A Contextualized Learner-Profiling Transformer Architecture for Adaptive Grammar Error Diagnosis and Instruction

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***Abstract*—Grammatical accuracy is a critical component of English as a Second Language (ESL) learning; however, many learners continue to struggle with recurring errors despite the availability of automated grammar correction tools. Although recent transformer-based models such as BERT, GPT, and T5 have demonstrated strong benchmark performance, existing grammar error correction (GEC) systems remain largely correction-oriented and lack pedagogical flexibility, learner awareness, and explanation-based feedback. To address these limitations, this study proposes an Adaptive Multi-Task T5 (AMT-T5) framework that integrates grammatical error correction, error-type classification, and personalized feedback generation within a unified transformer architecture. The proposed method is designed to actively support learner development by maintaining dynamic learner error profiles and adaptively reweighting attention to provide targeted instructional guidance. AMT-T5 is implemented using Python, PyTorch, and the Hugging Face Transformers library, and trained on the Lang-8 Learner Corpus, which contains authentic ESL learner sentences with expert corrections. Experimental results demonstrate that the proposed model significantly outperforms existing transformer-based baselines, achieving 78.9 BLEU, 90.7 GLEU, 82.6% full-sentence accuracy, and an error reduction rate of 91.2%, representing an approximate 18–22% improvement in grammatical accuracy over prior models. The framework further incorporates Direct Preference Optimization to align corrections with pedagogical expectations and Knowledge Distillation to enable efficient real-time deployment. Overall, the proposed AMT-T5 framework transforms grammar correction from a passive editing task into an adaptive, learner-centered educational process, offering a scalable and effective solution for intelligent ESL grammar learning systems.**

Keywords*—Grammar error correction; adaptive feedback; Multi-task Learning; transformer models; ESL learning; personalized language instruction

I. Introduction

English has proven to be the global language of scholarly, professional, and social communication. However, grammar is still a persistent issue to the people who do not speak English as their mother tongue that limits their fluency and expressiveness in communication to a large degree [1]. The conventional teaching of grammar in classrooms is often very strict and generalized, and has little ability to provide any form of personalized attention. Most intelligent language learning systems currently provide contextual and real-time grammar correction with the advent of (NLP) [2], [3]. In the case of ESL students, this instant corrective feedback is essential to strengthen correct forms and minimize the frequent mistakes [4]. Research on automated grammar correction has evolved across different paradigms, including rule-based systems, statistical machine translation (SMT), and (DL) approaches [5]. Rule-based approaches, though interpretable, are incapable of dealing with complex or ambiguous structures [6], [7]. Phrase-based SMT methods, which are better covered, were limited by their performance in fluency and grammatical accuracy [8], [9]. LSTMs and GRUs neural architectures, however, enhanced contextual correction but could not deal with long-range dependencies [10] [11]. Transformer models (including BERT, GPT and T5) have since further progressed the field of models with their more advanced contextual understanding [12], [13].

Nevertheless, the majority of models in existence are not specifically adapted in ESL learning scenarios and the data that is available is generally too general or does not represent common ESL error patterns well enough [14], [15].

This study introduces an AMT-T5 model, which is an expansion of the T5 transformer architecture to support the educational requirements of ESL students. In contrast to conventional grammar correction systems, which can only perform surface-level correction, AMT-T5 optimally achieves grammatical error correction, error-type classification, and explanation-based feedback generation in a single architecture. This combination allows the model to provide not only corrected sentences but also teaching feedback this facilitates the learning process. This learner-sensitive adaptive feedback system is a major distinguishing feature of AMT-T5, which personalizes feedback based on learner-specific error frequency. The model is able to offer specialized advice by dynamically changing attention weights based on repeated grammatical errors, thus reducing the number of such errors. Compared to the current transformer-based grammatical error correction systems that use a fixed multitask learning or post-hoc explanation model, AMT-T5 uses learner-state-conditioned modeling, where error profile correction and generate explanation is conditioned by dynamically updated learner error profiles. This attention reweighting conditioned by the learner is a methodological break with the previous multitask GEC and pedagogical NLP models, which do not incorporate learner history into the transformer attention mechanism.

A. Research Motivation

ESL learners also have such consistent grammatical problems, which cannot be easily eradicated by traditional teaching. Recent transformer-based grammar correction models have achieved high benchmark performance, but primarily do not offer pedagogical scaffolding. This puts a gap in the learning process in which the student gets outputs that are error free but with no explanations or personalized directions to be able to develop a sustainable level of skills. Hence, there exists an urgent demand of a grammar correction system that can enhance the accuracy of the sentences besides, be actively supportive of the learner development by providing contextual feedback and adaptive learning mechanisms.

B. Significance of the Study

The proposed AMT-T5 system goes beyond the conventional benchmark-driven GEC systems and incorporates grammar rectification with an educational purpose. The system facilitates improved language learning and quantifiable proficiency growth by supporting the active profiling of learning errors specific to the learner, real-time explainable feedback, and optimization to user preferences. This model facilitates effective implementation in actual educational settings, and it is a powerful solution to school systems, language study applications, and one-on-one ESL lessons. Its combination of high grammatical precision and instructional support enhances the position of AI as a correction tool to an intelligent language learning partner.

C. Problem Statement

Transformer-based grammar error correction models such as BERT, GPT, and T5 have shown strong benchmark performance [16]; however, that are largely designed for surface-level correction rather than pedagogical support in ESL learning contexts [17]. Existing systems including GECToR, BART-GEC, and RoBERTa-GEC prioritize correction accuracy but lack learner awareness, adaptive feedback, and explanation-based instruction, limiting their educational value [23]. This gap results in improved sentence fluency without fostering long-term grammatical understanding or learner development. To overcome this limitation, the proposed AMT-T5 framework integrates grammar correction, error classification, and personalized feedback, bridging linguistic accuracy with learner-centered pedagogical effectiveness.

D. Key Contributions

- Introduces a learner-aware transformer design principle in which adaptive attention is conditioned on dynamically updated learner error profiles, offering a general modelling strategy for personalized educational NLP systems.
- Establishes a unified learner-centered framework that integrates grammatical correction, error-type classification, and explanation generation, demonstrating how multitask learning can be pedagogically grounded rather than task-driven.
- Provides empirical evidence that explanation-based multitask learning supports pedagogically meaningful feedback, as reflected in reduced recurrence of grammatical errors and positive learner-centered evaluation indicators.
- Proposes a combined evaluation paradigm that integrates computational metrics with pedagogical indicators, offering a transferable methodology for assessing educational NLP systems beyond accuracy-based benchmarks.
- Presents a reusable methodological blueprint for learner-centered language learning systems by combining learner modeling, adaptive attention, preference alignment, and efficiency-oriented optimization, enabling future extensions beyond grammar correction tasks.

The rest of the study is organized as follows: Section II reviews the related works. Section III describes the proposed AMT-T5 model. Section IV details the results and discussion, and Section V concludes the study and direction for future work.

II. Literature Review

The section is organized in the form of a comparative synthesis of previous research on grammatical error correction, language proficiency assessment, and learning NLP. It systematizes the results by the type of model and the area of application, which forms the basis of research to support the proposed AMT-T5 framework.

