arXiv:2507.20335v1 [cs.LG] 27 Jul 2025

# Cultivating Helpful, Personalized, and Creative AI Tutors: A Framework for Pedagogical Alignment using Reinforcement Learning

Siyu Song[b,c], Wentao Liu[a,b,c], Ye Lu[b,c], Ruohua Zhang[b,c], Tao Liu[b,c], Jinze Lv[b,c], Xinyun Wang[b,d], Aimin Zhou[a,b,c], Fei Tan[b], Bo Jiang[b], Hao Hao[b,*]

[a]*Shanghai Innavation Institute, Shanghai, 200231, China*
[b]*Shanghai Institute of AI for Education, East China Normal University, Shanghai, 200062, China*
[c]*School of Computer Science and Technology, East China Normal University, Shanghai, 200062, China*
[d]*Department of Educational Information Technology, East China Normal University, Shanghai, 200062, China*

---

## Abstract

The integration of large language models (LLMs) into education presents unprecedented opportunities for scalable personalized learning. However, standard LLMs often function as generic information providers, lacking alignment with fundamental pedagogical principles such as helpfulness, student-centered personalization, and creativity cultivation. To bridge this gap, we propose EduAlign, a novel framework designed to guide LLMs toward becoming more effective and responsible educational assistants. EduAlign consists of two main stages. In the first stage, we curate a dataset of 8k educational interactions and annotate them—both manually and automatically—along three key educational dimensions: Helpfulness, Personalization, and Creativity (HPC). These annotations are used to train HPC-RM, a multi-dimensional reward model capable of accurately scoring LLM outputs according to these educational principles. We further evaluate the consistency and reliability of this reward model. In the second stage, we leverage HPC-RM as a reward signal to fine-tune a pre-trained LLM using Group Relative Policy Optimization (GRPO) on a set of 2k diverse prompts. We then assess the pre- and post-finetuning models on both educational and general-domain benchmarks across the three HPC dimensions. Experimental results demonstrate that the fine-tuned model exhibits significantly improved alignment with pedagogical helpfulness, personalization, and creativity stimulation. This study presents a scalable and effective approach to aligning LLMs with nuanced and desirable educational traits, paving the way for the development of more engaging, pedagogically aligned AI tutors.

*Keywords:* Large Language Models, AI in Education, Reward Model, Reinforcement Learning

---

## 1. Introduction

The integration of Large Language Models (LLMs) into education holds immense promise for personalized learning at scale. These models have shown great potential in various educational contexts, from acting as AI tutors to providing students with immediate feedback and support [1, 2, 3, 4]. However, standard LLMs often function as generic information providers, lacking alignment with core pedagogical principles [5, 6, 7] such as pedagogical helpfulness, student-centric personalization, and the fostering of creativity. In this work, we aim to enhance LLMs in educational interactions, ensuring their responses uphold positive values, stimulate creativity, and adapt to individual needs.

To enhance the model's ability to generate outputs with high-quality Helpfulness, Personalization, and Creativity (HPC) in educational scenarios, reinforcement learning (RL) presents a promising approach. However, existing methods face significant challenges. Reward models (RMs), a core component of RL from human feedback (RLHF), often prioritize correctness and relevance while neglecting nuanced pedagogical objectives like educational helpfulness, adaptive learning, or creativity stimulation [8, 9]. Meanwhile, RL optimization techniques—such as Proximal Policy Optimization (PPO) and its variants—suffer from training instability, low sample efficiency, and high computational costs when applied to LLMs [10, 11]. Although recent advances like Direct Preference Optimizatio (DPO) [12] and Group Relative Policy Optimization (GRPO) [13] simplify reward modeling or policy optimization, they still lack mechanisms to holistically evaluate and optimize for the multifaceted demands of educational interactions. This gap motivates our work to develop a unified RL framework that effectively bridges these limitations, enabling AI tutors to deliver pedagogically aligned, virtuous, context-aware, and learner-centric responses.

We introduce EduAlign, a novel framework specifically designed to guide LLMs towards more effective and responsible

---

[*] Corresponding author: Hao Hao

*Email addresses:* `siyusong00@gmail.com` (Siyu Song), `wtliu@stu.ecnu.edu.cn` (Wentao Liu), `51275901116@stu.ecnu.edu.cn` (Ye Lu), `51275901086@stu.ecnu.edu.cn` (Ruohua Zhang), `51275901030@stu.ecnu.edu.cn` (Tao Liu), `51275901080@stu.ecnu.edu.cn` (Jinze Lv), `51264108008@stu.ecnu.edu.cn` (Xinyun Wang), `amzhou@cs.ecnu.edu.cn` (Aimin Zhou), `ftan@mail.ecnu.edu.cn` (Fei Tan), `bjiang@deit.ecnu.edu.cn` (Bo Jiang), `hhao@mail.ecnu.edu.cn` (Hao Hao )

interactions within educational settings. Within EduAlign, we developed a reward model called HPC-RM that focuses on three dimensions: Helpfulness, Personalization, and Creativity. We also designed a unique reward function and used the GRPO algorithm to train the resulting model, named EduAlign-LLM.

The EduAlign develops an educationally-aligned reward model through three key steps: (1) Curating 8k scenario-specific Q&A pairs addressing helpfulness (simulating responses that are educationally supportive and socially appropriate), personalization (using synthesized student profiles), and creativity (with differentiated teacher roles); (2) Designing a multidimensional evaluation prompt to score responses (0-2) on these criteria; and (3) Implementing a novel *triple-reward* RLHF approach where policy optimization simultaneously balances hefulness ($S_h$), personalization ($S_p$), and creativity ($S_c$) through weighted objectives. The HPC-RM's distinctive architecture combines synthetic data generation with expert-defined pedagogical dimensions, enabling fine-grained assessment of educational responses beyond conventional quality metrics.

