Towards Pedagogically Aligned LLM Tutors for Math Mistake Remediation

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Abstract

Large language models have strong potential for use in intelligent tutoring systems, but they often fail to follow effective pedagogical strategies, such as guiding students without revealing final answers. We study the application of a two-stage alignment pipeline for math mistake remediation, combining supervised fine-tuning on tutoring dialogs with Direct Preference Optimization on synthetic preference pairs. We construct a dataset that integrates existing tutoring corpora with synthetic data generated along pedagogical dimensions, such as scaffolding and factuality, and study different input configurations that incorporate solution correctness and gold answers. Experiments show that this approach improves both factual accuracy and pedagogical quality over base models and existing tutoring models. Human evaluation further indicates that our best model is competitive with a strong proprietary baseline, while providing additional benefits in terms of openness, transparency, and reproducibility. Our results highlight the effectiveness of preference-based pedagogical alignment, while also revealing challenges in reliably evaluating tutoring quality. The code and data are released at https://github.com/Kpetyxova/towards-aligned-math-tutor.

1 Introduction

Human tutoring plays a fundamental role in education, supporting learner development and contributing to broader societal advancement. One-on-one tutoring has long been shown to be highly effective (Bloom, 1984), yet the scarcity of qualified human tutors limits its large-scale adoption. Recent progress in large language models (LLMs) has opened new opportunities for educational applications (Wang et al., 2024; Gan et al., 2023), enabling the development of LLM-driven intelligent tutoring systems (ITSs) (Pal Chowdhury et al., 2024; Liu et al., 2024b) as well as tutoring through prompting approaches (Jurenka et al., 2024; McNichols et al., 2023; Mollick and Mollick, 2024). These AI-based tutors support a wide range of instructional goals (Wollny et al., 2021), with particular emphasis on addressing student errors and misunderstandings – an area that continues to drive research in AI tutoring (Macina et al., 2023; Wang et al., 2023).

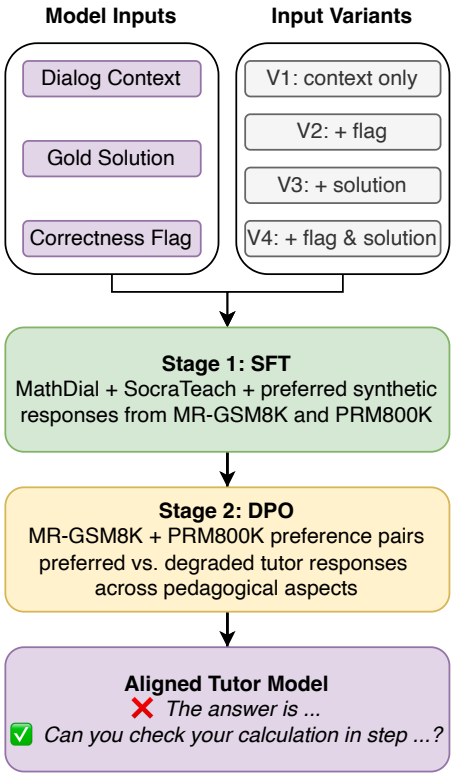

Figure 1: Overview of our two-stage pedagogical alignment pipeline. We first perform SFT on tutoring dialogs, then apply DPO using synthetic preference pairs for mistake remediation. We compare four input configurations (V1–V4) that vary in access to the student answer correctness flag and the gold solution.

Although LLMs are capable of producing natural-sounding conversations and performing well on various reasoning tasks, including commonsense and elementary mathematical reason-

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ing (Achiam et al., 2023; Kojima et al., 2022; Laskar et al., 2023; Yang et al., 2024), they are not immediately suitable for deployment in educational settings without careful adaptation. High-quality tutoring involves more than generating fluent responses – it requires guiding learners toward constructing their own understanding. Effective tutors rely on pedagogical strategies such as providing hints, engaging students through Socratic questioning (Carey and Mullan, 2004), and promoting active problem-solving. Consequently, LLM-based tutoring systems should be designed to align with established human tutoring practices (Nye et al., 2014) and active learning principles that have been shown to improve learning outcomes (Freeman et al., 2014).

To build reliable and pedagogically sound tutoring systems, models must embody these instructional principles. In particular, they should be factually accurate, avoid prematurely revealing final answers, and instead guide students toward understanding and self-correction. Existing tutoring models attempt to incorporate these principles to varying degrees. For example, `SocraticLM` (Liu et al., 2024a) adopts a Socratic "thought-provoking" paradigm, guiding students with step-by-step questions that encourage active participation and independent reasoning rather than directly providing answers. In contrast, `TutorRL-7B` (Dinucu-Jianu et al., 2025) optimizes tutoring behavior through reinforcement learning over simulated student-tutor interactions, using reward functions that balance pedagogical quality and student success (solve rate). While these approaches demonstrate promising results, they also highlight the remaining challenges. `SocraticLM` relies on the supervised imitation of pedagogical behavior, which may limit control over specific pedagogical attributes. Similarly, `TutorRL-7B` optimizes tutoring as a holistic policy using scalar rewards, where pedagogical behaviors are learned implicitly through interaction and reward design. This makes it difficult to explicitly control or disentangle individual aspects of tutoring, such as factual accuracy, mistake identification, or the degree of solution revealing. We argue that explicitly modeling and controlling these aspects can lead to more robust and interpretable tutoring systems. Motivated by this, we propose a two-stage pedagogical alignment pipeline (Figure 1) that combines supervised fine-tuning (SFT) with direct preference optimization (DPO) to align tutor responses with desired pedagogical behaviors directly. We further study different input configurations, varying the information provided to the model (e.g., correctness flags and gold solutions) to better disentangle sub-tasks such as error detection and response generation.

In summary, our key contributions are as follows:

- We construct a dataset for math mistake remediation by combining existing tutoring datasets with synthetic data derived from math-task datasets containing LLM-generated solutions. We treat these solutions as student responses and generate corresponding tutor responses using `GPT-5`, along with degraded variants across multiple pedagogical dimensions, resulting in a set of preference pairs for DPO.
- We study different input configurations, analyzing how access to additional information (e.g., student solution correctness flags and gold solutions) affects model performance.
- We fine-tune both open-source and proprietary models using SFT and DPO on the constructed dataset, showing that our best open-source-aligned model outperforms a strong proprietary baseline in the human evaluation.
- We release all resources developed in this work, including the synthetic dataset, trained models, and code, to support further research on pedagogically aligned AI tutors: `https://github.com/Kpetyxova/towards-aligned-math-tutor`.

2 Related work

2.1 Pedagogical alignment methods for LLM-based tutors

Large language models are frequently optimized for general-purpose helpfulness, which often leads to tutoring behaviors that are suboptimal for learning, such as prematurely revealing solutions or failing to diagnose student misconceptions. We refer to the objective of shaping the model's behavior toward guided problem-solving, targeted feedback, and adaptive scaffolding as *pedagogical alignment*. Early approaches address this by using tutoring-specific SFT, in which models are trained to imitate the pedagogical dialog style. `SocraticLM` (Liu et al., 2024a), for instance, fine-tunes `ChatGLM3-6B` (GLM et al., 2024) on large-scale Socratic dialogs

generated via a Dean-Teacher-Student multi-agent pipeline, yielding consistent gains across multiple teaching skill dimensions. However, its training remains a supervised imitation of synthesized teacher responses, rather than an explicit optimization of a preference-based objective over pedagogical attributes, which can limit direct control over trade-offs (e.g., hint granularity vs. answer revealing) and robustness to unseen tutoring situations.

In parallel, LearnLM (Team et al., 2024) introduces *pedagogical instruction following*, applying reinforcement learning from human feedback (RLHF) with human preference data to improve adherence to system-level pedagogical instructions in multi-turn settings. Although effective, this approach depends on large-scale human preference collection and expert evaluation infrastructure.

More recently, online reinforcement learning has been explored over simulated student-tutor interactions to optimize multi-turn teaching behavior. TutorRL (Dinucu-Jianu et al., 2025), for instance, trains tutoring policies via on-policy reinforcement learning using simulated student dialogs, optimizing rewards that reflect both student learning outcomes (student solve rate) and pedagogical quality assessed by LLM-based judges.

A more scalable alternative is offline preference optimization with synthetic supervision. Sonkar et al. (2024) show that DPO (Rafailov et al., 2023) and related objectives (KTO (Ethayarajh et al., 2024), IPO (Azar et al., 2023)) consistently outperform SFT in shifting model behavior toward scaffolded guidance, with gains that remain stable across longer multi-turn dialogs. The effectiveness of such methods depends critically on preference data quality: RMBoost (Shen et al., 2024) addresses this by pre-selecting a preference label and conditionally generating a contrastive response guided by predefined multi-aspect evaluation criteria, reducing label noise in synthetic pair construction. Our work follows the offline preference optimization paradigm, applying preference-conditional generation to pedagogical dimensions for remediation of math mistakes.

2.2 Datasets for pedagogical alignment and mistake remediation

Training pedagogically aligned tutoring models requires data that capture both tutoring interaction structure and student error patterns. On the dialog side, SocraTeach (Liu et al., 2024a) provides large-scale synthetic Socratic tutoring dialogs with various student cognitive profiles, while MathDial (Macina et al., 2023) is collected by pairing human teachers with LLM-simulated students exhibiting common math errors, annotated with a taxonomy of teacher moves that captures realistic scaffolding strategies. In our work, both datasets serve as instruction tuning data for the SFT stage, where each tutor turn is treated as a supervised target conditioned on the prior dialog context. Beyond dialog structure, grounding of mistake remediation scenarios also requires fine-grained signals about student errors. MR-GSM8K (Zeng et al., 2023) provides structured error-centric instances by defining the evaluation as meta-reasoning over solution correctness, while PRM800K (Lightman et al., 2023) contributes step-level correctness labels on MATH (Hendrycks et al., 2021) solutions, enabling precise identification of where reasoning errors occur. We repurpose both datasets to construct preference pairs, where tutor responses are generated to contrast pedagogically effective responses with suboptimal ones.

2.3 Evaluation methods for pedagogical ability

Evaluating tutoring quality is inherently multi-dimensional: an effective tutor response must identify the student's mistake, locate where it occurs, provide guidance without revealing the answer, and offer actionable next steps. Previous work, such as Liu et al. (2024a) and Team et al. (2024), relies on human ratings or scenario-based expert rubrics, which are reliable but expensive and difficult to scale. This has motivated the development of automated taxonomy-based evaluation frameworks grounded in learning sciences.

