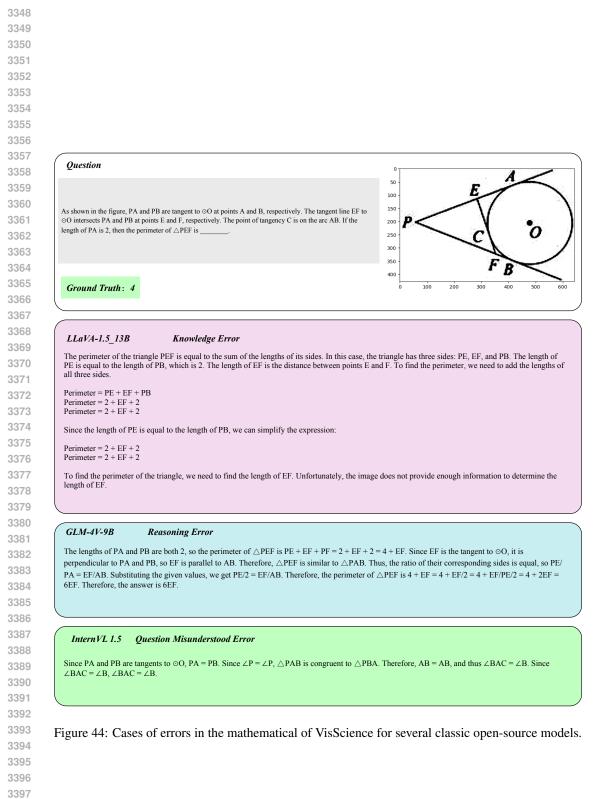


Figure 43: Cases of errors in the mathematical of VisScience for several classic close-source models.



Knowledge Error

Vision Recognition Error

Calculation Error

Knowledge Error

100

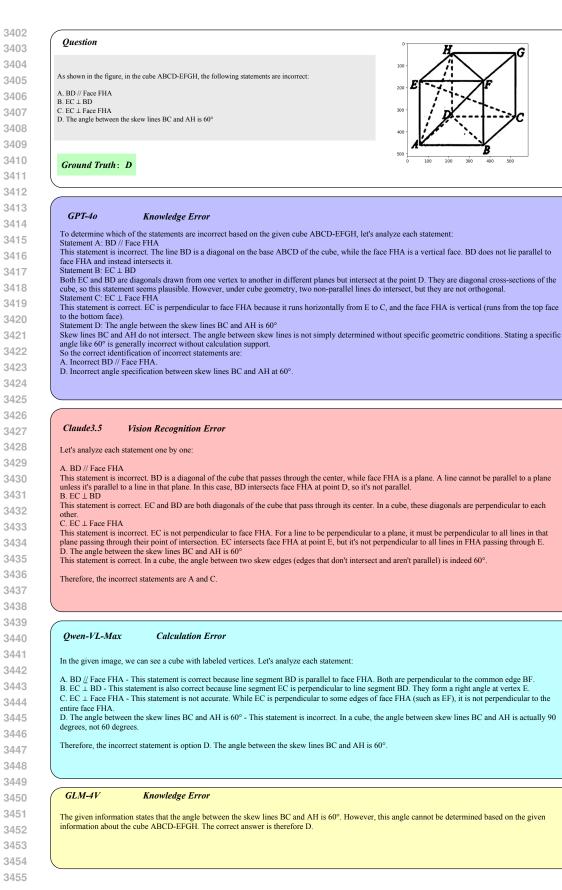
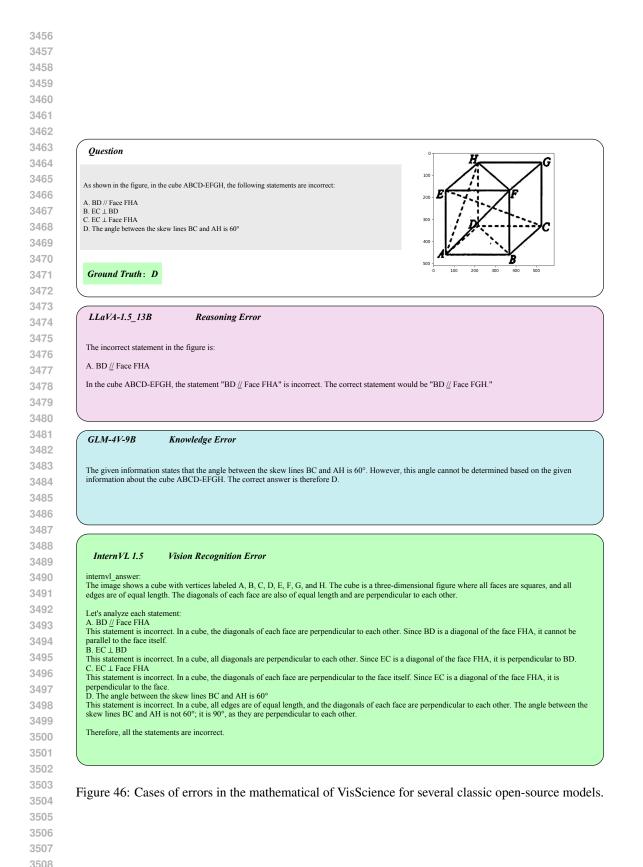
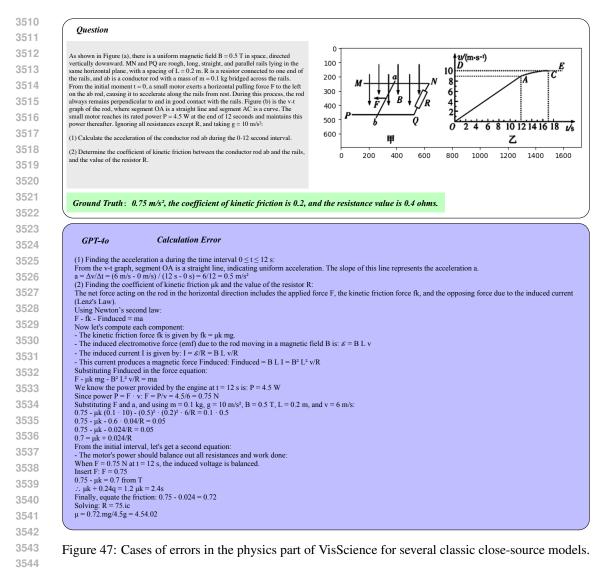
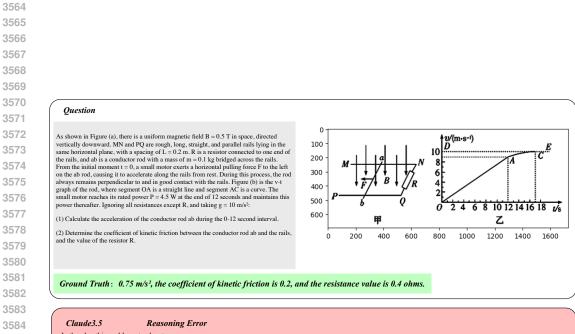


Figure 45: Cases of errors in the mathematical of VisScience for several classic close-source models.