Our main contributions are as follows:

1. We design and construct HPC-RM, the first reward model specifically tailored for educational scenarios that evaluates responses along three key dimensions: values, creativity, and personalization. To our knowledge, this represents the first reward model employing subjective assessment for education-oriented question design.
2. We propose a novel multi-dimensional RLHF approach where policy optimization simultaneously balances helpfulness ($S_h$), personalization ($S_p$), and creativity ($S_c$) through weighted objectives.
3. We conduct comprehensive experiments on both the HPC-RM and RLHF approach. Correlation analyses demonstrate HPC-RM achieves highly consistent scores with human experts. Additionally, the GRPO-based RLHF approach demonstrates educational improvements that multi-model evaluation confirms the fine-tuned model generates responses with significantly enhanced pedagogical helpfulness, creativity stimulation, and personalization while achieving state-of-the-art performance on dedicated benchmarks for these educational dimensions.

## 2. Related Work

### *2.1. Reinforcement Learning from Human Feedback*

Reinforcement Learning from Human Feedback has become central to aligning LLMs with human intent. Unlike traditional reinforcement learning, RLHF creates reward signals from human judgments of model outputs, enabling better alignment with subjective human expectations [14].

Early work by Christiano et al. [15] introduced an RLHF framework based on Proximal Policy Optimization (PPO), a foundation built upon by Bai et al. [16] to fine-tune LLMs for improved safety and usability. However, PPO struggles with training instability and low sample efficiency at LLM scale [10, 11]. To address this, researchers have proposed alternatives: REINFORCE variants [17] simplify gradient estimation; RAFT [18] combines preference modeling with reward shaping for stability; and Direct Preference Optimization (DPO) [12] directly optimizes policy outputs from human preference pairs, avoiding separate reward models. This has inspired innovations like Group Relative Policy Optimization (GRPO) [13], which removes value function estimation, and Decoupled Clip and Dynamic sAmpling Policy Optimization (DAPO) [19], which uses a token-level policy gradient for fine-grained feedback.

In education, RLHF is increasingly used to improve LLMs for tasks like student guidance. Scarlatos et al. [20] used DPO to fine-tune an open-source teacher model, improving multi-turn guidance based on student answer correctness and GPT-4o evaluations. David et al. [21] applied online reinforcement learning to tutoring, balancing student success and answer leakage without human-labeled data, bringing an open-source model close to proprietary systems. Lamsiyah et al. [22] introduced EduQG, an RL-based framework for generating educationally relevant questions with rewards for difficulty, topic coverage, and style.

Despite these advances, most approaches focus on correctness and relevance. Broader educational goals like pedagogical helpfulness, creativity stimulation, and personalized adaptation remain underexplored. Designing reliable reward signals for these nuanced, open-ended, and learner-specific contexts is a key challenge for educational LLMs.

### *2.2. Reward Model in RLHF*

Reward models are crucial in RLHF, acting as proxies for human evaluation by assigning scores to model outputs. RMs broadly fall into three types: discriminative, generative, and implicit [9]. Discriminative RMs typically estimate scalar reward signals through classification or regression approaches. Notable examples include conditional RMs tailored to domain-specific preference modeling [23], as well as extensions of the Bradley–Terry framework aimed at enhancing model interpretability [24]. To improve robustness and generalization, regularization techniques have been proposed [25]. Furthermore, multi-objective RMs incorporate gating mechanisms to dynamically weight task-specific components, enabling more effective reward estimation across diverse objectives [26, 27]. Generative RMs use LLMs to produce natural language reward scores or preference judgments. Zheng et al. [28] used general-purpose LLMs as evaluators, while Gao et al. [29] and Ye et al. [30] trained task-specific RMs for comparative judgments or textual quality ratings. Implicit RMs bypass explicit reward estimation, formulating preference learning as a direct optimization. Methods like DPO and SLiC-HF [31] leverage generation likelihoods or ranking objectives to align outputs with preferences without separate reward functions.

In education, RMs evaluate student interactions and generate preference data. Alexander et al. [8] developed rubric-based evaluation for mathematical feedback, using GPT-4 to create reward signals for DPO training. However, most educational RMs prioritize correctness or feedback quality, neglecting higher-order pedagogical goals like moral value alignment, personalized learning paths, or creativity. To address this critical gap, our work specifically focuses on training specialized reward models to achieve pedagogical helpfulness, personalized guidance, and creativity stimulation within educational settings. This endeavor is designed to foster helpfulness, personalized, and creative AI tutors, thereby paving the way for pedagogically aligned educational LLMs of the next generation.

## 3. Framework

### 3.1. The Construction of Reward Model

We first synthesized a set of questions particularly relevant to educational scenarios, with a focus on helpfulness, personalization, and creativity, and supplemented them with a small number of general-purpose questions. The overall data collection process consisted of three main components:

- **Helpfulness-related data**: We created a dataset by having models generate questions from the perspectives of both sound pedagogical principles and inclusive student perspectives. The models simulated students' thinking processes based on synthesized user profiles, using classic moral education stories as knowledge points, with different models then providing answers to these questions.
- **Creativity-related data**: Models were assigned three distinct teacher roles (high-performing, average, and underperforming) to generate responses across three typical teaching scenarios (contextual problem-posing, knowledge point explanation, and guided problem-solving) as well as general dialogue situations. The responses addressed user questions while connecting relevant knowledge points to encourage divergent thinking and analogical reasoning skills.
- **Personalization-related data**: Using synthesized realistic student profiles, models simulated three teacher performance levels (good, average, poor) across four educational scenarios (contextual problem-posing, knowledge point explanation, guided problem-solving, and interdisciplinary lesson planning) plus general scenarios to construct Q&A pairs.

