

# Can Vision Language Models Be Adaptive in Mathematics Education? A Learner Model-based Rubric Study

Anonymous ACL submission

## Abstract

Adaptive learning refers to educational technologies that track learners' learning progress and adapt the instructional process based on individual learners' learning performance. It is increasingly recognized as critical for developing an effective learning support tool. Vision Language Models (VLMs) have seen adoption in mathematics education, and students have been using them as learning aids for personalized instruction. However, it is unknown whether VLMs have the ability to provide appropriate mathematical instruction based on different learner profiles. Current VLMs lack a systematic evaluation framework for this assessment in mathematics education. To address this gap, we draw on the learner model from the adaptive learning framework and propose a learner model-based rubric. Our rubric formalizes adaptivity assessment into three aspects: cognitive aspects, motivational aspects, and complexity. We also evaluate two additional dimensions of VLM responses: correctness (of answers and solutions) and quality (of the response itself). Our experimental results show measurable differences in adaptivity across models, and also reveal that current VLMs struggle to consistently produce learner model-based instructional responses, especially when receiving limited learner information.

## 1 Introduction

As artificial intelligence shows growing use in education, there is a corresponding rise in large language model-powered tools for providing mathematical instructions and pedagogical support. Learners increasingly adopt VLMs as personal tutoring agents to answer mathematical problems and provide personalized solution feedback (Baral et al., 2025; Cherian et al., 2024; Gupta et al., 2025; Liu et al., 2024). Personalization is both a defining characteristic of personal tutoring and a critical principle in education, as educators have histori-

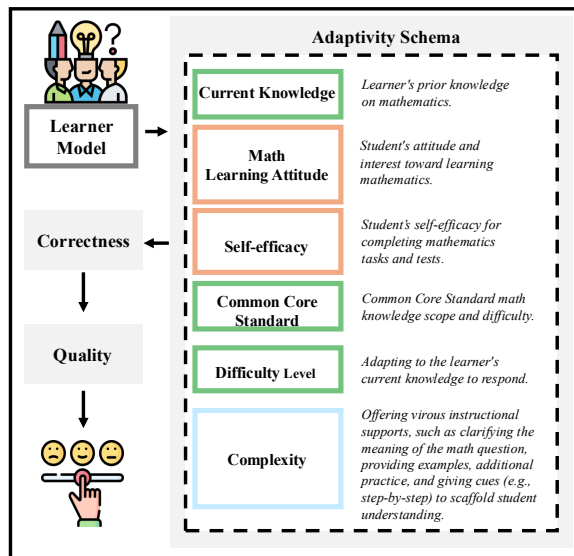


Figure 1: Overview of the learner model-based adaptivity schema. The framework delineates the interplay between learner profile and instructional scaffolding.

cally adapted their instruction to provide personalized and differentiated learning support based on diverse learner backgrounds (Bernacki et al., 2021).

To provide personalized learning to address different individuals' learning needs, it is vital to understand learners' learning performance before making instructional decisions. Adaptive learning, as one of the most effective educational approaches, can provide personalized learning instruction and feedback by adapting the learning process to different learners' needs continuously (Imhof et al., 2020; Shute and Towle, 2018; Vanzo et al., 2025; Zheng et al., 2022). Its goal is to maximize the effectiveness of instruction through tracking learners' prior academic background and learning performance, adjusting the content to suit different learners (Shute et al., 2000). A foundational component of adaptive learning is the learner model, which captures key aspects of a learner, such as learning performance and learning attitudes, in order to support individualized instruction. Several

064	studies have demonstrated that adaptive learning	<b>2 Background &amp; Related Work</b>	113
065	is superior to one-size-fits-all teaching approaches		
066	(Bloom, 1984; Vandewaetere et al., 2011).		
067	Current VLMs primarily collect learner information	<b>2.1 Adaptive Learning: The Learner Model</b>	114
068	from conversational interactions (Kumar et al.,	Adaptive learning was initially influenced by	115
069	2023). When learners do not explicitly share details	Snow’s book on aptitude-treatment interactions	116
070	about their learning performance, behaviors,	(Cronbach and Snow, 1981). Later in 1984, Bloom	117
071	or needs, it becomes difficult to infer these learners’	proposed the 2 Sigma problem, which highlighted	118
072	profiles, which limits instructional decision-making.	the importance of adaptive learning (Bloom, 1984).	119
073	Subsequently, it remains unclear whether VLMs	Subsequently, research spearheaded by Shute and	120
074	generate truly appropriate answers and solutions	Towle (2018) identified and established three core	121
075	to support individual learners’ needs (Sharma	models for adaptive learning, including the learner	122
076	et al., 2025).	model, content model, and instructional model.	123
077	This paper addresses this gap by developing an	The learner model forms the foundation of adap-	124
078	adaptive rubric grounded in the learner model of	tive learning by integrating assessment informa-	125
079	adaptive learning frameworks. Our rubric incorpo-	tion and supporting inferences about learners’	126
080	rates core evaluation factors from learner models,	proficiencies (Shute and Towle, 2018). Personalization	127
081	including cognitive and motivational aspects. For	within adaptive learning systems begins with sys-	128
082	example, learners’ attitudes are a key factor influ-	tematically appraising learner characteristics (Zhou	129
083	encing mathematics learning performance (Wen	et al., 2023). The systematic review of Bernacki	130
084	and Dubé, 2022). The adaptive rubric evaluates	et al. (2021) identified key learner characteristics	131
085	whether the VLMs’ responses offer positive guid-	across four dimensions: cognitive factors, beliefs	132
086	ance to address learners’ negative learning attitudes	and motivations, social and cultural factors, and	133
087	toward mathematics, rather than ignoring them.	emotions and affect. For instance, understanding	134
088	The rubric aims to assess VLMs’ adaptive capa-	a learner’s prior knowledge is essential before pro-	135
089	bilities in mathematics education and their capac-	viding instruction, as it helps avoid content that	136
090	ity to deliver pedagogical instruction that aligns	is either too simple or overly challenging. Sim-	137
091	with learners’ knowledge backgrounds. Accord-	ilarly, Plass and Pawar (2020) categorized vari-	138
092	ingly, our research question is: <b>“To what extent</b>	ables that can be adapted in instructional responses	139
093	<b>can VLMs demonstrate adaptive capabilities in</b>	into four domains: cognitive, motivational, affect-	140
094	<b>mathematics education?”</b>	ive, and sociocultural. Within the motivational	141
095	The rubric formalizes the design decisions un-	domain, self-efficacy reflects a learner’s perceived	142
096	derlying VLMs’ mathematical instruction and feed-	capacity to perform domain-specific tasks. As a re-	143
097	back across three dimensions: adaptivity, correct-	sult, a learner may display a generally positive atti-	144
098	ness, and quality. Among these, adaptivity is the	titude toward learning while simultaneously holding	145
099	core evaluation of the rubric, taking inspiration	low confidence in completing specific mathematics	146
100	from the taxonomy of adaptivity for learning. The	tasks (Kaskens et al., 2020; Wen and Dubé, 2022).	147
101	measurement of adaptivity focuses on three aspects,	Our work synthesized insights from previous re-	148
102	including cognitive aspects, motivational aspects,	search and considered the VLMs’ conversational	149
103	and complexity aspects, as illustrated in Figure 1.	attributes for the adaptive rubric construction.	150
104	Furthermore, to better understand if VLMs can	<b>2.2 The Role of (V)LMs in Education</b>	151
105	differentiate among learner profiles, we simulated	In the domain of mathematics, (V)LMs have	152
106	three learner profiles (high-, intermediate-, and low-	demonstrated remarkable proficiency as "solvers,"	153
107	performance) for evaluation. In general, we find	achieving superior performance on both text-based	154
108	that these VLMs struggle to provide feedback that	(e.g., GSM8K (Cobbe et al., 2021), MathQA	155
109	is appropriately tailored to different learner profiles.	(Amini et al., 2019)) and vision-based benchmarks	156
110	The constructed model generation pipeline and	(e.g., MATH-Vision (Wang et al., 2024), Math-	157
111	rubric design are available at <a href="https://anonymous.4open.science/r/Adaptive-LLMs-9C92/">https://anonymous.</a>	Verse (Zhang et al., 2024)). However, a critical dis-	158
112	<a href="https://anonymous.4open.science/r/Adaptive-LLMs-9C92/">4open.science/r/Adaptive-LLMs-9C92/</a> .	tinction exists between automated solvers and edu-	159
		cational agents: solvers prioritize problem-solving	160
		efficiency and final answer correctness (Yan et al.,	161
		2025), whereas educational agents must provide	162

