# Exploring Self-Reinforcement for Improving Learnersourced Multiple-Choice Question Explanations with Large Language Models

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#### Abstract

Learnersourcing involves students generating and sharing learning resources with their peers. When learnersourcing multiple-choice questions, creating explanations for the generated questions is a crucial step as it facilitates a deeper understanding of the related concepts. However, it is often difficult for students to craft effective explanations due to limited subject understanding and a tendency to merely restate the question stem, distractors, and correct answer. To help scaffold this task, in this work we propose a self-reinforcement large-language-model framework, with the goal of generating and evaluating explanations automatically. Comprising three modules, the framework generates student-aligned explanations, evaluates these explanations to ensure their quality and iteratively enhances the explanations. If an explanation's evaluation score falls below a defined threshold, the framework iteratively refines and reassesses the explanation. Importantly, our framework emulates the manner in which students compose explanations at the relevant grade level. For evaluation, we had a human subject-matter expert compare the explanations generated by students with the explanations created by the open-source large language model Vicuna-13B, a version of Vicuna-13B that had been finetuned using our method, and by GPT-4. We observed that, when compared to other large language models, GPT-4 exhibited a higher level of creativity in generating explanations. We also found that explanations generated by GPT-4 were ranked higher by the human expert than both those created by the other models and the original student-created explanations. Our findings represent a significant advancement in enriching the learnersourcing experience for students and enhancing the capabilities of large language models in educational applications.

## Introduction

Learnersourcing is a pedagogical approach where the task of generating learning content is distributed among students, applying their collective intelligence to enhance the learning experience (Khosravi et al. 2023). When learnersourcing multiple-choice questions on platforms such as PeerWise (Denny et al. 2008) and RiPPLE (Khosravi, Kitto, and Williams 2019), students are required to provide explanations for the questions they create. However, creating highquality explanations can be challenging for several reasons. Firstly, writing explanations requires a deep understanding of the question. While students may be able to answer a question correctly, they may struggle to accurately describe the underlying concepts or outline the problem-solving process and steps. Secondly, some students might neglect to provide an explanation, or merely restate the question stem, distractors, and the correct answer. Therefore, the automatic generation of high-quality explanations and the evaluation of these explanations offer enormous potential for scaffolding students in learnersourcing tasks.

Given the impressive performance of large language models in understanding and generating natural language, as demonstrated in (Wei et al. 2022; Brown et al. 2020), We aim to use large language models to auto-generate explanations for student questions, offering multiple advantages for learners: 1. instant feedback from large models boosts learning efficiency. 2. interaction with the model enhances student autonomy. 3. pre-trained large-scale resources enable multi-faceted, comprehensive explanations. For large language models, their application in a learnersourcing context also presents both advantage and challenge: 1. the advantage lies in the model's ability to refine explanations by learning from a diverse array of student-generated questions, thereby facilitating its effective deployment. 2. the challenge lies in the limited availability of high-quality, student-marked data and the absence of a feedback mechanism, both of which hinder the fine-tuning and quality of the model's output. We propose a framework for self-reinforcement and assessing explanations for multiple-choice questions sourced from students via PeerWise, a learnersourcing platform that is employed by more than 1,500 universities worldwide (Denny et al. 2008). Our system has three modules: explanation generation, explanation evaluation, and iterative explanation enhancement. It aims to improve the quality of automatically generated explanations for learnersourced MCOs by using feedback iterations between the modules.

To complement the automatic evaluation of the generated

Preprint. Under review.

explanations, we invited a subject instructor as an expert to assess and compare the explanations written by students and generated by different large language models.