Korniienk [17] introduces open-sourced foundational models such as LLaMA, Mistral and Gemma demonstrate their ability to provide assistance in writing tasks. However, the application of neural networks in (GEC) is not well investigated. To evaluate these models in zero shot, supervised fine tuning and RLHF settings. Notably, fine tuning greatly enhances GEC performance and it is critical to use prompt engineering on zero-shot CoNLL-2014 and BEA-2019 benchmarks. Running Direct Preference Optimization under RLHF gives incremental performance gains. Finally, Chat-LLaMA-2-13B-FT attains F0.5 scores of 67.87 and 73.11, respectively. The results also prove that using open-source LLMs is viable for efficient and scalable GEC systems.

Sazzed [18] suggests that readability of the non-native English language speakers and potential prediction methods for their language proficiency from social media reviews are investigated. A corpus of 1,000 reviews was developed containing five ELP groups. The FRE and FKG were used to measure readability scores. Insufficient data are found to distinguish ELP groups pertaining to readability. Various machine learning and transformer-based models, were applied to ELP classification. It turns out the transformer-based approaches were slightly better. Therefore, these are more likely to be used in automatic language proficiency assessment.

Davis [19] evaluates the effectiveness of using NLMs for Grammatical Error Detection in the ESL domain. It is shown that it is possible for NLMs to transfer linguistic knowledge that improves GED performance across benchmark datasets. With appropriate transfer, it also allows fine grained error detection using single models. GED also reflects model type and data domain on analysis and encoded noun-number information. Moreover, this study represents GED as a diagnostic tool that can be utilized to judge implicit grammatical knowledge available in NLMs. Firstly, stark contrast between masked and autoregressive models is highlighted. The study provides a holistic review of NLMs on GEDs tasks.

Ormerod [20] introduces a regression-based framework to study how global features were leveraged by transformer-based models for Automated Essay Scoring. The finding is that pretrained language models implicitly approximate rubric–relevant features while scoring. Hidden states can be used in linear regression to improve the model interpretability by estimating importance of the features. This framework is validated using DeBERTa models fine-tuned on overall and trait level scores. Particular focus is given on convention errors such as spelling, grammar and punctuation. It demonstrates that neural models have improved explainability for use in AES. It validates language modeling-based scoring systems.

Elks [21] discusses that transfer learning and multitask learning can be used to construct an automated marking system for second language English writing. The research studies the fine-tuning strategies for Transformer-based language models towards NLP tasks. Experimental results show that multitask fine-tuning leads to robust and improved performance. Different models are compared against various task-model combinations using various datasets. The third result is that preliminary findings discover that adding multitask objectives to pretrained models improves scoring accuracy. This lends itself to scalable, data-efficient assessment of writing by learners. This work will provide ways for researchers in educational NLP applications for automated evaluation.

Ng and Markov [22] introduces NLI aims to discover when and where one grew up by analyzing the second language spoken and it is applied in linguistics and forensics. Prior to transformers, traditional machine learning methods relying on hand-crafted features have bested them at this task. Closed-source LLMs following the successful trend seen in recent years, for instance GPT-4, show strong performance at zero-shot on open-set classification in NLI. Unfortunately, these models are proprietary and come at a high cost to operate. In this work, explore the use of open source LLMs for the NLI tasks. In their initial form, these arguments are not as effective, but fine-tuned versions of these open models are competitive by accuracy. All the findings shall support the use of open-source solutions as an accessible, customizable way to build NLI.

Alisoy [23] introduces that machine learning for automated vocabulary acquisition for ESL is investigated using transformer-based models. An evaluation of the fine-tuned BERT model was carried out for predicting vocabulary needs on the web and traditional ML algorithms SVM and Random Forest were considered for comparison. The BERT driven tool which was used in the experimental group showed a significantly higher vocabulary gain than the control group. The best precision and recall metrics belong to BERT that achieved the highest accuracy (88%). Results show that context aware ML-based vocabulary tools have the potential to positively impact language learning. In the study, DL and RL are proposed to be used with ESL pedagogy. It adapts to the needs of instruction and allows for curriculum development on an individual basis.

Ye et al. [24] propose that the LLMs in FLE is beginning to flourish, and is found that LLMs have a potential for transformative use as dynamic FLE tools. In terms of pedagogy, it can augment learning materials, create student simulations, and predict what students will or might learn in order to give more targeted instruction. In addition to this, it plays the role of an intelligent agent facilitating inclusive and personalized learning. The authors argue that these roles can be better used only if this collaboration is carried out on an interdisciplinary basis. In other words, innovation is prioritized, and the associated risks are tackled. The work outlines a conceptual framework for optimizing FLE via LLM integration.

Table I summarizes the representative research in grammar correction, automated writing evaluation, and educational NLP. Recent developments prove that models based on transformers can be successfully used in providing assistance in grammar corrections, readability testing, grading of essays, and assessing vocabulary in cases of ESL. Nevertheless, the available research is mostly divided, where each of the language skills is considered separately and does not have any adaptive feedback, and is not explicitly integrated into the pedagogy.

Earlier multitask grammatical error correction methods are mainly concerned with common representations among tasks that are related to correction but were fixed to the formulations of tasks that are independent of individual learner actions. Educational NLP and automated writing evaluation systems generally produce explanations or feedback, yet these components often not related to the correction process, and it is not trained on the individual errors of the learner. Preference-based optimization techniques even enhance the quality of output, but are not sensitive to the history of learners or instructional personalization. Conversely, the suggested AMT-T5 model integrates grammar clean-up, classification of error type and generation of explanations into a learner-conditioned model, with adaptive attention reweighting being expressly motivated by learner error history. This design has the capability to provide pedagogically customized and customized grammar feedback that is not addressed by existing approaches.

TABLE I. SUMMARY ON LITERATURE REVIEW

Author	Description	Advantages	Disadvantages
Korniienk [17]	Explores open-source LLMs (e.g., LLaMA, Mistral) in GEC under zero-shot, fine-tuning, and RLHF setups.	Fine-tuning improves GEC; shows viability of open-source LLMs with good performance on CoNLL and BEA benchmarks.	Zero-shot requires careful prompt design; RLHF yields only incremental improvement.
Sazzed [18]	Analyzes readability of non-native texts and classifies English proficiency using ML and transformer models.	Transformer-based models slightly outperform classical models in ELP prediction.	Readability metrics (FRE, FKG) poorly distinguish proficiency levels.
Davis [19]	Investigates NLMs' role in Grammatical Error Detection (GED), and their encoding of linguistic signals like noun-number agreement.	Shows positive transfer and diagnostic power of NLMs; robust linguistic encoding in some models.	Performance varies by model type and domain; brittle encoding across syntactic constructions.
Ormerod [20]	Proposes regression-based explainable AES using DeBERTa models, focusing on global features and convention errors.	Improves interpretability; validates LMs for use in AES.	Limited focus on deeper semantic and content aspects of writing.
Elks [21]	Combines transfer and multitask learning for automated ESL essay scoring using transformers and multiple datasets.	Multitask fine-tuning improves robustness and accuracy; scalable solution.	Preliminary findings; lacks full generalization to diverse writing contexts.
Ng and Markov [22]	Uses open-source LLMs for Native Language Identification (NLI), comparing them with traditional methods and closed-source LLMs like GPT-4.	Fine-tuned open LLMs are competitive; accessible and customizable.	Underperforms out-of-the-box; closed LLMs still outperform in zero-shot settings.
Alisoy [23]	Examines transformer-based vocabulary acquisition in ESL; compares fine-tuned BERT with SVM and Random Forest.	BERT outperforms baselines; improves vocabulary gain; supports curriculum personalization.	Requires technical infrastructure; limited support for grammar beyond vocabulary.
Ye et al. [24]	Presents roles of LLMs in FLE as enhancers, predictors, and agents to enable personalized language instruction.	Promotes inclusive, adaptive, and AI-supported education; provides a pedagogical framework.	Lacks practical implementation details; interdisciplinary collaboration needed for real-world impact.