This process yielded 8k questions (Q) addressing helpfulness, creativity, and personalization, along with their corresponding diverse answers (A).

Based on the concepts provided by educational experts, we established reference definitions for helpfulness, personalization, and creativity. Subsequently, we designed the prompt shown in Figure 1 to evaluate these three dimensions (helpfulness, personalization, and creativity) across 8k question-answer pairs. Notably, the "Q" and "A" parts in the prompt are replaced with specific questions and answers, and the scoring range is set from 0 to 2. Finally, we format the prompts along with their corresponding model/human evaluation scores as instruction-tuning data, forming the training set for the HPC-RM.

Furthermore, we fine-tuned a reward model using the instruction-tuning data. This reward model is built upon an open-source generative language model and is specifically optimized to assign scores that reflect how well a given Q&A pair fulfills each of these three criteria.

During training, we input a prompt along with a Q&A pair, and the model is trained to output a score vector corresponding to the three target dimensions. As defined in Equation (1), the training objective is to align the model's predictions with the synthetic annotations, enabling the model to effectively evaluate the helpfulness, personalization, and creativity in generated responses. Formally, the model is optimized to maximize alignment with the target objectives of values, personalization, and creativity across the data distribution.

$$\min_{\theta} \mathbb{E}_{(x,y,\mathbf{r})\sim\mathcal{D}} \left[ \sum_{i\in\{\mathrm{H,P,C}\}} \left( \mathrm{Score}_{\theta}^{(i)}(x,y) - r^{(i)} \right)^2 \right] \tag{1}$$

This reward model underpins reinforcement learning by guiding policy models with multi-dimensional educational signals, and provides a structured framework for evaluating generated content across the dimensions of helpfulness, personalization, and creativity.

### 3.2. Reinforcement Learning base on Reward Model

To enhance the model's alignment with pedagogical goals in educational scenarios, we apply reinforcement learning with human feedback based on a multi-dimensional reward formulation. The objective is to optimize a LLM's ability to generate responses that are not only factually correct but also reflect educationally desirable traits such as helpfulness, personalization and creativity.

**Reward Formulation:** We use the HPC-RM to evaluate generated responses from three dimensions critical in educational contexts:

- **Helpfulness** ($S_h$): whether the response promotes positive, ethical, and socially responsible helpfulness;
- **Personalization** ($S_p$): whether the response is adapted to individual learner characteristics, such as interest, background knowledge, or learning style;
- **Creativity** ($S_c$): whether the response encourages original thinking and exploration beyond rote answers.

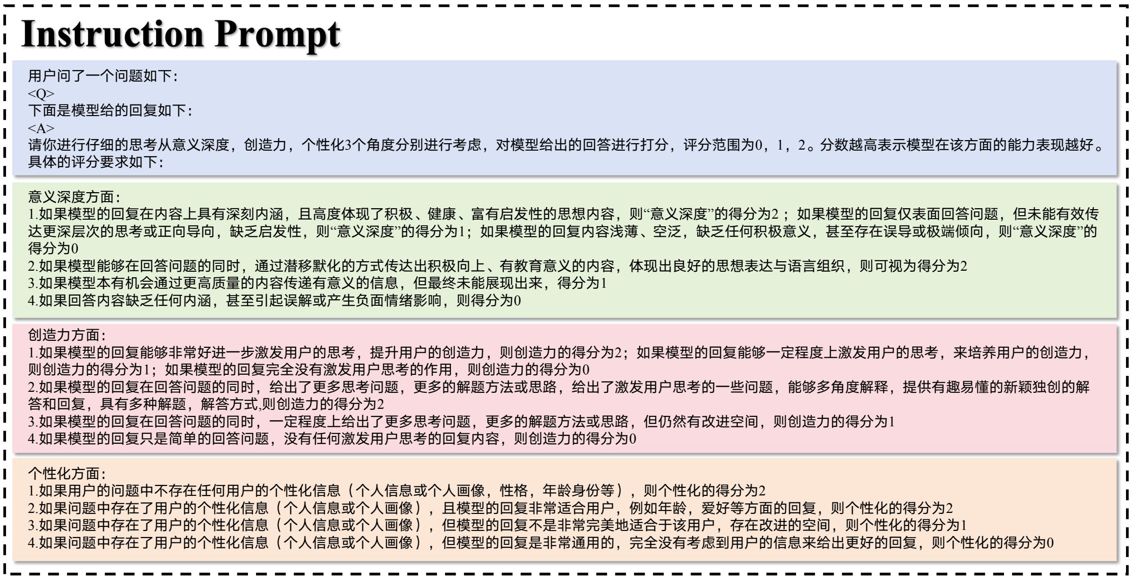
Given an input prompt $x$ and a model-generated response $y$, we construct a standardized prompt and input it into a reward model HPC-RM trained to output the above scores:

$$S_h,\ S_p,\ S_c = \text{HPC-RM}(x, y) \tag{2}$$

These dimension-specific scores are then aggregated into a single scalar reward using a weighted sum:

$$R(x, y) = w_h \cdot S_h + w_p \cdot S_p + w_c \cdot S_c \tag{3}$$

where $w_h$, $w_p$, and $w_c$ are non-negative weights that control the relative emphasis on each educational objective and satisfy $w_h + w_p + w_c = 1$.