We summarize our primary contributions as follows:

- We propose a self-reinforcement framework that comprises three modules aimed at enhancing the quality of automatically generated explanations for learnersourced multiple-choice questions. The framework iteratively refines the generated explanation by providing feedback to the explanation-generation module with the quality score of the explanation produced by the explanationevaluation module, until the score exceeds a pre-defined threshold. Both modules adopt pretrained large language models fine-tuned using *instruction fine-tuning* (explained in Methods).
- We provide a human-ranking evaluation of the appropriateness of the generated explanations.
- Our experiments affirm the effectiveness of our proposed self-reinforcement framework. After implementing our proposed framework, we find that on average 0.46 iterations are required in order to generate explanations that exceed our quality threshold. Based on the LLaMA2-13B model, our self-reinforcement framework demonstrates a performance improvement on five PeerWise datasets. achieving an average increase of 2.84% in BLEU score and 0.85% in BERT score when compared directly to a fine-tuned version of LLaMA2-13B. The experimental results show that a fine-tuned large language model is capable of emulating the manner in which students compose explanations at a relevant grade level. Furthermore, we discover that GPT-4 displays a heightened level of creativity in generating explanations, an ability that is not widely exhibited by other large language models.

## **Related Work**

In the context of learnersourcing, where students actively participate in creating educational content, existing systems like PeerWise and RiPPLE allow for the creation and evaluation of multiple-choice questions (MCQs) (Kulkarni et al. 2013; Denny et al. 2008; Khosravi, Kitto, and Williams 2019). These MCQs comprise a question stem, distractors, a correct answer, and an explanation. Currently, students are responsible for manually generating each of these elements. Our research focuses on automating the explanation component once students provide the question stem, distractors, and correct answer. This automation aims to simplify the question-creation process, thereby offering a more interactive and scalable learning experience.

While some research has encouraged students to write explanations alongside their multiple-choice questions to improve learner understanding (Singh, Brooks, and Doroudi 2022), limited research has focused on utilizing machine learning or large language models to assist students in generating these explanations. Learnersourcing, for example, has been integrated into the ASSISTments platform by prompting students to articulate the solutions to the questions they tackle (Heffernan et al. 2016). The AXIS system employs

learnersourcing to create, assess, and modify the explanations provided to a learner while they are solving mathematical problems (Williams et al. 2016). Additionally, a learnersourcing approach has been developed that encourages learners to explain their mistakes immediately after they have resolved a specific programming challenge (Guo, Markel, and Zhang 2020).

In the domain of automated explanation generation and question quality evaluation using deep learning, research remains sparse. Bhatnagar et al. employed a BERT-based model to assess the persuasiveness of learner-generated explanations, a key criterion for quality (Bhatnagar et al. 2020). However, this approach requires validation of explanation accuracy. Alternatively, Ni et al. utilized a Transformer model with contrastive learning to evaluate question quality, incorporating various elements such as question context and distractors (Ni et al. 2022). Despite its merits, this method necessitates some manual feature engineering.

## **Problem Formulation**

Here we formally define the *multiple-choice question explanation generation* and *evaluation* tasks. When authoring an MCQ in learnersourcing systems like PeerWise (Denny et al. 2008), a student needs to specify seven components: a question stem, a correct answer, (up to) four distractors, and a paragraph that explains the idea and rationale behind the question. The question is then submitted to an online repository of MCQs accessible by the class. After answering a question, a student may leave a holistic quality rating (from  $0, 1, \ldots, 5$ ) by considering the "language, quality of distractors, quality of explanation, and relevance to the course" as suggested by the system.

**Definition 1** (Multiple-Choice Questions (MCQs)) MCQs are a set of questions,  $\{M_1, M_2, \ldots, M_n\}$ , collected from a course, where each  $M_i$  consists of a stem  $S_i$ , a correct answer  $A_i$ , distractors  $D_{i,j}$  where  $j \in \{1, 2, 3, 4\}$ , explanation  $E_i$ , and is assigned a rating  $r_i$ .

**Task 1** (MCQ explanation generation) Multiple-Choice Question (MCQ) explanation generation aims to construct a model, G, which takes the question stem  $S_i$ , the correct answer  $A_i$ , and distractors  $D_{i,j}$  as inputs, and produces a generated explanation  $E_i$  as the output.