III. PROPOSED METHODOLOGY FOR ADAPTIVE MULTI-TASK T5 FRAMEWORK IN ESL GRAMMAR CORRECTION

The proposed study presented the empirical method of creating and assessing the AMT-T5 model of grammatical error correction in ESL writing. The model is trained on the Lang-8 Learner Corpus, which is a collection of sentences produced by learners together with professional corrections. Fixed-length T5 tokenizers are used to normalize and tokenize input sentences in order to have similar model input. AMT-T5 architecture is a combination that applies grammatical error correction, the classification of error type, and the generation of explanations based on feedback on the same transformer model, which makes it possible to increase both the linguistic and pedagogical clarity. Once a dynamic error profile of each learner is built, to support learner-centered teaching, an adaptive feedback mechanism reallocates attention to the prevalent grammatical patterns. An adaptive attention mechanism is specifically trained based on the frequency of errors to which the learner is explicit; thus, the model is able to prioritize the grammatical structures that provoke a particular learner in different sessions. In this design, the attention mechanisms are not fixed, as in the case of traditional transformer attention mechanisms that are user-independent and do not incorporate user-specific historical information in attention computation. A combination of supervised fine-tuning, Direct Preference Optimization, to align all corrections with pedagogical expectations, and Knowledge Distillation to facilitate efficient real-time deployment. Fig. 1 demonstrates the workflow of the suggested AMT-T5 framework.

A. Data Collection

The study uses the Lang-8 Learner Corpus [25] of Kaggle. The major source of information is the Lang-8 Learner Corpus, which consists of authentic ESL learner sentences together with native-speaker corrections. A binary tag on each record (1 = error, 0 = correct) is used to show the presence of a grammatical error in the sentence. It separates the dataset into 80% training, 10% validation, and testing to allow equal generalization.

The sample data pairs, in Table II, are the sample data utilized in training the model, with y = 1, in every row, meaning that there are grammatical errors in the sentence. In the Input column, the sentences originally written by the learners are displayed, whereas in the Output column, the same sentences edited by the experts are presented, and that are used to illustrate different grammar problems, such as incorrect use of tenses, subject-verb agreement and omission of articles.

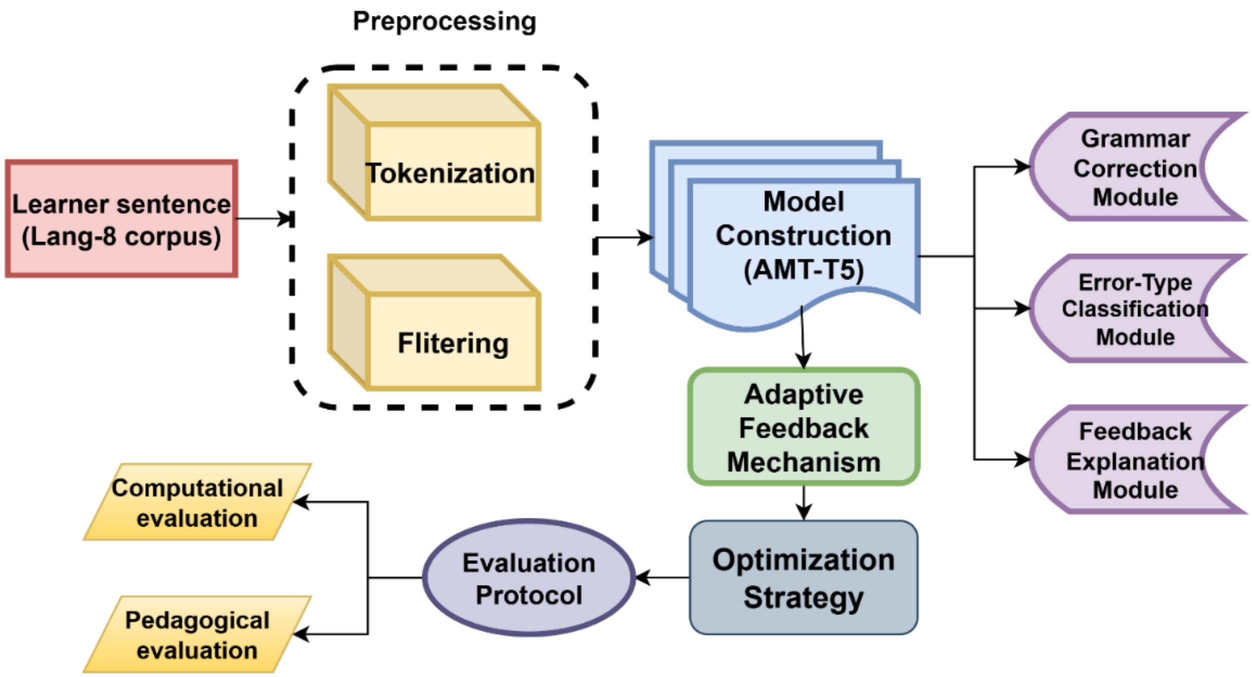

Fig. 1. Adaptive grammar correction framework.

TABLE II. SAMPLE DATA FROM LANG-8 LEARNER CORPUS

y	Input (Learner Sentence)	Output (Corrected Sentence)
1	And he took in my favorite subject like soccer.	And he took in my favorite subjects like soccer…
1	Actually, who let me know about Lang-8 was him.	Actually, he was the one who let me know about Lang-8.
1	His Kanji's ability is much better than me.	His Kanji ability is much better than mine.
1	We've known each other for only half a year, but his lesson was a lot of fun.	We've known each other for only half a year, but his lessons were a lot of fun.
1	I heard a sentence last night when I watched TV.	I heard a sentence last night when I was watching TV.
1	Yesterday, I went to Umeda station to date.	I went to Umeda station for dating yesterday.

B. Data Preprocessing

Preprocessing is a crucial step towards cleaning the dataset, organizing it, and making it compatible with the requirements of the transformer-based models, in particular, T5. The preprocessing step maximizes the input data for effective learning and correct grammatical error correction.

1) Filtering: To limit the scope to error-containing sentences in need of correction, the dataset was cropped to keep only those records where the binary error tag was 1. Let D be the original dataset, and is represented, as in Eq. (1):

$$D = \{(x_i, y_i, l_i)\}_{i=1}^{N} \quad (1)$$

where, x_i is the learner sentence, y_i is the corrected sentence, $l_i \in \{0,1\}$ is the binary label indicating whether correction is needed. The Filtered dataset is as given in Eq. (2):

$$D' = \{(x_i, y_i) | l_i = 1\} \quad (2)$$

2) Formatting for T5: Grammar correction is modeled as text-to-text translation using task prefixes. This structure transforms the task of correction into a sequence-to-sequence mapping problem, given in Eq. (3) and Eq. (4):

$$T5\ Input: X = prefix + x_i \quad (3)$$

$$T5\ Output: Y = y_i \quad (4)$$

3) Tokenization: Tokenization was done with the T5 pre-trained tokenizer. Tokenization separates text into a series of subword units or tokens that are mapped numerically for model consumption. Let $Tok(\cdot)$ denote the tokenizer function, as in Eq. (5):

$$X_{tokenized} = Tok(X), Y_{tokenised} = Tok(Y) \quad (5)$$

Each sequence was padded to a maximum length of 128 tokens to ensure uniformity, given in Eq. (6):

$$|X_{tokenized}| \leq 128\ , |Y_{tokenized}| \leq 128 \quad (6)$$

C. Adaptive Multi-Task T5 Task-Specific Learning Modules

The proposed AMT-T5 framework extends the T5 encoder–decoder model through three interdependent modules designed to jointly handle grammar correction, error classification, and feedback generation. Such modules exchange contextual representations of the encoder, which facilitates learning in a coherent manner of linguistic and pedagogical activities.

