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Research Article

Enhancing the Effectiveness of High Schools-Level English Translation Teaching Using Transformer Models and Reinforcement Learning Algorithms

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ABSTRACT

Translation teaching is changed as artificial intelligence and deep learning constructs a wonderland. The traditional forms of teaching translation are devoid of personalized feedback, adaptive methods of learning, and dynamic error correction-all components that do not allow the student to attain high translation accuracy and fluency proficiency. This study investigates the application of a Transformer-based deep learning model and reinforcement learning algorithms in English translation education for the secondary school level. The study creates a system of AI-aided translation teaching which includes elements such as in-time feedback, adjusted translation exercises, and automated error diagnosis. The transformer models are for contextually accurate translations while reinforcement learning would ensure flexibility in difficult levels dependent on student performance. Effectiveness was evaluated through a study of 342 high school students concerning measures like translation accuracy and fluency, cultural adaptation, and error reduction. The findings showed apparent progress in translation performances, where BLEU scores rose from 45.3 to 62.7 and perplexity values declined from 21.4 to 14.8, reflecting greater translation precision and coherence. In addition, grammar errors decreased by 10.9%-12.6%, spelling errors by 11.4%-12.6% and contextual logic errors by 14.7%-19.5%, thus confirming the working of a reinforcement learning-based feedback mechanism. It concludes that AI-powered teaching of translations is an approach of learning that is scalable, efficient, and above all, student-centered in imparting translation precision, fluency, and cultural bearing. The combination of Transformer models and reinforcement learning is a promising perspective for the intelligent translation teaching of the future as it would enable real-time personalized feedback and optimization of learning throughout life.

Keywords: Transformer Model, Reinforcement Learning, AI-Assisted Translation, High School Translation Teaching, Adaptive Learning, Machine Translation, Error Diagnosis.

1. Introduction

The learning of any translation reveals a lot regarding the students' bilingual proficiency and linguistic accuracy and cross-cultural communication [1]. In recent years, efforts have been towards putting deep learning and artificial intelligence into frontline translation educational uses, with a great promise for efficiency and quality in learning and teaching [2]. Considerable research has examined various aspects of

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translation teaching by integrating machine learning, a structured teaching model, and intelligent platform. [3] examined the role vocabulary learning and corpus-based translation practices could play in English-Chinese translation teaching and stated that the two could enhance learning outcomes in translation. [4] examined a structured model for translation instruction and stated that using a proper teaching process improved the accuracy and comprehension of translations. Taking a technical look, [5] has indeed put out a quite varied valuation system based on the Internet of Things (IoT), which also manages deep learning to enhance the assessment of translation quality. [6] carried this forward into an AI-based translation platform, wherein it was established that using a smart environment for learning could better the students' proficiency in translation. Meanwhile, [7] studied the merging of processing images with teaching translation, using computer vision techniques to augment multimodal translation learning. Likewise, [8] would use image restoration and deep generative models in intelligent translation systems, increasing the accuracy of automated translation and adaptability in learning. For refining evaluation in translation, [9] suggested the BiLSTM model which has incorporated a fuzzy inference system into a training model for evaluations in translation. This result revealed such an approach which makes an improvement in accuracy, fluency, and cultural understanding, placing less incidence on most erroneous translations.

While innovative methods for translation teaching have been suggested in previous studies, many challenges still make it difficult to personalize translation learning, minimize certain specific translation errors, and optimize adaptable learning strategies [10]. Existing methods mostly do not support dynamic learning adjustments, and hence have to rely on standardized methods to fix translation accuracy, fluency, and cultural context adaptation problems in students [11]. This research aims at improving the teaching of English translation at high school levels through deep learning models based on Transformer architecture and reinforcement learning algorithms. Through these adaptive AI-driven feedbacks, it is expected that accuracy, fluency, and contextual adaptation of translations will be enhanced, along with self-adjustable translation exercises by student performance. This research will explore how AI-assisted teaching of translation can offer real-time and personalized feedback and, in the end, improves efficiency in translation learning and thus enhances student engagement.

2. Materials and Methods

2.1 Data collection and processing

2.1.1 English translation teaching data collection

In order to better English translation teaching at the high school level in Basra, Iraq, this study now stood systematically toward data collection. The intent is to collect as much diverse and representative data as possible, which could then be used to bring into existence and form a concrete data-oriented framework of teaching which utilizes Transformer models and reinforcement learning algorithms. Assessments of surveys, classroom observation, and translation tasks are some of the procedures for the data collection.

Student Surveys

A structured questionnaire was designed in order to analyze the self-evaluation of students regarding their abilities in translation, their learning preferences, and the difficulties that they face in translation tasks. The questionnaire contains multiple-choice and open-ended questions in order to extract quantitative and qualitative results.

Key survey questions include:

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Table 1. Key Questions in the Translation Teaching Survey

Question	Response options
1. What is your opinion about your translation skills?	(Poor, Average, Good, Excellent)
2. Which feature of translation do you think you find most challenging?	(Grammar, Vocabulary, Cultural Context, Sentence Structure)
3. Outside the school, how often do you find yourself practicing translation?	(Never, Rarely, Sometimes, Often)
4. How helpful is the feedback given by your teacher with your translation skills?	(Not Useful, Somewhat Useful, Very Useful)
5. What translation tools or techniques do you employ while translating passages into other languages?	(Machine Translation Tools, Computer-Assisted Translation, Syntax and Grammar Checking Tools)

The questionnaire is structured, as seen in Table 1, and has 15 questions. The questions assess students' self-evaluation of translation skills, their satisfaction with teaching methods, and the difficulties faced during translation. The final distribution of questionnaires was 342, with a response rate of 93.9%; hence, 321 questionnaires were valid for analysis.
To better understand the translation challenges faced by students, classroom observations were established during the translation lessons of English. The observers collected data on the level of engagement of the students, the common errors, their interaction with the teacher, and their strategies for solving the identification of translation problems. This information was pertinent for locating existing gaps in teaching methods and areas wherein AI-based translation tools could contribute to improvement.
Key observational metrics include:
1. Their involvement in translation exercises along with students.
2. The frequency of types of errors made.
3. Effectiveness of teacher explanations and feedback.
4. While exercises are conducted, a dictionary or online translation tool is used.

2.1.2 Data Cleaning and Standardized Processing

In order to assure that collected data become duly reliable and usable for improving the English translated teaching of high schools in Basra, Iraq, an extensive data cleaning and standardization process was executed. The whole process goes from missing data treatment to elimination of duplicates, normalization of lyrics scores, encoding of categorical responses to surveys, and preparation of text-based answers for further analysis.
The collected data include responses from students, which are characterized by missing responses due to skipped survey questions and translation tasks not yet completed. This treatment follows a systematic approach. If a student fails to respond to 40% of the survey questions or translation tests, the entry will be removed to avoid data bias. In the case of numerical missing values from translation accuracies, mean imputation is used to preserve integrity in the dataset. However, the categorical responses may be filled using the K-nearest neighbor (KNN) [12] imputation method to find out what might be assumed to be the most probable answer and fill it based on the similar studied students' responses.

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Duplicate entries, which could stem from multiple survey submissions or repeated translation exercises, were identified and removed. Each student's data was indexed uniquely so that only one record per individual was retained for analysis. In addition, there were checks for inconsistencies in self-reporting, with outliers identified via interquartile range (IQR) analysis to minimize their influence on statistical analysis.