Maurya et al. (2025) propose a unified eight-dimension taxonomy for mistake remediation and release MRBench; they further directly assess LLM-based judging and find that Prometheus2's (Kim et al., 2024) pedagogical annotations correlate poorly (often negatively) with human labels on MRBench, suggesting that LLM-as-judge evaluation is unreliable for fine-grained tutoring dimensions. In parallel, the BEA 2025 Shared Task (Kochmar et al., 2025) formulates four pedagogical dimensions as supervised prediction problems and shows that scalable automatic evaluation remains challenging (best 3-class macro F1 ≈ 0.58–0.72), despite substantial inter-annotator agreement (Fleiss' $\kappa \approx 0.65$).

AITutor-EvalKit (Naeem et al., 2025) ad-

dresses this by providing an end-to-end evaluation toolkit for student mistake remediation (SMR), featuring a lightweight multi-task model (LoMTL) trained to assess the quality of tutor responses along these four dimensions jointly. We adopt this evaluation framework in our work because it aligns closely with our task definition and provides scalable, aspect-level feedback matching our training objectives.

3 Experimental Setup

3.1 Data

We use the MathDial and SocraTeach datasets to fine-tune our models on dialog data. Since both datasets consist of tutor-student conversations (2,861 in MathDial and 35K in SocraTeach), we preprocess each conversation by splitting it into dialog turns. Each tutor turn is treated as a training instance, where all preceding turns serve as context, and the current tutor utterance is used as the gold response. For each instance, we have the gold solution to the underlying math problem and a flag indicating whether the student has solved the task correctly. In MathDial, we assign the flag *No* to all student turns except the final one; for the final turn, we assign *Yes* if the self-correctness flag provided in the dataset is True. In SocraTeach, we assign *No* to all student turns except the final one, as dialogs are constructed to terminate after the student provides a correct solution and the tutor acknowledges it. This preprocessing yields 18,609 instances from MathDial and 171,296 from SocraTeach.

To align the models with pedagogical values and to augment the data beyond MathDial and SocraTeach, we adopt the RMBoost approach (Shen et al., 2024) to generate synthetic data from the MR-GSM8K and PRM800K datasets. Since PRM800K includes mathematical problems spanning a wide range of difficulty levels, with metadata indicating topic and difficulty (where levels correspond to relative difficulty tiers of competition-style math problems rather than curriculum-based grade levels), we filter it to leave only algebra problems of levels 1-2, number theory problems of level 1, and pre-algebra problems of levels 1-3. We convert each instance in these datasets into a single dialog turn: the tutor first introduces the task, and the student responds with a solution. The student response corresponds to the LLM-generated step-by-step solution provided in the original datasets. When the solution is incorrect, we use GPT-5 to generate an appropriate tutor response. Conditioning on this response, we then use GPT-4.1 to generate a lower-quality version by degrading specific aspects of the response. We use GPT-5 to generate high-quality tutor responses, motivated by its stronger capabilities compared to GPT-4.1; this assumption was validated through manual inspection of generated responses. We use GPT-4.1 to produce degraded variants, as it does not require a model of comparable capacity. We adapt the prompt structure from RMBoost, modifying the evaluation aspects to reflect pedagogical criteria. Specifically, we define the following pedagogical criteria: (1) *Factuality* – the response should be factually correct, should not contradict what the student has said, and should not contain irrelevant information; (2) *Mistake Identification* – the response should identify, either explicitly or implicitly, that there is a mistake in the student's solution (for example, saying "Nice try" would miss this aspect); (3) *Targetedness* – the response should address the core misconception/misunderstanding of a student; (4) *Revealing Answer* – while it is sometimes necessary and acceptable to share the answer to a substep, the tutor should avoid giving away the final answer; (5) *Clarity* – the tutor's response should be free of awkward, confusing or misleading wording. The prompts used in this process are shown in Appendix A. This results in a dataset of 29,390 preference pairs.

Because MR-GSM8K and PRM800K also include instances with correct student solutions, we use these cases to create dialog examples without student errors, ensuring that the model does not always assume that the student's solution is incorrect. For these instances, we prompt GPT-5 to generate tutor responses appropriate for correct solutions and randomly assign them as follow-up turns. This process yields 3,769 additional instances. The prompt used for this procedure is shown in the Appendix B.

The statistics of the collected dataset are shown in Table 1.

3.2 Model Training

We train our models using a two-stage pipeline consisting of SFT followed by preference optimization via DPO (Rafailov et al., 2023). All stages use parameter-efficient fine-tuning via LoRA (Hu et al., 2021).

We first fine-tune the base model on tutor feedback data using standard cross-entropy loss on the tutor responses. Training runs for up to 5 epochs using the AdamW and a cosine learning rate sched-

Dataset	SFT Turns		DPO Pairs
	Correct	Incorrect	
MathDial	2,855	15,754	–
SocraTeach	46,104	125,192	–
MR-GSM8K	1,390	1,387	6,935
PRM800K	2,379	4,491	22,455
Total	52,728	146,824	29,390

Table 1: Overview of the dataset statistics. Synthetically generated pairs are used for both DPO training and SFT (on preferred responses).

ule. We apply early stopping based on validation loss to prevent overfitting. The resulting LoRA is used to initialize the next training stage.

In the second stage, we align the model with pedagogical preferences using DPO on the synthetic preference dataset.

Manual inspection of our preference data revealed that responses with degraded *Clarity* are not consistently worse; in many cases, they are simply paraphrases that preserve similar pedagogical value (see Appendix F). Therefore, we do not treat this aspect as equally important as the others. Specifically, we weight each training sample by a factor w_i reflecting the importance of its associated pedagogical aspect: *Factuality*, *Mistake Identification*, *Targetedness*, and *Revealing Answer* are each assigned a weight of 1, while *Clarity* is assigned a weight of 0.5. Full details of the weighted DPO objective are in Appendix G.

We use `Qwen3-4B-Instruct-2507` and `Qwen3-8B` (Yang et al., 2025) as our pretrained base models. In addition, we include `GPT-4.1-nano`,[1] a proprietary model from a different family, to provide cross-family comparison. For `GPT-4.1-nano`, fine-tuning is performed using the SFT and DPO functionality available through the provider's interface. As a result, the training procedure is not fully identical to that used for the `Qwen` models.

3.3 Experiments

We compare four configurations:

- `V1`: The model conditions only on the dialog context when generating the next tutor response;
- `V2`: The model is additionally provided with a binary flag indicating whether the student's solution is correct;
- `V3`: The model is additionally provided with the gold solution to the underlying math problem;
- `V4`: The model is additionally provided with both the correctness flag and the gold solution.

This setup allows us to isolate the effect of different levels of available information on response quality. In particular, configurations that provide the correctness flag and/or the gold solution (V2-V4) assume access to signals that may not always be directly available in real-world deployment. However, such settings are consistent with the standard human tutoring practice, where tutors have access to the correct solutions when providing feedback. In practice, such information would need to be obtained either from curated solution sources or by automatically solving the task. The latter introduces an additional source of error, as mistakes in the solution process may propagate to the generated feedback. Our current work does not model this setting explicitly. Therefore, configurations with access to gold solutions can be interpreted as upper bounds on performance, reflecting a scenario with reliable solution supervision. The prompt template used for training is provided in Appendix C.

3.4 Baselines

We compare our models against the following baselines:

- Base models: `Qwen3-4B-Instruct-2507`, `Qwen3-8B`, and `GPT-4.1-nano`.
- `GPT-5`: An advanced proprietary model.
- `SocraticLM`: `ChatGLM3-6B` fine-tuned on the `SocraTeach` dataset (Liu et al., 2024a).
- `TutorRL-7B`: A fine-tuned variant of `Qwen/Qwen2.5-7B-Instruct`, aligned with pedagogical principles using reinforcement learning (GRPO) in a synthetic multi-turn classroom setting (Dinucu-Jianu et al., 2025).

Note that `SocraticLM` and `TutorRL-7B` use the V1 configuration, as we adopt their original training prompts.

[1] https://developers.openai.com/api/docs/models/gpt-4.1-nano

3.5 Evaluation

We randomly sample 1,000 responses from the test set, equally distributed across datasets, and evaluate them using models from `AITutor-EvalKit` (Naeem et al., 2025) – namely, `GPT-5` and `LoMTL`. We assess four pedagogical dimensions: *mistake identification*, *mistake location*, *providing guidance*, and *actionability*. Before conducting this evaluation, we perform a factuality check using `GPT-5` with the prompt provided in Appendix D. This ensures that we assess pedagogical qualities only for factually correct responses, as responses containing factual errors are considered poor by default.

In addition, we conduct a small-scale human evaluation on an additional randomly sampled subset of the test set.

4 Results & Analysis

4.1 Automatic Evaluation

We first evaluate 1,000 randomly sampled responses from the test set for factuality using `GPT-5`. This evaluation is intended to identify cases in which a tutor response contains factual errors, such as introducing incorrect numbers from the task definition or hallucinating details about the student's solution. Table 2 reports the factuality results, while Appendix E provides a breakdown of the error categories assigned by `GPT-5` to responses judged as non-factual. As shown in Table 2, `GPT-5` achieves the highest factuality scores, whereas `GPT-4.1-nano` performs substantially worse. While `GPT-5` may exhibit some degree of bias when evaluating its own outputs, the high scores may also reflect its strong factual accuracy. The open-source baselines are also considerably less factual overall. Although `SocraticLM` is factually correct in roughly 50% of cases, our manual analysis suggests that this is partly because it often produces generic follow-up questions about the task or the student's solution, rather than directly engaging with the specific misconception, thereby avoiding factual errors. For our models, both SFT and DPO generally improve factuality compared to their respective base models. For the `Qwen` models, DPO often provides additional gains beyond SFT, whereas for `GPT-4.1-nano`, DPO degrades factuality relative to SFT. For `Qwen3-8B`, the configuration that conditions on both the correctness flag and the gold solution (V4) yields the strongest factuality results, indicating that access to this additional information is beneficial. Our manual analysis further shows that the best-performing configuration, `Qwen3-8B + DPO V4`, still frequently fails by copying an incorrect number from either the task definition or the student's solution. To address this issue, we automatically created 20,000 additional preference pairs by perturbing the numerical values in the reference responses used during training. We then reran the DPO stage with this extended dataset. This led to an absolute factuality improvement of approximately 10 percentage points, resulting in the final `Qwen3-8B + DPO V4`* model.