**Task 2** (MCQ explanation evaluation) The goal of Multiple-Choice Question (MCQ) explanation evaluation is to build a model, G, which takes as input the question stem  $S_i$ , the correct answer  $A_i$ , distractors  $D_{i,j}$ , and the generated explanation  $E_i$ , and outputs a quality rating  $r_i$  for the MCQ. We indirectly evaluate the explanations for MCQ using the quality rating score  $r_i$ , since the learnersourcing system only provides a rating score for the MCQ itself, not for the explanation.

Our problem consists of two subtasks: (1) *MCQ explanation generation* aims to build an explanation generation model. (2) *MCQ explanation evaluation* aims to construct a prediction model for the question quality rating given the input question stem, distractors, answer and the generated

explanation. Since we do not have a specific score for evaluating the quality of explanation, we use the question quality rating score and take the explanation as part of the input to conduct the MCQ explanation evaluation. The predicted question rating score will be used to measure the quality of the generated explanation.

## Methods

## **System Architecture**

The architecture of our system is illustrated in Figure 1. The MCO Explanation Generation Module is designed to implement instruction-based fine-tuning for the automatic generation of explanations for MCQ. The generated explanations are then provided as input to the MCQ Explanation Evaluation Module. This latter module undergoes further instruction fine-tuning to automatically assess the quality of the generated explanations. When the evaluation score from the MCQ Explanation Evaluation Module falls below a predetermined threshold, the MCQ Explanation Generation Module is triggered to regenerate the explanation. This iterative process continues until the evaluation score exceeds the specified threshold. Subsequently, the evaluation score and the generated explanation are employed as feedback to refine the instruction set for future explanation generation. Depending on the operational context, the finalized explanation will either be archived in the MCQ repository - if the corresponding MCQs are already stored there - or displayed to students who are in the process of crafting the MCQs. Importantly, students retain the option to modify the generated explanation prior to its submission to the repository.

**PeerWise** Leveraging PeerWise, our model can be employed to scaffold students when generating multiple-choice questions. Upon receiving a question stem, distractors, and a correct answer from a student, our MCQs Explanation Generation Module produces an explanation. An accompanying Evaluation Module iteratively refines the quality of these explanations. This approach capitalizes on students' unique insights into common learning challenges, aiming to improve explanation comprehensibility.

**Instruction Fine-Tuning** adapts a pre-trained model to follow specific input instructions more accurately. It involves additional training with examples that pair these instructions with desired outputs, enhancing the model's task-specific performance while retaining its broad language understanding (Mishra et al. 2021; Wei et al. 2021). The instructions utilized for generating explanations and conducting evaluations are delineated in the system architecture, as depicted in Figure 1.

## **MCQ Explanation Generation**

As depicted in Fig. 1, we conducted instruction fine-tuning to train a model for generating explanations for MCQs. The model inputs include the instruction, question stem, correct answer, and distractors. We select the open-source large language model Vicuna-13B (Chiang et al. 2023) as the backbone for this model. The model outputs the explanation for the MCQs. During data preprocessing, we retain only the

MCQs with quality rating score of 3 or higher and explanations that are longer than 10 words. This step is undertaken to ensure that only high-quality MCQs are included in the training set, aiding us in building an MCQ explanation generator capable of producing high-quality explanations.

## **MCQ Explanation Evaluation**

Similar to the module above, we employ instruction finetuning to train a model to evaluate the generated explanations. In the absence of quality rating scores for explanations, we construct an evaluation model for MCQ explanations using the quality rating score for questions. The model's input comprises the instruction, question stem, correct answer, distractors, and the explanation. The model's output is the quality rating score for the MCQs.