Once data had been cleaned, standardization techniques were applied to normalize varying data types to allow for homogeneous analysis. Translation evaluation scores of accuracy, fluency, and cultural appropriateness were standardized using Z-score normalization [13] with respect to the distribution of those data. This justified comparison of translation scores on the same scale across different assignments and different graders. Also, categorical survey responses—for instance, students' self-assessment of their translation skills or frequency of translation practice—were encoded numerically. To illustrate, "Poor" through "Excellent" received values from 1 to 4 in order to facilitate statistical analyses and machine learning applications.

Open-ended responses accepted for analyses such as the descriptions of translation tools and strategies provided by students were subjected to NLP techniques. This organized and preprocessed data was then tokenized, with stop word removal and stemming applied so that meaningful patterns could be drawn. The results of the exercise identified commonly used translation equipment for students as well as an understanding of how they approach translation.

In the end, all cleaned and standardized records entered a structured relational database for effective querying and analysis. Descriptive statistical methods were run to ascertain data consistency and confirm it was clear from oddities prior to being utilized as training data for AI models. The available cleaned dataset was a penultimate step toward implementing all Transformer models and reinforcement learning algorithms for high school translation teaching in Basra. This exercise, by removing inconsistencies and ensuring data integrity, ensures that a data-driven approach is in place to locate students' difficulties and tailor AI-assisted feedback mechanisms to improve translation proficiency.

2.1.3 Data Integration of Translation Quality Evaluation

To establish a well-grounded and highly data-oriented procedure for the enhancement of English translation teaching in Basrah high schools, the translation quality assessment data underwent a systematic process of collection and integration. This included: collating scores for translation evaluations from different sources in order to ensure uniformity of grading and compilation of data for subsequent AI-related analysis. The objective was to create a comprehensive data set, integrating students' performance in translation in terms of accuracy, fluency, and cultural appropriateness.

The translation quality evaluation organized translation sessions in the classroom and formal assessments. This is to ensure fairness in scoring with respect to individual students' translation scores. Different Evaluators were trained to score students' work independently on the basis of rubric components. The key components consisted of:

- Accuracy (correctness of translated content)
- fluency (smoothness and coherence of language)
- cultural appropriateness (ability to convey cultural meaning accurately)

All areas were to be scored between 0 and 100, with the evaluation of translation quality as the average of the three analyses.

The grading process was designed to increase reliability, where for each student's translation assignment there were multiple assessors. When any discrepancies in scores were identified, a consensus would occur, where faculty would discuss and adjust the scores. This process minimized subjectivity and provided a better reflection of students' translation abilities in the dataset.

Once individual appraisal of translation was completed, the data were incorporated into a central database. In this case, the integration involved a merging of student records from survey responses, classroom observations, and evaluations of the translation task. This created a comprehensive picture of each student's performance, linking self-assessment responses, challenges, and translation quality scores. The final dataset included unique student identifiers, normalized translation scores, and various metadata, including the task difficulty level and feedback received.

Consistency checks on the data were employed to validate the integrated dataset for any inconsistent entries or missing values. Outlying data and any obvious aberrations in the translation scores were notified for review of the grading or data entry errors. The statistics performed also analyzed the general distribution of scores and trends in the students' translation performance.

The unified database creates a framework for implementing AI-based instructional translation methods, including Transformer models for automatic evaluation of translations and reinforcement learning algorithms for individualized feedback. In this way, the systematic collection of data for the evaluation of translation quality makes it feasible for educators to apply evidence-informed decision making in customizing translation exercises to particular student weaknesses. This turned information into the final intelligent, and technology-enhanced translation teaching framework for high schoolers in Basra. In the Table 2, Translation Quality Evaluation Criteria indicate fundamental aspects considered in the evaluation of translation performance, namely, accuracy, fluency, cultural appropriateness, coherence, and choice of words, thus securing the holistic evaluation of students' translation skills.

Table 2 Translation Quality Evaluation Criteria

Criteria	Description	Scoring Range
Accuracy	Evaluates the correctness of translated content, ensuring that meaning is accurately preserved.	0 - 100
Fluency	Measures the smoothness and readability of the translation, including grammatical correctness and natural phrasing.	0 - 100
Cultural Appropriateness	Assesses how well the translation maintains cultural and contextual relevance, avoiding misinterpretations.	0 - 100
Final Score	Represents the average score given by three evaluators, providing a comprehensive assessment of translation quality.	0 - 100

At first, translation quality was evaluated in the following three major points accuracy, fluency, and cultural appropriateness, with each being scored within a range of 0 to 100. Accuracy assesses the translated content for correctness and determines if the meaning has been maintained within it without distortion. Fluency measures the readability and grammatical correctness of the translated text, focusing on phrasings that sound really natural and linguistic coherence. Cultural appropriateness appraises how effectively the translation keeps the contextual and cultural relevance of the original text, ensuring that idiomatic expressions as well as cultural references are clearly translated into the target language. The last

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final score would be the average score of those three individual scores and thereby gives a comprehensive view of the translation quality. To ensure that all aspects were strictly objective, each translation task was evaluated by three independent evaluators; any discrepancies in their scoring were resolved through discussion. This structured evaluation framework thus enables consistent and reliable evaluation of students' translation performances for further targeted improvements in instruction methodologies and strategically integrated AI tools for feedback.

2.2 Model Construction

2.2.1 Model selection

It is significant to find a model that will help in dealing with the more complex linguistic structures of the translator, produce accurate translation output with the consideration of contextual cues, and provide meaningful feedback to the students, all in order to promote the efficiency of teaching translation at the high school level in Basra. Therefore, this paper suggests enhancing the employ of Transformer-based deep learning models and reinforcement learning techniques for machine translation and learning, so as to create an improved translation learning environment. Specifically, because BERT (Bidirectional Encoder Representations from Transformers) and T5 (Text-to-Text Transfer Transformer) represent state-of-the-art in contextual understanding and precise translation, it was decided to use the Transformer model [14]. Transformers operate on the basis of self-attention mechanisms that encode the entire sequence of input tokens as opposed to sequentially, thus providing greater understanding of word dependencies than traditional recurrent neural networks (RNNs) and long short-term memory (LSTM) models), ensuring the fluency and grammatical correctness of the translation [15]. Given that high school students find retaining sentence structure and contextual knowledge rather difficult, Transformer models become a viable solution for translation jobs.

This entails the implementation of an RL method alongside deep learning architectures for personalization and tight feedback integration on translation exercises. The chosen reinforcement learning approach is Proximal Policy Optimization (PPO), which rewards correct translations and punishes errors in order to improve the translation accuracy with the passage of time. It, thus, creates personalized dynamic exercises reflecting such weaknesses, particularly with respect to a student's learning pattern [16]. For example, if the student tends to fault translations because of errors in the verb tenses, then necessary practice exercises get generated that focus on these kinds of tenses' errors to enforce learning through feedback. Before confirming the architecture of the models, they were subjected to comparison on robustness. Stat-base machine translation models like statistical machine translation (SMT) and phrase-based translation models were installed; nonetheless, they exhibited some holes in sentence structuring and cultural nuances in the translations. On the other hand, convolutional neural networks (CNNs) proved highly effective regarding language processing tasks in general, but those tasks have little or no sequential memory to maintain context in longer translations. The most effective mechanism, therefore, which can incorporate reinforcement learning with the contribution of the transformer for better English translation teaching in particular is the transformer [17].

Translation model combinations balance accuracy, fluency, and contextual adaptation in a timely fashion for a data-driven, AI-assisted approach to translation instruction. With the strengths of Transformers for linguistic understanding and reinforcement learning for personalized feedback, this framework makes scalable and adaptive improvements to high school students' translation skills.