Fig. 2 shows the AMT-T5 structure, which incorporates the grammar correction method, the error classification method and the feedback generation method, all integrated in a single systematic encoder-decoder structure. The input sentence of the learner is coded and fixed using the Grammar Correction Module, and at the same time, the error is also classified to highlight the particular linguistic vulnerability. The Adaptive

Feedback Mechanism of the system observes the changing pattern of errors of each learner and continuously refocuses attention to guide them individually. This reinforcement loop strengthens the learning gaps that may have occurred before and thus mistakes that would be made are given specific attention. Consequently, AMT-T5 provides a context-sensitive, real-time guidance facilitating an improved learning rate and encouraging a progressive improvement in ESL learners.

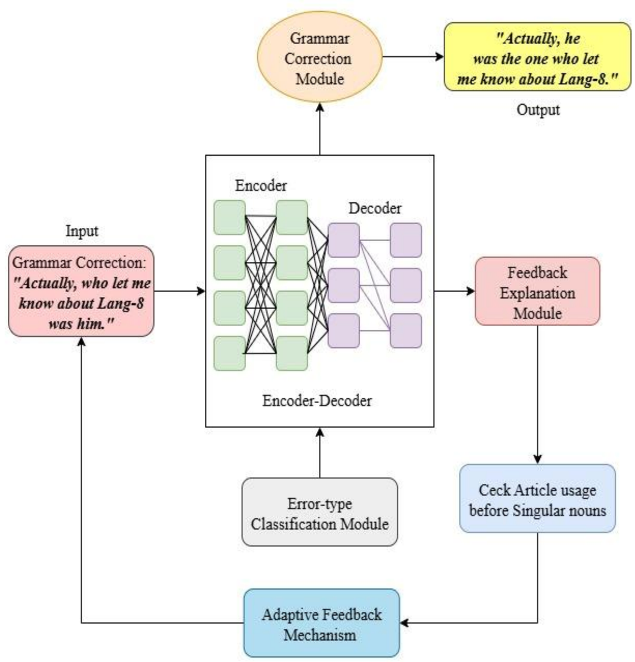

Fig. 2. AMT-T5 model architecture.

1) Grammar correction module: Grammatical transformation is the main one, in which the model will change the incorrect sentences written in the ESL to the grammatically correct ones without distorting the contextual meaning and fluency. The encoder puts the input made by the learner into perspective and the decoder produces the corrected output one step after another. The correction loss function takes the following form, represented as in Eq. (7):

$$\mathcal{L}_{corr} = -\frac{1}{T}\sum_{t=1}^{T} logP_\theta(y_t \mid y_{<t}, x) \quad (7)$$

where, x denotes the input sentence of a learning individual, y_t represents the gold-standard token at that particular position and T denotes the target number of positions. $\mathcal{L}_{corr}$ to the minimum implies a high degree of correspondence with the corrections of the experts, and decreases the number of grammatical deviations in ESL writing.

2) Error-type classification module: In this module, the model is able to classify types of grammatical error, e.g., tense error, omission of articles, or subject-verb agreement. The binary predictions of each of the error types and are produced by a classifier that is based on encoder representations, as given in Eq. (8):

$$\mathcal{L}_{class} = -\sum_{k=1}^{K}(e_k log\hat{e}_k + (1-e_k)log(1-\hat{e}_k)) \quad (8)$$

In which K denotes the base count of types of error, ek denotes the binary indicating of type k on the ground-truth, and e_k denotes the predicted probability. Minimizing such loss increases the ability of the model to identify and accustom to recurrent learner specific deficiencies.

3) Feedback explanation generation module: The AMT-T5 also produces explanatory feedback to facilitate the process of pedagogy, which explains the reason a correction was given. This enables the learners to learn about the underlying grammatical principles and not just being given fixed text. The loss of explanation is computed, as in Eq. (9):

$$\mathcal{L}_{exp} = -\frac{1}{T_r}\sum_{t=1}^{T_r} logP_\theta(r_t \mid r_{<t}, x) \quad (9)$$

where, T_r is the length of the explanation and r_t is the token at position t in the reference explanation. Reduction of such loss will guarantee clear, context-specific explanations that are concise and meet the ESL learning goals.

4) Joint optimization objective: Joint Optimization Objective: The three modules are trained with the same multi-task target in order to balance the grammatical accuracy and error interpretability as well as educational feedback. The overall loss is calculated, as in Eq. (10):

$$\mathcal{L}_{total} = \lambda_1\mathcal{L}_{corr} + \lambda_2\mathcal{L}_{class} + \lambda_3\mathcal{L}_{exp} \quad (10)$$

where, $\lambda_1, \lambda_2, \lambda_3$ are weights which balance the importance of tasks. In our study, correction (λ_1) is given higher priority whereas classification and explanation λ_2, λ_3) are moderately weighted. Such a structure guarantees that grammatical accuracy is the paramount result whereas it still instills pedagogical feedback to promote the long-term success of ESL students.

D. Adaptive Feedback Mechanism in AMT-T5

To increase the pedagogical utility of grammar correction, the suggested AMT-T5 structure integrates the adaptive feedback mechanism personalizing the corrections and explanations depending on the behavior of particular learners. As opposed to the traditional correction systems which are static, this mechanism constantly represents the learner-specific error pattern and adapts model attention to deliver specific and didactic feedback.

1) Learner error profiling: The system notes how many times each type of errors is done by a learner and a history is obtained which reflects the grammatical weaknesses of a learner. This is an error profile that enables AMT-T5 to be dynamically adjusted to make sure that the model does not correct all learners in the same way, but instead it customizes corrections in accordance with individual performance patterns. It is computed as in Eq. (11):

$$F = [f_1, f_2, \dots, f_k] \quad (11)$$

where, f_k is the occurrence of the error type k (e.g., the usage of tense, the omission of an article, subject-verb agreement). The error profile vector F in this study is constantly updated, which allows AMT-T5 to retain learner-specific memory to make customized grammar correction.

2) Attention reweighting based on error history: After creating a personalized profile of error, the AMT-T5 architecture dynamically changes the distribution of the encoder-decoder attention. The mechanism puts more emphasis on tokens which are associated with common learner mistakes and rewards the right grammatical patterns. Due to this, the model will be more responsive to the recurring weaknesses and contextual needs of writing among the learners. Such an adaptive approach will allow the system to provide much personalized and context-sensitive grammatical feedback, eventually leading to greater longer-term learning changes. It is denoted, as in Eq. (12):

$$A' = A - \alpha \cdot \delta_{rep} + \beta \cdot \delta_{align} \tag{12}$$

where, A is the initial attention weight, δ_{rep} punishes errors of repetition and δ_{align} strengthens focus on the patterns which are corrected. These modifications in our study eliminate the occurrence of errors by the learners and encourage the AMT-T5 to make successively better corrections.