3585Let's solve this problem step by step: 1) To find the acceleration during the 0-12s interval: From the v+1 graph, we can see that the velocity increases linearly from 0 to 9 m/s in 12 seconds. Acceleration = change in velocity / time a = $(9 - 0)/12 = 0.75$ m/s²35862) To find the coefficient of kinetic friction and the value of resistor R: First, let's consider the forces acting on the rod: - Traction force F = µmg (where µ is the coefficient of friction) - Magnetic force FB = BLv (where B is the magnetic field, L is the length of the rod, and v is the velocity)3590The equation of motion is: F - f - FB = ma Att = 12s, v = 9 m/s and a = 0.75 m/s²3591F = PV = 4.5/9 = 0.5 N (as Power = Force * Velocity) 0.5 - umg = BLv (where P = force * Velocity) 0.5 - 0.1 µ*10 - 0.5*0.2*9 = 0.9 V The current in the circuit 1 = FBR = BL/v = 0.9/R The power dissipated in the resistor = FR = (0.9/R)*R = 0.81/R Att = 12s, this should equal the motor's power: 0.81/R = 4.5 Solving this: µ = 0.18 Ω	0001	
3586From the v-t graph, we can see that the velocity increases linearly from 0 to 9 m/s in 12 seconds. Acceleration = change in velocity / time a = (9 - 0) / 12 = 0.75 m/s ² 35872) To find the coefficient of kinetic friction and the value of resistor R: First, lefs consider the forces acting on the rod: - Traction force F3588- Friction force f = µmg (where µ is the coefficient of friction) - Magnetic force FB = BLv (where B is the magnetic field, L is the length of the rod, and v is the velocity)3590The equation of motion is: F - f - FB = ma A t1 = 12s, v = 9 m/s and a = 0.75 m/s ² 3591F = P/v = 4.5/9 = 0.5 N (as Power = Force * Velocity)35920.5 - µmg = BLv = ma 0.5 - 0.1 # ¹⁰ 0.05 0.2 ² 9 = 0.1 ⁴ 0.7.53593Solving this: µ = 0.35Now, the induced EMF = BLv (w = 0.5*0.2 ² 9 = 0.9 V The current in the circuit 1 = FP/R = BLv/R = 0.9/R3594The power dissipated in the resistor = PR = (0.9/R) ² R = 0.81/R At t = 12s, this should equal the motor's power: 0.81/R = 4.5 Solving this: R = 0.18 Ω	3585	
$\begin{array}{llllllllllllllllllllllllllllllllllll$	3586	From the v-t graph, we can see that the velocity increases linearly from 0 to 9 m/s in 12 seconds.
$ \begin{array}{lll} \textbf{3588} & First, lefs consider the forces acting on the rod: \\ & - Traction force F = \mumg (where \mu is the coefficient of friction) \\ & - Friction force F = B = BL v (where B is the magnetic field, L is the length of the rod, and v is the velocity) \\ \textbf{3590} & - Herrichican force F = B = BL v (where B is the magnetic field, L is the length of the rod, and v is the velocity) \\ The equation of motion is: F - f - FB = ma \\ Att = 12s, v = 9 m/s and a = 0.75 m/s^2 \\ \textbf{3591} & F = P/v = 4.5/9 = 0.5 N (as Power = Force * Velocity) \\ 0.5 - \mumg - BLv = ma \\ \textbf{3592} & 0.5 - 0.1\mu^{+10} - 0.5^{+}0.2^{+}9 = 0.1^{+}0.75 \\ \textbf{3593} & \textbf{Solving this: } \mu = 0.35 \\ \textbf{3594} & \textbf{The current in the circuit 1 = FB/R = BLv/R = 0.9/R \\ The power dissipated in the resistor = PR = (0.9/R)^{-}R = 0.81/R \\ Att = 12s, this should equal the motor's power: 0.81/R = 4.5 \\ \textbf{Solving this: } R = 0.18 \Omega \\ \end{array} $	3587	
$ \begin{array}{lll} 3589 & - \mbox{Friction force } f = \mbox{\mumg} (\mbox{where } \mu \mbox{ is the coefficient of friction}) \\ - \mbox{Magnetic force } FB = BL \ (\mbox{where } B \ \mbox{is the magnetic field, } L \ \mbox{is the length of the rod, and } v \ \mbox{is the velocity}) \\ The equation of motion \ \mbox{is } F \ - \ F \ - \ FB = ma \\ At t = 12s, v = 9 \ \mbox{m/s and } a = 0.75 \ \mbox{m/s}^2 \\ F = P/v = 4.5/9 = 0.5 \ \mbox{N} (\mbox{as Power} = \mbox{Force } * \mbox{Velocity}) \\ 0.5 \ \ \mbox{mmg} - BLv = ma \\ 0.5 \ - \ 0.1\mu^{*}10 \ - \ 0.5^{*}0.2^{*}9 = 0.1^{*}0.75 \\ Solving \ \mbox{this } \mu = 0.35 \\ Solving \ \mbox{this } \mu = 0.35 \\ Now, \ \mbox{the induced EMF} = BLv = 0.5^{*}0.2^{*}9 = 0.9 \ \mbox{V} \\ The current in the circuit 1 = FB/R = BLv/R = 0.9/R \\ The power \ \mbox{dissipated in the resistor } = \ \mbox{R} = (0.9/R)^{*}R = 0.81/R \\ At t = 12s, \ \mbox{this suble dqual the motor's power} \ \ 0.81/R = 4.5 \\ Solving \ \mbox{this } R = 0.18 \ \Omega \\ \end{array}$	3588	First, let's consider the forces acting on the rod:
$ \begin{array}{lll} 3590 & \mbox{The equation of motion is: } F - F - FB = ma \\ 3591 & \mbox{Att} = 12s, v = 9 m/s \mbox{ and } a = 0.75 \mbox{ m/s}^2 \\ 3591 & \mbox{F} = P/v = 4.5/9 = 0.5 \mbox{ N} (as Power = Force * Velocity) \\ 0.5 - \mu mg = BLv = ma \\ 0.5 - 0.1 \mbox{ m/s} = 0.05 \mbox{ 0.2 } 9 = 0.1 \mbox{ m/s} 0.2 \\ 0.5 - 0.1 \mbox{ m/s} 0.2 \mbox{ m/s} 0.2 \\ 0.5 - 0.1 \mbox{ m/s} 0.2 \\ 0.5 \mbox{ m/s} 0.2$	3589	- Friction force $f = \mu mg$ (where μ is the coefficient of friction)
$ \begin{array}{lll} 3591 & F = P/v = 4.5/9 = 0.5 \ N \ (as \ Power = \ Force \ * \ Velocity) \\ 0.5 - \mu mg = BLv = ma \\ 0.5 - 0.1\mu^{+10} - 0.5^{+0} 0.2^{+9} = 0.1^{+0} 0.75 \\ \text{Solving this: } \mu = 0.35 \\ \text{Solving this: } \mu = 0.35 \\ \text{Now, the induced EMF } = BLv = 0.5^{+0} .2^{+9} = 0.9 \ V \\ \text{The current in the circuit } I = FB/R = BLv/R = 0.9/R \\ \text{The power dissipated in the resistor } = PR = (0.9/R)^{2}R = 0.81/R \\ \text{At } t = 12, \text{this should equal the motor's power: } 0.81/R = 4.5 \\ \text{Solving this: } R = 0.18 \ \Omega \\ \end{array} $	3590	The equation of motion is: F - f - FB = ma
$ \begin{array}{lll} 3592 \\ 0.5 & - 0.1 \mu^* 10 & - 0.5^* 0.2^* 9 & = 0.1^* 0.75 \\ \text{Solving this: } \mu & = 0.35 \\ \text{Solving this: } \mu & = 0.35 \\ \text{Now, the induced EMF} & = BL_V & = 0.5^* 0.2^* 9 & = 0.9 \text{ V} \\ \text{The current in the circuit } 1 & = FB/R & = BL_V/R & = 0.9/R \\ \text{The power dissipated in the resistor } & = 1^PR & = (0.9/R)^2R & = 0.81/R \\ \text{At } t & = 12s, this should equal the motor's power: } 0.81/R & = 4.5 \\ \text{Solving this: } R & = 0.18 \Omega \\ \end{array} $	3591	F = P/v = 4.5/9 = 0.5 N (as Power = Force * Velocity)
3593Now, the induced EMF = BLv = $0.5*0.2*9 = 0.9$ V3594The current in the circuit I = FB/R = BL·/R = $0.9/R$ 3595The power dissipated in the resistor = I'R = $(0.9/R)^2R = 0.81/R$ 3595At t = 12s, this should equal the motor's power: $0.81/R = 4.5$ Solving this: R = 0.18Ω	3592	$0.5 - 0.1\mu * 10 - 0.5*0.2*9 = 0.1*0.75$
3594The power dissipated in the resistor = $I^{PR} = (0.9/R)^{2}R = 0.81/R$ 3595At t = 12s, this should equal the motor's power: $0.81/R = 4.5$ Solving this: $R = 0.18 \Omega$	3593	
3595 At $t = 12s$, this should equal the motor's power: $0.81/R = 4.5$ Solving this: $R = 0.18 \Omega$	3594	
	3595	At $t = 12s$, this should equal the motor's power: $0.81/R = 4.5$
	3596	