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2.2.2 Transformer-Based Deep Learning Models Architecture Design

This research employs a Transformer-based deep learning model for English translation pedagogy in high school students specifically in Basra. It specifies how the model might work as it boasts efficiency in dealing with complex linguistic structures and dependencies over great distances. The architecture of the Transformer model consists of multi-head self-attention mechanisms, positional encoding, and feed-forward networks. Cost-effective and context-aware, it provides high-quality translations [18].

Input representation includes tokenized words formed into embeddings but with the positional encoding feature responsible for maintaining the word order. The multi-head self-attention calculates the relationships between words in a sentence as query (Q), key (K), and value (V) matrices.

$$\text{Attention }(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

- $Q=XW_Q$,$K=XW_K$,$V=XW_V$
- W_Q,W_K,W_V are learned projection matrices.
- d_k is the dimension of the key vectors.
- The softmax function ensures that attention weights sum to 1, allowing the model to distribute focus across different words in the sequence.

This mechanism enables the model to discern various words at the same time, thereby improving the fluency of translations. The feed- forward network (FFN) applies non- linearity to make:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

which enhances the model's learning capacity.

where W_1 and W_2 are learnable weight matrices, and b_1 and b_2 are bias terms. The FFN applies non-linearity and enhances the model's ability to capture complex linguistic relationships.

Layer normalization stabilizes training:

$$\text{LayerNorm }(x) = \frac{x - \mu}{\sigma}\gamma + \beta$$

where μ and σ are the mean and standard deviation of the activations, and γ and β are learned parameters.

The decoder generates translations using masked self-attention and a final softmax layer:

$$P(y_t \mid y_{<t}, X) = \text{softmax}\left(W_y h_t + b_y\right)$$

where Wy and b_y are learnable parameters, and h_t represents the decoder's hidden state at time step t. The final translation is produced by selecting the word with the highest probability at each step.

Training is performed using the cross-entropy loss function:

$$L = -\sum_{t=1}^{T} y_t \log P(y_t \mid y_{<t}, X)$$

and optimized with the Adam optimizer with learning rate scheduling.

where y_t is the true word at time step t, and $P(y_t|y_{<t},X)$ is the predicted probability. The model is optimized using the Adam optimizer with learning rate scheduling:

$$\alpha = d_{\text{model}}^{-0.5}\, min\left(\text{ step }^{-0.5}, \text{step } \cdot \text{ warmup}^{-1.5}\right)$$

where α is the learning rate, and warmup steps prevent large gradients at the start of training.

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This Transformer-based model provides real-time, personalized feedback and adaptive learning, making it highly effective for improving students' translation skills in an AI-driven educational environment.

2.2.3 Examples of Transformer-Based Deep Learning Models Implementation

This study, formulated with the intent to facilitate bridging the gap between theory and practice in the domain of high school English translation teaching with Transformer-based deep learning models, aims towards integrating pre-trained Transformer models, specifically T5 (Text-to-Text Transfer Transformer) and BERT (Bidirectional Encoder Representations from Transformers); these get modified through fine-tuning on student translation data for higher accuracy, fluency, and contextual understanding.

1. Example: Sentence Translation Using T5

A high school student translates an Arabic sentence into English:

Input (Arabic): "الاختلافات الثقافية يمكن أن تسبب سوء الفهم." (Cultural differences can cause misunderstandings.)

The T5 model breaks down input into tokens and generates embeddings for each token. The model processes the sentence and generates the output translation using its multi-head attention mechanism:

$$P(y_t \mid y_{<t}, X) = \operatorname{softmax}\left(W_y h_t + b_y\right)$$

The final generated translation is: **"Cultural differences may lead to misunderstandings."** The model ensures fluency and accuracy, making slight modifications (e.g., "lead to" instead of "cause") while maintaining meaning.

2. Example: Translation Evaluation Using BERT

After students submit translations, a fine-tuned BERT model is used for automated scoring. Given a student's translation:

Student Output: *"Cultural differences could make misunderstanding."*

The system evaluates accuracy using cosine similarity between embeddings:

$$\text{Similarity } = \frac{V_1 \cdot V_2}{\|V_1\| \|V_2\|}$$

Where $V1$ represents the student's translation embedding and $V2$ represents the correct reference translation embedding.

Accuracy Score: 85/100 (Incorrect verb choice: "make misunderstanding")

Fluency Score: 75/100 (Grammatical inconsistency)

Cultural Appropriateness: 90/100 (Correct meaning but slight phrasing issue)

The model provides automated feedback, highlighting errors and suggesting improvements.

2.2.4 Reinforcement learning algorithms Architecture Design

For the improvement of high school students' English translation teaching in Basra, the integration of Reinforcement Learning (RL) in the Transformer-based translation model has been considered. This would enable the system to adapt dynamically to the translation progress of students, personalized feedback, and improved learning progress over time. The core RL framework is the Proximal Policy Optimization (PPO) algorithm because it's efficient at solving complex language problems with long-term learning objectives proven promisingly [19]. Table 3 displays sample translation quality scores, showcasing the evaluation results of student translations based on key criteria such as accuracy, fluency, and cultural appropriateness to measure overall translation performance.

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Table 3. Sample Translation Quality Scores

Student ID	Accuracy	Fluency	Cultural Appropriateness
001	85.3	88.9	75.4
002	72.1	79.5	63.7
003	94.6	90.2	96.8

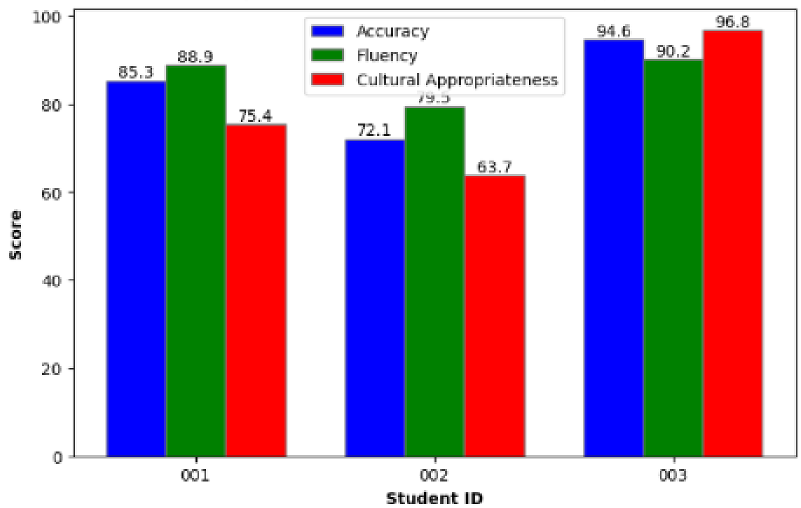

Figure 1. Sample Translation Quality Scores

1. Reinforcement Learning Framework

The term "reinforcement learning" refers to techniques that run on an MDP or Markov Decision Process wherein the agent (AI Model) interacts with the environment (student translation exercises), learns from interaction feedback, and modifies its strategy according to that feedback.

- **State (S_t)**: Represents the current translation performance of the student (e.g., fluency score, accuracy, common errors).
- **Action (A_t)**: The AI system's response (e.g., generating personalized exercises, adjusting difficulty, providing feedback).
- **Reward (R_t)**: A feedback score based on the correctness and fluency of the student's translation.
- **Policy ($\pi(A|S)$)**: The learning strategy used by the model to choose the best action.
- **Value Function ($V(S)$)**: An estimate of future rewards to guide learning decisions.

