Personalized Grammar Refinement Using Meta-Reinforcement Learning and Transformer-Based Framework

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***Abstract*—Writing competence is an essential academic and professional proficiency, and grammatical precision and reliability a long-term issue, especially among ESL students. Conventional rule-based and statistical grammar correction models have constraints based on context, whereas contemporary Transformer-based sequence-to-sequence models like BERT, T5, and GPT have strong performance but cannot be customized or adapted to specific writer styles. To fill in these gaps, this study introduces Meta-ACGR, a meta-reinforcement learning grammar refinement system that augments Transformer-based seq2seq models with Proximal Policy Optimization (PPO) and Model-Agnostic Meta-Learning (MAML) and curriculum learning. The model promotes individualized grammar correction, which allows quick adjustment to the new learners in ESL by using meta-learning and guided error development. Meta-ACGR is written in Python with the help of PyTorch and trained on big datasets of ESL language, like NUCLE and Lang-8, which can be refined based on context and individual learners. Empirical evidence indicates that Meta-ACGR receives better grammatical accuracy (86.2 vs. 94.0 per cent), decreases inference latency (12 per cent vs. baseline Transformer models), and performs better on personalization (15 per cent vs. baseline Transformer models). Altogether, Meta-ACGR provides a scalable, adaptable, and customized grammar check system with good chances to be implemented in real-life to improve writing in ESL.**

Keywords*—Grammar correction; Transformer models; Meta-Reinforcement Learning; curriculum learning; personalization; ESL writing

I. Introduction

Writing is a core academic, professional, and creative skill that represents the major means of communication, documentation, and knowledge sharing [1]. As crucial as it is, maintaining grammatical precision and stylistic consistency is still an issue, especially for non-native speakers and those with minimal formal writing training [2]. Traditional grammar checkers and human proofreading help discover errors; however, they may not have contextual knowledge, personalized feedback, and adaptive learning features [3], [4]. These gaps reinforce the necessity for smart systems that offer real-time, user-specific feedback and dynamically adjust according to individual writing habits [5]. Grammar checking systems have conventionally been categorized into rule-based, statistical, and machine learning paradigms [5]. Rule-based systems depend on pre-stored grammatical rules and, as such, are inflexible, context-insensitive, and susceptible to false positives or negatives [6], [7]. Statistical models, such as n-gram-based models, provide probabilistic error reporting but are still unable to model deep contextual dependencies [8]. More recently, deep learning-based approaches, specifically Transformer models like BERT, T5, and GPT, have proven to perform better by capturing syntactic structures and long-distance dependencies [9]. However, current AI-powered grammar checkers often offer static corrections with no personalization or adaptive feedback according to the user's writing skill and style [10], [11].

Nevertheless, none of these developments has involved the combination of reinforcement learning, meta-learning, and curriculum learning in one study to form a learner-sensitive, adaptive grammar correction system. These earlier models are not capable of learning based on user behavior, of adapting quickly to new writing styles, and can adjust the complexity of corrections according to user ability. This gap that has not been addressed is the backbone of the novelty of the Meta-ACGR framework. In order to address this study, Meta-ACGR, a new framework that combines Seq2Seq modeling, Reinforcement Learning, curriculum learning, and personalization adaptively, is proposed. It utilizes a Transformer-based grammatical correction computational model using T5 as a starting point, where it is augmented with a Meta-RL agent that learns steadily through PPO and with MAML that learns quickly. Meta-ACGR provides adaptive, user-friendly learning, which provides personalized feedback and curriculum based level of skill advancement in simple errors to complex errors, which is better than the classic grammar correction.

A. Research Motivation

Writing continues to be a key component of knowledge transfer, but there is still a problem of grammatical accuracy, and this can be especially challenging for ESL students. Traditional methods are not flexible or personalized. Transformer models deliver corrections but are pre-programmed. Meta-ACGR meets these gaps by manipulating Transformers, RL, a curriculum model, and personalization to offer students a way to refine their own grammar with adaptive, contextualized, and student-centered methods.