Whenever the MCQ Explanation Evaluation Model predicts a quality rating score below a pre-defined threshold, the MCQ Explanation Generation Module is prompted to regenerate the explanation. This regenerated explanation then replaces the low-quality explanation from the previous round. The new explanation, along with other inputs, is subsequently fed back into the MCQ Explanation Evaluation Model for re-evaluation. This cycle continues until the predicted quality rating score surpasses the pre-defined threshold. The pseudocode for the MCQ Explanation Generation and Evaluation is shown as follows:

Algorithm 1: MCQ Explanation Generation and Evaluation

**Require:** pre-defined threshold t, multiple-choice questions (MCQs), large language model (LLM), batch\_size bs, learning\_rate lr 1. MCQ explanation generation instruction fine-tuning for instruction, stem, answer, distractors from MCQs do LLM, Loss = next\_token\_prediction\_loss(LLM, instruction, stem, answer, distractors, lr) end for 2. MCQ explanation evaluation instruction fine-tuning for instruction, stem, answer, distractors, explanation from MCOs do LLM, Loss = next\_token\_prediction\_loss(LLM, instruction, stem, answer, distractors, explanation, lr) end for 3. Iterative MCQ explanation enhancement while rating\_score  $< t \operatorname{do}$ reg\_explanation = explanation\_generator(instruction, stem, answer, distractors) rating\_score = explanation\_evaluator(instruction, stem, answer, distractors, explanation) instruction = instruction + reg\_explanation + rating\_score + "Please generate a better explanation." end while

## **Iterative MCQ Explanation Enhancement**

Our solution comprises two components: Multiple-Choice Question (MCQ) Explanation Generation Module and MCQ Explanation Evaluation Module. The former is responsible for generating explanations, while the latter assesses the



Figure 1: Architecture of the self-reinforcement framework using large language models for multiple-choice question explanation generation and evaluation.

quality of these explanations by providing an evaluation score. During each iterative cycle, the explanation generated in the previous iteration, along with its corresponding evaluation score, is formulated into a new instructional input. This new input, which also includes the question stem, the correct answer, and the distractors, is then fed into the Explanation Generation Module to facilitate the creation of a potentially higher-quality explanation. The iterative process continues until the evaluation score from the Explanation Evaluation Module surpasses a pre-defined threshold.

#### **Human Expert Evaluation for Explanations**

The human expert evaluation was conducted by a subject matter expert on a set of 61 randomly sampled questions from one of the PeerWise datasets, namely the Sydney Biology dataset. During evaluation, the expert was shown the question stem, the answer options, and four explanations for the question. The evaluation was blind, i.e., the source of the explanation (student, Vicuna-13B, Vicuna-13B fine-tuned, GPT-4) was not shown to the evaluator.

The questions, options and answers were first evaluated to determine whether they were clear and accurate. The explanations were then evaluated as a whole by judging for accuracy, level of detail, relevance, and clarity. Accuracy and relevant detail were prioritised in the ranking, followed by clarity and succinctness if the former were judged to be to a similar standard.

Asterisks were used where explanations were ranked equally, with the remaining explanations numbered based on quality. To generalise, a ranking of 1 indicated the explanations were excellent—they were accurate, clearly written, and contained adequate and relevant details; explanations ranked as 2 were generally passable explanations that included many attributes typical of an excellent explanation; explanations ranked as 3 contained some inaccuracies or lacked detail; explanations receiving a ranking of 4 were inaccurate, irrelevant or only stated the answer without providing any explanation.

#### **Experiments**

#### **Experiment Setup**

**Datasets** We conducted our experiment on five learnersourced multiple-choice questions datasets Sydney Biology subject, Cardiff Biology subject, Auckland Law subject, UK Medical Year 1 (2015-2021), and UK Medical Year 2 (2015-2021) from PeerWise platform. To ensure reliability, only questions that receive at least 10 ratings are included. See Table 1 for the final dataset details. The average explanation length is calculated by how many words there are in a sentence, and dividing words according to spaces.