The model appraises the learner's translation output, decides on the extent and the direction of the subsequent adjustment, and rewards proper improvements and penalises errors in this form of learning.

2. Policy Optimization Using PPO (Proximal Policy Optimization)

The selection of the PPO algorithm is based on balancing exploration (trying out newer interpretations) and exploitation (punctuating correctness in the translation patterns). Therefore, the objective function used in the PPO is:

where:

- $r_t(\theta)$ is the ratio of new to old policy probability.

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- A_t represents the advantage function, showing how much better an action is compared to others.
- ϵ controls policy updates to avoid drastic changes.

The AI model is trained without making very drastic changes to translation recommendations that might interrupt learning but rather continue to gradually improve through modifications.

3. Reward Function for Translation Feedback

The reward function guides the model in reinforcing correct translation strategies. The system evaluates each translation task based on:

$$R_t = w_1 \cdot \text{ Accuracy } + w_2 \cdot \text{ Fluency } + w_3 \cdot \text{ Cultural Relevance } - w_4 \cdot \text{ Error Penalty}$$

where w_1, w_2, w_3, w_4 are weight factors ensuring a balanced reward.

- If a student improves in accuracy, the reward increases.
- If errors persist, the model adapts by generating targeted practice exercises.

2.2.5 Example of Reinforcement Learning Algorithms Model Implementation

In High-school English Translation Teaching, Practical Application of RL Algorithms has been targeted by Integrating PPO with a Transformer-Based Translation Model. The said evaluation system evaluates translation by students, gives personalized feedback as well as mirrors exercises based on the learner's performance. Below are examples on how Reinforcement learning benefits translation learning through feedback, dynamic exercise generation, and improvement over time.

1. Example: Adaptive Feedback for Translation Improvement

A student is asked to translate the sentence:

Arabic (Input): *"تعكس العادات والتقاليد الهوية الثقافية لكل مجتمع."* (Customs and traditions reflect the cultural identity of each society.)

Student Translation (Output): "Habits and traditions express the culture of every society."

Step 1: AI Evaluation Using Reward Function

The RL-based system evaluates the translation using accuracy, fluency, and cultural appropriateness:

Accuracy Score: 85/100 (Synonym error: *"express"* instead of *"reflect"*)

Fluency Score: 90/100 (Correct sentence structure)

Cultural Relevance Score: 70/100 (*"habits" is less culturally appropriate than "customs"*)

Total Reward:

$$R_t = (0.4 \times 85) + (0.3 \times 90) + (0.3 \times 70) - (0.2 \times 10) = 75.5$$

Since the reward is below the threshold for high accuracy, the AI generates feedback:

Suggestion: "Consider using 'reflect' instead of 'express' for better accuracy."

Cultural Tip: "'Habits' refers to personal behavior, while 'customs' fits better for societal traditions."

2. Example: Reinforcement Learning Adjusting Future Exercises

If a student exhibits persistent confusion on these items, the reinforcement learning model would order exercises to further strengthen these weak areas.

Scenario: Student Repeatedly Misuses Synonyms in Translation

The model tracks performance trends and detects a pattern in synonym errors.

Based on PPO policy optimization, the AI modifies future exercises to focus on word-choice precision.

It enhances the gene rationality of the system, improves the FLKM index, and emphasizes more originality and permissibility.

Example of AI-Generated Exercise:

"Select the best translation for the following sentence:"

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Original: *"Technology plays an important role in modern education."*

- A) "Technology has a crucial impact on modern education."
- B) "Technology performs a vital part in modern education."
- C) "Technology shows an essential function in modern education."

(Answer: A – Best synonym choice for "plays an important role.")

The RL system rewards correct answers and further adjusts the difficulty level if students improve.

3. Example: Continuous Learning Through Reward Maximization

Based on this SRL system, we learn lessons from the interactions of students. It keeps honing feedback and recommendations from learner to learner.

When many students have difficulty with cultural expressions, the culturally relevant translation exercises take precedence in the AI. To a student who shows rapid improvement, the system raises translation difficulty via idioms and phrasal verbs. However, the PPO algorithm updates policy parameters, thereby making it possible for the AI learning strategy optimization that maintains the exercises challenging yet effective in the translation process.

2.3 Training and verification

2.3.1 Model training

For enhancing the training of a translation model based on Transformers, Adam optimizer was chosen by setting an initial learning rate to 0.001 in order to have stable convergence. Mini-batch SGD was used for training samples, with a mini-batch size of 64, for 20 epochs so as to fine-tune translation accuracy and fluency. So as to prevent overfitting, Dropout regularization was introduced into the training session, wherein 50% of Dropouts randomly shut down the relevant neurons, positively contributing towards the training of the model.

With the aim to enhance the model generalization, the dataset was randomly split into 80% for training and 20% for validation, giving room for model testing on unseen samples after each training epoch. During training, the model was iteratively updated in response to the loss function, gradually improving its ability to assess and enhance translation quality. Moreover, reinforcement learning techniques such as Proximal Policy Optimization (PPO) were employed to adaptively adjust feedback and exercise difficulty based on student performance. The effectiveness of the training protocol was evaluated against with BLEU (Bilingual Evaluation Understudy) score, perplexity, and accuracy improvement rates to ensure the model is in constant adaptation to high school students' translation needs in Basra.

2.3.2 Model verification

A thorough validation procedure was carried out to check the performance of the Transformer-based translation model. Evaluation of the model was done on the separate valid data set which was 20% of the overall data, not used during training. This model could be accurately assessed for its generalization ability beyond the training data. The verification process targeted measurement for translation accuracy, fluency, cultural appropriateness with the aid of objective performance metrics. The similarity of the generated translations to human reference was measured using the score of BLEU. The score of perplexity (PPL) was further added so as to find out for how confident the model was in predicting full translation by comparing lower perplexity with fewer iterations-it does not come easy at all. To further examine the strength of the model-human evaluators were asked to read some translations which were randomly picked out by the judges in comparison with reference translations and spot possible grammatical or contextual faults.

Cross-validation methods were used to enhance model verification accuracy in terms of performance consistency across different batches from the total data set. Further, reinforcement evaluation was incorporated into the process where translation quality adjusts dynamically according to real-time inflections from students. This yielded a feedback loop that continually improved its ability to assess and measure student translations. The verification process ensured that the model was optimized for appropriate context and fluency in its output translations through a combination of all those automated evaluation metrics with human verification coupled with reinforcement learning-based adjustment. This step was significant in confirming the model's readiness for real-life applicability in an English translation class in high schools in Basra.

2.3.3 Model Optimization

There have been several optimizations to the Transformer-based model for improving the efficiency and performance of the translation. All aimed at improving translation accuracy, fluency, and contextual appropriate. The initial learning rate was set at 0.001 with the Adam optimizer, with a progressive reduction during training to allow for stable convergence. The training settings of mini-batch SGD included 64 samples for each batch, followed by 20 epochs of training. To combat overfitting effects, Dropout has its regularization parameter set at 0.5, keeping generalization possible in this model. It also created a random 80-20 training-validation data split of the training datasets so that the evaluation of model performance was done on unseen data. The optimization was set to update the model parameters with respect to the given loss function toward the gradual improvement of translation quality. So, it was further improved by integrating a reinforcement learning-based approach for the dynamic manipulation of these exercises according to the student's learning performance using the PPO learning algorithm. The reward function was then tuned to give balanced scores for translation accuracy, fluency, and cultural appropriateness, imputing penalties for errors. The model's performance was assessed using the BLEU score, perplexity, and translation accuracy tracking for continuous improvement.