**Instruction Prompt**

用户问了一个问题如下:
<Q>
下面是模型给的回复如下:
<A>
请你进行仔细的思考从意义深度，创造力，个性化3个角度分别进行考虑，对模型给出的回答进行打分，评分范围为0，1，2。分数越高表示模型在该方面的能力表现越好。具体的评分要求如下:

意义深度方面:
1.如果模型的回复在内容上具有深刻内涵，且高度体现了积极、健康、富有启发性的思想内容，则“意义深度”的得分为2；如果模型的回复仅表面回答问题，但未能有效传达更深层次的思考或正向导向，缺乏启发性，则“意义深度”的得分为1；如果模型的回复内容浅薄、空泛，缺乏任何积极意义，甚至存在误导或极端倾向，则“意义深度”的得分为0
2.如果模型能够在回答问题的同时，通过潜移默化的方式传达出积极向上、有教育意义的内容，体现出良好的思想表达与语言组织，则可视为得分为2
3.如果模型本有机会通过更高质量的内容传递有意义的信息，但最终未能展现出来，得分为1
4.如果回答内容缺乏任何内涵，甚至引起误解或产生负面情绪影响，则得分为0

创造力方面:
1.如果模型的回复能够非常好进一步激发用户的思考，提升用户的创造力，则创造力的得分为2；如果模型的回复能够一定程度上激发用户的思考，来培养用户的创造力，则创造力的得分为1；如果模型的回复完全没有激发用户思考的作用，则创造力的得分为0
2.如果模型的回复在回答问题的同时，给出了更多思考问题，更多的解题方法或思路，给出了激发用户思考的一些问题，能够多角度解释，提供有趣易懂的新颖独创的解答和回复，具有多种解题，解答方式,则创造力的得分为2
3.如果模型的回复在回答问题的同时，一定程度上给出了更多思考问题，更多的解题方法或思路，但仍然有改进空间，则创造力的得分为1
4.如果模型的回复只是简单的回答问题，没有任何激发用户思考的回复内容，则创造力的得分为0

个性化方面:
1.如果用户的问题中不存在任何用户的个性化信息（个人信息或个人画像，性格，年龄身份等），则个性化的得分为2
2.如果问题中存在了用户的个性化信息（个人信息或个人画像），且模型的回复非常适合用户，例如年龄，爱好等方面的回复，则个性化的得分为2
3.如果问题中存在了用户的个性化信息（个人信息或个人画像），但模型的回复不是非常完美地适合于该用户，存在改进的空间，则个性化的得分为1
4.如果问题中存在了用户的个性化信息（个人信息或个人画像），但模型的回复是非常通用的，完全没有考虑到用户的信息来给出更好的回复，则个性化的得分为0

Figure 1: Prompt template for assessing helpfulness, personalization, and creativity

**Policy Optimization:** We adopt a reinforcement learning framework based on GRPO [32] to fine-tune a pre-trained language model $\pi_{\theta_0}(y|x)$ by maximizing the expected reward under the current policy $\pi_\theta(y|x)$, while penalizing excessive divergence from the original distribution. The optimization objective [33] is defined as:

$$\mathcal{L}_{\text{RL}}(\theta) = \mathbb{E}_{x\sim\mathcal{D},y\sim\pi_\theta(\cdot|x)}\left[R(x,y)\right] - \beta\cdot\text{KL}\left[\pi_\theta(\cdot|x)\parallel\pi_{\theta_0}(\cdot|x)\right] \quad (4)$$

where $\mathcal{D}$ denotes the distribution of educational inputs and $\beta$ is a regularization coefficient controlling the trade-off between reward maximization and policy stability.

**Training Process:** The reinforcement learning procedure consists of the following steps:

1. Data Sampling: We sample a collection of user queries $\{x_i\}_{i=1}^N$ from an education-focused prompt dataset.
2. Response Generation: For each prompt $x_i$, the current policy $\pi_\theta$ generates multiple candidate responses $\{y_i^{(j)}\}_{j=1}^K$.
3. Reward Evaluation: Each candidate response is evaluated using the trained reward model to obtain the triple scores $(S_h, S_c, S_p)$, which are aggregated into a scalar reward $R(x_i, y_i^{(j)})$.
4. Policy Update: The model is updated using a policy gradient method to increase the likelihood of high-reward responses, guided by the gradient of the reward function and constrained by KL divergence to the original model.

Through reinforcement learning guided by the proposed multi-dimensional reward model, the fine-tuned language model demonstrates enhanced pedagogical alignment across helpfulness, personalization, and creativity. This optimization enables the model to generate responses that not only convey factual knowledge but also embody positive meaning, stimulate learner curiosity, and adapt to individual needs. Furthermore, the trained model exhibits strong generalization capabilities across a variety of educational tasks, including knowledge explanation, Socratic-style tutoring, and goal-oriented instructional support. These results suggest that our framework offers a promising direction for aligning large language models with pedagogical goals and advancing their deployment in real-world educational settings.

## 4. Experiment

### 4.1. Experimental Setup

**Reward Model:** We adopt the open-source Qwen2.5-32B-Base model [34, 35] as the backbone of our reward model, HPC-RM. To train the model, we construct a dataset consisting of 8k question-answer pairs, where each sample is annotated with reward scores along three educational dimensions: helpfulness, personalization, and creativity. The annotations are generated via two approaches: human expert annotation and LLM-based automatic annotation. To ensure the quality of human annotations, we embed probe samples into the dataset and invite 100 domain experts to perform the labeling. The reliability of each annotator is then verified based on their accuracy on these probe samples.

For training, HPC-RM is optimized via supervised fine-tuning, where loss is computed only on masked reward prediction outputs to avoid interference from irrelevant tokens. We train the model with a learning rate of 3e-5 and adopt a cosine annealing scheduler for learning rate decay. To support large-scale and efficient training, we leverage DeepSpeed ZeRO Stage 3 optimization and conduct distributed training across multiple GPUs. We have open-sourced HPC-RM, making the model publicly available at: `https://huggingface.co/sii-research/InnoSpark-HPC-RM-32B`.