Qwen-VL-Max Knowledge Error

The image you provided appears to be a combination of two separate diagrams or figures labeled as "\P" and "\Z". However, your question seems to describe a physics problem involving a conducting rod sliding on parallel rails under the influence of a magnetic field and an applied force, rather than providing a visual representation of the scenario. Here's a solution to the problem you've described: (1) Acceleration of the conductor rod ab during the 0-12s interval: To find the acceleration, we need more information about the forces acting on the rod. Please provide additional details such as the magnitude of the current flowing through the rod, if any, and the nature of the interaction between the rod and the magnetic field.

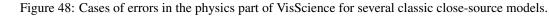
(2) Coefficient of kinetic friction between rold and the rails, and the rails, and the resistor R: Again, we need more information about the forces involved. In particular, we would need to know the values of the frictional force and the induced electromotive force (EMF) due to the motion of the rod in the magnetic field. Please provide these details so that we can proceed with the calculation.

Reasoning Error

GLM-4V

Solution:

> (1) Since B = 0.5 T and F = 4.5 W, we have μ = F/B = 4.5 W / 0.5 T = 9 N/T. Therefore, the acceleration of the conductor rod ab during the 0-12 s interval can be calculated as a = μ/m = 9 N/T / 0.1 kg = 90 m/s². (2) According to the given information, we know that R is the only resistance in the circuit, so I = U/R and $P = I^2 R$. When the motor reaches its rated power, we have P = 4.5 W and I = 4.5 W/R. Solving for R, we get $R = 4.5 \text{ W}/I = 4.5 \text{ W}/R = 10\Omega$.



3618 3619 3620 3621 3622 Ouestion As shown in Figure (a), there is a uniform magnetic field B = 0.5 T in space, directed vertically downward. MN and PQ are rough, long, straight, and parallel rails lying in the same horizontal plane, with a spacing of L = 0.2 m. R is a resistor connected to one end of the rails, and a bis a conductor of with a mass of m = 0.1 kg bridged across the rails. From the initial moment t = 0, a small motor exerts a horizontal pulling force F to the left on the abrid, causing it to accelerate along the rails from rescues. During this process, the rod always remains perpendicular to and in good contact with the rails. Figure (b) is the v-t graph of the rod, where segment OA is a straight line and segment AC is a curve. The small motor reaches is rated power P = 4.5 W at the end of 12 seconds and maintains this power threafter. Ignoring all resistances except R, and taking g = 10 m/s²: 0 D/(m·s-1) 3624 100 E 10 3625 200 r 3626 300 3627 400 3628 500 o 4 10 12 14 16 18 1/5 6 600 3629 (1) Calculate the acceleration of the conductor rod ab during the 0-12 second interval. Z Ħ 3630 (2) Determine the coefficient of kinetic friction between the conductor rod ab and the rails, 400 1000 1200 1400 1600 0 200 600 800 and the value of the resistor R. 3631 3632 3633 Ground Truth: 0.75 m/s², the coefficient of kinetic friction is 0.2, and the resistance value is 0.4 ohms. 3634 3635 LLaVA-1.5 13B Knowledge Error 3636 (1) To find the acceleration of the conductor rod ab during the 0-12s interval, we can use the equation: 3637 where F is the traction force, m is the mass of the rod, and a is the acceleration. Since the rod is moving along the rails, we can assume that the force is constant 3638 during this time. The traction force is given as: F = P / R3639 where P is the power of the motor and R is the resistance of the rod. Substituting this into the equation above, we get: 3640 P/R = maSince the motor reaches its rated power of 4.5W at the end of 12s, we can find the average power during this interval: $P_avg = (P_max - P_min) / \Delta t = (4.5W - 0W) / 12s = 0.375W$ 3641 Now, we can find the acceleration: $a = F / m = P_avg / m = 0.375W / 0.1kg = 375m/s^2$ 3642 (2) To find the coefficient of kinetic friction between rod ab and the rails, we can use the equation: 3643 friction = $\mu * F$ where F_friction is the frictional force, μ is the coefficient of kinetic friction, and F is the traction force. Since the rod is moving along the rails, we can assume that the frictional force is constant during this time. The traction force is given as: F = P / R 3644 3645 Substituting this into the equation above, we get: $F_{friction} = \mu * (P / R)$ 3646 Since the motor maintains constant power after 12s, we can find the average power during this interval: $P_avg = (P_max - P_min) / \Delta t = (4.5W - 0W) / 12s = 0.375W$ Now, we can find the coefficient of kinetic friction: 3647 3648 $\mu = F_{friction} / F = (P_{avg} / R) / (P / R)$ 3649 3650 GLM-4V-9B Reasoning Error 3651 (1) The graph in Figure B shows the velocity-time (v-t) relationship of the conductor rod ab. The OA segment is a straight line, indicating a constant acceleration. The slope of the OA segment is the acceleration of the rod, which can be calculated using the formula: a = (v2 - v1) / (t2 - t1)3652 Given that v1 = 0 (initial velocity is zero), v2 = v (final velocity), and t1 = 0 (start time), and t2 = 12 seconds (end time), the acceleration a can be calculated as: 3653 = v / 12 The graph shows that the final velocity v of the rod is 8 m/s, so the acceleration a is: 3654 $a = 8 / 12 = 2/3 \text{ m/s}^{2}$ (2) The graph in Figure B also shows that the traction force's power P is constant after 12 seconds. The power P is given by the formula: 3655 stant after 12 seconds, we can equate the power before and after 12 seconds. 3656 Since the power is con P = F * v1.P = F * 03657 This implies that the traction force F is zero before 12 seconds. Therefore, the coefficient of kinetic friction µ between the rod ab and the rails can be calculated using the formula: $\mu = F / N$ 3658 Since the traction force F is zero, the normal force N can be calculated using the formula: · mg Substituting the given values 3660 $N = 0.1 \text{ kg} * 10 \text{ m/s}^2 = 1 \text{ N}$ Now we can calculate the coefficient of kinetic friction: 3661 = 0 / 1 = 0 $\mu = 0 / 1 = 0$ The value of the resistor R can be calculated using the formula: 3662 3663 Since the power P is constant and the traction force F is zero, the current I can be calculated using Ohm's law = V / R

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Substituting the given values: I = 4.5 W / 1 V = 4.5 ANow we can calculate the value of the resistor R $R = 4.5 W / (4.5 A)^2 = 4.5 W / 20.25 = 0.225 ohm$

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Figure 49: Cases of errors in the physics part of VisScience for several classic open-source models.