Model	Overall	Stu. Inc.	Stu. Cor.
Proprietary Models			
GPT-5	96.20	97.49	95.01
GPT-4.1-nano	38.10	15.87	58.54
Existing Tutoring Models			
SocraticLM	50.20	51.17	49.34
TutorRL-7B	39.80	33.40	45.68
Open-Source Base Models			
Qwen3-4B	11.70	3.13	19.58
Qwen3-8B	13.70	2.09	24.38
Qwen3-4B Fine-tuned			
+ SFT V1	43.10	24.01	60.65
+ DPO V1	32.90	24.63	40.50
+ SFT V2	56.10	35.85	74.57
+ DPO V2	58.30	39.04	76.01
+ SFT V3	48.60	27.97	67.56
+ DPO V3	53.20	40.08	65.26
+ SFT V4	55.70	33.82	75.82
+ DPO V4	56.00	35.91	74.47
Qwen3-8B Fine-tuned			
+ SFT V1	46.30	21.50	69.10
+ DPO V1	48.40	42.17	54.13
+ SFT V2	55.60	35.91	73.70
+ DPO V2	39.20	28.39	49.14
+ SFT V3	49.70	26.51	71.02
+ DPO V3	51.50	38.83	63.15
+ SFT V4	59.70	39.67	78.12
+ DPO V4	60.10	42.59	76.20
+ DPO V4*	**70.10**	**56.99**	**82.15**
GPT-4.1-nano Fine-tuned			
+ SFT V4	**84.40**	**75.57**	**92.51**
+ DPO V4	66.70	70.56	63.15

Table 2: Factuality metrics (%) across models. Columns report overall factuality, factuality when the student is incorrect (Stu. Inc.), and when they are correct (Stu. Cor.). Best results per group are in **bold**. `Qwen3-8B + DPO V4`* denotes the rerun of the DPO stage using the extended dataset.

Table 3 presents the results of the automatic evaluation for the pedagogical dimensions of *Mistake Identification* (*MI*), *Mistake Location* (*ML*), *Providing Guidance* (*PG*), and *Actionability* (*AC*) as assessed by `GPT-5` and `LoMTL`. These metrics are

computed only for responses classified as factually correct in the previous stage. A notable observation is the substantial disagreement between the two evaluators. In particular, GPT-5 assigns significantly higher scores to its own responses than LoMTL does, especially for the Actionability dimension (76.23 vs. 20.49). Manual analysis suggests that GPT-5 responses often reveal the full solution and final answer to the student. While this may appear helpful, it leaves little room for further student engagement. It therefore reduces the student's opportunity to solve the problem actively, making such responses less actionable from a pedagogical perspective. This behavior may indicate a potential bias of GPT-5 when evaluating its own outputs.

SocraticLM is rated poorly by both evaluators on the MI, ML, and PG dimensions, but receives relatively high Actionability scores from LoMTL (92.08). Our manual analysis shows that SocraticLM frequently produces general follow-up questions about the task, which are actionable because they prompt the student to respond. However, these questions are often not directly related to the student's specific mistake. Because LoMTL is based on a smaller 2B model, it may fail to detect this lack of targeted feedback, whereas GPT-5 appears better able to capture this issue, resulting in lower Actionability scores (64.58).

TutorRL-7B is consistently rated as highly actionable by both evaluators, but performs poorly on MI and ML according to GPT-5 evaluation.

For GPT-4.1-nano fine-tuning, SFT V4 outperforms DPO V4 across all dimensions under GPT-5. However, under LoMTL, DPO V4 achieves uniformly strong results, with zero "No" cases across all dimensions. Notably, GPT-4.1-nano + DPO V4 is the top-performing model according to LoMTL.

Finally, Qwen3-8B + DPO V4* outperforms existing tutoring models (SocraticLM, TutorRL-7B) and GPT-4.1-nano fine-tuned models across most dimensions under GPT-5, with the exception of Actionability. Under LoMTL, it slightly underperforms GPT-4.1-nano fine-tuned models but still consistently surpasses SocraticLM and TutorRL-7B.

Examples illustrating models outputs are shown in Appendix I.

4.2 Human Evaluation

In addition to automated metrics, we conducted a human evaluation with 10 annotators, including Master's and PhD students in NLP and professors. The study was designed to test two hypotheses: (**H1**) within a fixed backbone, our post-training pipeline improves pedagogical tutoring quality (DPO $>$ SFT $>$ Base); and (**H2**) our best post-trained model is competitive with a strong proprietary baseline.

We randomly selected 35 dialogs from the test set, balanced across dataset sources, and conducted pairwise comparisons. Each annotator evaluated a subset of dialogs (5 shared and 3 unique per annotator), resulting in 105 total pairwise comparisons (15 shared and 9 unique per annotator). For each dialog, we included one response from each of the following models: Qwen3-8B Base, Qwen3-8B SFT V4, Qwen3-8B DPO V4*, and GPT-5. This setup resulted in the following evaluation pairs: **H1a:** Qwen3-8B Base vs. Qwen3-8B SFT V4; **H1b:** Qwen3-8B SFT V4 vs. Qwen3-8B DPO V4*; and **H2:** Qwen3-8B DPO V4* vs. GPT-5. Annotators were shown the dialog context, the reference (gold) solution, and the flag indicating whether the student's solution was correct. They were then asked to select which response was better or whether both were equally good or poor (see Figure 2 and Appendix J). Based on majority voting and individual annotator judgments over pairwise comparisons, Qwen3-8B SFT V4 was preferred over Qwen3-8B Base in 67.6% of cases, Qwen3-8B DPO V4* was preferred over Qwen3-8B SFT V4 in 35.3% of cases, and Qwen3-8B DPO V4* was preferred over GPT-5 in 54.3% of cases. Inter-annotator agreement, measured using Fleiss κ, was 0.55, indicating moderate agreement.

Analysis of the reasons chosen by annotators shows consistent patterns across comparisons. Qwen3-8B Base is frequently judged as factually incorrect, less clear, and less coherent, and as providing less helpful guidance than Qwen3-8B SFT V4. Similarly, Qwen3-8B SFT V4 is often rated worse than Qwen3-8B DPO V4* for the same reasons. Compared with Qwen3-8B DPO V4*, GPT-5 is most often not chosen for revealing the final answer and providing less effective scaffolding for student reasoning.

We also evaluated the same responses with GPT-5 and LoMTL, again applying factuality filtering first. We then converted the four pedagogical annotations into scalar scores (1 for *Yes*, 0.5 for *To some extent*, and 0 for *No*; non-factual responses were assigned a score of 0 by default), summed these scores, and compared the resulting totals for the same response pairs used in the human evaluation. Under GPT-5-based evaluation, GPT-5 was ranked above Qwen3-8B DPO V4* in

Model	Mistake Ident.			Mistake Loc.			Providing Guid.			Actionability		
	Yes	Some	No	Yes	Some	No	Yes	Some	No	Yes	Some	No
Proprietary Models												
GPT-5 (GPT-5)	**94.00**	0.86	5.14	**81.37**	9.42	9.21	90.15	5.35	4.50	76.23	10.28	13.49
GPT-5 (LoMTL)	***85.08***	1.56	13.36	66.15	3.56	30.29	63.92	12.69	23.39	20.49	9.35	70.16
GPT-4.1-nano (GPT-5)	81.58	6.58	11.84	42.11	26.32	31.58	**93.42**	3.95	2.63	48.68	39.47	11.84
GPT-4.1-nano (LoMTL)	53.95	1.32	44.74	44.74	1.32	53.95	42.11	7.89	50.00	9.21	5.26	85.53
Existing Tutoring Models												
SocraticLM (GPT-5)	4.58	8.33	87.08	1.67	8.33	90.00	22.92	28.75	48.33	64.58	10.00	25.42
SocraticLM (LoMTL)	5.42	88.33	6.25	5.42	62.92	31.67	15.42	80.00	4.58	92.08	7.08	0.83
TutorRL-7B (GPT-5)	27.50	35.62	36.88	10.62	30.63	58.75	66.88	29.38	3.75	**87.50**	10.00	2.50
TutorRL-7B (LoMTL)	81.25	14.37	4.38	56.88	31.87	11.25	63.75	33.12	3.12	91.88	7.50	0.62
Qwen3-8B Fine-tuned												
+ SFT V4 (GPT-5)	42.63	23.16	34.21	28.95	25.79	45.26	61.58	22.11	16.32	57.89	27.37	14.74
+ SFT V4 (LoMTL)	68.95	22.11	8.95	51.05	26.32	22.63	61.05	27.37	11.58	81.58	12.63	5.79
+ DPO V4* (GPT-5)	57.14	24.18	18.68	45.05	26.74	28.21	73.63	17.95	8.42	61.54	28.57	9.89
+ DPO V4* (LoMTL)	82.35	12.16	5.49	68.24	20.39	11.37	74.51	19.61	5.88	92.16	5.49	2.35
GPT-4.1-nano Fine-tuned												
+ SFT V4 (GPT-5)	47.24	26.24	26.52	38.12	28.45	33.43	73.20	19.06	7.73	80.11	17.13	2.76
+ SFT V4 (LoMTL)	83.70	12.98	3.31	73.76	16.85	9.39	80.66	16.30	3.04	***97.51***	1.93	0.55
+ DPO V4 (GPT-5)	34.62	34.62	30.77	27.51	39.35	33.14	46.45	33.14	20.41	38.17	45.56	16.27
+ DPO V4 (LoMTL)	84.62	15.38	*0.00*	***78.99***	21.01	*0.00*	***85.50***	14.50	*0.00*	96.75	3.25	*0.00*

Table 3: Feedback quality metrics (%) across models, evaluated along four dimensions: Mistake Identification, Mistake Location, Providing Guidance, and Actionability. Each dimension reports the percentage of responses rated *Yes*, *To some extent* (Some), and *No*. The evaluator is indicated in parentheses (`GPT-5` or `LoMTL`). **Bold** and ***bold italic*** denote the highest *Yes* scores, while underline and *underline italic* denote the lowest *No* scores for the `GPT-5` and `LoMTL` evaluations, respectively. Results for `Qwen3-4B` and V1-V3 configurations are provided in Appendix H.

most cases, whereas under `LoMTL`-based evaluation, our model was more often ranked above `GPT-5` (see Appendix K). We further computed the average pairwise Cohen's κ between model-based rankings and human judgments, obtaining 0.44 for `GPT-5` and 0.52 for `LoMTL`. This indicates that `LoMTL`-based rankings are more consistent with human preferences than those produced by `GPT-5`.