pedagogically transparent guidance and scaffolding appropriate to the learner’s zone of proximal development (Cai et al., 2025). Recent work suggests that LLMs can mimic tutor-like behavior in interactive sessions (Vanzo et al., 2025), and Scarlatos et al. (2025) further highlights their potential role in knowledge tracing. Despite this progress, existing work tends to overlook the multimodal nature of authentic mathematics learning. Real-world mathematical tasks often require students to reason across modalities, integrating textual instructions with geometric diagrams, data visualizations, and function plots. The emergence of VLMs, including GPT-4V, LLaVA, and Qwen-VL, enables joint visual-textual reasoning (Lu et al., 2023). Current evaluation paradigms, however, largely mirror text-only settings, emphasizing visual question-answering accuracy rather than instructional reasoning quality (Lee and Zhai, 2025). Such accuracy-focused evaluations fail to capture a model’s ability to explain visual concepts or adapt guidance to a learner’s context, leaving limited empirical evidence on whether multimodal models can serve as effective adaptive tutors.

### 2.3 Empirical Study in Adaptive Learning

The integration of VLMs into educational technologies represents a paradigm shift for intelligent tutoring systems (Liu et al., 2025). While generative model-based systems offer the potential for real-time customization of instructional content based on student behavior (Banjade et al., 2024; Lin et al., 2023), their capacity to deliver contextually appropriate guidance remains questionable. Notably, Borchers and Shou (2025) employed a prompt variation framework to assess pedagogical adaptivity, revealing that even state-of-the-art models frequently fail to adjust their feedback strategies when critical context (e.g., student performance or knowledge components) is introduced or removed. This suggests a "context insensitivity" where models revert to generic tutoring scripts rather than responding to the specific state of the learner. To address this gap, we aim to provide a rigorous, rubric-based assessment of how well VLMs adhere to specific learner profiles.

## 3 Rubric Design for Adaptivity Evaluation

Our rubric is designed to evaluate whether VLMs demonstrate adaptive capabilities in adapting in-

struction and feedback for learners with different abilities and backgrounds in mathematics education. The axes on which the initial construction of the adaptive rubric was mainly based on three key evaluation dimensions: adaptivity, correctness, and quality. Among these, adaptivity constitutes the core focus of the rubric, while correctness and quality serve as complementary control dimensions. In this work, we define a VLM response as comprising two components: an answer and a solution. Here, the "solution" encompasses all explanatory and instructional content beyond the final answer, including reasoning steps, feedback, and guidance. The proposed rubric is designed to evaluate whether model outputs meet a baseline standard of adaptive instructional behavior. At a high level, the adaptivity dimension assesses whether model responses are appropriately aligned with both the instructional intent of the prompt and the learner’s background. The correctness dimension evaluates whether the answers and solutions are mathematically valid. The quality dimension examines overall VLM response quality.

**Adaptivity.** The adaptivity dimension includes a total of nine key questions (Q1–Q9; see Appendix A.1). The evaluation elements of these questions were selected based on the core factors of the adaptive learning environments (Bernacki et al., 2025; Plass and Pawar, 2020), while considering the interactive characteristics of VLMs. The primary factors in this rubric include: the learner’s current mathematical knowledge, the learner’s math learning attitude, the learner’s self-efficacy, the solution’s mathematical knowledge scope, the solution difficulty, and the solution complexity. For instance, when a learner presents a negative math learning attitude, an adaptive response should offer positive feedback and instruction to help the learner address the math problem, rather than continuing the conversation in a negative tone or ignoring it. Solution complexity is assessed across Q6–Q9, examining whether the LLM response helps the learner understand and explain the math question, providing relevant examples, offering additional similar math exercises for reinforcement, and delivering step-by-step and detailed instructions.

**Correctness.** This dimension mainly focuses on assessing if the VLM responses provide valid and correct instruction and feedback, addressing the specific math questions. Both the answer and the solution should be correct and consistent to determine the correctness of the response (Q10–Q12;

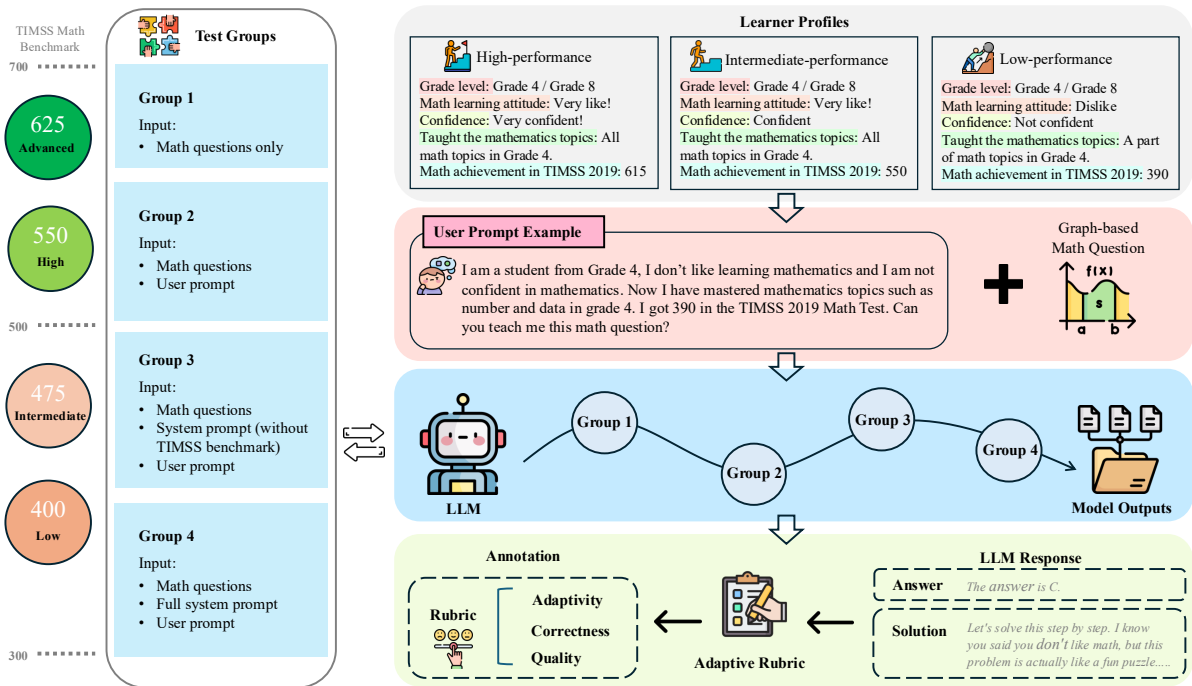


Figure 2: Overview of the adaptive rubric-based evaluation pipeline. Learner profiles and mathematics questions are combined under four test groups with increasing learner-specific information, provided to VLMs to generate instructional responses, and annotated by experts using the proposed rubric.

see Appendix A.2). In this dimension, three questions were used to evaluate the correctness of the answer and its solution. Notably, a completely correct solution is defined as one that includes both complete and valid mathematical reasoning and yields a correct final answer. If the solution demonstrates accurate mathematical reasoning but ends with an incorrect final answer, it should be labeled as partially correct.

**Quality.** In contrast to the correctness dimension, this dimension primarily focuses on broader VLM performance and overall response quality. The quality dimension includes a total of seven questions (Q13–Q19; see Appendix A.3). These questions are used to explore whether the response has any quality issues, such as hallucinations, mathematical reasoning, faithfulness, coherence, consistency, grammatical and formatting, and length.

## 4 Methodology

To empirically evaluate the adaptive capabilities of VLMs in mathematics education, we implement a structured evaluation pipeline grounded in the proposed learner model-based rubric. As illustrated in Figure 2, the pipeline constructs learner profiles, pairs them with mathematics questions under varying contextual conditions, elicits instructional responses from VLMs, and evaluates the

resulting outputs through expert annotation. This methodology adopts a quasi-experimental design that simulates realistic tutoring interactions by systematically varying two key factors: learner profiles and test groups (the availability of learner-specific contextual information). The following subsections describe the dataset construction process, the formalization of learner profiles, and the expert annotation procedure used to quantify model performance across the rubric’s dimensions.