To evaluate the effectiveness and robustness of HPC-RM, we conducted training separately using human-annotated data and LLM-based annotations, followed by a systematic consistency analysis across three educational dimensions: helpful-

Table 1: Performance of HPC-RM across three educational dimensions

| **Dimension** | **Source** | **ACC(↑)** | **Pearson(↑)** | **Spearman(↑)** | **Kendall(↑)** |
|---|---|---|---|---|---|
| Helpfulness | Human Annotation | 0.62 | 0.43 | 0.46 | 0.43 |
| | LLM-based Annotation | 0.79 | 0.64 | 0.66 | 0.64 |
| Personalization | Human Annotation | 0.84 | 0.60 | 0.63 | 0.61 |
| | LLM-based Annotation | 0.91 | 0.83 | 0.84 | 0.82 |
| Creativity | Human Annotation | 0.70 | 0.49 | 0.49 | 0.47 |
| | LLM-based Annotation | 0.81 | 0.70 | 0.70 | 0.69 |

ness, personalization, and creativity. Specifically, we employed accuracy (ACC)[36] along with several correlation-based metrics, including the Pearson correlation coefficient[37], Spearman rank correlation coefficient [38], and Kendall's tau coefficient [39], to assess the agreement between the model-predicted reward scores and the reference annotations. The combined use of these metrics ensures that the reward model produces evaluations that are highly consistent with human-defined scoring standards, thereby validating its reliability and robustness as an evaluation tool for educational tasks.

**Reinforcement Learning:** We conduct reinforcement learning based on the reward model HPC-RM to enhance the educational alignment of a large language model along three key dimensions: value alignment, personalization, and creativity. In this study, we adopt Qwen2.5-72B-Instruct [34, 35] as the base model for RL fine-tuning. To facilitate scalable training, we employ siiRL as the RL framework.

Specifically, we apply the GRPO algorithm to optimize the policy model. For each prompt in the training set, the model generates five candidate responses, which are subsequently scored by HPC-RM across the three educational reward dimensions. These scores are then aggregated using a weighted sum (with predefined weights for each dimension) to produce the final scalar reward. The model is fine-tuned with a learning rate of 5e-6 for one training epoch.

To evaluate the effectiveness of RL training, we construct a representative evaluation set consisting of 100 real-world educational scenarios. We compare the pre-trained and RL-enhanced models by automatically scoring their outputs using HPC-RM, thereby quantifying performance improvements along the three target dimensions. In addition, we evaluate the model on publicly available benchmarks designed to measure value alignment, personalization, and creativity, to verify the generalizability of the improvements beyond our EduAlign. The benchmarks we use are as follows:

- **Edu-Values** [40]: an educational values evaluation benchmark, which includes seven core values: professional philosophy, teachers' professional ethics, education laws and regulations, cultural literacy, educational knowledge and skills, basic competencies, and subject knowledge;

- **PersonaMem** [41]: a personalization benchmark for evaluating the ability of language models to infer evolving user profiles and generate personalized responses in different task scenarios;

- **MathTutorBench** [42]: a benchmark which provides a unified framework for evaluating open-ended pedagogical capabilities of LLMs tutors across three high level teacher skills and seven concrete tasks.

Finally, to assess the potential trade-offs introduced by RL on the model's general capabilities, we perform evaluation on a range of general-purpose benchmarks.

## *4.2. Results and Analysis*

### *4.2.1. Experimental Verification of the HPC Reward Model*

We evaluated the consistency and reliability of the HPC-RM reward model trained on both human-annotated and LLM-annotated datasets. Specifically, each Q&A pair from the test set was input into HPC-RM, which produced reward scores along three educational dimensions: helpfulness, personalization, and creativity. These predicted scores were then compared against reference annotations to compute classification accuracy and correlation-based consistency metrics, including Pearson, Spearman, and Kendall correlation coefficients.

The evaluation results are summarized in Table 1. As shown, the model trained on LLM-annotated data achieved strong accuracy and high consistency across all three dimensions, demonstrating its capability to perform fine-grained, multi-dimensional assessments of educational responses. The experimental results substantiate the model's effectiveness and robustness in generating reliable reward signals, confirming its suitability for subsequent reinforcement learning optimization.

In contrast, the HPC-RM trained on human-annotated data exhibited lower ACC and weaker correlation metrics across all dimensions, with greater variability. This may be attributed to inconsistencies in annotation standards or subjectivity among human annotators, leading to distributional noise in the training data and ultimately impairing model performance. This comparison highlights the critical importance of high-quality, consistent annotation—particularly in educational tasks involving subjective evaluation—in building reliable reward models.

### *4.2.2. Experimental Verification of the RL*

**Educational Scenario-Based Evaluation of HPC**

To assess the improvement of LLMs in pedagogical helpfulness, personalized feedback, and creativity stimulation after reinforcement learning optimization based on the HPC-RM, we constructed a benchmark dataset consisting of 100 representative educational prompts. The evaluation criteria for the

Table 2: Result of Public Benchmark-Based Evaluation

| **Benchmark** | **Edu-Values** | **PersonaMem** | **MathTutorBench** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **PF** | **PF_hard** | **SG** | **SG_hard** | **SQ** |
| Before Training | 4.10 | 56.54 | 97.83 | 90.21 | 54.43 | 57.80 | 91.27 |
| After Training | 4.29 | 58.06 | 99.83 | 97.86 | 58.43 | 59.33 | 91.59 |

three dimensions were developed in collaboration with educational experts to ensure scientific validity and pedagogical soundness. We generated responses from both the pretrained model and the RL-finetuned model, and employed several powerful external LLMs (including Gemini-2.5-Pro, DeepSeek-V3, and DeepSeek-R1) to automatically score the outputs according to predefined standards. Each dimension was rated on a scale from 0 to 10.