5 Conclusions

In this work, we compiled a dataset for math mistake remediation by combining existing tutoring datasets with synthetic data derived from math-task datasets containing LLM-generated solutions. We treat these solutions as student responses and generate the subsequent tutor responses with `GPT-5`; we also generate degraded variants of the `GPT-5` responses along several pedagogical dimensions, resulting in a set of preference pairs used for DPO.

We compare different input variants and show that, as expected, providing the model with additional information, such as the gold solution to the task and a flag indicating whether the student's solution is correct, substantially improves factual correctness. This suggests that intelligent tutoring systems may benefit from being designed not as a single model responsible for solving the task and checking the student's work, but rather as a system of multiple components that solve the task, verify the student's solution, and generate appropriate feedback. This setting is also natural, since human tutors typically have access to the correct solution.

We further show that applying a two-stage post-training pipeline, SFT followed by DPO, with the compiled dataset improves performance according to human evaluation, leading to a preference for our 8B model over a strong proprietary baseline. We also observe improvements for a proprietary model (`GPT-4.1-nano`): while factual accuracy decreases relative to its SFT variant according to `GPT-5`, the DPO version performs best on pedagogical dimensions according to `LoMTL` evaluation. This highlights the generalizability of our approach for pedagogical alignment across models.

Finally, we highlight the challenges of evaluation in this setting, demonstrating that existing automatic evaluators have significant limitations.

Limitations

Our work has several limitations. First, our evaluation focuses on the quality of tutor responses rather than direct learning outcomes. Although *Factual-*

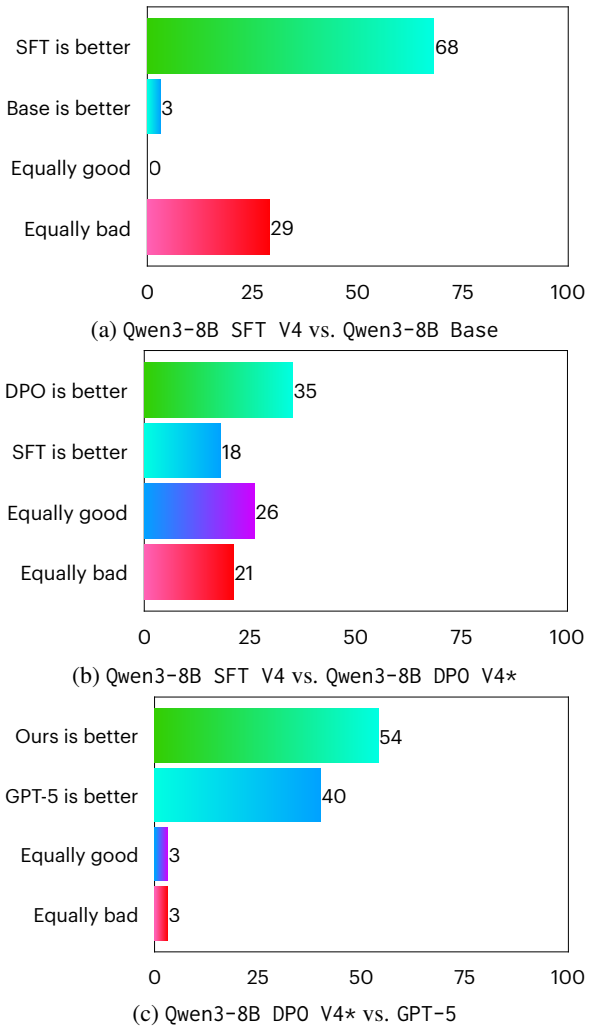

Figure 2: Results of human evaluation (percentages). Four annotators were asked to choose the better response or indicate if both were equally good or bad.

ity, *Mistake Identification*, *Targetedness*, and other aspects are important prerequisites for effective tutoring, we do not evaluate whether students learn better from interacting with such an aligned model. Evaluating learning outcomes would require a controlled user study with real learners, including pre- and post-tests or longitudinal interaction logs. We therefore interpret our results as evidence of improved pedagogical response quality for mistake remediation, rather than as direct evidence of improved educational effectiveness. Notably, most concurrent research on LLM-based tutoring similarly evaluates response quality rather than student learning, highlighting a broader gap in the field.

Second, our evaluation relies in part on LLM-based judges. As demonstrated by our results, different evaluators (`GPT-5` and `LoMTL`) often disagree substantially. This suggests that current automated evaluators are not yet fully reliable for assessing tutoring quality. While we partially mitigate this through a human evaluation, it remains relatively limited in scale, as the evaluation set is small (105 pairs) and relies primarily on single-annotator judgments, which may introduce noise despite moderate inter-annotator agreement. Similarly, due to resource constraints, the automatic evaluation is conducted on 1,000 test samples only.

Third, the preference data is generated using LLMs. We note that constructing fully human-authored preference data for math mistake remediation is prohibitively costly, as it would require expert tutors to inspect student solutions, identify mistakes, write pedagogically appropriate feedback, and provide controlled lower-quality alternatives across multiple dimensions. Therefore, we view synthetic preference generation as a scalable approximation, but not a substitute for richer human-authored or human-validated data. Moreover, our synthetic preference pairs are generated through minimal revisions produced by two proprietary models from the same family (`GPT-5` and `GPT-4.1`). As a result, the generated data may reflect family-specific stylistic biases and may not fully capture the diversity of natural student-tutor interactions.

Future work should, therefore, focus on several directions. First, it is important to evaluate whether pedagogically aligned models improve learning outcomes for real students. In addition, future work should scale up human and automatic evaluation, incorporate multi-annotator judgments, explore larger backbone models, and design multi-model or human-in-the-loop generation pipelines to improve data diversity and reliability.

Ethical Considerations

The proposed models are trained on synthetic data, which may encode biases in phrasing, tone, or instructional style. As this work is exploratory and the model outputs have not been evaluated with real students, we do not anticipate immediate risks associated with the current study. However, we acknowledge that LLMs may pose risks when deployed in real-world educational settings. In particular, they may generate outputs that appear plausible but are factually incorrect or nonsensical, potentially leading to misguided learning outcomes or reinforcing existing biases. While no direct risks arise from the present work, future applications of these methods in real-world settings should

incorporate appropriate safeguards, such as fact-checking, human oversight, and bias-mitigation strategies.

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A Prompt Templates for Preferred and Non-Preferred Next Tutor Turns

See Figures 3 and 4.

Preferred Tutor Response Generation Prompt (Template)

```
You are an expert math tutor
    helping a student understand
    and fix a mistake in their
    solution. Your goal is to guide
     the student toward the correct
     reasoning without revealing
    the final answer. Keep your
    response concise and focused on
     the core misunderstanding. You
     will be shown the problem, the
     student's incorrect solution,
    and the step where the mistake
    occurs; produce the next
    helpful tutor response.

<task_description>
You will be shown:
1. A detailed guideline describing
     evaluation aspects of a good
    tutor response.
2. A math problem, the correct (
    gold) solution, the student's
    solution, and the specific step
     where the mistake occurs.
3. A scaffolding level that has
    been selected for you.
Your task is to produce a high-
    quality tutor response that
    helps the student progress
    meaningfully while adhering to
    the guideline AND the assigned
    level.
</task_description>

<guideline>
A good tutor response is evaluated
     along the following aspects:
1. Factuality + Non-contradiction
    + No Nonsense: The response
    should be factually correct,
    should not contradict what the
    student has said, and should
    not contain irrelevant
    information. Example:
Conversation history: [the task
    about gift cards]
Bad: If Ms. Jones received 5 gift
    cards worth $10 each, then 1/3
    of the thank you cards
    contained a gift card, meaning
    3 out of every 5 cards had a
    gift card, and you can use this
     information to solve for the
    total number of students in her
     class. --> Factually incorrect
Better: That's correct! Now, if
    1/3 of the thank you cards
    contained a gift card, how many
     thank you cards did she
    receive in total?

2. Mistake Identification +
    Location: The response should
    identify, either explicitly or
    implicitly, that there is a
    mistake in the student's
    solution. For example, saying "
    Nice try" would miss this
    aspect. Example:
Conversation history: Student: yay
Tutor: Next, we have to find the
    value of 6 times 9 + 2. Tutor:
    What is the value of 6 times 9
    + 2?
Student: 99
Better: That's a great start!
    Remember, we need to follow the
     order of operations (PEMDAS).
    Let's multiply 6 times 9 first,
     then add 2.
Bad: Very good try. --> Mistake
    Identification + Location
    aspect is missing

3. Targetedness: The response
    should address the core
    misconception/misunderstanding
    of a student. Example:
Conversation history: [the task
    about eggs]
Worse: Ok, remember there are only
     12 eggs to begin with -->
    doesn't point to any
    misconception
Better: It looks like you've got a
     good start, but let's revisit
    the single yolks calculation -
    since 5 eggs had double yolks,
    that means there are actually
    12 - 5 = 7 eggs with single
    yolks, not 12.

4. Not revealing the final answer:
     While it is sometimes
    necessary and acceptable to
    share the answer to a substep,
    the tutor should avoid giving
    away the final answer. Example:
Conversation history: [the task
    about average speed]
Worse: You're close, but let's re-
    examine this - if Jason already
     drove 30 minutes at 60 miles
    per hour, that means he covered
     30 miles, and he still has 90
    miles left, so to cover those
    90 miles in 1 hour (60 minutes)
    , not 1 hour 30 minutes, he
    needs to average a speed of
    90/1 = 90 miles per hour. -->
    Reveals the final answer
Better: You're very close, but
    remember the question asks for
    the average speed needed for
    the *remaining* portion of the
    drive, not the overall trip.
```

```
5. Clarity + Coherence: The tutor's response should be free of awkward, confusing or misleading wording. A good tutor response acknowledges the student's input and connects it to the next step. Example:
Conversation history: [the task about gift cards]
Student: She got 5 gift cards since $50 divided by $10 is equal to 5.
Worse: That's correct! Now, if 1/3 of the thank you cards contained a gift card, how many thank you cards did she receive in total?
Better: Ok. And if she got 5 thank you cards that had gift cards in them, and these were 1/3 of the total number of thank you card, she got, how many thank you cards did she get total?
--> More explicit connection between the student's input and the next step

Scaffolding level:
- Assigned scaffolding level: {level}
- Level notes: {level_notes}
</guideline>

<problem>
{question}
</problem>

<correct_solution>
{correct_solution}
</correct_solution>

<student_solution>
{attempt}
</student_solution>

<erroneous_step>
Error step: {error_step}
Reason: {error_reason}
</erroneous_step>

Read everything carefully.
Use the assigned scaffolding level above when crafting the tutor response-match its tone, pacing, and support budget.

Wrap your output in <response>...</response> tags.
```

Figure 3: Prompt template used to generate preferred next tutor turn. Curly-brace fields denote placeholders filled per instance. The scaffolding level and notes used are: *L0 (metacognitive) – tone-first, Socratic nudge, and one check question, with a maximum of two sentences*.