### 4.1 Dataset and Model Selection

We draw mathematics items from the Trends in International Mathematics and Science Study (TIMSS) 2019 and 2023 with official permission from the International Association for the Evaluation of Educational Achievement (IEA) (Fishbein et al., 2021, 2025). From the full assessment pool, we construct a stratified dataset of  $Q = 10$  representative questions, with five questions sampled from Grade 4 and five from Grade 8. To emphasize multimodal reasoning, we prioritize visually grounded items, resulting in 90% of the selected questions requiring graphical or diagrammatic interpretation. We evaluate a set of  $M = 5$  VLMs spanning both proprietary and open-source paradigms. The proprietary models include GPT-5, GPT-o1, and Gemini-2.5-Flash, while the open-

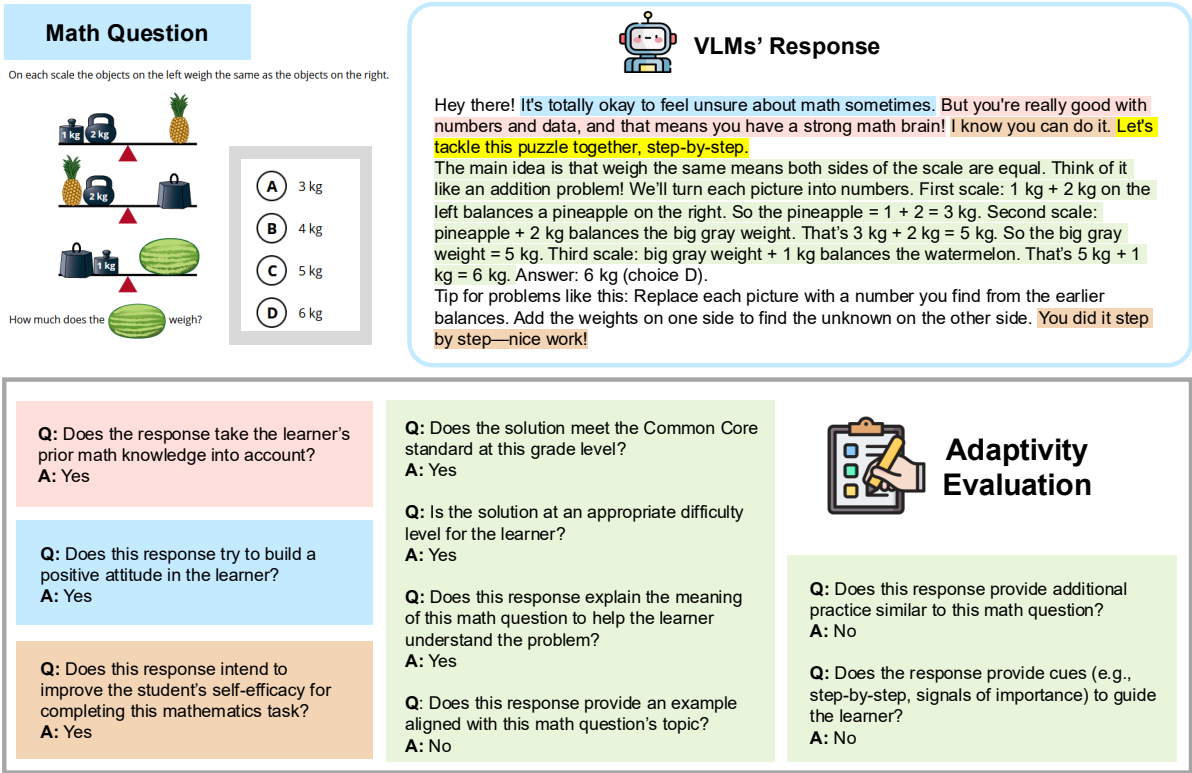


Figure 3: A case study of the adaptive evaluation process for a Grade 4 math problem. The upper panel shows the VLM-generated response with motivational support and step-by-step scaffolding, while the lower panels illustrate the annotation workflow, where Q1–Q9 map directly to the adaptivity rubric in Appendix A.1.

source models consist of Qwen3-VL-30B-A3B-Instruct and Llama3.2-11B-Vision-Instruct. The detailed computational costs and model selection are provided in Appendix B.

#### 4.2 Learner Profiles and Context Conditions

To simulate realistic tutoring scenarios, we construct learner profiles derived from authentic TIMSS statistics and formalize each learner as a tuple  $\ell = (a, c, p, s)$ , where  $a$  denotes learning attitude,  $c$  denotes self-reported confidence,  $p$  represents prior topic coverage, and  $s$  corresponds to the learner's TIMSS achievement score; across Grade 4 and Grade 8, we instantiate six profiles spanning three performance tiers (high, intermediate, and low). Building on this formulation, we study context sensitivity by defining four input context conditions  $C_k$  with monotonically increasing learner-specific information:

$$C_1 = \{q\}, \quad C_2 = \{q, (a, c, p)\},$$

$$C_3 = \{q, S, (a, c, p)\}, \quad C_4 = \{q, S, (a, c, p, s)\}.$$

where  $q$  denotes the mathematics question and  $S$  denotes a system prompt specifying grade-level learning objectives.

#### 4.3 Expert Annotation and Evaluation

Our experimental design follows a full factorial structure. The total volume of model-generated responses is calculated as:

$$N = \underbrace{|G|}_{\text{Learner Profile}} \times \underbrace{|P|}_{\text{Context}} \times \underbrace{|Q|}_{\text{Task}} \times \underbrace{|M|}_{\text{Model}} = 600$$

where we account for  $|G| = 2$  grades,  $|P| = 3$  performance tiers,  $|C| = 4$  context conditions,  $|Q| = 5$  questions per grade, and  $|M| = 5$  models. Data annotation was conducted by four domain experts trained in the Learning Sciences program. Prior to annotation, each expert completes a one-hour one-on-one training session that introduces the rubric and includes discussion of at least three representative case studies to calibrate the scoring criteria. Each response was evaluated using structured numerical ratings defined by the rubric (see Appendix A). The rubric items were implemented in a Google Form, and annotators rated each VLM response using this instrument. Adaptivity score and Correctness score were positively keyed, whereas Quality score was computed as one minus the error score, such that higher values consistently indicate better performance. A case



















Model	Adaptivity (Q1-9)			Correctness (Q10-12)			Quality (Q13-19)		
									
GPT-5 	52%	51%	<u>64%</u>	<u>72%</u>	<u>70%</u>	<u>79%</u>	<u>90%</u>	<u>89%</u>	<u>92%</u>
GPT-o1 	46%	44%	47%	68%	63%	65%	<u>90%</u>	88%	91%
Gemini-2.5-Flash 	<u>65%</u>	<u>68%</u>	<b>70%</b>	<b>82%</b>	<b>80%</b>	<b>85%</b>	<b>95%</b>	<b>94%</b>	<b>96%</b>
Llama3.2-11B-VL  	50%	53%	48%	19%	28%	20%	65%	63%	65%
Qwen3-30B-VL 	<b>71%</b>	<b>71%</b>	<b>70%</b>	56%	57%	52%	76%	74%	72%

Table 1: Performance comparison of VLMs across dimensions. Values denote the average percentage of scores achieved across the rubric for each dimension. Learner profiles are denoted by icons: High- () , Intermediate- () , and Low-performance () . **Bold** denotes the best performance; underline denotes the second best.

study is shown in Figure 3, the color-coded groupings represent the distinct dimensions of adaptivity. These annotations demonstrate how qualitative text outputs are converted into binary numerical scores (Yes=1, No=0). To validate the reliability of the annotation process, a subset of 120 responses was independently annotated by core coders, yielding a strong inter-rater agreement with a Cohen’s Kappa of  $\kappa = 0.87$ . Detailed agreement metrics for each model are reported in Appendix C.