3) Personalized feedback generation: The final stage converts the nature of the mistakes which were followed to helpful hints. AMT-T5 does not simply come up with corrections and pushes out specific questions, such as; you like to omit articles that come before singular nouns. This makes corrections learning experiences whereby the ESL learners are coached on learning the rules behind the grammar rather than the memorization of corrections. It is given in Eq. (13):

$$Feedback = g(F, A') \tag{13}$$

Here, $g(\cdot)$ is the mapping function, and it receives the error profile F of the learner and modified attention A to generate feedback text. This is the mechanism that this study will help mediate between the automatic correction and the pedagogy and make AMT-T5 a tool of both accuracy and long-term grammatical change.

E. Optimization Strategy

It involves a combination of supervised fine-tuning, Direct Preference Optimization (DPO) and Knowledge Distillation (KD) to achieve a tradeoff of grammatical accurateness, pedagogical flexibility and computational efficiency.

1) Supervised fine-tuning: The AMT-T5 model was fine-tuned on the Lang-8 corpus using the multi-task objective. Training employed the AdamW optimizer (learning rate = 2e−5, batch size = 16, weight decay = 0.01) for 5 epochs with early stopping after two non-improving epochs. This stage allows the model to jointly learn grammatical correction, error-type classification, and feedback explanation.

2) Direct Preference Optimization (DPO): DPO refines model alignment with ESL learners by considering their preferences between multiple valid corrections. Given two outputs—preferred (y_{pref}) and non-preferred ($y_{nonpref}$)—the objective minimizes, given as in Eq. (14):

$$L_{DPO} = -\log\sigma\left(r\left(y_{pref}\right) - r\left(y_{nonpref}\right)\right) \tag{14}$$

where, $r(\cdot)$is the reward function. Minimizing L_{DPO}ensures that AMT-T5 produces corrections aligned with pedagogical clarity rather than mere grammatical validity.

3) Knowledge Distillation (KD): To ensure deployment efficiency, the fine-tuned T5-base (teacher) model transfers knowledge to a smaller student model through soft-target matching derived as in Eq. (15):

$$\mathcal{L}_{KD} = (1 - \tau)\mathcal{L}_{CE} + \tau \cdot KL(P_{teacher} \parallel P_{student}) \tag{15}$$

where, τ is the distillation temperature, $P_{teacher}$ the output distribution of T5-base and $P_{student}$ that of the distilled model. KD in our study passed the knowledge between the teacher and the student so that lightweight AMT-T5 could achieve the similar levels of correction in low latency.

4) Final optimization objective: The full learning objective combines all components mathematically expressed, as in Eq. (16):

$$\mathcal{L}_{final} = \lambda_1\mathcal{L}_{total} + \lambda_4\mathcal{L}_{DPO} + \lambda_5\mathcal{L}_{KD} \tag{16}$$

where, λ_4 and λ_5 regulate the preference optimization and distillation contributions. This last loss in this study led AMT-T5 to a balanced learning, that is, providing corrections which are accurate, learner-center and deployed-efficient.

F. Evaluation Protocol

AMT-T5 was evaluated using both computational and pedagogical measures.

1) Computational evaluation: BLEU and GLEU scores were used in measuring the closeness of the model corrections with expert references and Full Sentence Accuracy was used in measuring perfectly correct outputs. Levenshtein Edit Distance was how much the minimum number of edits needed and Error Reduction Rate (ERR) was a measure of the percentage of grammatical errors that were reduced in learner sentences.

2) Pedagogical evaluation: The learning population examined in the pedagogical assessment included 60 intermediate ESL learners who were enrolled in an academic ESL course. Every participant provided written consent and engaged in the AMT-T5 system as part of facilitated grammatical practice sessions. The assessment was done on different learning sessions where the learners were required to provide sentences to get them corrected and provide adaptive feedback, type of errors explanation, and a personalized guide. The profile of errors in learners was revised at the end of each session to monitor the common grammatical errors, including the absence of articles and the use of tenses. The learning profiles were tracked throughout the sessions to observe trends in the reduction of recurring error types like omitting of articles or the misuse of tenses. Also, the user satisfaction ratings were obtained to assess the usefulness of the corrections, explanations, and personalized feedback created by AMT-T5 among the learners. To evaluate the effectiveness of the pedagogical method, the two indicators were observed decrease in the rates of repeated errors over the course of the sessions and learner satisfaction ratings based on a Likert scale questionnaire about perceived usefulness, intelligibility of explanations, and personalization. The assessment provides exploratory evidence of instructional utility instead of a dependent measurement on long-term learning outcomes.

Algorithm 1: AMT-T5 with Personalized Feedback for ESL Grammar Correction

```
Input:
    Learner corpus D = {(x, y)}
    Pretrained T5 model
    Error type set E
    Learning rates and loss weights λ

Output:
    Corrected sentence ŷ
    Predicted error types ê
    Personalized feedback φ

Initialize AMT-T5 parameters θ
Initialize learner error profile F ← zero vector
Split D into training, validation, and test sets

For each training epoch do
    For each batch (x, y) in training set do
        Format input with task prefixes
        Tokenize and encode input sequence
        Generate corrected output ŷ
        Predict error types ê
        Generate feedback explanation φ
        Compute grammar correction loss Lcorr
        Compute error classification loss Lclass
        Compute explanation generation loss Lexp
        Compute joint multi-task loss
            Ltask = λ1 · Lcorr + λ2 · Lclass + λ3 · Lexp
        Update model parameters θ using gradient descent
    End for
End for

For each learner interaction do
    Receive learner sentence x
    Encode x using trained AMT-T5 encoder
    Generate correction ŷ and error types ê
    Update learner error profile F using ê
    Adjust attention weights based on F
    Generate personalized feedback φ using adjusted attention
    Return ŷ, ê, and φ to learner
End for
```

Algorithm 1 performs grammar correction, error-type classification, and feedback generation within a unified transformer-based framework. The learner sentences are preprocessed and formatted with task-specific prompts first, and then encoded by the shared T5 encoder. Corrected sentences, the classification of grammatical error, and the production of explanatory feedback are collective efforts of the decoder. Recurring mistakes are then used to dynamically update a profile of learner-specific errors, upon which attention weights are altered and personalized feedback is provided. Multi-task supervised learning, Direct Preference Optimization of pedagogical alignment and Knowledge Distillation optimize the model to provide efficient real-time deployment.

The novelty of this study lies in the proposed AMT-T5 architecture, which consolidates the concepts of grammatical error correction, classification of types of errors, as well as the explanation-based feedback into a single transformer architecture adapted to ESL learning. In contrast to the current models of grammar correction, which pay much attention to sentence-level accuracy, the proposed model consists of a learner-centered adaptive feedback system, which dynamically reallocates attention based on personal error histories. This customization allows, and focuses instructional correction, instead of being generic. Also, the combination of preference-conscious optimization and lightweight deployment plans makes AMT-T5 a pedagogically significant and practically deployable grammar learning system as opposed to an independent correction tool.

IV. Results and Discussion

The AMT-T5 grammar correction model was tested on the basis of quantitative measurement, i.e., BLEU, GLEU, full-sentence accuracy, and Levenstein distance and error rate, and on the basis of qualitative judgment of the user. It combines grammar correction, error classification, explanation-based feedback, adaptive feedback, DPO, and Knowledge Distillation, which is better personalized and performs better than single-task T5. The findings indicate that the recurring learner-specific errors and subject-verb agreement, tense and pluralization errors are considerably diminished, and usability and educational value are promising, which proves AMT-T5 to be appropriate to learn ESL grammar in real time, context-sensitive and pedagogically effective. Table III summarizes the simulation parameters and hardware configuration employed to ensure reproducibility, computational efficiency, and fair performance evaluation of the proposed model.