Non-Preferred Tutor Response Generation Prompt (Template)

```
You are an expert tutor teaching another tutor how not to respond to a student's response.

When revising tutor responses, only focus on the following aspect(s):
{aspects}

Details for the aspect(s):
{aspect_instructions}

Your Task

Below is a task student is solving:
{question}

The student's incorrect solution is:
{attempt}

The correct (gold) solution to the task is:
{correct_solution}

Error step: {error_step}
Reason: {error_reason}

The ideal tutor's next response is:
{good_response}

Your job is to minimally revise the tutor's response so that it clearly fails to align with the criteria above.
    * Do not rewrite the response completely.
    * Keep as much of the original wording as possible.
    * Only adjust what's necessary to make the response misaligned.

Put your generated bad response in <response></response> tags.
```

Figure 4: Prompt template used to generate non-preferred next tutor turn. Curly-brace fields denote placeholders filled per instance.

B Prompt for Correct Student Solutions

See Figure 5. Example responses include *You got it right. Would you like more practice?*" Although we do not specify any particular format in the prompt, we observe that all generated responses consist of two sentences: the first acknowledges the correct-

ness of the solution, and the second asks about next steps. We therefore create combinations by mixing the first and second sentences, yielding 10,000 unique responses.

Prompt for Correct Student Solutions

```
You are an expert, encouraging
    math tutor.
Generate exactly 100 distinct one-
    line tutor responses suitable
    for cases where a student's
    solution is correct.
    Requirements:
- Each response must be concise,
    natural-sounding, and
    encouraging.
- Vary the structure; do NOT start
     most lines with the same word
    or pattern.
- Avoid semicolons entirely.
- Avoid overly specific
    instructions such as asking for
     diagrams, substitution methods
    , coding, graphs, etc.
- Follow-up suggestions must be
    general and applicable across
    many math topics (e.g., ask if
    they'd like another problem,
    another challenge, a summary,
    questions, etc.).
- Tone should vary: praise,
    curiosity, invitations to
    continue, quick check-ins, etc.
- Number each line 1) through 100)
    .
- No bullet points, no quotes, no
    emojis, no extra commentary.
- Output plain text with exactly
    ONE response per line and
    EXACTLY 100 lines.
```

Figure 5: Prompt template used to generate 100 tutor responses for correct student solutions.

C Prompt Template Used for Training

See Figure 6.

Tutor Response Generation Prompt (Template)

```
You are a careful, precise, and
    supportive math tutor.

Your task is to produce the next
    tutor response in an ongoing
    dialog.

You will be given:
1) The dialog history between the
    student and the tutor. # V1-V4
2) A boolean flag indicating
    whether the student's solution
    is mathematically correct. # V2
    , V4
3) A gold solution to the task. #
    V3, V4

Guidelines for your response:
- If the student's solution is
    incorrect, guide the student
    toward the correct reasoning.
- If the student's solution is
    correct, clearly acknowledge
    correctness and optionally
    provide brief reinforcement,
    intuition, or a natural next
    step.
- Do NOT invent errors or suggest
    corrections if the solution is
    correct.

Your Task

[Dialog History] # V1-V4
{dialog_history}

[Student solution is correct] # V2
    , V4
{is_correct}

[Gold solution to the task] # V3,
    V4
{gold_solution}

[Next tutor response]
```

Figure 6: Prompt template used for training. Curly-brace fields denote placeholders filled for each instance. The # symbol indicates comments included here to show which parts of the prompt are present in different configurations.

D Prompt Template for Factuality Checking

See Figure 7.

Factuality Checking Prompt (Template)

```
[System Prompt]

You are an expert pedagogical
    judge.
Your task is to evaluate a math
    tutor's response to a student
    based on factuality and
    categorize any factual issue.

**Factuality**: The response
    should not invent numbers,
    calculations, or details not
    present in the problem or the
    student's history.
```

```
Return fields:
- is_factual: true/false
- student_has_mistake: true/false
- tutor_acknowledged_no_mistake:
    true/false/null
- category: one of
    - student_hallucination: Tutor
        hallucinates something in
        the student's solution
    - task_hallucination: Tutor
        hallucinates something in
        task definition
    - response_incorrect: Tutor's
        feedback/solution is not
        factually correct
    - other: Explain what is wrong
  If is_factual is true, set
     category to null.
- reasoning: brief explanation

Be strict: if any factual issue
    exists, set is_factual to false
     and choose the best-fitting
    category.

Provide your evaluation in the
    strictly defined structure.

[User Prompt Template]

[Dialog History]
{conversation}

[Gold Solution to the Task]
{gold_solution}

[Is student's solution correct?]
{is_correct}

[Gold Tutor Response]
{gold_tutor_response}

[Generated Response to Evaluate]
{response}
```

Figure 7: Prompt template used for factuality checking.

E Breakdown of Non-Factual Error Categories

See Table 4.

F Examples of Preference Pairs

Table 5 presents an example of a generated preferred response alongside its degraded variants across different aspects. Compared to the others, the response degraded in *Clarity* is relatively less problematic; it is simply less detailed, making it slightly less clear but still appropriate. Based on this observation, we assign a lower weight to this dimension.

Model	Task H.	Resp. Inc.	Stu. H.	Other
Proprietary Models				
GPT-5	2.63	65.79	23.68	7.89
GPT-4.1	12.66	53.16	31.65	2.53
GPT-4.1-nano	0.81	20.84	77.54	0.81
Existing Tutoring Models				
SocraticLM	60.04	36.35	3.01	0.60
TutorRL-7B	38.04	44.85	15.95	1.16
Open-Source Base Models				
Qwen3-4B	38.39	42.81	18.57	0.23
Qwen3-8B	37.43	50.41	11.59	0.58
Qwen3-4B Fine-tuned				
+ SFT V1	36.73	37.43	22.85	2.99
+ DPO V1	34.87	28.32	32.49	4.32
+ SFT V2	34.85	34.85	23.69	6.61
+ DPO V2	33.81	38.37	24.46	3.36
+ SFT V3	34.82	49.03	14.01	2.14
+ DPO V3	35.26	37.18	22.65	4.91
+ SFT V4	34.09	34.76	27.77	3.39
+ DPO V4	34.09	39.55	21.82	4.55
Qwen3-8B Fine-tuned				
+ SFT V1	40.60	37.80	17.88	3.72
+ DPO V1	30.43	27.33	37.60	4.65
+ SFT V2	32.21	36.71	26.13	4.95
+ DPO V2	14.31	16.12	8.55	61.02
+ SFT V3	40.56	34.99	20.48	3.98
+ DPO V3	40.21	33.81	20.82	5.15
+ SFT V4	31.76	34.49	28.04	5.71
+ DPO V4	31.08	40.60	23.31	5.01
+ DPO V4*	23.08	48.16	21.40	7.36

Table 4: Breakdown of non-factual (NF) error categories (%) across models, identified by GPT-5: task hallucination (Task H.), incorrect response (Resp. Inc.), student hallucination (Stu. H.), and other errors (e.g., inventing a student's name, typos, or introducing unrelated examples).

G Training Objective

The weighted DPO loss is:

$$\mathcal{L}_{\text{DPO}} = - \mathbb{E}_{(x_i, y_i^+, y_i^-)\sim\mathcal{D}}\Big[w_i \cdot \log\sigma\Big(\beta \log \frac{\pi_\theta(y_i^+ \mid x_i)}{\pi_{\text{ref}}(y_i^+ \mid x_i)} - \beta \log \frac{\pi_\theta(y_i^- \mid x_i)}{\pi_{\text{ref}}(y_i^- \mid x_i)}\Big)\Big] \quad (1)$$

where y_i^+ and y_i^- denote the preferred and dispreferred responses, respectively, and $\beta = 0.3$ (was chosen empirically based on validation performance) controls the strength of the KL penalty. To further stabilize training, we augment the DPO loss with a chosen-response negative log-likelihood (NLL) regularization term:

Dialog history	**Tutor:** A gasoline tank is $\frac{7}{8}$ full. After 12 gallons have been used, it is half full. How many gallons does this tank hold when it is full? **Student:** I want to find the capacity of the tank, so I will let x be the number of gallons it can hold when full. Since the tank is $\frac{7}{8}$ full, it has $\frac{7}{8}x$ gallons of gasoline in it. After 12 gallons are used, it has $\frac{7}{8}x - 12$ gallons left, and this is half of the capacity, so $\frac{1}{2}x$. I can set up an equation to relate these expressions: $\frac{7}{8}x - 12 = \frac{1}{2}x$. I want to solve for x, so I will add 12 to both sides and then multiply both sides by 8: $7x - 96 = 4x + 96$, then $3x = 192$. Dividing both sides by 3, I get $x = 64$. This means the tank can hold 64 gallons when full. # Answer 64
Gold solution	Let x represent the number of gallons the tank holds when it is full. We know that the difference between $\frac{7}{8}$ full and $\frac{1}{2}$ full is 12 gallons, so we set up an equation and solve for x: $12 = \frac{7}{8}x - \frac{1}{2}x$, so $12 = \frac{3}{8}x$, and therefore $12 \cdot \frac{8}{3} = x$. Thus, $x = 32$. The tank holds $\boxed{32}$ gallons when it is full.
Preferred response	Great setup! After you add 12 to both sides, what exact equation do you have – and when you then multiply by 8, which side gets the +96?
Non-preferred: Factuality	Great setup! After you add 12 to both sides, you should get $7x - 96 = 4x + 96$, so when you then multiply by 8, you get the correct equation. That means your final answer of $x = 64$ is correct.
Non-preferred: Mistake Identification	Nice work! That's a clever approach.
Non-preferred: Targetedness	Great setup! Remember, you need to carefully combine like terms and isolate x to solve the equation.
Non-preferred: Revealing Answer	Great setup! After you add 12 to both sides, you should get $7x = 4x + 96$ and then $3x = 96$, so $x = 32$. That means the tank holds 32 gallons when full.
Non-preferred: Clarity	Great setup! After you add 12 to both sides, what do you get next? And when you then multiply by 8, what happens?