## 5 Results

We examine the relationship between learner profiles and VLMs’ performance in adaptivity, correctness, and quality. Our analysis investigates whether these dimensions exhibit systematic variation across learner profiles and model-related factors (VLMs and test group), reflecting models’ sensitivity to learner differences and available contextual information. Table 1 summarizes overall performance patterns across VLMs and learner profiles. The reported values represent the mean percentage of total possible points achieved within each dimension. For example, a 70% Adaptivity score indicates the model satisfied 70% of the Q1–Q9 criteria. To provide deeper insight into specific adaptive behaviors, Table 2 disaggregates the Adaptivity dimension. It reports detailed performance on individual sub-metrics (e.g., Cognitive, Motivational, Complexity) across the four test groups (G1–G4), revealing how the availability of context influences specific instructional strategies. To provide evidence for these relationships, we employ a series of two-way analyses of variance (ANOVA), with learner profile and model-related factors as independent variables. Further details of the analysis are reported in Appendix D and Appendix E.

### 5.1 Experimental analysis

**Adaptivity (Q1–Q9).** We analyzed how adaptivity scores relate to learner profiles (high-, intermediate-, and low-performance), VLMs, and test groups. Overall, adaptivity scores showed significant relationships across VLMs and across test groups, with no significant interaction involving learner profiles.

Adaptivity varied substantially across models, with a significant main effect of VLMs,  $F(4, 705) = 41.81, p < .001$ , indicating differences in adaptivity performance across models. Tukey HSD post hoc comparisons indicated that Gemini-2.5-Flash and Qwen3-VL-30B achieved significantly higher adaptivity scores than GPT-5, GPT-o1, and Llama3.2-11B-VL, whereas differences between Gemini-2.5-Flash and Qwen3-30B-VL were not statistically significant. In contrast, adaptivity scores showed no significant association with learner profiles,  $F(2, 705) = 1.72, p = .18$ , and no significant interaction between learner profile and VLMs,  $F(8, 705) = 1.63, p = .11$ .

A complementary analysis examined adaptivity as a function of learner profile and test group (Groups 1–4, reflecting increasing contextual information). The results showed a significant relationship between contextual information and adaptivity: responses generated with access to additional context exhibited higher adaptivity scores. This pattern was supported by a significant main effect of test group,  $F(3, 708) = 92.73, p < .001$ . Tukey HSD comparisons revealed that Group 1 (math question only) scored significantly lower than Groups 2, 3, and 4, with no significant differences emerging among Groups 2, 3, and 4.

**Correctness (Q10–Q12).** Correctness scores showed a similar pattern, with variation driven primarily by model differences rather than learner profiles or test groups. Across both analyses, cor-

Dimensions		Model Performance by Group and Overall (O)																								
		Proprietary Models (%)										Open-Source Models (%)														
		GPT-5 🌀					GPT-o1 🌀					Gemini-2.5-flash ⚡					Llama3.2-11B-VL 🌀 🌀					Qwen3-30B-VL 🌀				
⚡ Metric	G1	G2	G3	G4	O	G1	G2	G3	G4	O	G1	G2	G3	G4	O	G1	G2	G3	G4	O	G1	G2	G3	G4	O	
Cognitive	CK (Q1)	31	94	94	89	77	53	66	68	67	63	53	100	100	100	88	36	47	83	78	61	67	100	100	100	92
	CCS (Q4)	61	94	94	89	85	83	97	100	97	94	83	94	100	100	94	72	92	72	86	81	94	97	94	97	96
	DL (Q5)	44	94	86	89	78	61	86	86	89	81	72	74	89	97	83	67	72	58	75	68	92	100	86	86	91
Motiv.	LA (Q2)	3	92	89	78	65	22	43	27	47	35	6	97	100	100	76	11	33	86	81	53	39	94	100	100	83
	SE (Q3)	0	53	47	53	38	8	11	8	3	8	0	100	97	97	74	3	11	61	53	32	17	94	92	97	75
Complexity	Expl. (Q6)	6	75	81	61	56	17	83	51	42	48	64	100	97	97	90	69	86	72	86	78	92	100	89	97	94
	Exam. (Q7)	0	8	11	6	6	6	14	0	0	5	3	12	8	8	8	3	8	8	3	6	8	8	3	0	5
	Prac. (Q8)	0	42	44	22	27	0	0	0	0	0	0	0	0	0	0	0	0	0	8	8	4	0	0	0	0
	SBS (Q9)	17	86	86	86	69	58	86	78	89	78	92	100	97	94	96	72	64	58	78	68	100	100	100	100	100
Average		19	68	68	63	55	33	60	51	52	49	36	77	78	78	76	37	50	61	64	55	45	86	85	86	81

Table 2: Detailed adaptivity dimension performance. Values represent the percentage (%) of responses satisfying rubric criteria. Row metrics are: Cognitive (CK: Current Knowledge, CCS: Content Scope, DL: Difficulty Level), Motivational (LA: Learning Attitude, SE: Self-Efficacy), and Complexity(Expl.: Explanation, Exam.: Examples, Prac.: Practice, SBS: Step-by-Step). Background colors distinguish Proprietary vs. Open-Source models.

rectness did not systematically align with learner profiles. When examining learner profile and VLMs, correctness scores exhibited no association with learner performance level, as reflected by a non-significant main effect of learner profile,  $F(2, 705) = 0.01, p = .99$ , and no significant interaction,  $F(8, 705) = 0.65, p = .74$ . There was, however, a significant main effect of VLMs,  $F(4, 705) = 64.28, p < .001$ . Post hoc analyses indicated that Gemini-2.5-Flash and GPT-based models outperformed Llama3.2-11B-VL, and that Gemini-2.5-Flash also scored significantly higher than Qwen3-30B-VL.

**Quality (Q13–Q19).** Quality scores further reinforced the pattern observed for adaptivity and correctness: learner profiles did not systematically relate to the model response quality, whereas substantial differences emerged across VLMs.

Across learner profiles and VLMs, quality did not vary as a function of learner performance level, with no significant main effect of learner profile,  $F(2, 705) = 0.62, p = .54$ , and no interaction effect,  $F(8, 705) = 0.18, p = .99$ . However, quality differed significantly across models, as indicated by a significant main effect of VLMs,  $F(4, 705) = 69.44, p < .001$ . Tukey HSD comparisons showed that Llama3.2-11B-VL produced significantly higher error counts than all other models, while Gemini-2.5-Flash achieved significantly lower error scores than GPT-5, GPT-O1, and Qwen3-30B-VL.

Consistent with the model-driven effects reported above, Gemini-2.5-Flash showed strong overall performance, achieving high correctness ( $M = 82\%$ ) and quality ( $M = 95\%$ ) while maintaining competitive adaptivity ( $M = 68\%$ ). Qwen3-30B-VL obtained the highest average adaptivity score across learner profiles ( $M = 71\%$ ). However, its correctness and quality were comparatively lower. This is mainly due to overly long model generations that were more likely to be truncated or incomplete, which in turn produced formatting issues and partial non-adherence to prompt instructions. GPT-o1 performed the opposite profile, with weaker adaptivity but robust correctness and quality. We also observed a correctness gap between Llama3.2-11B-VL and the closed-source models, with the latter consistently outperforming Llama3.2-11B-VL. Finally, within the closed-source models, responses for low-performance learners showed higher correctness and quality.

## 5.2 Observations

This subsection summarizes key empirical observations derived from rubric-based annotations of VLM responses. These observations are grounded in aggregated rubric scores across learner profiles and context conditions, supplemented by qualitative inspection of representative model outputs. Together, they reveal systematic limitations in current VLMs’ adaptive instructional behavior.

**VLMs exhibit minimal behavioral adaptation to learner attitudes and self-efficacy.** As adaptivity constitutes the core dimension of the proposed rubric, we first examine how VLMs respond to learner-specific motivational factors, particularly learning attitude and self-efficacy (Q3–Q5). Across models, GPT-5, GPT-o1, and Llama3.2-11B-Vision-Instruct exhibit consistently low response rates in addressing these factors. For example, GPT-o1 addresses self-efficacy concerns in only 8% of applicable cases, with a 0% response rate for Grade 4 intermediate-performing learners. In contrast, low-performance learners receive substantially more motivational feedback, with an average response rate of 36.8% when low confidence is explicitly indicated. Among all evaluated models, Qwen3-30B-VL (33.1%) and Gemini-2.5-Flash (32.5%) demonstrate comparatively stronger engagement with learners’ self-efficacy. Interestingly, some Qwen3-30B-VL responses include explicit encouragement (e.g., “You got this!”), suggesting partial instructional responses using motivational language. These patterns suggest models implicitly equate lower performance with greater motivational need, overlooking the importance of supporting confidence and learning attitudes among high- and intermediate-performing learners.