**Models** We selected the open-source generative large language model Vicuna-13B (Chiang et al. 2023) and LLaMA2-13B (Touvron et al. 2023) as the backbone models to conduct the instruction fine-tuning for MCQ explanation generation and evaluation. We also selected Vicuna-13B and LLaMA2-13B without instruction fine-tuning, GPT-3.5 (OpenAI 2023a) and GPT-4 (OpenAI 2023b) as the baseline model.

Table 1: Details about the PeerWise datasets used for conducting this experiment.

Subject	Sydney Biology	Cardiff Biology	Auckland Law		
# MCQs	2311	6955	3449		
# Ratings	57585	581937	65645		
# Ratings per MCQ	24.91	83.67	19.03		
Av. explanation length	108.82	75.09	48.13		
Subject	UK Medical Year 1	UK Medic	UK Medical Year 2		
# MCQs	3991	2789			
# Ratings	305067	271524			
# Ratings per MCQ	76.43	97.35			
Av. explanation length	68.94	83.38			

**Data Preprocessing** For training the explanation generator, we filtered out questions which met any of the following criteria: the quality rating score is lower than 3, the question stem length is lower than 10, or the question stem includes an image. Finally, we removed html tags to clean the data.

**Settings** We conducted all the instruction fine-tuning for Vicuna-13B and LLaMA2-13B MCQ explanation generation and evaluation experiments on 8 NVIDIA A100 GPUs with 80G GPU memory. We trained our model for 5 epochs, using a batch size of 1 and a maximum sequence length of 512. We set the learning rate to 2e-05 and the warmup ratio to 0.03. To leverage the power of multi-GPUs, we utilized the torchrun tool for training. The source code is available<sup>2</sup>.

#### **MCQ Explanation Generation**

We used instruction fine-tuning for Vicuna-13B and LLaMA2-13B to train the explanation generator, and we compared four other baseline models: Vicuna-13B and LLaMA2-13B without instruction fine-tuning, GPT-3.5 and GPT-4. Considering the cost of calling GPT-4 API, we randomly selected 100 samples from the whole test set. We used BLEU (Papineni et al. 2002) and BERT scores (Zhang et al. 2019) to evaluate generated explanations and ground truth explanations (student-authored explanation). In our experiments, GPT-4 consistently outperformed other models, achieving the highest BLEU and BERT scores across the majority of datasets, as delineated in Table 2. We further investigated the impact of instruction-based fine-tuning on large language models such as Vicuna-13B. Remarkably, this fine-tuning led to a significant improvement in both BLEU and BERT scores in comparison to using Vicuna-13B without any modifications. We extended this fine-tuning approach to another large model, LLaMA2-13B, and observed even more encouraging results. Specifically, instructionfine-tuned LLaMA2-13B surpassed the performance of its Vicuna-13B counterpart and even exceeded GPT-4 in certain tasks. Notably, it achieved higher scores in the Sydney Biology and Auckland Law subjects and outperformed GPT-3.5 in four out of five datasets, with the exception being the UK Medical Year 2 subject. For LLaMA2-13B, two fine-tuning strategies were employed. In the first, denoted as "Fine-tuned LLaMA2-13B," we applied instruction finetuning individually to each task. In the second approach,

labeled as "Fine-tuned LLaMA2-13B Merged," we amalgamated the training sets from the five tasks for a unified instruction fine-tuning process. Our findings suggest that both instruction fine-tuned Vicuna-13B and LLaMA2-13B effectively learned to emulate the characteristics inherent in student-generated explanations.

Table 2: We compared a fine-tuned Vicuna-13B with the non-fine-tuned Vicuna-13B, a fine-tuned LLaMA2-13B, and GPT-4 using 100 test cases. These were randomly collected from Biology subjects in Sydney and Cardiff, a Law subject in Auckland, and Medical Year 1 and Year 2 subjects in the UK for the MCQ explanation generation task.