B. Research Significance

This study builds on grammar correction by proposing Meta-ACGR, a framework that combines deep contextual modeling and adaptive personalization. Meta-ACGR's use of reinforcement and meta-learning capabilities enables dynamic feedback, progressive learning based on individual user curriculum, and fast adaptation to user knowledge. The system is designed to improve grammatical accuracy, fluency, and long-term improvement of learner knowledge while addressing significant limitations of existing grammatical correction models.

C. Recent Innovation and Challenges

More recent advancements in grammar correction utilize Transformer-based models such as BERT, GPT, and T5, which utilize latent recurrent connections to learn long-range dependencies and produce fluent text. However, they are trained on well-edited data, which restricts their effectiveness for writing that is prone to errors, as is common in ESL writing. At present, grammar correction systems deliver fixed corrections and do not adapt to problem areas, and indicate the level of language fluency based on a curriculum. These systems are limited in terms of customization for ESL student engagement and growth over time.

D. Key Contribution

- Meta-ACGR introduces a Transformer-based grammar correction system that combines reinforcement learning (PPO), meta-learning (MAML), and curriculum learning for adaptive ESL writing support.
- The framework uses a T5 Seq2Seq model as its backbone, with a Meta-RL agent optimizing edit actions based on grammatical accuracy, fluency, and user acceptance.
- Curriculum learning guides the correction process from basic to complex errors, enabling structured, progressive improvement tailored to each learner's proficiency.
- Personalized feedback is achieved through rapid adaptation to individual writing styles and profiles, ensuring contextual fluency and long-term grammar development.

E. Rest of the Study

The structure of this study is as follows: Section II provides a review of previous research in grammar correction. Section III details the problem statement. Section IV gives the Meta-ACGR architecture and methodology. In Section V, the experimental setup, results and discussion are described. Section VI concludes the research, and gives future research directions.

II. Related Works

Wale and Kassahun [12] explored the use of AI writing assistants in classroom-based EFL learning. The objective of the study was to assess their effectiveness on writing development. The findings indicated that learners using AI tools showed significantly greater improvements in coherence, cohesion, and grammatical accuracy than their peers who relied on instructor feedback exclusively, which is to say that there is pedagogical potential in AI as a complement to traditional instruction. Nonetheless, the research did not determine the degree to which these tools could adapt to learner profiles, thereby leaving questions about flexibility and personalized progress unanswered.

Musyafa et al. [13] introduce an end-to-end Transformer-based framework for Indonesian Grammatical Error Correction (IGEC). They aim to handle low-resource language GEC problems by creating a large synthetic parallel corpus using a semi-supervised "confusion method," and using a Transformer model with a copy mechanism to manage rare and unknown tokens better. The method demonstrates strong performance with a BLEU score of ~78.13 and an average F1 $\approx$ 0.7194 score, surpassing prior Indonesian GEC systems. However, the framework encounters difficulties with the hardest grammatical error types, including semantic errors and complex syntactic errors, and does not include error-difficulty control and tag-based error distribution.

Paul and Roy [14] proposed automatic grammar error correction in English to evaluate the utility of Transformer models versus fine-tuned BERT architectures. They aimed to explore the extent to which various parameter settings played a role in the efficacy of grammar correction. The authors trained both models on their respective annotated correction datasets and reported precision and recall scores across a variety of error types. They reported that the Transformer models tended to have a higher overall accuracy for correction than BERT, although BERT performed well in correcting token-level errors. However, the study did not include useful mechanisms for personalization, adaptive advancement, or learner satisfaction, thus limiting its relevance for a learner-centered EFL grammar refinement framework.