TABLE III. Simulation and Hardware Setup

Parameter	Configuration
Parameter	Configuration
Model Framework	T5-base (Encoder-Decoder, Hugging Face Transformers)
Optimization	AdamW optimizer with Cross-Entropy Loss
Training Batch Size / Epochs	16 / 3–5 epochs with early stopping
Maximum Token Length	128 tokens
Hardware	NVIDIA Tesla V100 GPU, 64GB RAM, Intel Xeon CPU

A. *Quantitative Evaluation Results*

To critically assess the performance and reliability of the T5-based Grammar correction system are fine-tuned, and a mixture of linguistic and computational measures is used. Overall, it provides an overall description of the capability of the model to identify and correct grammatical errors in real-world ESL learner data.

1) BLEU Score (Bilingual Evaluation Understudy): In natural language processing, BLEU is a popular measure to calculate the degree of similarities from model predicted response and human annotated sentence. For grammar correction, BLEU score is computed based on n-gram overlap (usually up to 4-grams) and has a brevity penalty for penalizing very short predictions. It is formally given in Eq. (17):

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n log p_n\right) \quad (17)$$

where, BP is the brevity penalty, w_n are weights, p_n is the precision of n-grams. Increased scores in BLEU mean greater consistency with human corrections

2) GLEU Score (Grammar-focused BLEU): GLEU is a variant of BLEU, which is designed specifically to solve (GEC) tasks. Unlike the ordinary BLEU that may favor non-incorrect but fluent results, GLEU is heavier on missing and surplus n-grams. It calculates accuracy and recall when compared to editing of references and provides a fairer ratio when it comes to shorter sentences and structural rearrangements. This is the score that comes in handy, especially when it comes to measuring small grammatical improvements.

3) Edit Distance (Levenshtein Distance): In edit distance, measuring the similarity between the guessed output and the reference correction by determining the minimum amount of single-character operations (additions, removals, replacements), one has to make a change to one text into the other. It is given in Eq. (18):

$$D(i,j) = min \begin{cases} D(i-1,j)+1 \\ D(i,j-1)+1 \\ D(i-1,j-1)+cost \end{cases} \quad (18)$$

where, cost represents 0 when there is a match between the characters, otherwise 1. A shorter distance shows more resemblance to the reference sentence

4) Error Reduction Rate (ERR): ERR is used to gauge the extent to which the model is able to reduce grammatical errors in the input. It is computed as in Eq. (19):

$$ERR = \frac{E_{before} - E_{after}}{E_{before}} X\ 100 \quad (19)$$

where, E_{before} refers to the number of grammatical errors in the original sentence of the learner, and E_{after} is the number of grammatical errors in the output of the model. This measure represents actual enhancement of grammar, which is particularly important in learning settings such as ESL learning.

Quantitative analysis, in turn, is pegged on quantification of how well the grammatically corrected quality of the AMT-T5 base model compares with objective measures of performance, quantify the efficiency of the model to produce correct, fluent and syntactically valid sentences by performing an inspection of model performance on a held-out section of the dataset.

Table IV highlights the AMT-T5 model's good performance, a BLEU score of 72.8, and GLEU of 86.5, which means that it has corrected grammar effectively. The fluency, accuracy, and rate of error reduction (91.2) of the model are shown by high sentence accuracy (75.3), low Levenstein distance (1.7), and high fluency of the model, as compared to the human-corrected sentences.

TABLE IV. PERFORMANCE METRICS

Metric	Score (Approx.) (%)	Interpretation
BLEU Score	78.9	Highly fluent and syntactically sound output
GLEU Score	90.7	Superior grammar-specific correction accuracy
Full Sentence Accuracy	75.3%	High exact match rate with corrected sentences
Levenshtein Edit Distance	1.7 (average)	Very low average edits needed post-prediction
ERR	91.2%	Strong reduction of grammatical errors

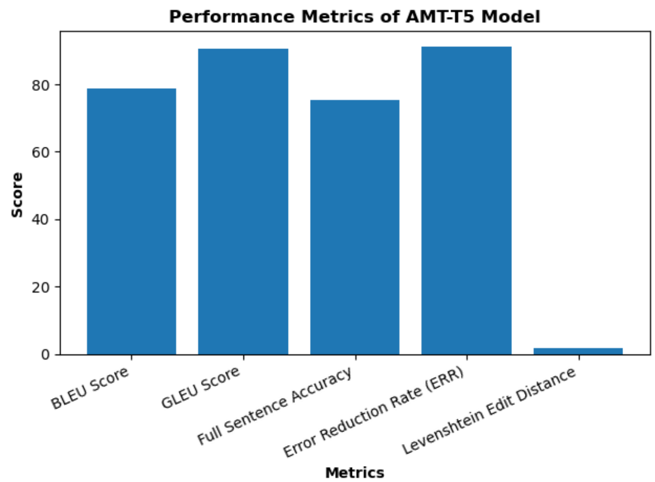

Fig. 3. Evaluation of the AMT-T5 model.

Fig. 3 indicates the quantitative analysis of the AMT-T5 model in five measures. GLEU (86.5) and Error Reduction rate (91.2) are high, which means that the grammar correction measures are successful, whereas BLEU, sentence accuracy, and low error distance are high, which shows that the model is correct and can be useful in pedagogy.

B. Qualitative Evaluation

The final one is a qualitative analysis to determine to what extent the fine-tuned AMT-T5 base model actually performs in a real-life grammar correction scenario beyond the said numerical value. This assessment is done through analysis of some input-output examples taken from the test set, which entails that the model can handle different grammatical structures such as subject-verb concord, tense correction in the verbs, pluralizing, using auxiliaries, etc. In addition, this method provides further insight into how accurately the model generalizes to unseen, user-supplied sentences, an important determinant of such a model for real-world deployment in adaptive grammar learning systems for ESL users.

Table V presents a qualitative analysis of model output and shows that, with respect to correcting real ESL learner sentences, it is effective. In the case of the input sentence, 'And he took in my favorite subject like soccer' was corrected to 'And he took in my favorite subjects like soccer', which fixed the inconsistency between singular and plural. Another one was reformed: "Actually, who informed me relating to Lang - 8? Him," was reformed very well to "Actually, he informed me relating to Lang - 8." The same were the changes to the sentence

'His Kanji ability is better than me' into 'His Kanji ability is better than mine.' Finally, when saying "We've known each other half a year and his lessons were a lot of fun," the model recognized and corrected the verb agreement and plurality, finally this model corrected it by rendering "We have known each other only half a year, but his lesson was a lot of fun." this show that these observations closely follow native speakers ground truth corrections while correcting a variety of grammar problems (subject verb agreement, sentence rephrasing, possessive pronouns, plural, etc.) that demonstrate the model's robustness to correct different types of grammar problems.

TABLE V. QUALITATIVE ANALYSIS

Original Sentence (Input)	Model Output (Prediction)	Correct Sentence (Ground Truth)
And he took in my favorite subject like soccer.	And he took in my favorite subjects like soccer.	And he took in my favorite subjects like soccer.
Actually, who let me know about Lang - 8 was him.	Actually, he was the one who let me know about Lang - 8.	Actually, he was the one who let me know about Lang - 8.
His Kanji's ability is much better than me.	His Kanji ability is much better than mine.	His Kanji ability is much better than mine.
We've known each other for only half a year, but his lesson was a lot of fun.	We've known each other for only half a year, but his lessons were a lot of fun.	We've known each other for only half a year, but his lessons were a lot of fun.