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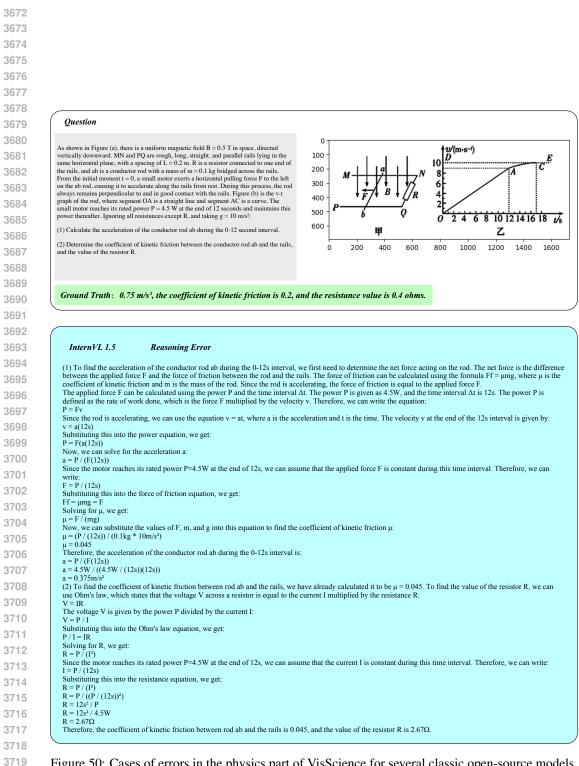
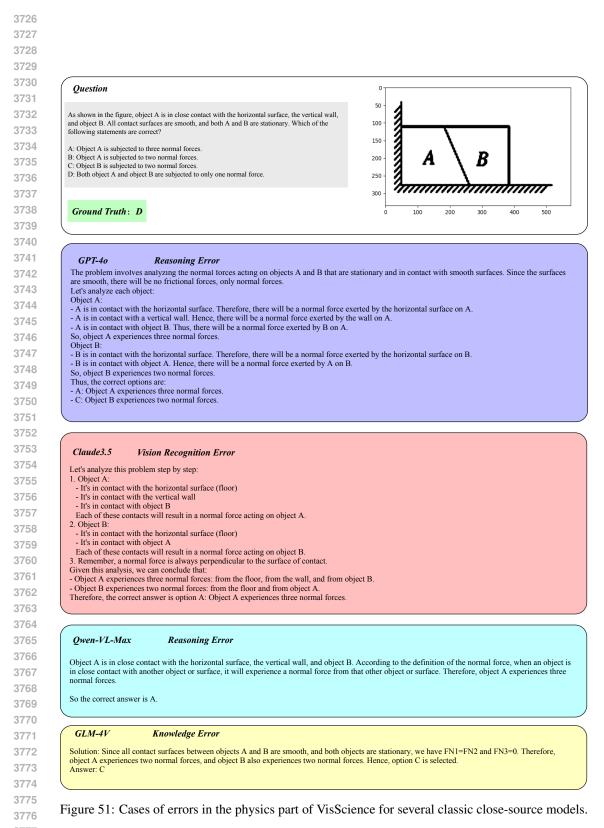
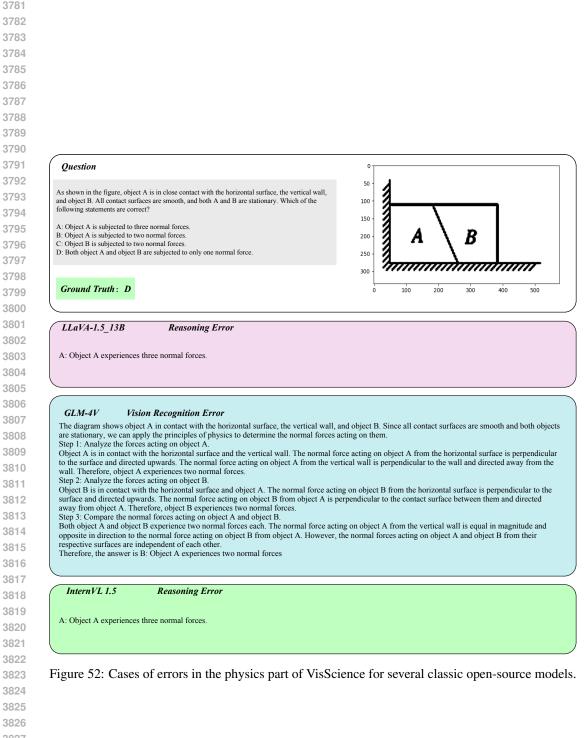


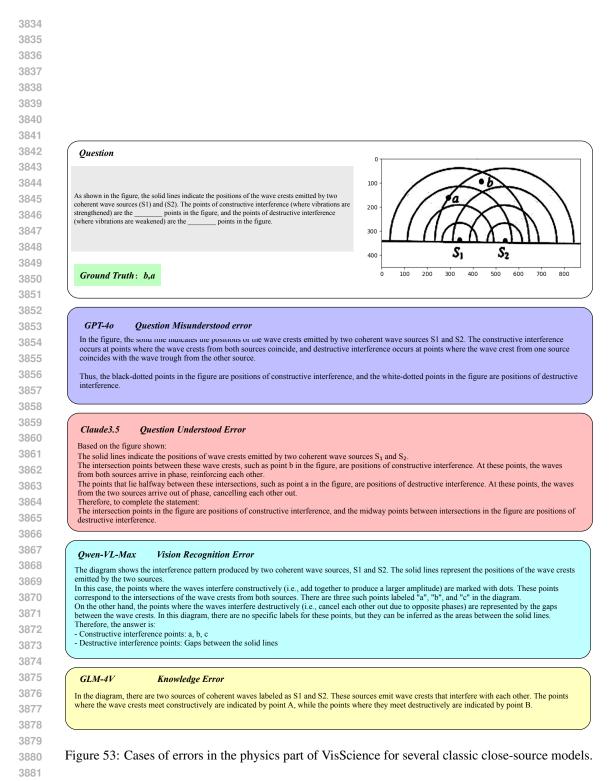


Figure 50: Cases of errors in the physics part of VisScience for several classic open-source models.