**Providing learners’ knowledge backgrounds to the VLM does not guarantee appropriate feedback.** It is essential to understand learners’ current knowledge level before providing them with feedback. However, such an understanding does not mean that the VLMs have the capabilities to provide appropriate differentiated feedback. In several cases, responses to different learners are nearly identical, suggesting weak sensitivity to learner distinctions. The VLMs frequently misunderstand how to deliver suitable content to specific groups. Table 2 illustrates that GPT-5 generates longer and more detailed explanations for high-performance learners than for intermediate-performance learners, despite the latter typically requiring greater instructional scaffolding. These findings indicate that access to learner background information alone does not guarantee appropriate or pedagogically aligned feedback.

**Multimodal misinterpretation and response quality failures.** Beyond adaptivity, our rubric-based evaluation surfaces notable correctness and quality issues, particularly for visually grounded mathematics problems. Geometry items pose a sig-

nificant challenge: for instance, a Grade 4 geometry question (G4Q5) required comparing four choices’ rectangles to identify the correct one. Although the task structure is clear, only 10 out of 60 model responses produced correct answers. This error pattern persists despite the problem’s clear structure, pointing to limitations in visual–spatial reasoning rather than ambiguity in the task itself. These errors are consistently reflected in low correctness scores across multiple models and learner profiles. Moreover, a common failure mode involves conflating multiple-choice option labels with their embedded numerical content. When presented with options like “D. 6kg”, the correct response should identify the label (D) rather than the embedded value (6kg). However, models regarded the embedded value as the final answer, omitting the required option label. Additionally, when questions integrate images, formulas, and text, models often extract misaligned or inaccurate information. This manifests as hallucinations or inaccurate extraction in solution, compromising mathematical reasoning and instructional reliability, even when the final answer appears superficially plausible.

## 6 Conclusion

This paper evaluates whether VLMs demonstrate adaptive capabilities in mathematics education. To this end, we introduce a learner model–inspired rubric that provides a structured framework for assessing adaptivity beyond surface-level personalization. Applying this rubric to VLMs across learner profiles reveals that, while models exhibit some sensitivity to learner context, their adaptive behavior remains limited and inconsistent. In particular, models often fail to differentiate instructional strategies across learners with distinct academic backgrounds, indicating a gap between generic tutoring responses and genuinely adaptive instruction.

The proposed rubric offers a principled tool for systematically comparing adaptive capabilities across models. Looking forward, future work may extend this rubric to distinguish baseline adaptivity from more sophisticated forms of instructional adaptation and to examine additional components of adaptive learning frameworks. More broadly, this work highlights the need for evaluation methodologies that prioritize pedagogical alignment with learners, providing guidance for the development of more adaptive and educationally grounded multimodal models.

## 601 Limitations

602 While we have developed the adaptive rubric and  
603 accompanying worksheet to identify the VLMs’  
604 adaptive capabilities, the rubric questions for adap-  
605 tivity are not exhaustive. Other adaptivity variables,  
606 including those from affective and socio-cultural  
607 aspects, are also important for evaluation. In ad-  
608 dition, our study simulated the learner rather than  
609 testing with real students, which cannot include  
610 all the learning behavior factors of real students.  
611 Moreover, there might be other differences inher-  
612 ent in using an automated tutoring system com-  
613 pared to human tutors that are not addressed in  
614 the current adaptive learning framework. For in-  
615 stance, human tutors may create more social pres-  
616 sure, which might be helpful or harmful for learn-  
617 ing. A further limitation is that the proposed rubric  
618 is designed as a baseline that evaluates whether re-  
619 sponses have adaptive capabilities in mathematics  
620 education. However, a response classified as adap-  
621 tive in this study does not represent a high-quality,  
622 high-level adaptive response.

## 623 Ethical Consideration

624 This study involves the evaluation of vision lan-  
625 guage models using synthetic and publicly avail-  
626 able mathematical problem data. No personally  
627 identifiable information or human subject data were  
628 used in model evaluation. We obtained official per-  
629 mission from the International Association for the  
630 Evaluation of Educational Achievement (IEA) to  
631 use the Trends in International Mathematics and  
632 Science Study (TIMSS) 2019 and 2023 mathemat-  
633 ics items from Grade 4 and Grade 8. Thus, the  
634 data has no potential privacy or content safety con-  
635 cerns. Additionally, the learner characteristics of  
636 learner profile data were extracted from the TIMSS  
637 2019 and TIMSS 2023 public reports and datasets  
638 (Fishbein et al., 2021, 2025).

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## 824 A Detailed Rubric

825 This section comprehensively documents the rubric  
826 criteria, scoring hierarchies, and reference exam-  
827 ples established in the evaluation framework. To  
828 ensure reproducibility and transparency, each entry  
829 below specifies the exact text used to prompt evalu-  
830 ators, the theoretical dimensions underpinning the  
831 metric (e.g., *Cognitive Aspects* vs. *Motivational As-*  
832 *pects*), and the precise logic required to assign val-  
833 ues (e.g.,  $-1$  vs.  $0$  vs.  $1$ ). Additionally, we provide  
834 the canonical examples that define the boundary  
835 conditions for each score, presenting the material  
836 verbatim from the study’s design documents.

### 837 A.1 Adaptivity

#### Q1. Does the response take the learner’s prior math knowledge into account?

Cognitive aspects - Current knowledge (Plass and Pawar, 2020)

**Criteria:** The response should match the learner’s stated math level. A response fails when it: 1) The content area is more than the learner’s. 2) The content area is out of this grade’s scope.

#### Scoring & Examples:

- **0 = No:** Prompt: I just learned algebra in grade 8. Could you teach me this question " $y = ab$ . Which is the value of  $y$  when  $a = 1$  and  $b = 2$ "  
Response: Sure! Think about a  $x \times b$  in a higher-dimensional space...

- **1 = Yes**

#### Q2. Does this response try to build a positive attitude in the learner?

Motivational aspects - Learning attitude (Bernacki et al., 2021)

**Criteria:** Definition of Learning Attitude in Math: Kibrislioglu (2015) defines attitude towards mathematics as liking or disliking of the subject; a tendency to engage in or avoid mathematical activities; a belief that one is good or bad at mathematics; and a belief that mathematics is useful or useless.

#### Scoring & Examples:

- **-1 = No, it responds negatively**
- **0 = No**
- **1 = Yes:** Prompt: I don’t like math. Can you help me understand  $2 \times 3$ ?  
Response: "I can help you with that...."

839

#### Q3. Does this response intend to improve the student’s self-efficacy for completing this mathematics task?

Motivational aspects - Self-efficacy (Plass and Pawar, 2020)

**Criteria:** Math self-efficacy is a situational or problem-specific assessment of an individual’s confidence in her or his ability to successfully perform or accomplish a particular mathematical task or problem (Hackett and Betz, 1989). The response should help the student feel capable of solving the math question.

#### Scoring & Examples:

- **-1 = No, it responds negatively**
- **0 = No**
- **1 = Yes:** Prompt: I am not confident in math learning. Can you help me understand  $2 \times 3$ ?  
Response: "Math can be tricky, but we can solve this together."

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#### Q4. Does the solution meet the Common Core standard at this grade level?

Cognitive aspects - Difficulty (Marraffino et al.,

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2021)

**Criteria:** The response aligns with the Common Core standard math knowledge scope and difficulty.

**Scoring & Examples:**

- **0 = No:** Not followed the Common Core Standard
- **1 = Yes:** Prompt: I'm not sure I can solve  $12 \times 13$ . Can you teach me?  
Response: Of course! This is a Number and Operation question in Grade 4.....?

**Q5. Is the solution at an appropriate difficulty level for the learner?**

Cognitive aspects - Difficulty (Marraffino et al., 2021)

**Criteria:** The response should match the learner's skill level. A response fails when the explanation is too advanced, too complex, or uses concepts the learner is not ready for.