Table 5: Example of a generated preferred response and corresponding non-preferred responses across different aspects.

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{DPO}} + \alpha \sum_i w_i \cdot \mathcal{L}_{\text{NLL}}(y_i^+ \mid x_i) \quad (2)$$

with $\alpha = 0.005$ (was chosen empirically to stabilize training). Training runs with early stopping based on validation reward margins. After training, the learned adapter is merged into the base model to produce the final inference model.

H Full Automatic Evaluation Results

See Table 6.

I Generation Examples

See Tables 7 to 9.

J Human Evaluation Form

See Figures 8 and 9.

K GPT-5 and LoMTL Evaluation on the Human Evaluation Set

See Figures 10 and 11.

Model	Mistake Ident.			Mistake Loc.			Providing Guid.			Actionability		
	Yes	Some	No	Yes	Some	No	Yes	Some	No	Yes	Some	No
Proprietary Models												
GPT-5 (GPT-5)	**94.00**	0.86	5.14	**81.37**	9.42	9.21	90.15	5.35	4.50	76.23	10.28	13.49
GPT-5 (LoMTL)	***85.08***	1.56	13.36	66.15	3.56	30.29	63.92	12.69	23.39	20.49	9.35	70.16
GPT-4.1-nano (GPT-5)	81.58	6.58	11.84	42.11	26.32	31.58	**93.42**	3.95	2.63	48.68	39.47	11.84
GPT-4.1-nano (LoMTL)	53.95	1.32	44.74	44.74	1.32	53.95	42.11	7.89	50.00	9.21	5.26	85.53
Existing Tutoring Models												
SocraticLM (GPT-5)	4.58	8.33	87.08	1.67	8.33	90.00	22.92	28.75	48.33	64.58	10.00	25.42
SocraticLM (LoMTL)	5.42	88.33	6.25	5.42	62.92	31.67	15.42	80.00	4.58	92.08	7.08	0.83
TutorRL-7B (GPT-5)	27.50	35.62	36.88	10.62	30.63	58.75	66.88	29.38	3.75	**87.50**	10.00	2.50
TutorRL-7B (LoMTL)	81.25	14.37	4.38	56.88	31.87	11.25	63.75	33.12	3.12	91.88	7.50	0.62
Qwen3-4B Fine-tuned												
+ SFT V1 (GPT-5)	49.57	15.65	34.78	39.13	19.13	41.74	66.96	13.91	19.13	74.78	11.30	13.91
+ SFT V1 (LoMTL)	66.96	24.35	8.70	56.52	24.35	19.13	57.39	27.83	14.78	79.13	12.17	8.70
+ DPO V1 (GPT-5)	13.56	16.10	70.34	6.78	16.95	76.27	27.97	33.05	38.98	38.98	28.81	32.20
+ DPO V1 (LoMTL)	43.22	44.07	12.71	35.59	34.75	29.66	45.76	39.83	14.41	66.95	22.88	10.17
+ SFT V2 (GPT-5)	39.77	25.73	34.50	27.49	28.07	44.44	63.74	14.62	21.64	58.48	27.49	14.04
+ SFT V2 (LoMTL)	63.89	27.78	8.33	41.67	30.56	27.78	52.78	38.89	8.33	77.78	16.67	5.56
+ DPO V2 (GPT-5)	47.06	17.11	35.83	31.55	22.46	45.99	67.91	14.97	17.11	59.36	26.20	14.44
+ DPO V2 (LoMTL)	68.98	22.46	8.56	57.22	23.53	19.25	63.10	24.06	12.83	81.82	11.76	6.42
+ SFT V3 (GPT-5)	32.84	20.15	47.01	14.93	26.12	58.96	50.75	19.40	29.85	58.96	14.93	26.12
+ SFT V3 (LoMTL)	45.52	32.09	22.39	31.34	29.10	39.55	45.52	30.60	23.88	64.18	15.67	20.15
+ DPO V3 (GPT-5)	57.29	18.75	23.96	42.19	28.12	29.69	72.40	16.15	11.46	64.58	26.56	8.85
+ DPO V3 (LoMTL)	76.56	13.54	9.90	69.27	13.54	17.19	76.04	14.06	9.90	88.54	4.69	6.77
+ SFT V4 (GPT-5)	47.53	20.99	31.48	35.19	23.46	41.36	62.96	23.46	13.58	59.88	20.99	19.14
+ SFT V4 (LoMTL)	71.60	20.99	7.41	58.64	24.69	16.67	65.43	23.46	11.11	80.86	13.58	5.56
+ DPO V4 (GPT-5)	51.16	23.26	25.58	30.23	30.81	38.95	70.93	20.93	8.14	59.88	20.99	19.14
+ DPO V4 (LoMTL)	74.42	17.44	8.14	61.05	23.84	15.12	70.93	16.28	12.79	84.88	8.72	6.40
Qwen3-8B Fine-tuned												
+ SFT V1 (GPT-5)	26.21	26.21	47.57	15.53	27.18	57.28	61.17	19.42	19.42	61.17	21.36	17.48
+ SFT V1 (LoMTL)	58.25	25.24	16.50	53.4	23.3	23.3	68.93	15.53	15.53	79.61	9.71	10.68
+ DPO V1 (GPT-5)	53.96	18.81	27.23	43.56	24.26	32.18	74.75	15.84	9.41	72.28	21.29	6.44
+ DPO V1 (LoMTL)	74.75	19.80	5.45	68.32	16.34	15.35	75.25	16.34	8.42	90.59	6.44	2.97
+ SFT V2 (GPT-5)	42.44	23.84	33.72	26.16	27.33	46.51	63.95	19.77	16.28	52.91	31.40	15.70
+ SFT V2 (LoMTL)	65.12	27.33	7.56	52.33	26.16	21.51	59.88	26.16	13.95	79.07	12.21	8.72
+ DPO V2 (GPT-5)	42.65	22.79	34.56	35.29	19.85	44.76	65.44	15.44	19.12	63.97	18.38	17.65
+ DPO V2 (LoMTL)	73.53	16.91	9.56	50.74	32.35	16.91	63.24	26.47	10.29	80.88	10.29	8.82
+ SFT V3 (GPT-5)	58.27	15.75	25.98	38.58	29.92	31.50	77.17	14.17	8.66	81.10	8.66	10.24
+ SFT V3 (LoMTL)	69.29	22.05	8.66	64.57	21.26	14.17	72.44	18.11	9.45	85.04	7.87	7.09
+ DPO V3 (GPT-5)	54.30	27.42	18.28	43.55	30.65	25.81	75.81	17.20	6.99	74.73	18.28	6.99
+ DPO V3 (LoMTL)	77.42	18.28	4.30	70.97	19.89	9.14	75.81	19.89	4.30	93.01	4.84	2.15
+ SFT V4 (GPT-5)	42.63	23.16	34.21	28.95	25.79	45.26	61.58	22.11	16.32	57.89	27.37	14.74
+ SFT V4 (LoMTL)	68.95	22.11	8.95	51.05	26.32	22.63	61.05	27.37	11.58	81.58	12.63	5.79
+ DPO V4 (GPT-5)	50.00	23.53	26.47	33.82	33.33	32.84	67.16	19.12	13.73	59.80	29.41	10.78
+ DPO V4 (LoMTL)	72.55	18.14	9.31	59.80	24.02	16.18	66.67	25.98	7.35	86.27	8.33	5.39
+ DPO V4* (GPT-5)	57.14	24.18	18.68	45.05	26.74	28.21	73.63	17.95	8.42	61.54	28.57	9.89
+ DPO V4* (LoMTL)	82.35	12.16	5.49	68.24	20.39	11.37	74.51	19.61	5.88	92.16	5.49	2.35
GPT-4.1-nano Fine-tuned												
+ SFT V4 (GPT-5)	47.24	26.24	26.52	38.12	28.45	33.43	73.20	19.06	7.73	80.11	17.13	2.76
+ SFT V4 (LoMTL)	83.70	12.98	3.31	73.76	16.85	9.39	80.66	16.30	3.04	***97.51***	1.93	0.55
+ DPO V4 (GPT-5)	34.62	34.62	30.77	27.51	39.35	33.14	46.45	33.14	20.41	38.17	45.56	16.27
+ DPO V4 (LoMTL)	84.62	15.38	*0.00*	***78.99***	21.01	*0.00*	***85.50***	14.50	*0.00*	96.75	3.25	*0.00*

Table 6: Feedback quality metrics (%) across models, evaluated along four dimensions: Mistake Identification, Mistake Location, Providing Guidance, and Actionability. Each dimension reports the percentage of responses rated *Yes*, *To some extent* (Some), and *No*. The evaluator is indicated in parentheses (`GPT-5` or `LoMTL`). **Bold** and ***bold italic*** denote the highest *Yes* scores, while underline and *underline italic* denote the lowest *No* scores for the `GPT-5` and `LoMTL` evaluations, respectively.