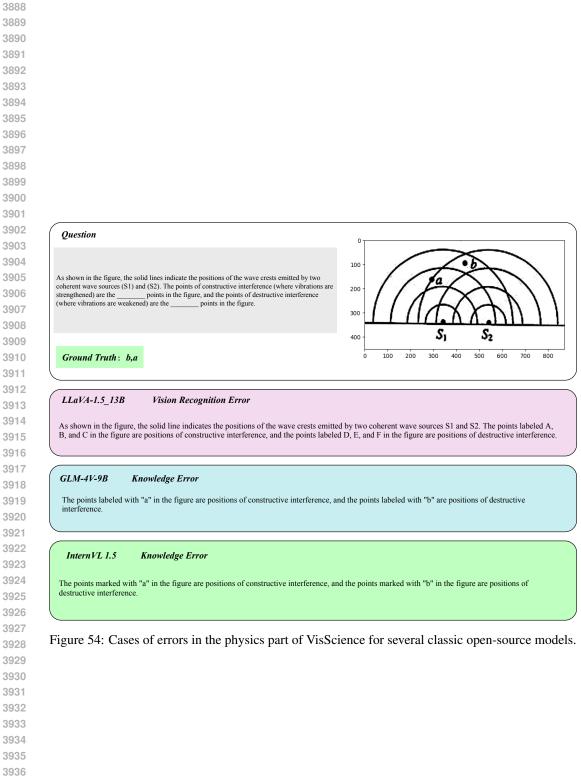












As shown in the figure, molecule A is fixed at the origin O of the coordinate system, and molecule B moves along the x-axis. The relationship between the molecular potential energy E_p and the

distance between the two molecules is shown by the curve in the figure. The minimum value of the molecular potential energy in the figure is -E_0. If the total energy of the two molecules is 0,

then which of the following statements is correct?

Ouestion

3943 3944 3945 3946 3947 3948 3950 3951 3952 3953 3954 3955 3956 3957

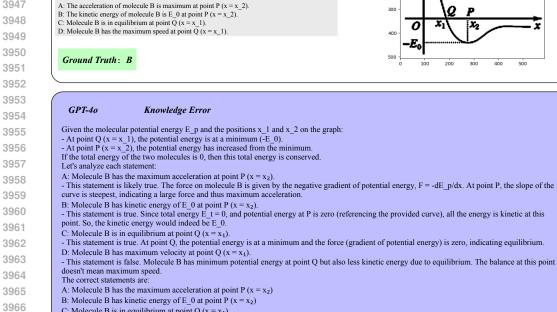
3967 3968

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.*E*,

100

200

C: Molecule B is in equilibrium at point Q $(x = x_1)$

Claude3.5 Knowledge Error

3969 Let's analyze each statement based on the information provided in the image and the question: 3970 A: Molecule B has the maximum acceleration at point P(x = x2)3971 - This is correct. At point P, the slope of the potential energy curve is steepest (most negative), which means the force (negative gradient of potential energy) is maximum here. Since F = ma, the acceleration will also be maximum at this point. 3972 B: Molecule B has kinetic energy of E0 at point P ($x = x^2$) - This is correct. The total energy is 0, and at point P, the potential energy is -E0. Since total energy = kinetic energy + potential energy, we have: 0 = 3973 (-E0), so KE = E0. C: Molecule B is in equilibrium at point Q (x = x1) - This is incorrect. Point Q is not at the bottom of the potential well, so there is still a net force acting on molecule B at this point. Equilibrium would 3974 occur at the minimum of the potential energy curve. D: Molecule B has maximum velocity at point Q (x = x1) - This is incorrect. The velocity will be maximum at the bottom of the potential well, where the potential energy is minimum (-E0) and thus the kinetic energy is maximum. Point Q is not at this location. 3977 Therefore, the correct statements are A and B 3978 3979 Qwen-VL-Max **Reasoning Error** 3980 The correct statement is: 3981 B: Molecule B has kinetic energy of $(E \{0\})$ at point P (x = x $\{2\}$) and C: Molecule B is in equilibrium at point Q (x = x 1). Explanatio From the given information, we know that the minimum value of the molecular potential energy is $(-E_{0})$, which occurs at some point on the x-axis. Since the total energy of the system is 0, it follows that the kinetic energy of molecule B must be equal to (E_{0}) when its potential energy is 3984 minimized

At point P (x = x_{2}), the potential energy of molecule B is at its minimum value of $(-E_{0})$, so its kinetic energy must be equal to (E_{0}) . Therefore, option B is the correct statement

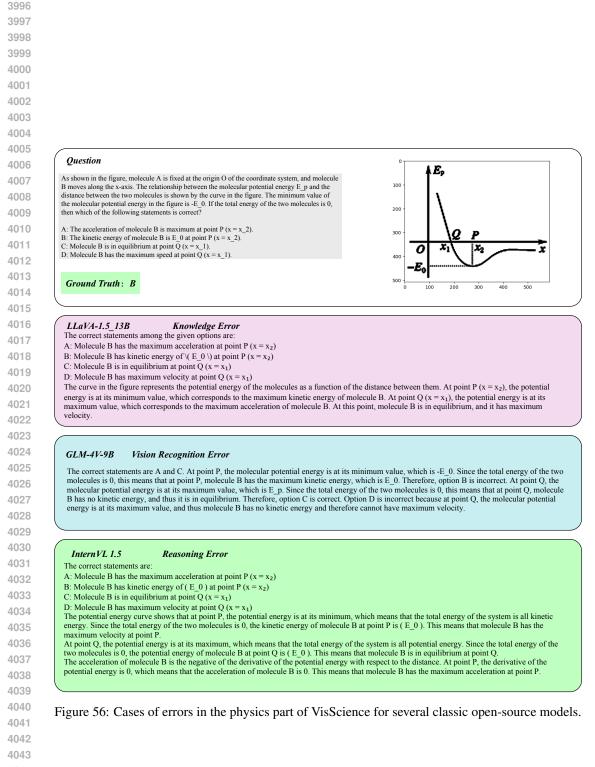
Option A is incorrect because the acceleration of molecule B depends not only on its position but also on its velocity and mass. Option D is incorrect because the velocity of molecule B depends on both its kinetic energy and its mass. While molecule B may have a higher velocity

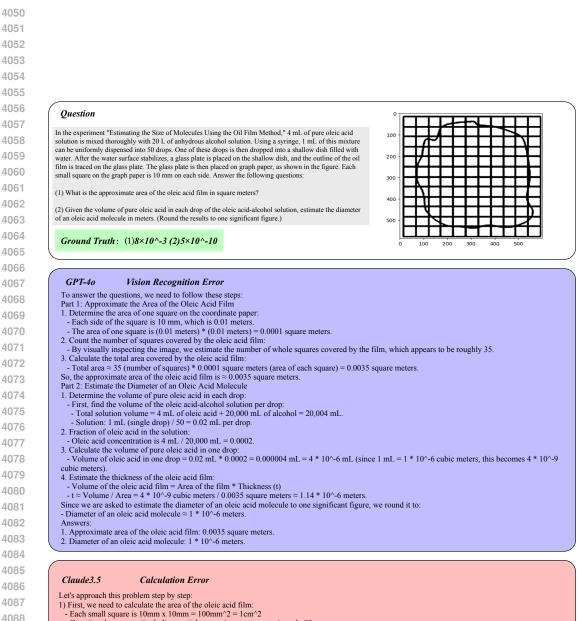
at point Q compared to other points with lower kinetic energy, it does not necessarily have the maximum velocity possible for the system.

GLM-4V **Knowledge Error**

Solution: At point P, the slope of the curve is equal to zero, indicating that the force on molecule B is zero. Since the total energy is 0, the kinetic energy of molecule B must also be 0. Therefore, option B is incorrect. 3990 3991 At point Q, the derivative of the potential energy with respect to position is negative, which means that molecule B is moving away from the origin and gaining kinetic energy. Therefore, option D is incorrect. The correct answer is C. When molecule B is in equilibrium at point Q, its kinetic energy is 0, not (E_{0}) . Answer: C 3994

Figure 55: Cases of errors in the physics part of VisScience for several classic close-source models.