**Scoring & Examples:**

- **0 = No:** Not provided a solution at an appropriate difficulty level
- **1 = Yes:** Prompt: What is  $2 + 2$ ?  
Response: It is 4 because adding two items to another two items makes four items.

**Q6. Does this response explain the meaning of this math question to help the learner understand the problem?**

Complexity

**Criteria:** The response should explain the meaning of the math question to help the learner know its logic and better know how to solve it. A response fails when the response does not provide an explanation of the meaning of the math question.

**Scoring & Examples:**

- **0 = No:** Not explained
- **1 = Yes:** Response: ...This question means...?

**Q7. Does this response provide an example aligned with this math question's topic?**

Complexity

**Criteria:** The response should give an example that matches the math topic in the question. A response fails when the example is unrelated, off-topic, or does not help illustrate the math idea being asked about.

**Scoring & Examples:**

- **0 = No:** No example provided
- **1 = Yes:** Response: ...Here is an example...

**Q8. Does this response provide additional practice similar to this math question?**

Complexity

**Criteria:** The response should give extra practice problems that match the math concept in the question. A response fails when the response does not provide extra practice.

**Scoring & Examples:**

- **0 = No:** No additional practice provided
- **1 = Yes:** Response: ...Let's practice...

**Q9. Does the response provide cues (e.g., step-by-step, signals of importance) to guide the learner?**

Complexity

**Criteria:** The response should include helpful cues such as steps, hints, or pointing out important parts of the problem. A response fails when it gives the answer with no guidance or offers no structure to help the learner follow the process.

**Scoring & Examples:**

- **0 = No:** No cues provided
- **1 = Yes:** Response: ...Let's go step by step. First...

**A.2 Correctness**

**Q10. Does the response provide a correct answer to this math question?**

The response provides a correct answer.

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**Criteria:** The final answer provided by the model must be mathematically correct.

**Scoring & Examples:**

- **0 = No:** Prompt:  $2 + 2 = ?$   
Response: 5
- **1 = Yes:** Prompt:  $2 + 2 = ?$   
Response: 4

**Q11. Does the solution support and align with the answer?**

**Criteria:** The key explanation and logic should clearly match the final answer.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes:** Prompt: Can you teach me how to solve  $12 \times 13$ ?  
Response: The answer is 156. This is a number & operation math question...

**Q12. Does the response provide a correct solution to this math question?**

**Criteria:** The response should give the correct and accurate solution based on the math problem.

**Scoring & Examples:**

- **0 = No :** More than 50% incorrect
- **1 = Mostly correct:** Minor error that doesn't affect logic
- **2 = Completely correct**

### A.3 Quality

**Q13. Does the response have hallucinations or inaccurately extracted information?**

**Criteria:** The model responds with content that contains hallucinations and/or extracts inaccurate information from the provided prompt.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes**

**Q14. Does the response have failures in mathematical or logical reasoning?**

**Criteria:** The model in its responses makes errors in arithmetic calculations, statistical analysis, or other quantitative conceptual or numerical operations.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes**

**Q15. Does the response fail to accurately and completely follow the prompt instructions?**

**Criteria:** The model doesn't follow explicit or clearly implied instructions in the model input. This includes responding in the wrong language, ignoring the math exercise's key information, or not adhering to the user's requirement.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes**

**Q16. Is the response incoherent?**

**Criteria:** The model's reasoning contains logical fallacies, contradicts itself within the same response, or reaches conclusions that don't follow from the premises. It includes cases where the model presents information and then contradicts it later in the same response.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes**

**Q17. Does the response provide irrelevant information?**

**Criteria:** The model in its responses includes information that doesn't address the user's query or goes beyond the scope of what was asked. This includes discussing tangential topics, adding unnecessary background, or focusing on aspects not central to the query.

**Scoring & Examples:**

- **1 = No**
- **0 = Yes**

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**Q18. Does the response have formatting, grammatical, or vocabulary errors?**

**Criteria:** This failure mode occurs when the model’s response contains errors in formatting, grammar, or word usage.

**Scoring & Examples:**

- 1 = No
- 0 = Yes

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**Q19. Is the response overly brief or lacking necessary detail?**

**Criteria:** The model provides a response that lacks sufficient detail or explanation to adequately address the query, given the complexity of the topic and the apparent depth of information requested.

**Scoring & Examples:**

- 1 = No
- 0 = Yes

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862

**B Model Sources and Computational Cost**

863 The models evaluated in this paper are obtained

864 from the following sources:

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- 868
1. **GPT-5** and **GPT-o1** are provided by OpenAI. The corresponding API documentation is available at <https://platform.openai.com/docs/models>.
  2. **Gemini-2.5-Pro** is provided by Google Gemini, with API documentation available at <https://ai.google.dev/gemini-api/docs>.
  3. **Qwen3-VL-30B-A3B-Instruct**<sup>1</sup> and **Llama-3.2-11B-Vision-Instruct**<sup>2</sup> are open-source base model weights obtained from Hugging Face (<https://huggingface.co/>).

877 For large proprietary models (e.g., GPT-5), a

878 one-time evaluation on 600 samples incurs a cost

879 of approximately \$6 for generating explanations.

880 All open-source model evaluations are conducted

881 on a system equipped with two NVIDIA RTX 4090

<sup>1</sup><https://huggingface.co/Qwen/Qwen3-VL-30B-A3B-Instruct>

<sup>2</sup><https://huggingface.co/meta-llama/Llama-3.2-11B-Vision-Instruct>

882 GPUs (32GB memory each). Overall, the mod-

883 est computational requirements demonstrate that

884 our evaluation protocol is accessible to researchers

885 with limited computational resources, while still

886 enabling comprehensive assessment of state-of-the-

887 art models.

**C Human Annotation Details**

888

889 To verify the reliability of our evaluation rubric, we

890 conducted a human annotation study on a strat-

891 ified subset of 120 model responses. Two ex-

892 pert annotators independently evaluated these in-

893 stances, achieving an overall inter-rater agreement

894 of 87.11%. As detailed in Table 3, these results

895 demonstrate strong consistency across different

896 models and learner profiles, confirming the repro-

897 ducibility of our scoring framework.

Model	Agreement (%)
GPT-o1	100.00
GPT-5	89.47
Qwen3-VL-30B	84.21
Gemini-2.5-Flash	73.68
Llama3.2-11B-VL	73.68
<b>Average</b>	<b>87.11</b>

Table 3: Detailed inter-rater agreement metrics for each evaluated model on the annotated subset ( $N = 120$ ). The overall average agreement across all models is 87.11%.

## D Statistical Analysis of Model Performance

We conducted a Repeated Measures ANOVA to statistically evaluate the performance differences between VLMs and test items. As detailed in Table 4, the analysis revealed a statistically significant main effect for the LLM ( $F = 41.39, p < .001$ ), confirming that the choice of model significantly impacts performance quality.

Additionally, we observed a significant main effect for Item ( $F = 721.61, p < .001$ ) and a significant Item  $\times$  LLM Interaction ( $F = 21.75, p < .001$ ). This interaction indicates that the performance gap between models is not uniform; rather, it varies depending on the specific difficulty or type of math question presented.

Cases	Sum of Squares	df	Mean Square	F	p
<i>Within Subjects Effects</i>					
Item	593.60 <sup>a</sup>	8 <sup>a</sup>	74.201 <sup>a</sup>	721.61 <sup>a</sup>	< .001
Item * LLM	71.56 <sup>a</sup>	32 <sup>a</sup>	2.236 <sup>a</sup>	21.75 <sup>a</sup>	< .001
Residuals	588.17	5720	0.103		
<sup>a</sup> Mauchly's test indicates sphericity assumption is violated ( $p < .05$ ).					
<i>Between Subjects Effects</i>					
LLM	61.25	4	15.312	41.39	< .001
Residuals	264.49	715	0.370		

Table 4: Repeated Measures ANOVA Results. Analysis of Within-Subjects Effects (Item, Interaction) and Between-Subjects Effects (LLM).

Figure 4 visualizes these descriptive trends. While some items (e.g., Item 7) proved uniformly difficult for all models, causing performance to converge near zero, other items (e.g., Item 1 and 9) exhibit distinct stratification, where higher-performing models separate clearly from lower-performing ones.