Dialog Context
Tutor: Matt wants cookies for a snack, but his dad wants him to eat healthily. He tells Matt he can have half as many cookies as the number of carrot sticks he eats, plus two extra for cleaning his room. If Matt wants to eat five cookies in total, how many carrot sticks does he have to eat? **Student:** Step 1: Matt wants to eat five cookies in total. Step 2: His dad tells him he can have half as many cookies as the number of carrot sticks he eats, plus two extra for cleaning his room. Step 3: So, if Matt wants to eat five cookies, he can have 5/2 = 2.5 carrot sticks. Step 4: But since you can't have half a carrot stick, Matt needs to eat at least three carrot sticks. Step 5: Therefore, Matt needs to eat three carrot sticks in order to eat five cookies. Step 6: #### 3 Step 7: The answer is: 3
Correct Solution
First subtract the two cookies Matt gets for cleaning his room from the total number he wants to eat: 5 - 2 = 3 Then double the number of cookies to find how many carrot sticks he has to eat: 3 * 2 = 6. 6

Model	**Response**
GPT-5	You've mixed up the relationship in Step 3. The rule is: cookies = (1/2)(carrot sticks) + 2. Set this equal to 5 and solve: (1/2)c + 2 = 5 (1/2)c = 3 c = 6. So Matt needs to eat 6 carrot sticks to have 5 cookies.
SocraticLM	How many carrot strips can Matt have?
TutorRL-7B	It looks like you've made some progress, but there's a small mistake in your reasoning. Let's break it down step-by-step: 1. Matt wants 5 cookies in [garbled text: 89] [garbled text: teacher] Let's start over with the problem. We know Matt can have cookies based on the number [garbled text] (carrot sticks) he eats. Can you write an equation that represents this relationship? The rule is: the number [garbled text] (cookies) Matt gets is half the number [garbled text] (carrots) he [garbled text] + 2 extra for doing chores. If we let c be the number [garbled text] (carrots), can you write what Matt gets in terms of c?
Qwen3-8B SFT V4	Quick check on Step 3—what part of "half as many [carrot sticks] + 2" gives you that equation? Try defining x as the carrot sticks first; then write an expression equaling 5 based only on that definition (and remember those two bonus cookies).
Qwen3-8B DPO V4*	Nice start! Pause on "half as many": if x carrot sticks means $(x/2) + 2$ cookies equals 5, what equation should you set up before solving it?
GPT-4.1-nano SFT V4	Nice start. Can you write an equation for the number of carrot sticks (call it c) in terms of the cookies Matt eats (call it b)?
GPT-4.1-nano DPO V4	"Plus two for cleaning": is "half as many … plus 2" a "Carrots = (Cookies/2) + 2" or "Carrots = (Cookies - 2) $\times$ 2"?

Table 7: Example of model responses. The [garbled text] markers highlight instances of corrupted or nonsensical output (e.g., mixed-language tokens) produced by the model.

Dialog Context
Tutor: Max has 8 children and each of his children has the same number of children as he does except for 2 who have 5 children each. How many grandchildren does he have? **Student:** Max has 8-2 = 6 children who have 8-1 = 7 children each. So, the total number of grandchildren from these 6 children is 6 x 7 = 42. The 2 children who have 5 children each will contribute an additional 2 x 5 = 10 grandchildren. Therefore, Max has a total of 42+10 = 52 grandchildren. 52 **Teacher:** Hi Michael, can you guide me through your solution? **Student:** Sure. I started by subtracting 2 from 8 to get the number of children Max has that have the same number of children as he does. Then I subtracted 1 from that number to get the number of grandchildren each of those children have. I multiplied that number by 6 to get the total number of grandchildren from those 6 children. Then I added the two children who had 5 children each, which gave me an additional 10 grandchildren. So, the total number of grandchildren is 42 + 10 = 52.
Correct Solution
Out of his 8 children, 2 have only 5 children so the rest who have 8 (the same number as him) are 8-2 = 6 6 of Max's children have 8 children each for a total of 6*8 = 48 grandchildren 2 of Max's children have 5 children each for a total of 5*2 = 10 grandchildren In total he has 48+10 = 58 grandchildren 58

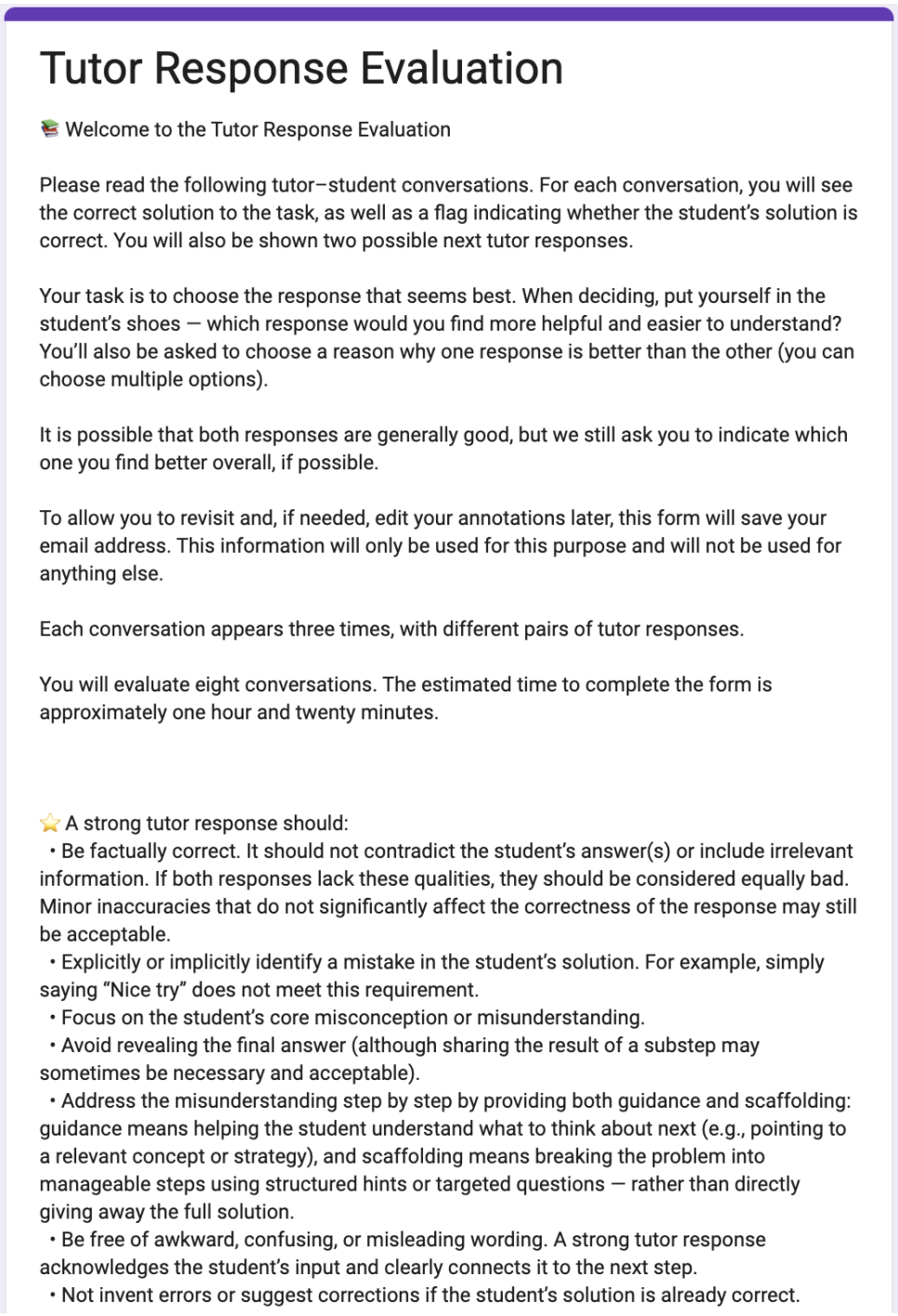
Model	**Response**
GPT-5	You've got the right structure, but there's one key misread: "the same number of children as he does" means those 6 children each have 8 children, not 7. There's no reason to subtract 1. - 6 children have 8 grandchildren each: $6 \times 8 = 48$ - 2 children have 5 grandchildren each: $2 \times 5 = 10$ Total grandchildren: 48 + 10 = 58.
SocraticLM	How many children does Max have?
TutorRL-7B	That's a great start, Michael! Let's break it down step-by-step to ensure we're on the right track: 1. Max has 6children with 8children each. 2. You correctly calculated that each of these 8-child families contributes 6×7 grandchildren. 3. The other 2children each have 3children (since they don't have 7 like the others). Now, let's see if we can simplify or double-check any part of your calculation. Can you calculate the number [garbled text] grandchildren from the 6.children first without adding the 2.children yet?
Qwen3-8B SFT V4	What do we know about how many children max has?
Qwen3-8B DPO V4*	Let's start with this part "I subtracted one from that [number]". Why did you do that?
GPT-4.1-nano SFT V4	That's a good start. Can you tell me how many children Max has who have the same number of children as he does?
GPT-4.1-nano DPO V4	"Same number as he"— whom does "he" refer to—Max or one child—and why "-1"?

Table 8: Example of model responses. The [garbled text] markers highlight instances of corrupted or nonsensical output (e.g., mixed-language tokens) produced by the model.

Dialog Context
Tutor: Tommy is fundraising for his charity by selling brownies for $3 a slice and cheesecakes for $4 a slice. If Tommy sells 43 brownies and 23 slices of cheesecake, how much money does Tommy raise? **Student:** Step 1: Tommy sells 43 brownies for $3 each, so he raises 43 * $3 = 129 from the brownies. Step 2: Tommy sells 23 slices of cheesecake for $4 each, so he raises 23 * $4 = 92 from the cheesecake. Step 3: In total, Tommy raises $129 + $92 = $221. Step 4: #### 221 Step 5: The answer is: 221
Correct Solution
Student's solution is correct

Model	**Response**
GPT-5	Correct! Your calculations are spot on: - Brownies: 43 × 3 = 129 - Cheesecake: 23 × 4 = 92 - Total: 129 + 92 = 221 dollars Nice work including each step and the units.
SocraticLM	How much money did Tommy raise from the Brownies?
TutorRL-7B	Great job working through the steps, Tommy! You've calculated the money raised from brownies[garbled text] separately. Let's take a small step back to make sure we're on the right track. Can you tell me how much Tommy makes from selling one brownie and one slice of cheesecake?
Qwen3-8B SFT V4	That's right on. Want another try?
Qwen3-8B DPO V4*	Nicely completed. Would you like more practice?
GPT-4.1-nano SFT V4	Well done. Want a quick summary?
GPT-4.1-nano DPO V4	"Slices"— did "23 slices of cheesecake" mean " 23 × $4 " or " 4 × 23 "?

Table 9: Example of model responses. The [garbled text] markers highlight instances of corrupted or nonsensical output (e.g., mixed-language tokens) produced by the model.