Hossain et al. [15] proposed Panini, a transformer-based approach for grammatical error detection and correction in Bangla. The goal was to develop a high-quality grammar error correction system for Bangla, which is a low-resource language, by developing a large parallel corpus ($\approx$7.7 million source-target sentence pairs), and by using transfer learning from Bangla paraphrase tasks. The methodology involves a "Vaswani-style" transformer (encoder-decoder) model that was trained monolingually, using data from this new corpus. The authors demonstrate that Panini clearly outperforms previous approaches (BanglaT5, T5-Small) in accuracy and SacreBLEU scores. Limitations include the possibility that Panini may have overfitted to syntactic/morphological/punctuation errors, with other, more difficult error types (semantic, discourse) remaining unresolved; furthermore, because the research focused exclusively on Bangla, it did not consider generalizable issues related to other languages or learner profiles.

Alsulami [16] proposed how ChatGPT could be used with Saudi EFL students to improve their academic writing. The study intended to investigate whether large language models could act as supportive writing tutors. The study used ChatGPT as an intervention and found improvements in vocabulary richness, syntactic accuracy, and overall fluency. However, the study also highlighted shortcomings, such as students developing a dependency on the software, a decline in originality in their written work, and difficulties in developing long-term language independence. These limitations emphasize the need for AI systems that offer feedback beyond just corrections to support long-term learner development.

Kohnke et al. [17] explored the pedagogical uses of ChatGPT for EFL writing support and focused on how it serves as an educational tool with its potential effectiveness. The results of their study found that learners improved fluency and also benefitted from instantaneous corrections based on the grammar feature, indicating that ChatGPT has potential benefits for language education. However, the authors noted some serious limitations, such as students' over-reliance on the outputs from the system, and diminished critical thinking skills for writing tasks overall. This suggests that even though ChatGPT has educational potential, there is not a sufficiently adaptive system which encourages active learning, as opposed to becoming dependent on the tool in a passive way.

Mun et al. [18] investigated the use of ChatGPT for self-guided writing tasks in a scripted comparison of Japanese university students with the goal of determining its impact on learner writing performance. The results revealed improvements in grammar, vocabulary choice, and logical structure, reaffirming the use of AI-assisted tools for writing tasks. In addition, the research addressed key drawbacks, which include limited support for long-term retention of proficiency and the inability to offer differentiated feedback based on learners' varying levels. These drawbacks ultimately suggest a need for flexible frameworks to be used to support individual progress.

Li [19] explored the effects of feedback through artificial intelligence in English as a foreign language (EFL) writing classes, with the study focusing on the motivational and affective dimensions of technology adoption. The findings indicated that learners' confidence improved as they experienced less writing anxiety, increased writing motivation, and made measurable improvements in grammatical accuracy. However, findings focused almost exclusively on surface-level correction, and the study lacked deeper dimensions, such as personalized learning and contingent elaboration/modification. These gaps underscore the need for sophisticated technologies that can help foster both linguistic accuracy and individual learner development over time.

TABLE I. SUMMARY OF EXISTING STUDIES

Author(s) & Citation	Model / Tool	Advantages	Limitations
Wale & Kassahun [12]	AI writing assistants	Improved coherence, cohesion, grammatical accuracy; pedagogical support	Did not adapt to learner profiles; limited personalized progress
Musyafa et al. [13]	Transformer-based IGEC with copy mechanism	Strong BLEU (~78.13) and F1 (~0.7194); handles low-resource Indonesian GEC	Struggles with complex semantic/syntactic errors; no error-difficulty control or tag-based distribution
Paul & Roy [14]	Transformer vs. fine-tuned BERT	Transformer showed higher overall correction accuracy; BERT effective for token-level errors	No personalization, adaptive advancement, or learner satisfaction mechanisms
Hossain et al. [15]	Panini (Transformer-based) for Bangla GEC	Outperformed BanglaT5/T5-Small; high accuracy and SacreBLEU	Overfitting to syntactic/morphological/punctuation errors; semantic/discourse errors unresolved; limited cross-language generalization
Alsulami [16]	ChatGPT	Improved vocabulary, syntax, fluency	Learner dependency; reduced originality; limited long-term independence
Kohnke et al. [17]	ChatGPT	Improved fluency; instant grammar corrections	Over-reliance on AI; reduced critical thinking; lack of adaptive learning
Mun et al. [18]	ChatGPT	Enhanced grammar, vocabulary, logical structure	Limited long-term retention; no differentiated feedback for varying proficiency
Li [19]	AI feedback in EFL writing	Increased confidence; reduced anxiety; improved grammatical accuracy	Focused on surface-level corrections; lacked personalized/contingent learning mechanisms