Descriptives plots

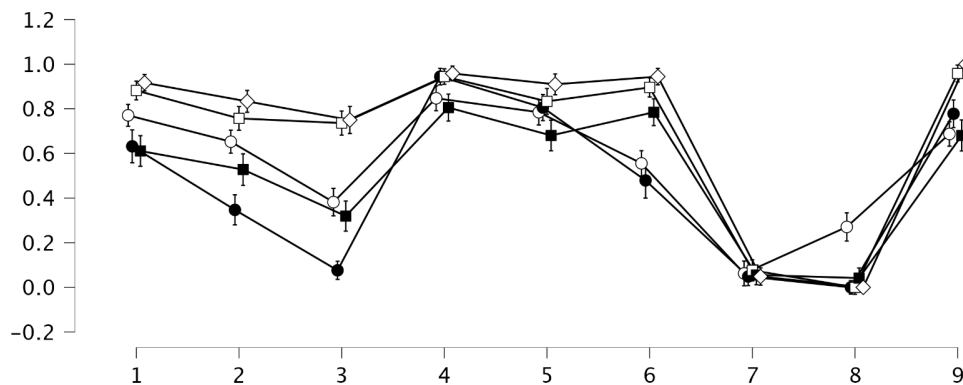


Figure 4: Descriptive Plots of Model Performance by Item. The x-axis represents the math items, and the y-axis represents the normalized performance score. The divergence of lines illustrates the Item  $\times$  LLM interaction effect.

## E Statistical Analysis by Test Group

We extended our analysis to evaluate performance differences between distinct Test Groups using a Repeated Measures ANOVA. As presented in Table 5, we found a statistically significant main effect for TestGroup ( $F(3, 716) = 92.73, p < .001$ ), with a substantial effect size ( $\eta_p^2 = 0.280$ ). This indicates that the grouping factor accounts for 28% of the variance in between-subjects performance.

Furthermore, the Item  $\times$  TestGroup interaction was significant ( $F(24, 5728) = 19.13, p < .001$ ), suggesting that performance gaps between groups are dependent on the specific item being solved.

Cases	SS	df	MS	F	p	$\eta_p^2$	$\omega^2$
<b>Within Subjects Effects</b>							
Item	593.64 <sup>a</sup>	8 <sup>a</sup>	74.205 <sup>a</sup>	695.91 <sup>a</sup>	< .001	0.493	0.412
Item * TestGroup	48.95 <sup>a</sup>	24 <sup>a</sup>	2.040 <sup>a</sup>	19.13 <sup>a</sup>	< .001	0.074	0.022
Residuals	610.78	5728	0.107				
<sup>a</sup> Mauchly's test indicates sphericity assumption is violated ( $p < .05$ ).							
<b>Between Subjects Effects</b>							
TestGroup	91.14	3	30.381	92.73	< .001	0.280	0.088
Residuals	234.59	716	0.328				

Table 5: Repeated Measures ANOVA (Test Group). Comparison of Within-Subjects and Between-Subjects effects, including effect sizes ( $\eta_p^2$  and  $\omega^2$ ).

As illustrated in Figure 5, while all groups struggled similarly on the most difficult items (e.g., Item 7), the lower-performing group (bottom line) showed significantly higher divergence on Items 1, 3, and 5 compared to the clustered higher-performing groups.

Descriptives plots

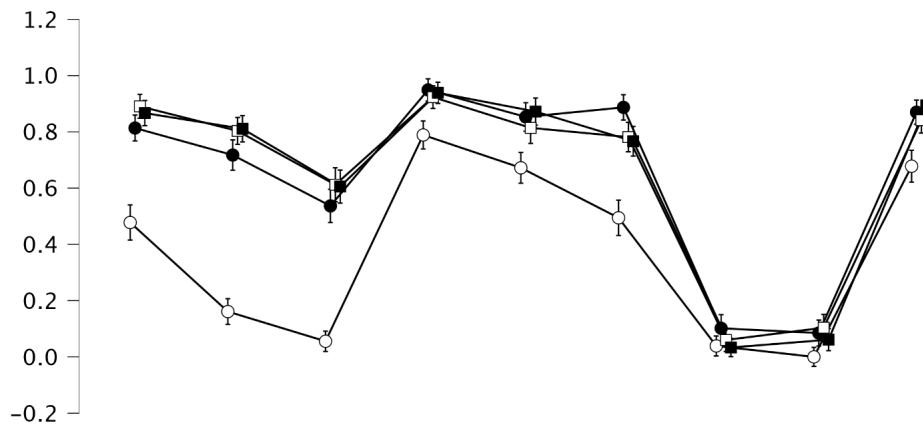


Figure 5: **Descriptive Plots by Test Group.** Performance stratification across 9 items. The x-axis represents the items, and the y-axis represents the normalized score. One group (open circles) consistently underperforms compared to the others.

## F Case Profiles

To qualitatively illustrate the adaptive capabilities of the evaluated models, we present a case study of a Grade 4 measurement problem. Figure 6 displays the responses generated by the model for the same math question across three distinct learner profiles: High-performance, Intermediate, and Low-performance. This visual comparison demonstrates how the model adjusts its pedagogical strategy, ranging from direct calculation to scaffolded instruction, based on the learner's stated confidence and prior knowledge.

### G4Q5 Responses Across Learner Profiles

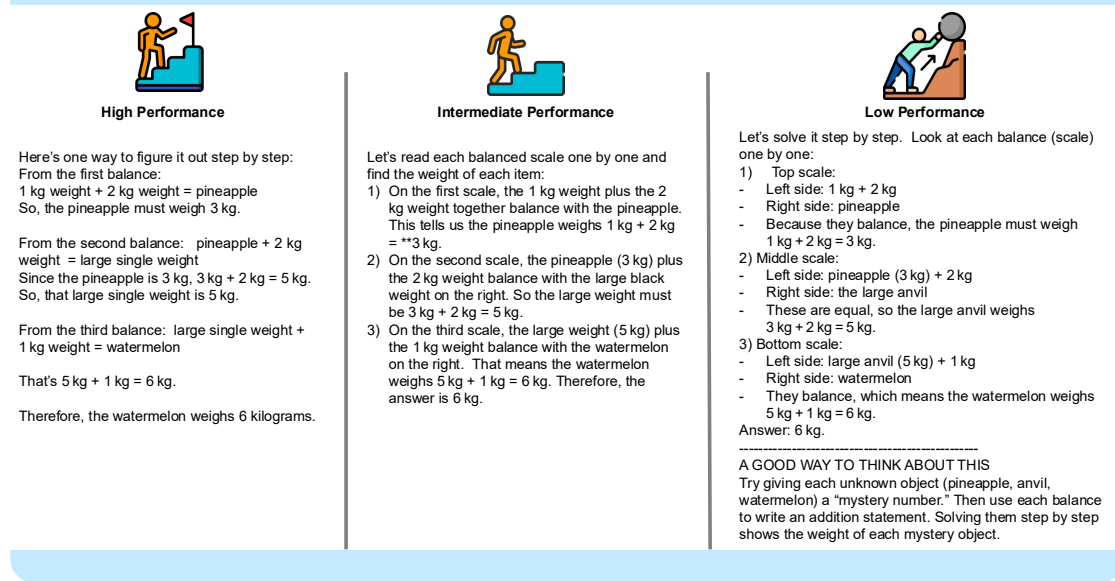


Figure 6: Case profiles for three learner profiles in G4Q5.

## G Prompt Design Strategies

This section provides a comprehensive documentation of the evaluation rubric, presenting the specific criteria, scoring hierarchies, and illustrative examples utilized in the study. To ensure full transparency and reproducibility, the content below reproduces the definitions exactly as they appear in the evaluation framework. Each entry details the theoretical sub-dimension (e.g., Cognitive vs. Motivational aspects), the precise conditions required for each score (e.g., the distinction between a score of 0 and 1), and the reference examples that serve as ground truth for annotators.