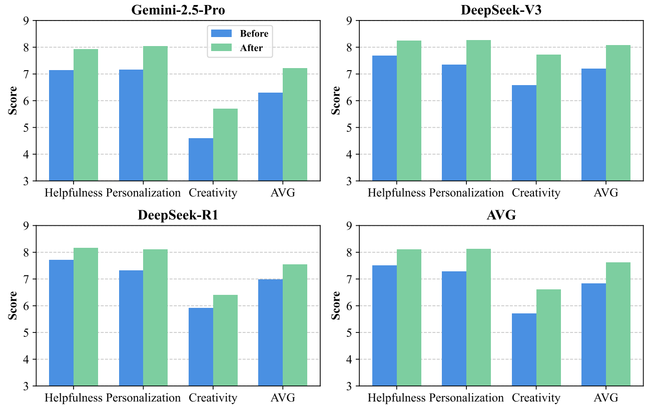


Figure 2: Result of HPC Evaluation

As illustrated in Figure 2, the RL-finetuned model achieved significantly higher scores than the pretrained model across all three dimensions: helpfulness, personalization, and creativity. These results demonstrate that reinforcement learning guided by the HPC-RM can substantially enhance the model's alignment with pedagogical helpfulness, as well as its capacity to provide personalized guidance and foster creative thinking. Furthermore, the approach exhibits strong generalization across a variety of educational tasks, providing solid support for the broader deployment of LLMs in educational settings.

### Public Benchmark-Based Evaluation

To further assess the generalization of helpfulness, personalization, and creativity capabilities across diverse tasks, we conducted evaluations on multiple public benchmark datasets. For Edu-Values, we evaluated both the pre-trained and fine-tuned models by having them respond to subjective analysis questions, which were then scored on a scale from 0 to 5 using Gemini-2.5-Pro. For PersonaMem, the models were tasked with answering choice questions, and their performance was assessed by calculating accuracy against the corresponding labels. For MathTutorBench, five key indicators were employed to evaluate the models: pedagogy following (PF), pedagogy following (hard) (PF_hard), scaffolding generation (SG), scaffolding generation (hard) (SG_hard), and Socratic questioning (SG). These indicators were used to assess the models both before and after training.

As shown in the Table 2, the RL-finetuned model demonstrates consistent improvements across all three dimensions—helpfulness, personalization, and creativity—compared to its pre-trained counterpart. These results indicate that reinforcement learning with the HPC-RM reward framework enhances the model's ability to generalize these educationally desirable traits to broader tasks.

### General Capability Evaluation

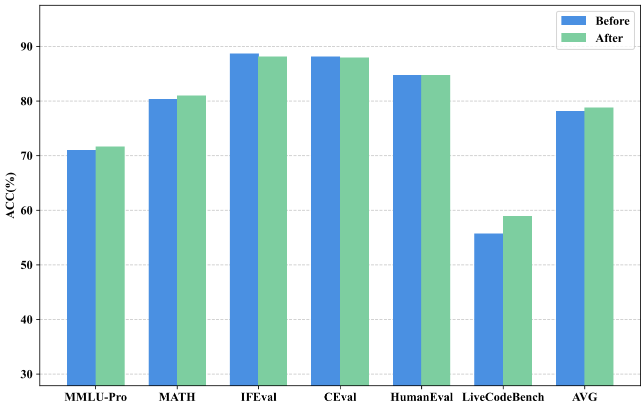


Figure 3: Result of General Capability Evaluation

To evaluate whether reinforcement learning guided by HPC-RM compromises the model's general capabilities, we conducted a comprehensive assessment on a range of widely adopted general-purpose benchmarks, including MMLU-Pro [43], CEval [44], IFEval [45], and other benchmarks, to compare model performance before and after fine-tuning. As shown in Figure 3, the model exhibits consistent overall performance across all tasks, with negligible differences observed pre- and post-training.

These findings demonstrate that reinforcement learning guided by the HPC-RM can effectively enhance the model's alignment with educational objectives—particularly in terms of helpfulness, personalization, and creativity—while maintaining its general reasoning and language understanding capabilities.

## 5. Conclusion

In this work, we introduced **EduAlign**, a novel framework designed to enhance the pedagogical alignment of LLMs in educational settings. Our approach focused on three key dimensions: **Helpfulness**, **Personalization**, and **Creativity**. We constructed a specialized reward model, **HPC-RM**, trained on 8k annotated educational interactions, which demonstrated strong consistency with human evaluations. Using this reward model, we fine-tuned a pre-trained LLM with GRPO, resulting in **EduAlign-LLM**. Experimental results showed significant improvements across all HPC dimensions while maintaining the model's general capabilities. This framework provides a scalable solution for developing AI tutors that are not only factually accurate but also virtuous, adaptive, and creativity-stimulating, paving the way for more engaging and pedagogically-sound educational AI systems.

## References

[1] D. R. Thomas, C. Borchers, S. Bhushan, E. Gatz, S. Gupta, K. R. Koedinger, Llm-generated feedback supports learning if learners choose to use it, arXiv preprint arXiv:2506.17006 (2025).

[2] E. Grassucci, G. Grassucci, A. Uncini, D. Comminiello, Beyond answers: How llms can pursue strategic thinking in education, arXiv preprint arXiv:2504.04815 (2025).

[3] L. J. Jacobsen, K. E. Weber, The promises and pitfalls of large language models as feedback providers: A study of prompt engineering and the quality of ai-driven feedback, AI 6 (2) (2025) 35.