Tutor Response Evaluation

📚 Welcome to the Tutor Response Evaluation

Please read the following tutor–student conversations. For each conversation, you will see the correct solution to the task, as well as a flag indicating whether the student's solution is correct. You will also be shown two possible next tutor responses.

Your task is to choose the response that seems best. When deciding, put yourself in the student's shoes — which response would you find more helpful and easier to understand? You'll also be asked to choose a reason why one response is better than the other (you can choose multiple options).

It is possible that both responses are generally good, but we still ask you to indicate which one you find better overall, if possible.

To allow you to revisit and, if needed, edit your annotations later, this form will save your email address. This information will only be used for this purpose and will not be used for anything else.

Each conversation appears three times, with different pairs of tutor responses.

You will evaluate eight conversations. The estimated time to complete the form is approximately one hour and twenty minutes.

⭐ A strong tutor response should:

- Be factually correct. It should not contradict the student's answer(s) or include irrelevant information. If both responses lack these qualities, they should be considered equally bad. Minor inaccuracies that do not significantly affect the correctness of the response may still be acceptable.
- Explicitly or implicitly identify a mistake in the student's solution. For example, simply saying "Nice try" does not meet this requirement.
- Focus on the student's core misconception or misunderstanding.
- Avoid revealing the final answer (although sharing the result of a substep may sometimes be necessary and acceptable).
- Address the misunderstanding step by step by providing both guidance and scaffolding: guidance means helping the student understand what to think about next (e.g., pointing to a relevant concept or strategy), and scaffolding means breaking the problem into manageable steps using structured hints or targeted questions — rather than directly giving away the full solution.
- Be free of awkward, confusing, or misleading wording. A strong tutor response acknowledges the student's input and clearly connects it to the next step.
- Not invent errors or suggest corrections if the student's solution is already correct.

Figure 8: Introduction page of the human evaluation form.

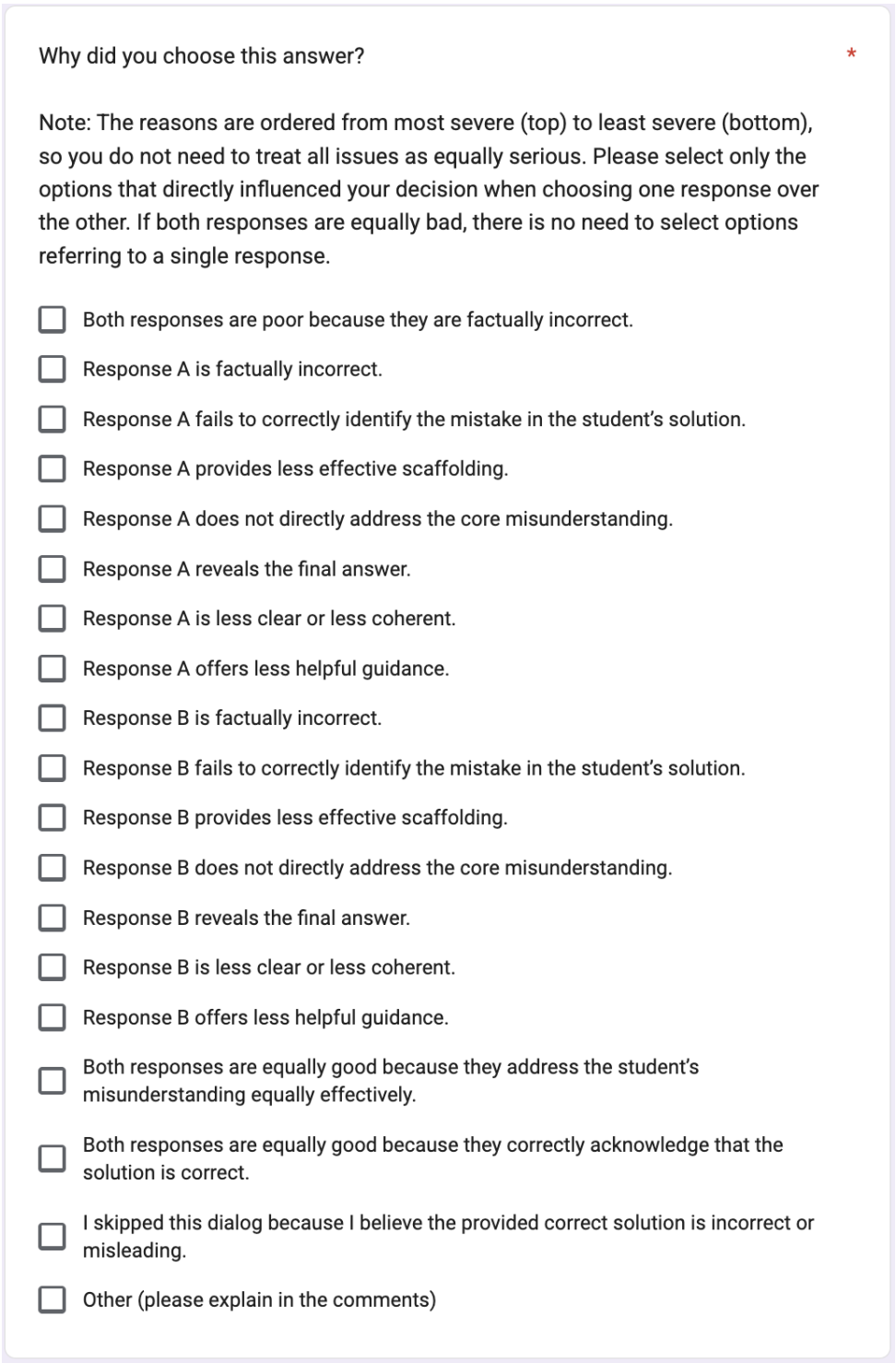
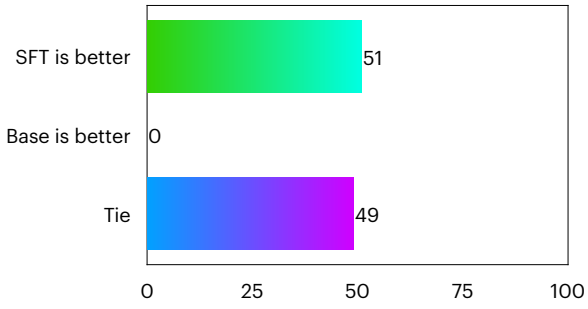
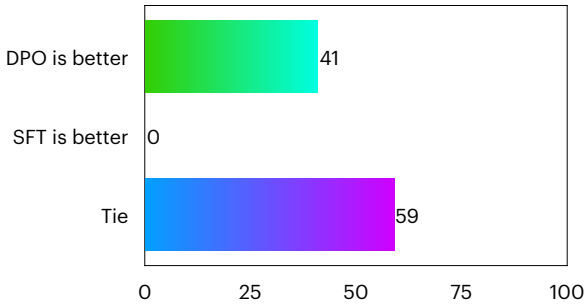


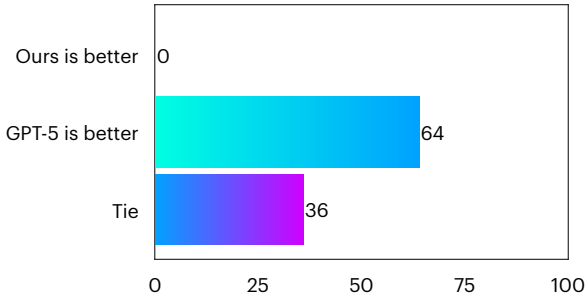
Figure 9: List of reasons provided to human evaluators for selecting a preferred response or indicating that both responses are equally good or bad.



(a) Qwen3-8B SFT V4 vs. Qwen3-8B Base

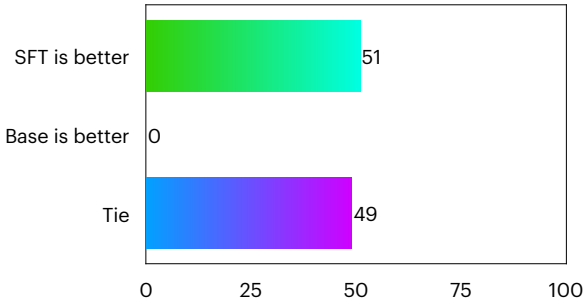


(b) Qwen3-8B SFT V4 vs. Qwen3-8B DPO V4*

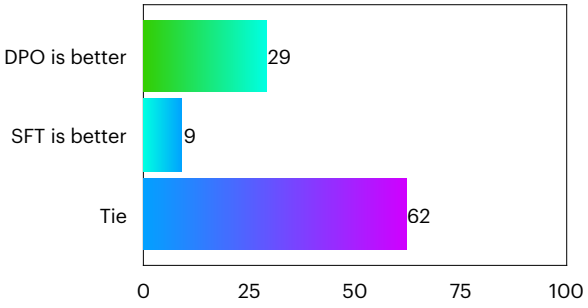


(c) Qwen3-8B DPO V4* vs. GPT-5

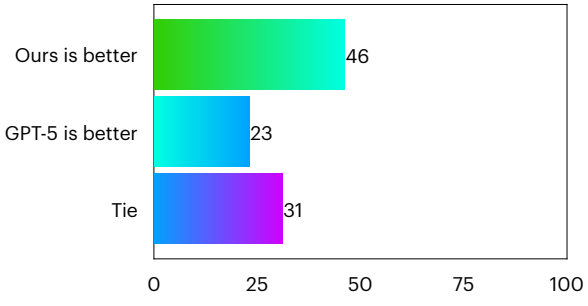
Figure 10: Results of **GPT-5** evaluation (percentages) on the human evaluation set. We convert the four pedagogical annotations into scalar scores (1 for *Yes*, 0.5 for *To some extent*, and 0 for *No*; non-factual responses are assigned a score of 0), sum these scores, and compare the resulting totals across response pairs.



(a) Qwen3-8B SFT V4 vs. Qwen3-8B Base



(b) Qwen3-8B SFT V4 vs. Qwen3-8B DPO V4*



(c) Qwen3-8B DPO V4* vs. GPT-5

Figure 11: Results of **LoMTL** evaluation (percentages) on the human evaluation set. We convert the four pedagogical annotations into scalar scores (1 for *Yes*, 0.5 for *To some extent*, and 0 for *No*; non-factual responses are assigned a score of 0), sum these scores, and compare the resulting totals across response pairs.