$\begin{array}{l} \text{Models} \rightarrow \\ \text{Metrics} \downarrow \end{array}$	Vicuna-13B	Fine-tuned Vicuna-13B	Fine-tuned LLaMA2-13B	Fine-tuned LLaMA2-13B Merged	GPT-3.5	GPT-4
		Svdnev E	Biology Subject			
Avg BLEU Score	0.0859	0.3391	0.3480	0.3434	0.3025	0.3424
Avg BERT Score 0.2017 0.6333		0.6333	0.6226	0.6162	0.6356	0.6372
		Cardiff E	Biology Subject			
Avg BLEU Score	0.0336	0.1533	0.2537	0.2559	0.2565	0.2908
Avg BERT Score	0.0876	0.5172	0.5685	0.5860	0.5769	0.5872
		Aucklan	d Law Subject			
Avg BLEU Score	0.0309	0.0936	0.2639	0.2782	0.2216	0.2431
Avg BERT Score	3ERT Score 0.0799 0.4538 0.5707		0.5801	0.5711	0.5719	
		UK Medic	al Year 1 Subject			
Avg BLEU Score	0.0192	0.1509	0.2617	0.2760	0.2544	0.2829
Avg BERT Score	0.0622	0.5206	0.5723	0.5845	0.5844	0.5947
-		UK Medic	al Year 2 Subject			
Avg BLEU Score	0.0423	0.1772	0.2476	0.2389	0.2661	0.3067
Avg BERT Score	0.1247	0.5162	0.5591	0.5682	0.5715	0.5817

## **MCQ Explanation Evaluation**

As Table 3 shows, we compared a fine-tuned LLaMA2-13B model with the non-fine-tuned LLaMA2-13B model and GPT-4 on 100 test cases. These were randomly collected from Sydney and Cardiff Biology subjects, Auckland Law subject, and UK Medical Year 1 and 2 subjects, for the MCQ explanation evaluation task. Since we have the question quality rating labels for each question, we can use these labels to train a question quality rating model. We rely on this model to evaluate the explanation by replacing the explanations in the MCQs. In Table 3, we use accuracy as the metric. If the predicted question quality rating falls within a 0.25 range of the ground truth, it is labeled as correct.

As demonstrated in Table 3, the Fine-tuned LLaMA2-13B and Fine-tuned LLaMA2-13B Merged models significantly outperform the two baseline models in terms of accuracy. This suggests that these fine-tuned models have successfully captured the underlying distribution of evaluation scores generated by students. We observed that both LLaMA2-13B, without task-specific instruction fine-tuning, and GPT-4 underperform in the evaluation of explanations for MCQs. Specifically, these models tend to over-estimate quality, frequently assigning scores greater than 4 on a scale where 5 is the maximum. This inflation of scores may be an artifact of the Reinforcement Learning from Human Feedback (RLHF) approach, predisposing the models to offer overly positive evaluations. Such biases could have significant implications in educational contexts where these models are deployed for automated student feedback. To enhance performance in specific tasks, such as predicting evaluation

<sup>&</sup>lt;sup>2</sup>https://github.com/Strong-AI-Lab/Explanation-Generation

scores for student-generated content, it is advisable to employ instruction fine-tuning on task-specific datasets to better approximate the target distribution.

Table 3: We compared the fine-tuned LLaMA2-13B with the non-fine-tuned LLaMA2-13B and GPT-4 on 100 test cases for MCQ explanation evaluation.

$\begin{array}{l} \text{Models} \rightarrow \\ \text{Metrics} \downarrow \end{array}$	LLaMA2-13B	Fine-tuned LLaMA2-13B	Fine-tuned LLaMA2-13B Merged	GPT-4
	Sydn	ey Biology Subje	ct	
Accuracy	0.0500	0.3100	0.4400	0.0100
	Card	iff Biology Subje	ct	
Accuracy	0.0600	0.6500	0.6800	0.0100
	Auc	kland Law Subjec	t	
Accuracy	0.0200	0.5800	0.5900	0.1900
	UK M	edical Year 1 Sub	ject	
Accuracy	0.0100	0.7000	0.6300	0
	UK M	edical Year 2 Sub	ject	
Accuracy	0	0.6200	0.5600	0