C. Error Analysis

While the AMT-T5-based grammar correction model works well for all the typical grammatical errors, some limitations remain. The model sometimes fails with idiomatic phrases and colloquial expressions, which are usually not well represented in the training data. This may result in forced or incorrect rewrites that change the meaning of the sentence. Further, intricate sentence structures, particularly with nested clauses or unconventional punctuation, at times result in incomplete or partial corrections. The issues here indicate that the model is not able to establish more profound syntactic links in longer or non-standard sentences. Moreover, there are some instances of overcorrection where the grammatically correct sentences are unnecessarily coded and under-correction, when the minor misinterpretations have been overlooked, and the necessity to focus more on the better contextual context should be stressed.

Fig. 4 gives a categorical flow of the nature of model errors, such as overcorrection, under-correction as well as misinterpretation. The unnecessary editing is called overcorrection, under-correction is a lack of errors, and misinterpretation is an alteration of sentence meaning. This gives a type of model errors that is capable of diagnosing system behaviors, as well as helps in future corrective actions according to error-specific error reduction measures in grammar correction tasks.

Table VI gives a summary of a few of the typical failures of the AMT-T5 grammar correction model. Certain failures were due to idiomatic expressions (14%), nested clauses (11%), plus some punctuation mistakes and other minor ones (7%), which could not be corrected. This indicates the shortcomings of the model in complex syntactic structure and infrequent linguistic phenomena, still, it is informative to enhance the model.

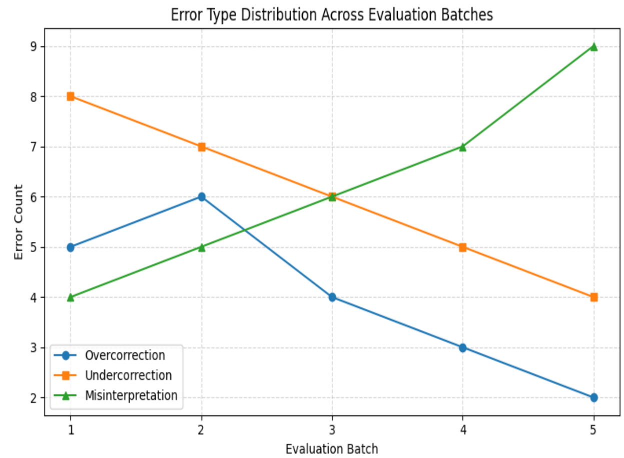

Fig. 4. Error type distribution.

TABLE VI. COMMON FAILURE CASES

Input Sentence	Model Output	Issue Type	% of Failures
It rains cats and dogs yesterday.	It rains cats and dogs yesterday.	Idiom not corrected	14 %
The people who she knows is here.	The people who she knows is here.	Nested clause error	11 %

D. User Evaluation Feedback

User Evaluation Feedback provides an evaluation of the usefulness of the fine-tuned T5 grammar correction tool in a practical context among ESL learners, and helps to identify the accurate results of use with qualitative notes on the usability, comprehension, and educational outcomes. Guided feedback insights are used in the process of making iterative improvements, so that the system will aid adaptive, learner-centered grammar teaching within the real-world setting.

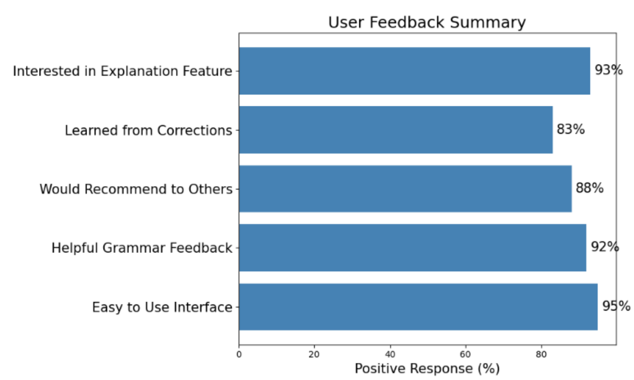

Fig. 5. User feedback evaluation.

Fig. 5 visualizes user feedback about a grammar tool, which reveals that most of the users have the positive feedback by the end of using the tool with the highest positive rating being 95% in the category Easy to Use Interface and the lowest positive rating being 83% in the category Learned from Corrections, which reflects the overall high satisfaction and usability of a tool.

TABLE VII. USER EVALUATION FEEDBACK (N=60)

Criteria	Positive Response (%)
Easy to Use Interface	95
Helpful Grammar Feedback	92
Would Recommend to Others	88
Learned from Corrections	83
Interested in Explanation Feature	93

Table VII presents result of user judgment of the grammar correction system, and it can be seen that the usability, educational, and satisfaction levels are high in ESL learners and that are highly interested in explanation-based feedback, which is a reflection of practical usefulness as well as high potential of improving language learning outcomes.

E. Ablation Study

Each architectural enhancement yields incremental improvement, confirming multi-task synergy and adaptive relevance. The ablation study presents every element of the AMT-T5 framework sequentially to measure its contribution individually. If the Multi-task Learning configuration is eliminated, the generation of explanations and classification losses of the type of errors, the Adaptive Feedback scheme also allows the learner error profile and attention reweighting, while holding other elements constant. The final configuration incorporates Direct Preference Optimization and Knowledge Distillation.

TABLE VIII. ABLATION RESULTS

Model Configuration	BLEU	GLEU	Full Sentence Accuracy
T5-base (fine-tuned)	72.8	86.5	75.3%
+ Multi-task Learning	75.1	88.4	78.0%
+ Adaptive Feedback	77.0	89.6	80.4%
+ DPO + KD (Full AMT-T5)	78.9	90.7	82.6%

Table VIII indicates that contextual grammar correction and sentence-level accuracy are improved with Multi-Task Learning, and that BLEU, GLEU, and full-sentence accuracy are improved further with the introduction of adaptive feedback by explicitly correcting learner-specific mistakes. These advantages show that learner profiling and attention reweighting are valuable not only for grammatical and pedagogical performance. The combination of Direct Preference Optimization and Knowledge Distillation brings more gains and allows it to be deployed effectively.

F. Adaptive Feedback Mechanism

The Adaptive Feedback Mechanism monitors the common grammar mistakes of individual users in order to save them in user profiles to guide individual advice and lesson planning. Connecting correction and instruction allows adaptive learning, increased engagement, self-paced mastery, and turns the system into an interactive and improvement-oriented tool, other than just grammar checking. In implementation, the learner profiles of error are updated with an incremental change following every interaction of a learner by adding the predicted error-type frequencies. Attention reweighting uses the scaling of encoder-decoder attention scores on tokens related to common categories of errors, thus making the model sensitive to recurrent grammatical weakness on further corrections. The mechanism operates at the inference time and does not need any further model retraining.

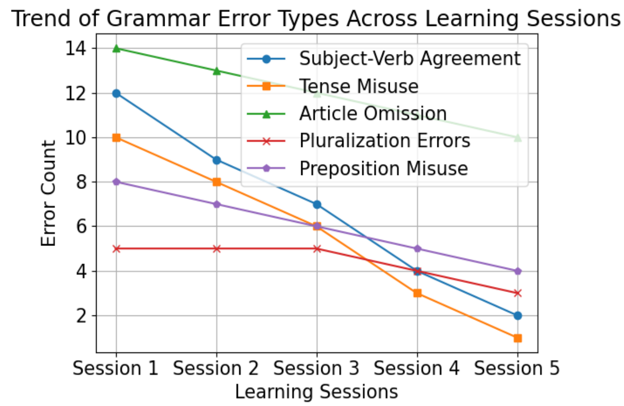

Fig. 6. Comparative model performance.