Learner Profile Type	Grade	Prompt
High-performance	4	I am a student from Grade 4, I like learning mathematics very much and I am very confident in mathematics. Now I have mastered all mathematics topics in grade 4, including number, measurement and geometry, and data. I got 615 in the TIMSS 2019 Math Test. Can you teach me this math question?
High-performance	8	I am a student from Grade 8, I like learning mathematics very much and I am very confident in mathematics. Now I have mastered all mathematics topics in grade 8, including number, algebra, geometry and measurement, and data and probability. I got 625 in the TIMSS 2019 Math test. Can you teach me this math question?
Intermediate-performance	4	I am a student from Grade 4, I like learning mathematics very much and I am confident in mathematics. Now I have mastered all mathematics topics in grade 4, including number, measurement and geometry, and data. I got 550 in the TIMSS 2019 Math Test. Can you teach me this math question?
Intermediate-performance	8	I am a student from Grade 8, I like learning mathematics very much and I am very confident in mathematics. Now I have mastered all mathematics topics in grade 8, including number, algebra, geometry and measurement, and data and probability. I got 550 in the TIMSS 2019 Math test. Can you teach me this math question?
Low-performance	4	I am a student from Grade 4, I don't like learning mathematics and I am not confident in mathematics. Now I have mastered mathematics topics such as number and data in grade 4. I got 390 in the TIMSS 2019 Math Test. Can you teach me this math question?
Low-performance	8	I am a student from Grade 8, I don't like learning mathematics and I am not confident in mathematics. Now I have mastered mathematics topics such as number and geometry in grade 8. I got 390 in the TIMSS 2019 Math Test. Can you teach me this math question?

Table 6: **User prompts.** User prompts across learner profiles (high-performance, intermediate-performance, and low-performance) and grade levels (grade 4 and 8).

## H Learning Goals & Content Areas

Content Area	Topic	Learning Goal
<b>GRADE 4</b>		
Number	Whole Numbers	<ol style="list-style-type: none"> <li>1. Demonstrate knowledge of place value (2-digit to 6-digit numbers); represent whole numbers with words, diagrams, number lines, or symbols; order numbers.</li> <li>2. Add and subtract (up to 4-digit numbers), including computation in simple contextual problems.</li> <li>3. Multiply (up to 3-digit by 1-digit and 2-digit by 2-digit numbers) and divide (up to 3-digit by 1-digit numbers), including computation in simple contextual problems.</li> <li>4. Solve problems involving odd and even numbers, multiples and factors of numbers, rounding numbers (up to the nearest ten thousand), and making estimates.</li> <li>5. Combine two or more properties of numbers or operations to solve problems in context.</li> </ol>
	Expressions, Simple Equations, and Relationships	<ol style="list-style-type: none"> <li>1. Find the missing number or operation in a number sentence (e.g., <math>17 + w = 29</math>).</li> <li>2. Identify or write expressions or number sentences to represent problem situations that may involve unknowns.</li> <li>3. Identify and use relationships in a well-defined pattern (e.g., describe the relationship between adjacent terms and generate pairs of whole numbers given a rule).</li> </ol>
	Fractions and Decimals	<ol style="list-style-type: none"> <li>1. Recognize fractions as parts of wholes or collections; represent fractions using words, numbers, or models; compare and order simple fractions; add and subtract simple fractions, including those set in problem situations. (Fractions may have denominators of 2, 3, 4, 5, 6, 8, 10, 12, or 100.)</li> <li>2. Demonstrate knowledge of decimal place value including representing decimals using words, numbers, or models; compare, order, and round decimals; add and subtract decimals, including those set in problem situations. (Decimals may have one or two decimal places, allowing for computations with money.)</li> </ol>
Measurement and Geometry	Measurement	<ol style="list-style-type: none"> <li>1. Measure and estimate lengths (millimeters, centimeters, meters, kilometers); solve problems involving lengths.</li> <li>2. Solve problems involving mass (gram and kilogram), volume (milliliter and liter), and time (minutes and hours); identify appropriate types and sizes of units and read scales.</li> <li>3. Solve problems involving perimeters of polygons, areas of rectangles, areas of shapes covered with squares or partial squares, and volumes filled with cubes.</li> </ol>
	Geometry	<ol style="list-style-type: none"> <li>1. Identify and draw parallel and perpendicular lines; identify and draw right angles and angles smaller or larger than a right angle; compare angles by size.</li> <li>2. Use elementary properties, including line and rotational symmetry, to describe, compare, and create common two-dimensional shapes (circles, triangles, quadrilaterals, and other polygons).</li> <li>3. Use elementary properties to describe and compare three-dimensional shapes (cubes, rectangular solids, cones, cylinders, and spheres) and relate these with their two-dimensional representations.</li> </ol>
Data	Reading, Interpreting, and Representing Data	<ol style="list-style-type: none"> <li>1. Read and interpret data from tables, pictographs, bar graphs, line graphs, and pie charts.</li> <li>2. Organize and represent data to help answer questions.</li> </ol>
Data	Using Data to Solve Problems	Use data to answer questions that go beyond directly reading data displays (e.g., solve problems and perform computations using data, combine data from two or more sources, draw conclusions based on data).

Table 7: **Content Areas & Learning Goals.** TIMSS mathematical content areas and learning goals in Grade 4.

Content Area	Topic	Learning Goal
<b>GRADE 8</b>		
Number	Integers	<ol style="list-style-type: none"> <li>1. Demonstrate understanding of properties of numbers and operations; find and use multiples and factors, identify prime numbers, evaluate positive integer powers of numbers, evaluate square roots of perfect squares up to 144, and solve problems involving square roots of whole numbers.</li> <li>2. Compute and solve problems with positive and negative numbers, including through movement on the number line or various models (e.g., losses and gains, thermometers).</li> </ol>
	Fractions and Decimals	<ol style="list-style-type: none"> <li>1. Using various models and representations, compare and order fractions and decimals, and identify equivalent fractions and decimals.</li> <li>2. Compute with fractions and decimals, including those set in problem situations.</li> </ol>
	Ratio, Proportion, and Percent	<ol style="list-style-type: none"> <li>1. Identify and find equivalent ratios; model a given situation by using a ratio; divide a quantity according to a given ratio.</li> <li>2. Solve problems involving proportions or percents, including converting between percents and fractions or decimals.</li> </ol>
Algebra	Expressions, Operations, and Equations	<ol style="list-style-type: none"> <li>1. Find the value of an expression or a formula given values of the variables.</li> <li>2. Simplify algebraic expressions involving sums, products, and powers; compare expressions to determine if they are equivalent.</li> <li>3. Write expressions, equations, or inequalities to represent problem situations.</li> <li>4. Solve linear equations, linear inequalities, and simultaneous linear equations in two variables, including those that model real life situations.</li> </ol>
	Relationships and Functions	<ol style="list-style-type: none"> <li>1. Interpret, relate and generate representations of linear functions in tables, graphs, or words; identify properties of linear functions including slope and intercepts.</li> <li>2. Interpret, relate and generate representations of simple non-linear functions (e.g., quadratic) in tables, graphs, or words; generalize pattern relationships in a sequence using numbers, words, or algebraic expressions.</li> </ol>
Geometry	Geometric Shapes and Measurements	<ol style="list-style-type: none"> <li>1. Identify and draw types of angles and pairs of lines and use the relationships between angles on lines and in geometric figures to solve problems, including those involving the measures of angles and line segments; solve problems involving points in the Cartesian plane.</li> <li>2. Identify two-dimensional shapes and use their geometric properties to solve problems, including those involving perimeter, circumference, area, and the Pythagorean Theorem.</li> <li>3. Recognize and draw images of geometric transformations (translations, reflections, and rotations) in the plane; identify congruent and similar triangles and rectangles and solve related problems.</li> <li>4. Identify three-dimensional shapes and use their geometric properties to solve problems, including those involving surface area and volume; relate three-dimensional shapes with their two-dimensional representations.</li> </ol>
Data and Probability	Data	<ol style="list-style-type: none"> <li>1. Read and interpret data from one or more sources to solve problems (e.g., interpolate and extrapolate, make comparisons, draw conclusions).</li> <li>2. Identify appropriate procedures for collecting data; organize and represent data to help answer questions.</li> <li>3. Calculate, use, or interpret statistics (i.e., mean, median, mode, range) summarizing data distributions; recognize the effect of spread and outliers.</li> </ol>
	Probability	For simple and compound events: a) determine theoretical probability (based on equally likely outcomes, e.g., rolling a fair die) or b) estimate the empirical probability (based on experimental outcomes).

Table 8: **Content Areas & Learning Goals.** TIMSS mathematical content areas and learning goals in Grade 8.