#### **Iterative MCQ Explanation Enhancement**

We iterate this process of explanation generation and evaluation five times, with each interaction comprising one instance of explanation generation and evaluation. We recorded the score for each evaluation, the similarity between the generated explanation and the original explanation written by the student. We then computed the number of iterations required to improve the evaluation score, the generated explanation, and the similarity to the original studentwritten explanation. In our experiment, we set a threshold for halting iterations: if the model generates an explanation with an evaluation score exceeding the original rating score, the iteration process stops. The specific results are shown in Table 4. Utilizing our self-reinforcement framework, we find that by substituting the explanations in multiple-choice questions, the explanation generation module necessitates approximately 0.46 additional iterations to produce explanations that outperform the original ones in terms of question quality rating, BLEU score, and BERT score.

Table 4: We recorded the average number of steps and the average question quality rating score during the explanation generation process. The model being used in this experiment is the fine-tuned LLaMA2-13B (merged) for both MCQ explanation generation and evaluation.

	# iteration step	Avg question quality rating score	Avg BLEU Score	Avg BERT Score	
Sydney Biology Subject	1	2.8468	0.3434	0.6162	
	1.36	2.8705	0.3601	0.6209	
Cardiff Biology Subject	1	3.0709	0.2559	0.5860	
	1.36	<b>3.0932</b>	0.2874	<b>0.5905</b>	
Auckland Law Subject	1	4.1140	0.2782	0.5801	
	1.60	4.1599	0.3135	0.5984	
UK Medical Year 1 Subject	1	3.0759	0.2760	0.5845	
	1.46	<b>3.0966</b>	0.3098	0.5928	
UK Medical Year 2 Subject	1	3.0517	0.2389	0.5682	
	1.52	3.0703	<b>0.2636</b>	0.5750	

Table 5: We invited a subject matter expert to evaluate the explanations by ranking them. The evaluations being ranked were generated by students, the instruction finetuned Vicuna-13B model, the non-fine tuned Vicuna-13B model, and GPT-4 on the 61 questions randomly sampled from the Sydney Biology Subject dataset.

$\begin{array}{l} \text{Rank} \rightarrow \\ \text{Explanation source} \downarrow \end{array}$	1	1*	2	2*	3	3*	4	4*
GPT-4	47	3	7	0	2	0	0	2
Student	10	2	28	4	8	3	5	1
Vicuna-13B (fine-tuned)	1	0	6	4	12	3	14	21
Vicuna-13B	0	1	9	0	10	0	20	21

## Human Expert Evaluation for Explanations

Table 5 shows the result of the human ranking of the generated explanations. The main finding is that the explanations generated by GPT-4 were ranked the best, followed by the original student-created explanations. Both the finetuned Vicuna-13B and the non-fine-tuned Vicuna-13B were rated low, being ranked with the highest scores of 1 or 2 only a couple of times. One example question with the human rankings is shown in Figure 2.

This result suggests that generic, large, non-fine-tuned models such as GPT-4 surpass the ability of students to generate good explanations of multiple-choice questions. On the other hand, smaller models, even when fine-tuned, are not capable of this. The finding that the explanations generated by GPT-4 often surpassed the original student-created explanations suggests that GPT-4 could be used to show students an example explanation that is likely to be correct when they create explanations for MCQs. In addition, even though the Vicuna-13B base and fine-tuned models performed worse, providing students with the explanations generated by them could be useful too for some use cases. For example, students could be provided explanations and their task could be to improve the explanations, which could be beneficial for learning.