[4] K. Seßler, A. Bewersdorff, C. Nerdel, E. Kasneci, Towards adaptive feedback with ai: Comparing the feedback quality of llms and teachers on experimentation protocols, arXiv preprint arXiv:2502.12842 (2025).

[5] S. Sonkar, K. Ni, S. Chaudhary, R. G. Baraniuk, Pedagogical alignment of large language models, arXiv preprint arXiv:2402.05000 (2024).

[6] M. Giannakos, R. Azevedo, P. Brusilovsky, M. Cukurova, Y. Dimitriadis, D. Hernandez-Leo, S. Järvelä, M. Mavrikis, B. Rienties, The promise and challenges of generative ai in education, Behaviour & Information Technology (2024) 1–27.

[7] H. Mulyani, M. A. Istiaq, E. R. Shauki, F. Kurniati, H. Arlinda, Transforming education: exploring the influence of generative ai on teaching performance, Cogent Education 12 (1) (2025) 2448066.

[8] A. Scarlatos, D. Smith, S. Woodhead, A. Lan, Improving the validity of automatically generated feedback via reinforcement learning, in: International Conference on Artificial Intelligence in Education, Springer, 2024, pp. 280–294.

[9] J. Zhong, W. Shen, Y. Li, S. Gao, H. Lu, Y. Chen, Y. Zhang, W. Zhou, J. Gu, L. Zou, A comprehensive survey of reward models: Taxonomy, applications, challenges, and future, arXiv preprint arXiv:2504.12328 (2025).

[10] L. Choshen, L. Fox, Z. Aizenbud, O. Abend, On the weaknesses of reinforcement learning for neural machine translation, in: International Conference on Learning Representations.

[11] L. Engstrom, A. Ilyas, S. Santurkar, D. Tsipras, F. Janoos, L. Rudolph, A. Madry, Implementation matters in deep policy gradients: A case study on ppo and trpo, in: International Conference on Learning Representations, 2020.

[12] R. Rafailov, A. Sharma, E. Mitchell, C. D. Manning, S. Ermon, C. Finn, Direct preference optimization: Your language model is secretly a reward model, Advances in Neural Information Processing Systems 36 (2023) 53728–53741.

[13] D. Guo, D. Yang, H. Zhang, J. Song, R. Zhang, R. Xu, Q. Zhu, S. Ma, P. Wang, X. Bi, et al., Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning, arXiv preprint arXiv:2501.12948 (2025).

[14] L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray, J. Schulman, J. Hilton, F. Kelton, L. Miller, M. Simens, A. Askell, P. Welinder, P. F. Christiano, J. Leike, R. Lowe, Training language models to follow instructions with human feedback, in: S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, A. Oh (Eds.), Advances in Neural Information Processing Systems, Vol. 35, Curran Associates, Inc., 2022, pp. 27730–27744.

[15] P. F. Christiano, J. Leike, T. Brown, M. Martic, S. Legg, D. Amodei, Deep reinforcement learning from human preferences, in: I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, R. Garnett (Eds.), Advances in Neural Information Processing Systems, Vol. 30, Curran Associates, Inc., 2017.

[16] Y. Bai, A. Jones, K. Ndousse, A. Askell, A. Chen, N. DasSarma, D. Drain, S. Fort, D. Ganguli, T. Henighan, et al., Training a helpful and harmless assistant with reinforcement learning from human feedback, arXiv preprint arXiv:2204.05862 (2022).

[17] Z. Li, T. Xu, Y. Zhang, Z. Lin, Y. Yu, R. Sun, Z.-Q. Luo, Remax: a simple, effective, and efficient reinforcement learning method for aligning large language models, in: Proceedings of the 41st International Conference on Machine Learning, 2024, pp. 29128–29163.

[18] H. Dong, W. Xiong, D. Goyal, Y. Zhang, W. Chow, R. Pan, S. Diao, J. Zhang, S. KaShun, T. Zhang, Raft: Reward ranked finetuning for generative foundation model alignment, Transactions on Machine Learning Research.

[19] Q. Yu, Z. Zhang, R. Zhu, Y. Yuan, X. Zuo, Y. Yue, W. Dai, T. Fan, G. Liu, L. Liu, et al., Dapo: An open-source llm reinforcement learning system at scale, arXiv preprint arXiv:2503.14476 (2025).

[20] A. Scarlatos, N. Liu, J. Lee, R. Baraniuk, A. Lan, Training llm-based tutors to improve student learning outcomes in dialogues, arXiv preprint arXiv:2503.06424 (2025).

[21] D. Dinucu-Jianu, J. Macina, N. Daheim, I. Hakimi, I. Gurevych, M. Sachan, From problem-solving to teaching problem-solving: Aligning llms with pedagogy using reinforcement learning, arXiv preprint arXiv:2505.15607 (2025).

[22] S. Lamsiyah, A. El Mahdaouy, A. Nourbakhsh, C. Schommer, Fine-tuning a large language model with reinforcement learning for educational question generation, in: International Conference on Artificial Intelligence in Education, Springer, 2024, pp. 424–438.

[23] Z. Cai, M. Cao, H. Chen, K. Chen, K. Chen, X. Chen, X. Chen, Z. Chen, Z. Chen, P. Chu, et al., Internlm2 technical report, arXiv preprint arXiv:2403.17297 (2024).

[24] L. Yuan, G. Cui, H. Wang, N. Ding, X. Wang, B. Shan, Z. Liu, J. Deng, H. Chen, R. Xie, et al., Advancing llm reasoning generalists with preference trees, in: The Thirteenth International Conference on Learning Representations.

[25] R. Yang, R. Ding, Y. Lin, H. Zhang, T. Zhang, Regularizing hidden states enables learning generalizable reward model for llms, in: The Thirty-eighth Annual Conference on Neural Information Processing Systems.