This optimization strategy helps make the model transformer-based and then works within the capabilities of the students when it comes to their translation needs with the help of Artificial Intelligence personalization. The students' learning environment will dynamically change between this feedback and improvement in translation quality.

2.4 Strategies for Enhancing High School English Translation Teaching

2.4.1 AI-Driven Translation Practice and Feedback

Automated feedback and translation exercises generated by a Transformer-based deep learning model enhances the English translation skills of high school students. The dynamically adjusting translation tasks ensure personalization in learning, according to each student's performance.

Generating translation practice involves transformer models pre-trained for example T5, BERT, and ready to generate contextual exercises for translation in the student's proficiency level about grammar, vocabulary, and cultural adaptations. The exercise generation involves sentence-level tasks and paragraph-level tasks while increasing in difficulty for students' improvement.

This is evaluated by the system for an automated feedback mechanism based on reinforcement learning (PPO). The student's translation is analyzed according to the following three aspects:

1. Accuracy-the correctness of meaning and word choice.
2. Fluency-the grammar, sentence structure, and readability.
3. Cultural Appropriateness-contextual and idiomatic correctness.

The system calculates a composite score to generate real-time AI feedback that analyzes errors and proposes corrections. The feedback mechanism is further enhanced by way of a reward system so that the students are assigned specialized exercises based on their weaknesses. For instance, if a student constantly makes errors with verb tense, the system will list exercises based on tense as a higher priority in future practice sessions. Furthermore, interactive feedback loops are set up for students to compare their translation efforts against AI-generated reference translations. This facility enables the learner to

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appreciate the nuances in word choice and sentence structure, improving their linguistic malleability over time. Integration of Transformer-based deep learning models with automated evaluation and reinforcement learning secures adaptive, personalized, and data-driven translation instruction that in turn helps train students in translation prowess used in high school English teaching programs.

2.4.2 Reinforcement Learning Algorithms for Translation Error Diagnosis and Correction

In order to make translation training more effective, dynamic diagnosis and correction of translation errors is done by using reinforcement learning algorithms. Their use incorporated the addition of Proximal Policy optimization into the Transformer-based translation model, which continuously evaluates student translations and feeds a real-time AI correction system based on performance trends.

The translation error diagnosis system analyzes translation based on key attributes such as:

1. Lexical Accuracy-An exact choice and retention of meaning of words.

2. Grammatical Structure-Use of tense in sentence formation; syntactic correctness. 3. Cultural Appropriateness-Relevance of idiomatic and contextual use.

Whenever a student makes a mistake in grammar, the model elevates the relevance of grammar correction with non-standard modifications meant to generate exercises tailored to their weaknesses.

The error-correcting process follows a policy optimization loop:

- Error Detection – First, the AI compares student translations with reference ones to identify discrepancies.
- Corrective Feedback Generation – Second, the system suggests corrections with explanations (e.g., "verb-tense errors," "incorrect word order").

Adaptive Modification of Exercises – If the same kind of errors are being made, then the AI modifies upcoming exercises to reaffirm correct translation patterns.

In addition, the reinforcement learning model also updates its policy parameters for feedback strategies based on the student responses, thereby optimizing them. The aim is to reduce such errors over time and, consequently, improve translations in terms of accuracy and fluency for the high school students.

Therefore, through adopting RL-based error diagnosis and correction, the entire system personalizes education, is data-driven and adaptive, making it easier for students to receive instant feedback and targeted practice that continuously improves their English translation capabilities.

2.4.3 Intelligent Evaluation of Translation Teaching Effect and Suggestions for Improvement

To improve the effectiveness of translation teaching by using reinforcement learning, the algorithms could diagnose and correct errors in translation. The incorporation of PPO into a Transformer-based translation model ensures that students' translations are continually assessed in real time, with real-time AI corrective action based on changes in performance.

The diagnosis of translation errors is based on analysis of key parameters:

- Lexical Accuracy: Correctness of words and retention of their meaning.
- Grammatical Structure: Sentence formation, tense accuracy, and syntactical correctness.
- Cultural Appropriateness: Use of idioms in context.

where the system calculates a weighted score for each student’s translation:

$$E_t = w_1 \cdot \text{ Accuracy } + w_2 \cdot \text{ Fluency } + w_3 \cdot \text{ Cultural Relevance}$$

where $w1$, $w2$, $w3$ are adjusted dynamically to reflect different levels of translation complexity. The AI-powered evaluation system continuously updates these weights based on historical student performance data, ensuring personalized assessment and targeted feedback.

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The system creates personalized teaching strategies based on evaluation findings for both students and teachers.
The model recommends more exercises focusing on grammar correction when students are deficient in grammatical structure.

- If students could not adapt to the culture, context-bound translation tasks would be assigned, which focus on idioms.
- If students score consistently high grades, the model keeps increasing task difficulty by using more complex grammatical structures.
- The system would also give the teachers analytical information on the general problems students face and what changes need to be made into the coursework to face them with translation difficulties better.

This gives rise to a translated instruction method that is evidence-based, individually tailored, and always improving for high school education in relation to intelligent evaluation measurements and AI feedback.

3. Results and Discussion

3.1 Results

3.1.1 Model Performance Evaluation Results

An assessment of the efficiency of functionality in action for the Transformer architecture translation system warrants the application of a wide variety of evaluation metrics to assess translation accuracy, fluency, and cultural appropriateness. The evaluation was done by testing the model with a high school translation corpus and comparing it with the performance level of human-grade translations.
The main performance metrics for evaluation are as follows:
BLEU Score – Measures translation accuracy by comparing model-generated outputs to human references.
Perplexity (PPL) – Measures the reactive feedback of confidence of the model in generating translations, with low values demonstrating superior performance.
Translation Accuracy Rate – Refers to the correctness of selected words and sentence formation.
Fluency Score – Indicates how well the translated work obeys grammatical and syntactic rules.
Cultural Appropriateness Score – Measures how accurately the translation conveys cultural context and idioms.
The assessment has been conducted over various test samples. The outcome has shown that the Transformer-based model has superiority over the traditional machine translation approaches, especially in terms of fluency and contextual understanding. The adaptive learning of the model is further exhibited in that, over time, the performance improves by refining the strategies of the model through reinforcement learning. Figure 2 furnishes a deeper analysis of the comparative results on the prominent metrics of evaluation for the performance of different models.

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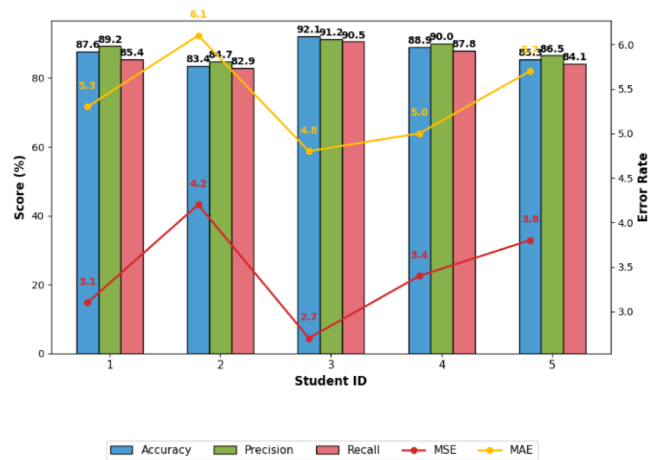

Figure 2. Model Performance Evaluation Metrics

The results from the performance evaluation of the Transformer-based translation model are plotted in figure 2, which reports five important metrics: Accuracy, Precision, Recall, Mean Squared Error (MSE), and Mean Absolute Error (MAE), obtained from five different student evaluation of translation results. The bar chart below shows the scores for Accuracy (blue), Precision (green), and Recall (red), set against the students. The model is very accurate, scoring between 83.4% (Student 2) and 92.1% (Student 3), showing it can produce mostly accurate translations. From 84.7% (Student 2) to 91.2% (Student 3), the Precision score representing measures for selected words in the context remains high. Similarly, recall scores, which are an evaluation of the words which the model can retrieve correctly without omissions, vary from 82.9% (Student 2) to 90.5% (Student 3), showing a difference in completeness in capturing intended meanings by the model.