Let's approach this problem step by step:
1) First, we need to calculate the area of the oleic acid film:

Each small square is 10mm x 10mm = 100mm²2 = 1cm²2
Counting the squares (including partial squares), we get approximately 80 squares
So the area is about 80 cm²2 = 0.008 m²2

2) Now, let's calculate the volume of pure oleic acid in each drop:

4mL of oleic acid is mixed into 20L of alcohol
1mL of this mixture produces 50 drops
So each drop contains (4mL / 20000mL) * (1mL / 50) = 4 * 10^-6 mL of pure oleic acid

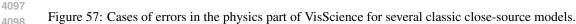
3) The thickness of the film will be:

Volume / Area = (4 * 10^-6 mL) / (0.008 m²2)
= (4 * 10^-9 m²3) / (0.008 m²2)
= 5 * 10^-7 m

4) Assuming the oleic acid molecules form a single layer, this thickness represents the diameter of one oleic acid molecule. Therefore, the answers are:

(1) The area of the oleic acid film is approximately 0.008 m²2

(2) The estimated diameter of an oleic acid molecule is 5 * 10^-7 m, which rounded to one significant figure is 5 * 10^-7 m.



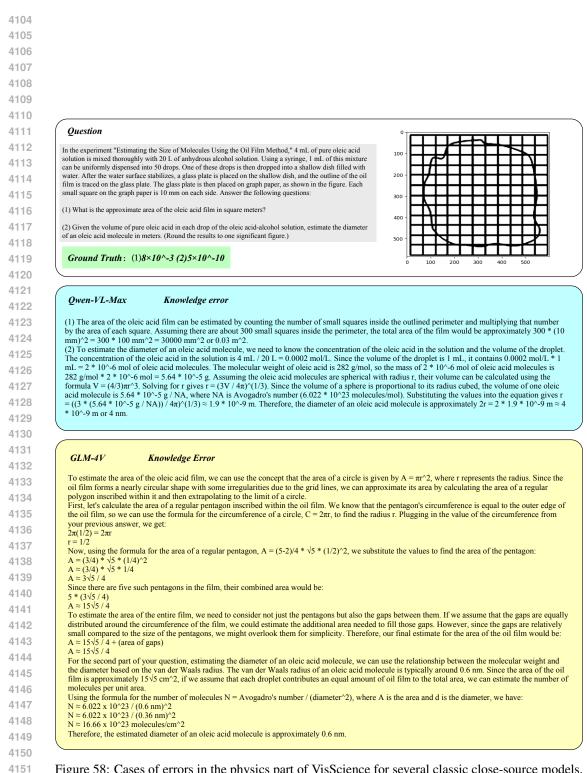
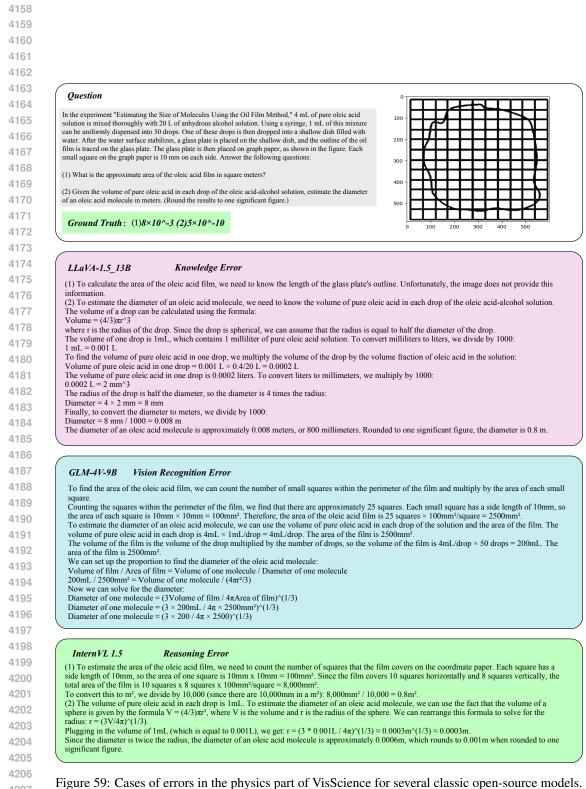
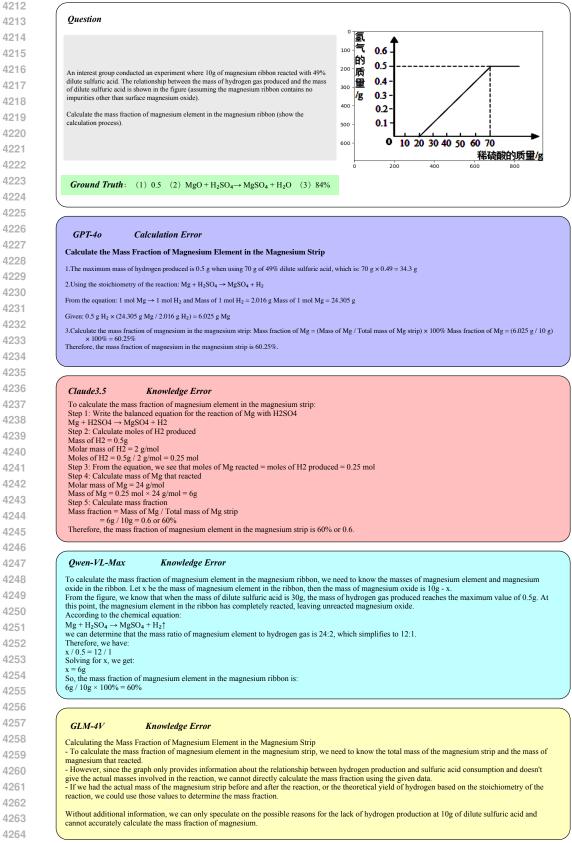




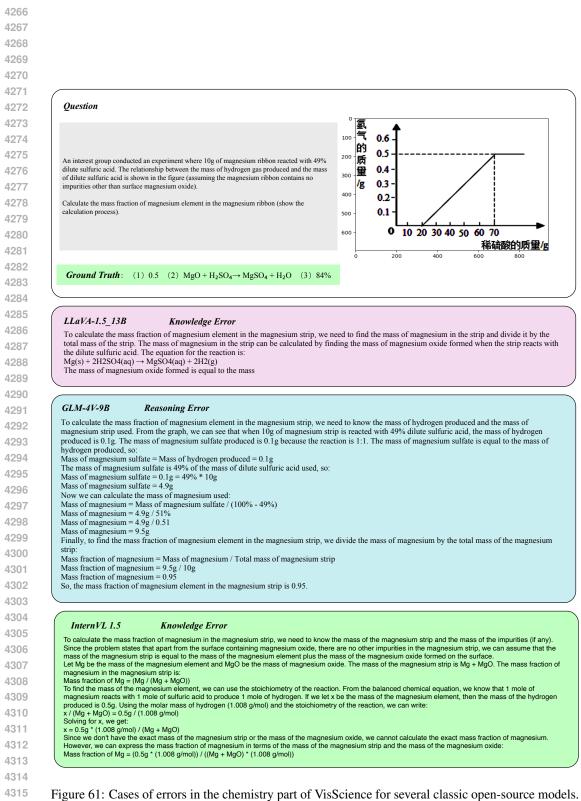
Figure 58: Cases of errors in the physics part of VisScience for several classic close-source models.





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Figure 60: Cases of errors in the chemistry part of VisScience for several classic close-source models.