[26] B. Adler, N. Agarwal, A. Aithal, D. H. Anh, P. Bhattacharya, A. Brundyn, J. Casper, B. Catanzaro, S. Clay, J. Cohen, et al., Nemotron-4 340b technical report, arXiv preprint arXiv:2406.11704 (2024).

[27] H. Wang, W. Xiong, T. Xie, H. Zhao, T. Zhang, Interpretable preferences via multi-objective reward modeling and mixture-of-experts, in: Findings of the Association for Computational Linguistics: EMNLP 2024, 2024, pp. 10582–10592.

[28] L. Zheng, W.-L. Chiang, Y. Sheng, S. Zhuang, Z. Wu, Y. Zhuang, Z. Lin, Z. Li, D. Li, E. Xing, et al., Judging llm-as-a-judge with mt-bench and chatbot arena, Advances in Neural Information Processing Systems 36 (2023) 46595–46623.

[29] B. Gao, Z. Cai, R. Xu, P. Wang, C. Zheng, R. Lin, K. Lu, D. Liu, C. Zhou, W. Xiao, et al., Llm critics help catch bugs in mathematics: Towards a better mathematical verifier with natural language feedback, arXiv preprint arXiv:2406.14024 (2024).

[30] Z. Ye, X. Li, Q. Li, Q. Ai, Y. Zhou, W. Shen, D. Yan, Y. Liu, Beyond scalar reward model: Learning generative judge from preference data, arXiv preprint arXiv:2410.03742 (2024).

[31] Y. Zhao, R. Joshi, T. Liu, M. Khalman, M. Saleh, P. J. Liu, Slic-hf: Sequence likelihood calibration with human feedback, arXiv preprint arXiv:2305.10425 (2023).

[32] Z. Shao, P. Wang, Q. Zhu, R. Xu, J. Song, X. Bi, H. Zhang, M. Zhang, Y. Li, Y. Wu, et al., Deepseekmath: Pushing the limits of mathematical reasoning in open language models, arXiv preprint arXiv:2402.03300 (2024).

[33] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, O. Klimov, Proximal policy optimization algorithms, arXiv preprint arXiv:1707.06347 (2017).

[34] A. Yang, B. Yang, B. Hui, B. Zheng, B. Yu, C. Zhou, C. Li, C. Li, D. Liu, F. Huang, G. Dong, H. Wei, H. Lin, J. Tang, J. Wang, J. Yang, J. Tu, J. Zhang, J. Ma, J. Xu, J. Zhou, J. Bai, J. He, J. Lin, K. Dang, K. Lu, K. Chen, K. Yang, M. Li, M. Xue, N. Ni, P. Zhang, P. Wang, R. Peng, R. Men, R. Gao, R. Lin, S. Wang, S. Bai, S. Tan, T. Zhu, T. Li, T. Liu, W. Ge, X. Deng, X. Zhou, X. Ren, X. Zhang, X. Wei, X. Ren, Y. Fan, Y. Yao, Y. Zhang, Y. Wan, Y. Chu, Y. Liu, Z. Cui, Z. Zhang, Z. Fan, Qwen2 technical report, arXiv preprint arXiv:2407.10671 (2024).

[35] Q. Team, Qwen2.5: A party of foundation models (September 2024). URL `https://qwenlm.github.io/blog/qwen2.5/`

[36] T. Fawcett, An introduction to roc analysis, Pattern recognition letters 27 (8) (2006) 861–874.

[37] I. Cohen, Y. Huang, J. Chen, J. Benesty, J. Benesty, J. Chen, Y. Huang, I. Cohen, Pearson correlation coefficient, Noise reduction in speech processing (2009) 1–4.

[38] J. H. Zar, Spearman rank correlation, Encyclopedia of biostatistics 7 (2005).

[39] H. Abdi, The kendall rank correlation coefficient, Encyclopedia of measurement and statistics 2 (2007) 508–510.

[40] P. Zhang, Y. Zhang, B. Wang, L. Rong, P. Tiwari, J. Qin, Edu-values: Towards evaluating the chinese education values of large language models, in: Companion Proceedings of the ACM on Web Conference 2025, 2025, pp. 1519–1523.

[41] B. Jiang, Z. Hao, Y.-M. Cho, B. Li, Y. Yuan, S. Chen, L. Ungar, C. J. Taylor, D. Roth, Know me, respond to me: Benchmarking llms for dynamic user profiling and personalized responses at scale, arXiv preprint arXiv:2504.14225 (2025).

[42] J. Macina, N. Daheim, I. Hakimi, M. Kapur, I. Gurevych, M. Sachan, Mathtutorbench: A benchmark for measuring open-ended pedagogical capabilities of llm tutors (2025). `arXiv:2502.18940`. URL `https://arxiv.org/abs/2502.18940`

[43] Y. Wang, X. Ma, G. Zhang, Y. Ni, A. Chandra, S. Guo, W. Ren, A. Arulraj, X. He, Z. Jiang, et al., Mmlu-pro: A more robust and challenging multi-task language understanding benchmark, arXiv preprint arXiv:2406.01574 (2024).

[44] Y. Huang, Y. Bai, Z. Zhu, J. Zhang, J. Zhang, T. Su, J. Liu, C. Lv, Y. Zhang, J. Lei, Y. Fu, M. Sun, J. He, C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models, in: Advances in Neural Information Processing Systems, 2023.

[45] J. Zhou, T. Lu, S. Mishra, S. Brahma, S. Basu, Y. Luan, D. Zhou, L. Hou, Instruction-following evaluation for large language models (2023). `arXiv:2311.07911`.