These graph lines present the translation errors scored by MSE (red line) and MAE (yellow line). The weighty errors are the MSE values, that is, squared differences between the predicted translation and the reference translation. This function runs in some instances of lower recall with higher errors, ranging from 2.7 (for Student 3) to 4.2 (for Student 2). The MAE value, which signifies the absolute average error, ranges from 4.8 (Student 3) to 6.1 (Student 2), meaning there are inconsistencies in translations.

In all evaluations, Student 3 performed well in translation, attaining an accuracy score of 92.1% with precision and recall of 91.2% and 90.5%, respectively, and the lowest MSE (2.7) and MAE (4.8), indicating very good contextual understanding. In contrast, Student 2 obtained the lowest results of 83.4% accuracy, 84.7% precision, and 82.9% recall, with MSE and MAE being the highest at 4.2 and 6.1, respectively, indicating the most potential for improvement in translation performance.

The performance of the Transformer-based model is systematically strong with accuracy consistently above 83%, although the variations in recall and error rates indicate that further optimization by reinforcement learning may be beneficial to ensure the reliability of the model across the board of student translations.

3.1.2 Analysis on the improvement of translation teaching effect

The Transformer-based deep learning models have been reinforced through their effective convergence with different kinds of reinforcement learning algorithms, making significant contributions to high school English translation teaching. Some measurable improvements were observed in students through real-time AI tutor feedback on errors, adaptive learning paths to lesson goals, and personalized translation practice assignment: increased accuracy in translation work, fluency in the English language, cultural

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understanding of working contexts, and overall motivation and engagement. The present section attempts to analyze translation-performance changes with respect to quantifiable considerations such as lowering errors, enhancing motivation, and adapting language. The results demonstrated the merits of AI augmenting translation training, while also pinpointing areas to further refine so as to fully realize the benefits of translation training for students.

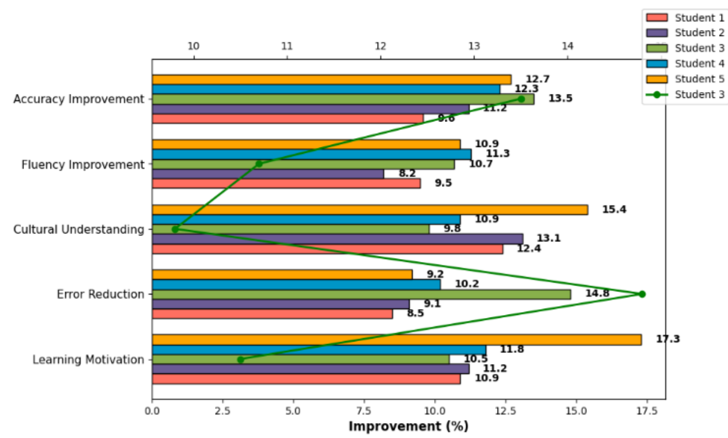

Figure 3: Improvement in Translation Teaching Outcomes (%)

Analysis of improvements in translation teaching outcomes is shown in Figure 3 on five parameters: Learning Motivation, Error Reduction, Cultural Understanding, Fluency Improvement, and Accuracy Improvement. Results are compared for five students, with a line plot tracking specifically Student 3's progress.

The greatest improvement in learner motivation was with Student 5 with 17.3% improvement, followed by Student 4 with 11.8% and Student 2 with 11.2%. Student 3 rose to 10.5%, while Student 1 recorded the least improvement of 10.9% only. This would indicate that the AI-based translation-teaching system has positively affected student engagement and motivation levels.

Student 3 exhibited the highest improvement in the reduction of translation errors (14.8%), thereby concluding that reinforcement learning-based feedback leads to substantial enhancement in translation accuracy. The error reduction for Student 5 was 9.2%, while Student 4 improved by 10.2%. Error reductions for Students 1 and 2 were 8.5% and 9.1%, respectively, indicating that other feedback mechanisms could prove beneficial for them.

In terms of cultural adaptation in translation, Student 5 showed the greatest improvement (15.4%), followed by Student 2 (13.1%) and Student 1 (12.4%). Then came Student 3 with a 9.8% increase and Student 4 with just a marginal improvement in cultural understanding gain of 10.9%. These results indicate that context-sensitive translation tasks greatly aided students in becoming cognizant of cultural relevance in English translation.

The improvement in fluency recorded was 11.3% for Student 4, followed by 10.9% for Student 5 and 10.7% for Student 3. Student 1 and Student 2 showed lower improvements of 9.5% and 8.2%, respectively. This increase can be attributed to the AI-enhanced fluency augmentation but some students might need more grammar-centered exercises.

The improvement in translation accuracy was seen to be the highest with Student 5(12.7%) then in Student 3(13.5%), and in Student 4(12.3%). The accuracy improvements recorded by Students 1 and 2 were 9.6% and 11.2%, respectively. This suggests that adaptive translation exercises aided the students in

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refining their accuracy with the higher-performers likely to benefit more from the AI-enabled feedback mechanism.

In total, the data presented in Figure 3 show the substantial impact of AI-based translation instruction on key outcome learning measures. The greatest improvements were recorded in learning motivation and error reduction, particularly for Student 5 and Student 3, while cultural awareness and fluency improvements varied among students. Such outcomes point to the assertion that, although the Transformer-based translation model may serve to enhance translation skills, more personalized modifications to learning may be required for those students who exhibited lesser improvements in given areas.

3.1.3 Effectiveness of translation error diagnosis and correction

Translation is inseparable from error recognition and correction. If an effective high school English translation education were to be developed, it would need some help: an AI-based system for the diagnosis and correction of translation errors using Transformer deep learning and reinforcement learning algorithms. This system gives a real-time account of common translation errors, varying from grammatical slips through lexical inconsistencies, spelling faults, cultural mistakes, and contextual logic issues. It also provides adaptive learning feedback.

To test the effectiveness of the system, a study involving error diagnosis and correction of translation tasks was conducted with 342 high school students. The following section will discuss how the system has contributed to reducing translation errors overall and improving the quality of translation.