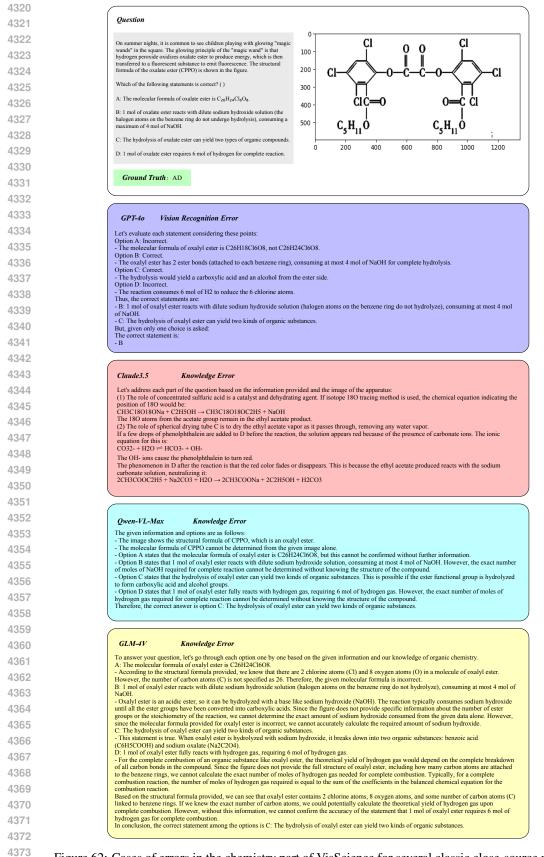
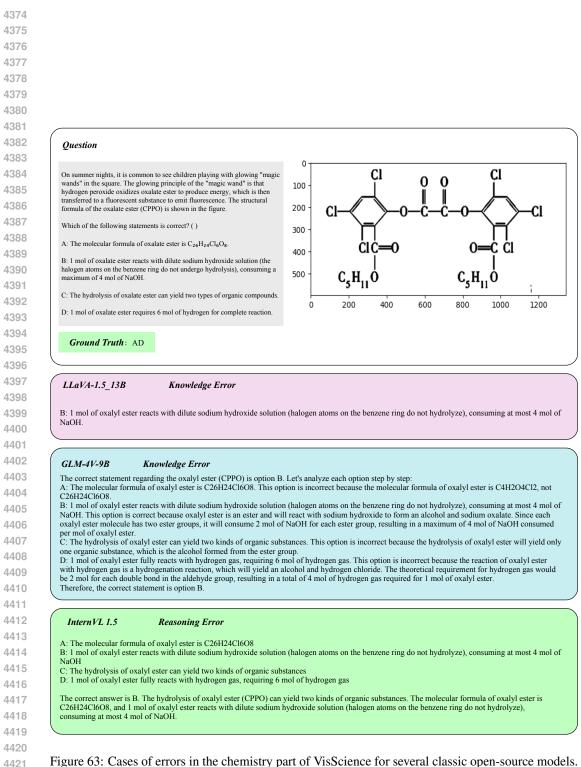


Figure 62: Cases of errors in the chemistry part of VisScience for several classic close-source models.





4481

Figure 64: Cases of errors in the chemistry part of VisScience for several classic close-source models.

Question

ionic equation)

A certain extracurricular group designed a laboratory apparatus for the preparation of ethyl acetate, as shown in the figure. Concentrated sulfuric acid is placed in A, ethanol and anhydrous sodium acetate are placed in B, and saturated sodium carbonate solution is placed in D.
Given:
1. Anhydrous calcium chloride can form an insoluble compound with ethanol, CaCl2·6C2H5OH.
2. Boiling points of related organic compounds:
- Reagent: Diethyl ether, Ethanol, Acetic acid, Ethyl acetate
- Boiling point/°C: 34.7, 78.5, 118, 77.1
Please answer the following:
(1) The role of concentrated sulfuric acid is; if the isotope ^180 tracer method is used to determine the provider of the oxygen atom in the water molecule of the reaction product, write the chemical equation that
indicates the position of ^18O:
(2) The function of the spherical drying tube C is If a few drops of phenolphthalein
are added to D before the reaction, the solution turns red. The reason for this phenomenon is (expressed by the

; the phenomenon in D after the reaction is

 $\textit{Ground Truth}: \ (1) \ Catalyst, \ dehydrating \ agent \ , CH_3COOH + C_2H_5{}^{18}OH \rightarrow CH_3CO{}^{18}OC_2H_5 + H_2OB_3COC_3H_5 + H_2OC_3H_5 + H_2OC_3H_5 + H_2OC_3H_5 + H_$ (2) To prevent backflow, condensation , $CO + H_2O \rightleftharpoons HCO + OH^-$, The solution separates into layers, with the upper layer being a colorless oily liquid, and the lower solution becoming lighter in color.

GPT-40 Knowledge Error

(1) The role of concentrated sulfuric acid is as a catalyst and dehydrating agent. The chemical equation indicating the position of ^18O when using isotope ^18O tracing is: $\mathrm{CH_3COONa} + \mathrm{C_2H_5^{18}OH} \rightarrow \mathrm{CH_3COOC_2H_5} + \mathrm{Na^{18}OH}$ (2) The role of the spherical drying tube C is to remove moisture from the gas. If a few drops of phenolphthalein are added to D before the reaction, the solution appears red because: $CO_3^{2^-} + H_2O \rightarrow HCO_3^- + OH^-$ The phenomenon in D after the reaction is that the red color dissipates due to the neutralization reaction resulting in the formation of CO2: H^+ (from H_2SO_4) + $CO_3^{2-} \rightarrow H_2O + CO_2$ Claude3.5 Knowledge Error Let's address each part of the question based on the information provided and the image of the apparatus: (1) The role of concentrated sulfuric acid is a catalyst and dehydrating agent. If isotope 18O tracing method is used, the chemical equation indicating the osition of 180 would be:

 $CH3C18O18ONa + C2H5OH \rightarrow CH3C18O18OC2H5 + NaOH$

The 18O atoms from the acetate group remain in the ethyl acetate product. (2) The role of spherical drying tube C is to dry the ethyl acetate vapor as it passes through, removing any water vapor

If a few drops of phenolphthalein are added to D before the reaction, the solution appears red because of the presence of carbonate ions. The ionic

equation for this is: $CO32- + H2O \rightleftharpoons HCO3- + OH-$

The OH- ions cause the phenolphthalein to turn red.