## **Conclusions and Future Work**

In summary, this study presents a novel self-reinforcement framework that utilizes large language models for the generation and assessment of explanations corresponding to learner-sourced multiple-choice questions. Experimental findings indicate that our self-reinforcement methodology enables advanced language models, such as LLaMA2-13B and Vicuna-13B, to produce explanations with superior BLEU and BERT scores when compared to GPT-3.5 and GPT-4. Remarkably, GPT-4 outperforms all other models by generating explanations that exceed the quality of those composed by students, as assessed by a human expert. Future research endeavors will focus on expanding the dataset, fine-tuning the models across a diverse range of academic disciplines and educational levels, integrating the framework into a live learner-sourcing platform to examine learner engagement with the generated explanations, and exploring a meta-learning approach for continual refinement based on

#### Example Explanations Created and Human Ranker Comments

**Stem:** The following is a sequence of mRNA: CAG UCA AAG AUG GCC CCA AGA CAG UCG CGG UGA GAA How many amino acids would the translated polypeptide have?

Correct answer: 7

Distractor 1:8 Distractor 2:6 Distractor 3:5

Distractor 4: We can not determine the amount of amino acids just from looking at an mRNA sequence.

**Original student explanation (ranked as 2):** The stop codons are UAA, UGA, UAG. AUG is our start codon, and amino acid Met joins. The following is our 'active' region: AUG GCC CCA AGA CAG UCG CGG UGA 1. 2. 3. 4. 5. 6. 7. NO amino acid B is the only correct answer as there are NO tRNAs with anticodons complementary to our aforementioned stop codons (no amino acid attaches).

**GPT-4 explanation** (ranked as 1): The mRNA sequence given is CAG UCA AAG AUG GCC CCA AGA CAG UCG CGG UGA GAA.

To understand how many amino acids the translated polypeptide would have, we need to understand how translation works in cellular biology.

During translation, every three nucleotides or 'codons' in the mRNA sequence are read to produce one amino acid. So we generally divide the total number of nucleotides by three to determine the number of amino acids.

But, there's an important thing to note: the sequence starts with an initiation codon (AUG) and ends with a termination codon (UGA), both of which do not code for amino acids. The initiation codon signals the start of translation, and the termination codon signals the end of translation.

Therefore, we ignore these two codons and count only the codons in between. The sequence from AUG to UGA in the given mRNA is: AUG GCC CCA AGA CAG UCG CGG UGA.

Removing the initiation and termination codons, we have: GCC CCA AGA CAG UCG CGG.

This gives us 6 codons, each of which will code for one amino acid.

So, the translated polypeptide would have 6 amino acids. Therefore, the correct answer is Option C: 6.

**Vicuna-13B fine-tuned explanation (ranked as 4\*):** 7 amino acids will be obtained after translation because the mRNA has 7 different codons (or nucleotide triplets) that each encode for a specific amino acid.

Vicuna-13B explanation (ranked as 4\*): 7

**Comments from the human ranker:** This one is tricky. They need to recognise that AUG is the start codon and possible stop codons are UAA, UAG and UGA. The number of amino acids is given by the numbers of these triplets, excluding the stop. The AUG may or may not be counted –as the start is removed in some cases. I would accept both 6 and 7 as correct.

GPT-4 was ranked 1 here as it explains about the codons encoding amino acids, and correctly identified the start and stop codons in this sequence. In this case, the start codon was not counted to give 6 (although previously overlooked the inaccuracy about AUG not encoding an amino acid). The student answer came close, and noted all the other possible stop codons, but the rest of the explanation was less thorough. The two Vicuna did not really explain. Perhaps was a bit harsh on Vicuna-ft here as it at least mentioned about codons encoding amino acids whereas Vicuna-base just said 7. Neither mentioned about the start or stop and not counting all the codons, though.

Figure 2: Example of ranked explanations for one question.

user feedback.

**Ethical Statement** All experiments conducted and data used in this paper have been approved by the Ethics Committee of the main authors' employer. All the code used to run the experiments is written using open-source libraries or adapted from published code from other papers. We also release our code to ensure that the work can be reproduced.

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