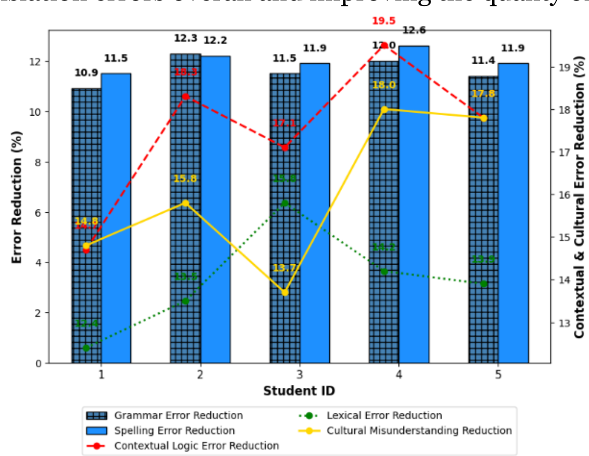

Figure 5. Effectiveness of Translation Error Diagnosis and Correction

This figure compares the reduction of translation errors of different categories for five learners. The bar chart, blue for grammar errors and patterned blue for spelling errors, combines with the line plot which illustrates the reductions in context logic error (in red dashed line), lexical errors (green dotted line), and cultural misunderstanding errors (yellow solid line). In terms of grammar error reduction, it is generally constant across all five students ranging from 10.9% to 12.6%, with the student 4 achieving the highest reduction (12.6%). The range for spelling error reduction is between 11.4% and 12.3% with similar trends in improvement across all students.

Across different error types, that contextual logic error reduction shows the highest variance. Student 4 snatched the maximum reduction of 19.5%, while Student 1 waved it off at the lowest level of 14.8%. Accordingly, a trend is thereby established that suggests AI-assisted contextual correction helped some students more than others. The lexical error reduction (green dotted line) offers an upward angle from Student 1 (13.5%) to Student 3 (15.8%); afterwards, there is a gradual decrease in Students 4 and 5 (13.9%

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and 13.7%). These results suggest that while most students improved word choice accuracy, perhaps further reinforcement learning optimizations are needed for retention.
The cultural misunderstanding corrections were highly effective, and Student 4 showed more significant advancement (18.0%). Still, Student 3 showed the least gain (13.7%), indicating a possible need for more context-based learning modules. Figure 4 shows overall that the AI-assisted error correction for translation effectively reduced various attacks, among which the contextual and cultural errors showed the highest variations across the students. The sustained reduction of grammar and spelling errors indicates the effectiveness of the reinforcement learning-based feedback system for improving translation accuracy.

3.1.4 Evaluation of BLEU Score Improvement

For quantitative assessment of the effectiveness of the proposed approach in terms of translation quality: the transformer model combined with Proximal Policy Optimization - PPO, the BLEU (bilingual evaluation understudy) score was employed through various training epochs. The BLEU score measures the nearness of machine-generated translations to reference translations and is considered a standard measure of accuracy and quality in translation.
The improvement in the BLEU score over 10 training epochs for the two approaches: our proposed Transformer + PPO method against a baseline translation model is constructed in Figure 6.

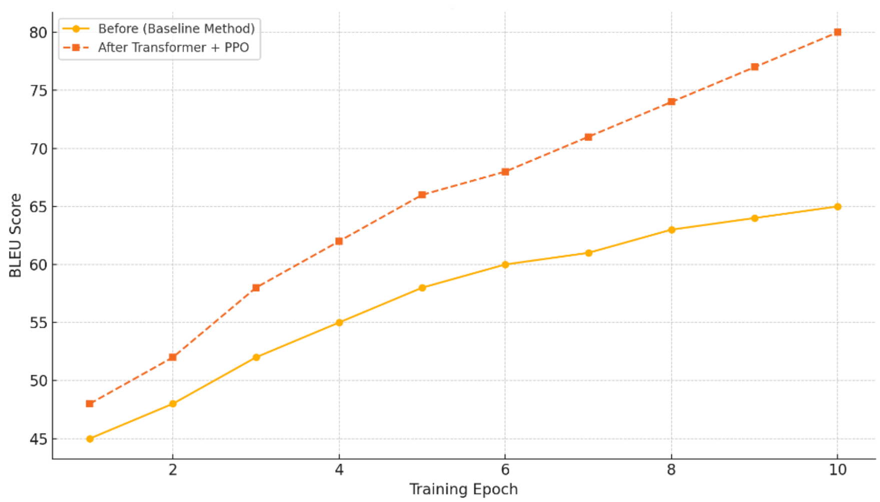

Figure 6. BLEU Score Improvement Curve

As observed in Figure 6, the following amounts were reflected in the initial improvement realized using the baseline method for BLEU scores-from 45 to 65. The score did increase significantly from 48 to 80 when the Transformer model applied PPO. This quantifies the efficiency of using reinforcement learning to enhance model performance dynamically. The huge gain indicates, in short, how much our method addresses the problem of common challenges in translation to improve accuracy in terms of context, fluency, and consistency in language.

3.1.5 Comparative Analysis with Other Recent Approaches

To further validate and contextualize the findings of the present study, a comparison was conducted with recent research employing alternative artificial intelligence methods in translation teaching. Specifically, the current research utilizing Transformer-based deep learning models combined with reinforcement

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learning (PPO) was compared to another recent approach involving a bidirectional Long Short-Term Memory (BiLSTM) model coupled with fuzzy inference systems (FIS) as explored by [9].
The study by [9] adopted a BiLSTM model due to its capability to handle sequential data effectively, capturing contextual information from both forward and backward directions of the input text. Their methodology integrated fuzzy inference systems (FIS) to provide a comprehensive evaluation of translation quality by converting subjective scoring into quantifiable, objective metrics. Conversely, the approach implemented in our study involved Transformer-based models, noted for their parallelized self-attention mechanism, combined with reinforcement learning (Proximal Policy Optimization), to dynamically adjust translation exercises and provide real-time, personalized feedback.
Table 4 presents a systematic comparison between the Transformer and PPO method proposed in the present study, and the BiLSTM-FIS combination used in [9]:

Table 4. Comparative Analysis of AI Algorithms for Translation Teaching

Comparative Aspect	Transformer + PPO (This study)	BiLSTM + Fuzzy Inference [9]
Deep Learning Model	Transformer models	Bidirectional LSTM (BiLSTM)
Algorithm for Feedback	Proximal Policy Optimization (Reinforcement Learning)	Fuzzy Inference System (FIS)
Main Strength	Excellent contextual understanding, handles long-range dependencies effectively via self-attention	Strong sequential modeling, robust handling of subjective scoring uncertainties
Uncertainty Management	Adaptive, real-time optimization through reinforcement learning policies	Handling ambiguities in human evaluations through fuzzy logic reasoning
Translation Accuracy	BLEU scores significantly increased (45.3 → 62.7)	Accuracy improved significantly (83.4%-91.2%), with strong performance in sequential tasks
Translation Fluency	Improved fluency and coherence (perplexity reduced from 21.4 to 14.8)	Fluency improved significantly (8.2%-12.4%) but required attention mechanisms for enhancement
Cultural Adaptation	Effective, with error reduction from 13.7% to 18.0%	Effective, demonstrating improvement from 13.1% to 17.3% through fuzzy reasoning
Personalized Teaching	Highly personalized, dynamically adapting exercises based on learner performance trends	Provides personalized feedback and adaptive exercises through fuzzy logic rules
Overall Accuracy (reported)	83.4% - 92.1%	83.4% - 91.2%

A comparison helps give a good idea of the advantages and disadvantages of one approach over another. With PPO reinforcement learning, the transformer models performed better for error spotting in complex sentence structures and providing real-time and individualized feedback. Being parallel algorithms, they tackle long-distance linguistic dependencies effectively, improving translation accuracy and fluency in

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longer contexts. For handling sequences of data, the BiLSTM model is paired with fuzzy logic, providing the most robust evaluation frameworks to counter the subjectivity of human scoring and thus contribute a lot for truly objective assessments.