The phenomenon in D after the reaction is that the red color fades or disappears. This is because the ethyl acetate produced reacts with the sodium nate solution, neutralizin

2CH3COOC2H5 + Na2CO3 + H2O → 2CH3COONa + 2C2H5OH + H2CO3

Owen-VL-Max Knowledge Error

(1) The role of concentrated sulfuric acid is to act as a catalyst for the esterification reaction between ethanol and acetic acid. Using isotopic tracing with 180, the chemical equation showing the position of 180 would be: $CH3CO18OH + C2H5OH \rightarrow CH3COOC2H5 + H18O$

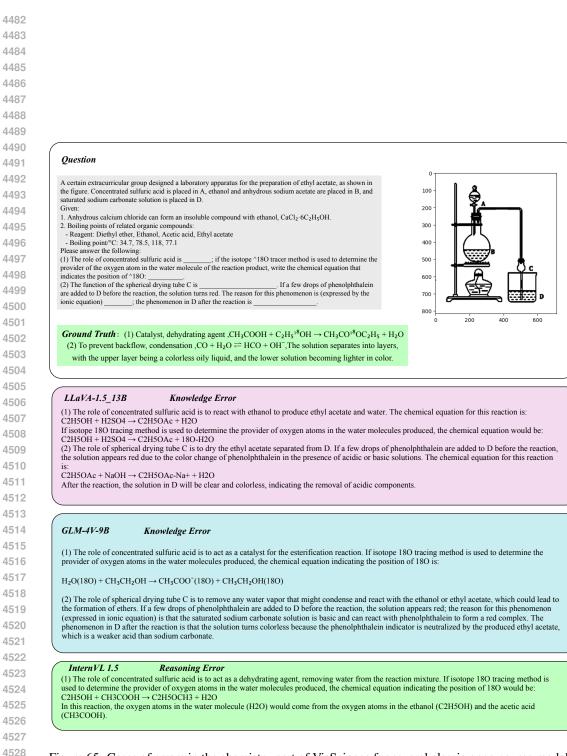
(2) The role of spherical drying tube C is to prevent the entry of moisture into the system, which could interfere with the reaction or cause unwanted side

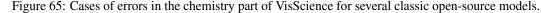
When phenolphthalein is added to D before the reaction, it turns red due to the presence of excess sodium carbonate, which is basic. The ionic equation r this reaction is $CO2(aq) + H2O(1) + CO3^2(aq) \rightarrow 2HCO3^{-}(aq)$

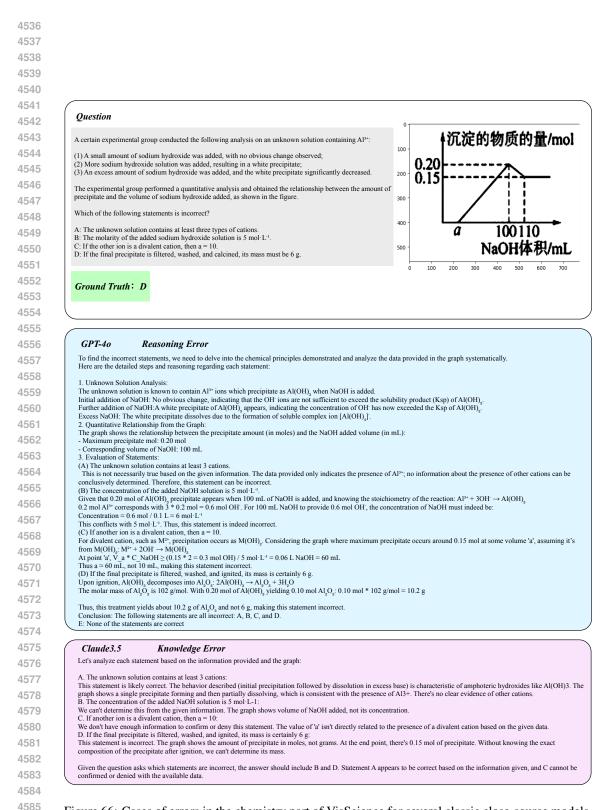
After the reaction, the solution in D will turn colorless because the ethyl acetate formed will react with the solution arbonate, consuming the excess base and neutralizing the solution.

GLM-4V Knowledge Error

Solution (1) Since the boiling point of ethanol is 78.5°C and that of ethyl acetate is 77.1°C, we can use the difference in boiling points to separate them. Adding concentrated sulfuric acid can increase the boiling point of the ethanol-water mixture, which can then be distilled to separate ethanol and water. Therefore, the role of concentrated sulfuric acid is to increase the boiling point of ethanol-water mixtures. The chemical equation for the reaction between ethanol and sulfuric acid is $C2H5OH + H2SO4 \rightarrow C2H5OSO4\downarrow + H2O$. When 18O tracing method is used, the oxygen atom in the water comes from the 18O-labeled ethanol. Therefore, the chemical equation is $C2H5OH18 + H2SO4 \rightarrow C2H5OSO4\downarrow + H2O18$. (2) The saturated sodium carbonate solution can absorb water, so when the hot ethanol-acetic acid mixture is poured into the flask, it will not overflow Therefore, the role of spherical drying tube C is to absorb excess water. The phenolphthalein solution turns pink when there are enough hydrogen ions in solution. In the presence of sodium carbonate, the hydrogen ions from the reaction are consumed, so no color change occurs. After the reaction, the pH of the solution increases, causing the phenolphthalein solution to turn pink. 4480







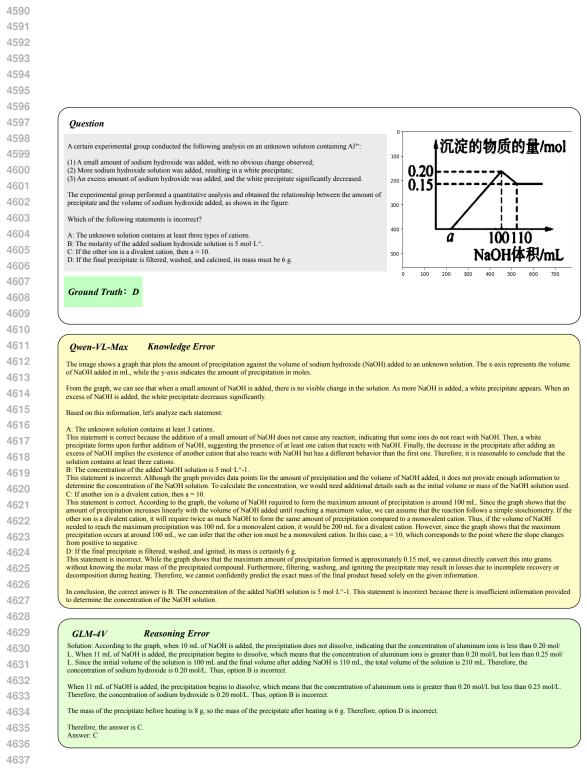
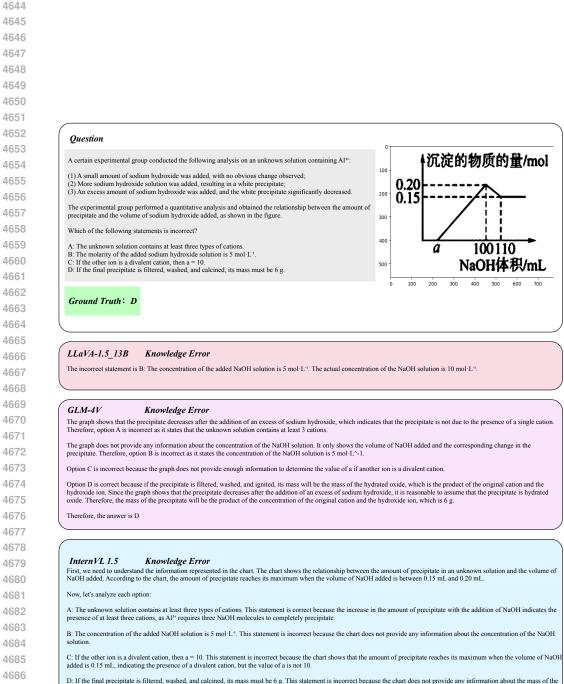


Figure 67: Cases of errors in the chemistry part of VisScience for several classic close-source models.



D: If the final precipitate is filtered, washed, and calcined, its mass must be 6 g. This statement is incorrect because the chart does not provide any information about the mass of the precipitate

Therefore, option B is incorrect.

Figure 68: Cases of errors in the chemistry part of VisScience for several classic open-source models.