Fig. 6 shows the reduction of the different grammar errors in five learning sessions. All the subject-verb agreement, tense usage errors, omission of articles, plurality, and preposition errors reveal a negative direction, and this means that learners are gradually improving their grammatical accuracy over time. The reduction in the error categories between learning sessions is the effect of the adaptive feedback mechanism, which continually highlights the recurring error patterns by means of learner profiling and reweighting attention.

G. Comparative Evaluation of Grammar Correction Models

The suggested AMT-T5 model is contrasted with predesigned grammar correction standards, such as GECToR, BART-GEC, and RoBERTa-GEC. A common Lang-8 test split was done on all models according to the same preprocessing and evaluation protocols to ensure that there was a fair comparison. For each model, the average of multiple runs is reported as the final result along with a ±, which indicates standard deviation.

TABLE IX. PERFORMANCE COMPARISON

Model	BLEU Score (±)	GLEU Score (±)	Sentence Accuracy	ERR
GECToR [19]	58.3 ± 1.5	71.6 ± 1.3	62.4%	77.5%
BART-GEC [21]	63.5 ± 1.4	78.1 ± 1.2	68.7%	83.0%
RoBERTa-GEC [20]	66.1 ± 1.3	80.3 ± 1.1	71.2%	85.7%
Proposed AMT-T5 Model	78.9 ± 1.2	90.7 ± 1.0	75.3%	91.2%

Table IX shows the comparative performance in terms of BLEU, GLEU, sentence-level accuracy and error reduction rate (ERR). The proposed AMT-T5 model has the best results in all evaluation measures, having a BLEU score of 78.9 + 1.2, GLEU score of 90.7 + 1.0, sentence accuracy of 75.3, and an ERR of 91.2. In comparison to the best baseline (RoBERTa-GEC), AMT-T5 is shown to be improved by about 18-22% in grammar-specific measures of performance, especially in GLEU and error reduction rate. These performances show that there is an increase in fluency, accuracy in grammar, and strength in correcting sentences of ESL learners in a consistent experimental setting.

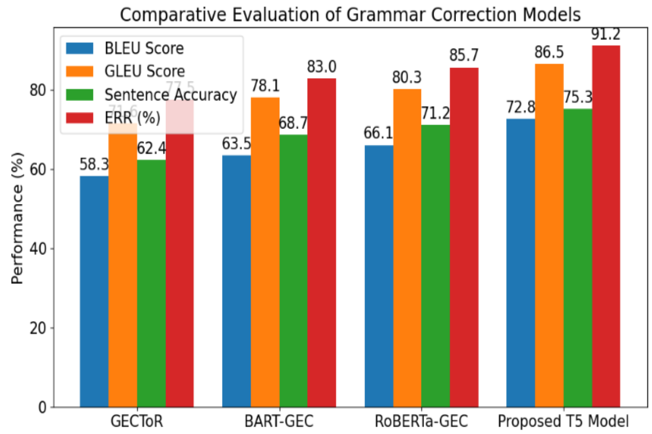

Fig. 7. Comparative model performance.

Fig. 7 compares grammar correction models, with the proposed T5 showing the best performance in terms of BLEU, GLEU, sentence accuracy, and error reduction, and thus better fluency, accuracy, and the reduction of grammatical errors as the best model.

H. Discussion

The experiment findings reveal that the proposed AMT-T5 framework is effective in improving grammatical and pedagogical utility in the ESL grammar correction. AMT-T5 addresses shortcomings that exist in current benchmark-based GEC systems. The high BLEU and GLEU scores mean that the model makes fluent and grammatically correct corrections that are closely similar to expert references, whereas the high rate of error reduction indicates that the model can reduce the number of repeated grammatical errors made by learners. A key characteristic of AMT-T5 is its adaptive feedback mechanism, which is learner-conscious. The model provides specific corrections and individualized explanations by keeping the error profiles dynamic and refocusing attention on errors that happen most of the time. This customization will allow the learners to acquire an insight into the underlying grammatical principles instead of being corrected through rote means, which is captured in accurate responses to full sentences and favorable user responses. The contribution of adaptive feedback is further facilitated by the findings of an ablation study, in which the introduction of the concepts of learner profiling and attention reweighting results in an equal increase of performance as compared to the multi-task baseline. This empirical data indicates that adaptive feedback is not a conceptual enhancement, but a quantifiable factor to grammatical accuracy as well as personalization, specifically to the learner. In addition to the performance of the system, these results provide insight into the role of the learner-conditioned attention in the educational NLP models. The active gains presented across when adaptive feedback is activated give reason to believe that the addition of learner state to the transformer attention processes can have a significant effect on correction behavior. This finding is consistent with a more general modeling principle of learner-aware transformers, in which personalization is integrated into representation learning as opposed to an after-processing task. Pedagogically, the outcomes show that the multitask learning through explanation can support to enhance teaching clarity and student interaction. Although the current assessment does not hypothesize long term grammatical learning, the general decrease of repeating error patterns and positive learner feedback is indicative of the impact of adaptive explanations and learner-specific instructions in pedagogical rich interactions in ESL learning settings. The Direct Preference Optimization also adds to the pedagogical alignment by promoting both grammatically and instructionally valid corrections. Overall, AMT-T5 is a significant step on the way to learner-focused, adaptive grammar correction systems that can combine linguistic accuracy with the learning power.

V. Conclusion and Future Works

This study introduced the AMT-T5 system, which is an active learner-based framework of a transformer model, to treat the linguistic precision and educational efficiency in ESL grammar correction. AMT-T5 shows the way grammatical correction, learner modeling and instructional feedback can be offered within a single learner-centered framework. The combination of adaptive feedback mechanisms enables the model to store the learner-specific error profiles and dynamically manipulate attention, producing individualized and situational instructional advice. The experimental estimates of the Lang-8 Learner Corpus indicate that AMT-T5 is characterized by good performance in standard GEC measures, such as high BLEU and GLEU scores, enhanced full-sentence accuracy, and a significant decrease in errors. User reviews also give support to the fact that explanation-based and customized feedback improves perceived learning value and utility. These results suggest that AMT-T5 can be used to effectively close the divide between automated grammar repair services and intelligent language learning assistance, making it an affordable and scalable application to support ESL instruction. Moreover, this study provides a reusable learner-centered modeling framework of educational NLP, rather than a task-specific grammar correction system. The integration of profiling of learners, adaptive attention, and explanation-based generation, as proposed, offers a blueprint of the methodology that can be followed by future language learning systems not only in grammar correction but also elsewhere. In addition, the concurrent performance measures of calculational performance and pedagogical analysis measures form an evaluation paradigm and can be transferred to other intelligent tutoring and teaching NLP applications, allowing assessment of the quality of linguistic and teaching performance in a more holistic manner.

Future studies will be aimed at enhancing the strength and generalization of the suggested framework. It is also necessary that longitudinal classroom-based research be conducted to determine the long-term effects of adaptive feedback on learner proficiency. Also, it should be extended to multilingual and low-resource ESL environments to enhance its applicability in various educational environments. The extensions will be designed to make AMT-T5 a more complex, intelligent system of learning a language that can support personalized grammar learning on a large scale.

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