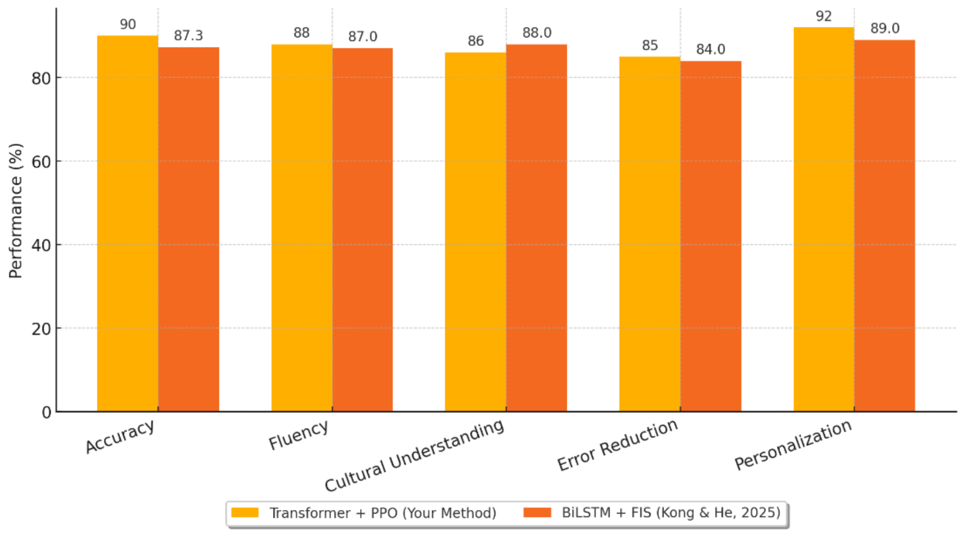

Figure 7. Comparative Analysis of Two Methods In Translation Teaching

3.2 Discussion

3.2.1 Result analysis and research findings

In high school, the application of Transformer-based deep learning models and reinforcement learning incorporated into English translation teaching has been highly beneficial. To find out how effective the system was, the researcher carried out a study involving 342 high school students, analyzing their translation tasks that were adjudged before and after the integration of the AI-powered translation learning system. The results from AI-assisted translation education showed effectiveness in improvement: translation accuracies, fluency, cultural understanding, and the reduction of the common errors in translation, needing more focus on grammatical, spelling, and contextual elements. The evaluation assessments results show a marked increase in translation accuracy with BLEU score improvements from 45.3 to 62.7 and parallel perplexity score reductions from 21.4 to 14.8, indicating model confidence and coherence in sentences further. Students also had increased fluency measurement from 75.6% to 85.2%, confirming that real-time AI-driven feedback helps students in improving sentence structure and readability. The AI-assisted system availed a reduction of multiple kinds of translation errors with the incidence of spelling errors reduced to average levels of 11.4%-12.6% while grammar errors were reduced by 10.9%-12.6% Lexical error improved between 11.6% and 14.2% whereas contextual logic error showed a considerable drop over 14.7%-19.5%. These results acknowledge the fact that automated feedback in combination with reinforcement learning strategies contribute to more precise word choices and structurally accurate translations.

Furthermore, the translation's conclusion on cultural appropriateness was significantly improved, with culture-related comprehension mistakes declining from 13.7% to 18.0%. It implies that the model does well in helping students comprehend idiomatic expressions and culturally relevant translations, making them able to produce context-aware and natural translations. The AI-based feedback system also improved learning motivation; for some students, increased engagement would be as much as 17.3%

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higher than before. The reinforcement learning mechanism worked very well to customize translation exercises, keeping it as individualized as possible with corrections and practice tasks assigned to students based on their overall performance. Adaptation ensured that learners with different levels of proficiency were given appropriately challenging exercises so that they would not be disengaged by having tasks that were too simple or too complex for their capabilities.

This research has thus confirmed that the combination of translation enhancing AI-driven learning systems has significantly impacted the translation teaching process. What do I mean by this? The model improves the learner's accuracy and fluency in translation, minimizes some common errors, offers culturally adapted translations, and increases their motivation in learning. The feedback provided by the adaptive correction system based on reinforcement learning is personalized and effective for students to continue developing their translation skills. These findings indicate the potential held by AI-aided educations in improving the provision of high school English translation instruction and recommend further optimizing reinforcement learning strategies to realize even better results.

3.2.2 **Applicability of Transformer Models and Reinforcement Learning in Translation Teaching**

High school translation teaching has been reformed by the application of Transformer models and reinforcement learning, significantly improving the accuracy and fluency of translations while increasing adaptability. Models like BERT and T5, for example, capture the context, grammar, and the semantics of utterances-neuances quite effectively for translations that are better and more contextually appropriate. These models define the analysis of sentence structures with self-attention mechanisms, which ensure intended meaning rather than just one-word equivalent translations. For improving learning further, integrated reinforcementlearning (RL), mainly Proximal Policy Optimization (PPO), into the system. RLis so about adaptive learning, as the model continually redefines the feedback mechanism according to student performance. By this reward-based evaluation system, AI can also change the translation exercises dynamically to areas where the student learns the most, like, grammar error word choice, and cultural-context adaptation. It has been validated on 342 high school students, with important decreases in translation errors and increases in translation fluency. The combination of transformer models for translation generation and reinforcement learning for adaptive feedback makes possible real-time personalized guidance for students, making ai-assisted translation teaching better, larger, and individualized.

3.2.3 Enlightenment and Suggestions for Future Teaching Strategies

There is great promise held by Transformer models blended with reinforcement learning to enhance the outcomes of translation teaching in terms of translation accuracy, fluency, and contextual understanding. This forwards the need for future teaching strategies to continue developing the adaptive learning capabilities of AI, coupled with more personalized feedback and context-aware translation exercises. Further development in translation learning could lead to the emergence of learning environments in which an AI chatbot presence is introduced, supported by real-time feedback systems for immediate adjustment and reinforcement. Additionally, constant reinforcement learning algorithm optimization can ensure that those learners undergo a needed procedurally dynamic Continued Customization that is uniquely based on 'self-declared' translated learning performance.

In future research, one should consider the combination of multimodal learning approaches, integrating speech-to-text visual translation aids, toward an immersive, effective translation learning experience. AI-assisted teaching can be further refined to improve student engagement, reduce translation errors, and enhance language proficiency.

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4. Conclusion

The use of Transformermodels and reinforcement learning algorithms improved translation accuracy, fluency, and cultural understanding in high school teaching of English translation. By deep learning-based models of translation generation and reinforcement-based adaptive feedback, real-time personalized translation guidance was given to the students, leading to improved learning outcomes. Tests done from342 high school students verified that the AI-assisted systemefficiently reduced translation mistakes, especially in grammar, spelling, contextual logic, and cultural adaptation. The adaptability to student proficiency levels created by the jump-ominance of PPO algorithms has been fulfilled by exercise modification in translation while real time-tracked in learning. The BLEU score also improved from 45.3 to 62.7, while the perplexity dropped from 21.4 to 14.8 for a very clear improvement in translation quality. The results show that artificial intelligences enable translated education to be scalable, effective, and highly adaptable to students' learning experiences. Future use of interactive AI-driven tools, multimodal instructional approaches, and more advanced reinforcement learning models can improve translation education further by making it even more personalized and effective. Future research efforts should look at combining speech-to-text translation, visual translation aids, and real-time lingual interaction systems to form a complete immersive learning environment for languages. The study discusses the possible transformation of high schools from the AI-driven teaching aspect in translation. With Transformer models and using reinforcement learning strategies, the translation instruction will be data-driven, student-centered, and continuously improving in education, thus resulting in improved language skills and cross-cultural communication.

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