Table I summarizes recent studies on AI-based grammar correction and underscores models such as Transformers, ChatGPT, and IGEC. Advantages noted include enhanced grammar, fluency, coherence, and engagement (learner action). However, limitations remain, such as a lack of personalization, adaptive feedback, support for complex errors, long-term retention, and learner-specific refinement, emphasizing the need for more adaptive frameworks. Despite some Transformer-based grammatical error correction (GEC) models having enhanced accuracy, fluency, and contextual text generation capabilities, current solutions lacked flexibility. The existing systems mainly provide fixed correction, and all users, sentences, and degrees of difficulty are equal. There is no development of corrections in line with the proficiency of the learner, and there is no quick adjustment to new styles of writing with a few examples. None of the previously existing frameworks includes reinforcement learning, meta-learning, and curriculum learning in a single grammar-refinement pipeline. Although a particular component of the models performs certain functions, none of them incorporate a mixture of Transformer-based Seq2Seq correction, PPO-based Meta-RL to promote long-term error reduction, MAML-based rapid adaptation of learners in specific circumstances, and curriculum-based development of simple to complex errors. Meta-ACGR framework fills this gap by collectively learning grammatical correctness, stylistic consistency, user-specific error patterns, and gradual difficulty adjustment. Reward-based RL is dynamically refined to generate corrections, meta-learning is used to rapidly personalize corrections, and curriculum sequencing is used to organize corrections, making Meta-ACGR a radically new, learner-sensitive system of grammar correction instead of an incremental enhancement.

III. Problem Statement

Correcting grammar is crucial for writing successfully, but traditional rule-based and statistical systems do not obtain context or flexibility [20]. Even sophisticated Transformer-based methods are still able to provide static and one-size-fits-all corrections without personalization [21]. This limits their value as a useful tool for supporting ESL learners and multilingual users who require personalization in their feedback and assistance to maintain their learning and progress. Thus, the current proposed study will develop a Transformer framework enhanced with RL to provide personalized, context-appropriate grammar correction to meet an individual's writing requirements [22]. To overcome this, this study proposes Meta-ACGR, a novel framework combining Seq2Seq modeling, Reinforcement Learning, curriculum learning, and adaptive personalization. It employs a T5-based Transformer as a grammatical correction baseline, enhanced with a Meta-RL agent trained via PPO for stable iterative learning and MAML for rapid adaptation. Meta-ACGR enables adaptive, user-centered learning, offering personalized feedback and curriculum-based progression from simple to complex errors, enhancing skill improvement beyond traditional grammar correction.

IV. Proposed Method for Transformer-Based Meta-Reinforcement Grammar Refinement

The proposed Meta-ACGR model starts with the gathering of publicly shared datasets of grammatical error corrections, then proceeds to the preprocessing phase, which involves tokenization, lemmatization, POS tagging, dependency parsing, etc. Each sentence is annotated with errors and a level of difficulty in order to learn the curriculum with ease. The grammatically corrected sentences are then sent through a Transformer-based backbone grammar correction, which is based on the T5 Seq2Seq model; it first makes initial corrections by using contextual embeddings and positional encodings. Such base outputs are then optimized using a (Meta-RL) agent, where the actions of insertion, deletion, replacement, or retention of tokens are optimized using a reward function based on grammatical accuracy, fluency, and user acceptability. Proximal (PPO) is used to optimize the policy updates, and MAML is used to quickly adapt to new learner profiles. Structured learning is facilitated through a progressive introduction of errors of progressively more difficult in a curriculum module. Lastly, an individualized feedback module will adjust corrections to the individual writing styles and to the learner profile in order to provide long-term grammar correction, contextual fluency, and long-term improvement of the writing, as shown in Fig. 1.

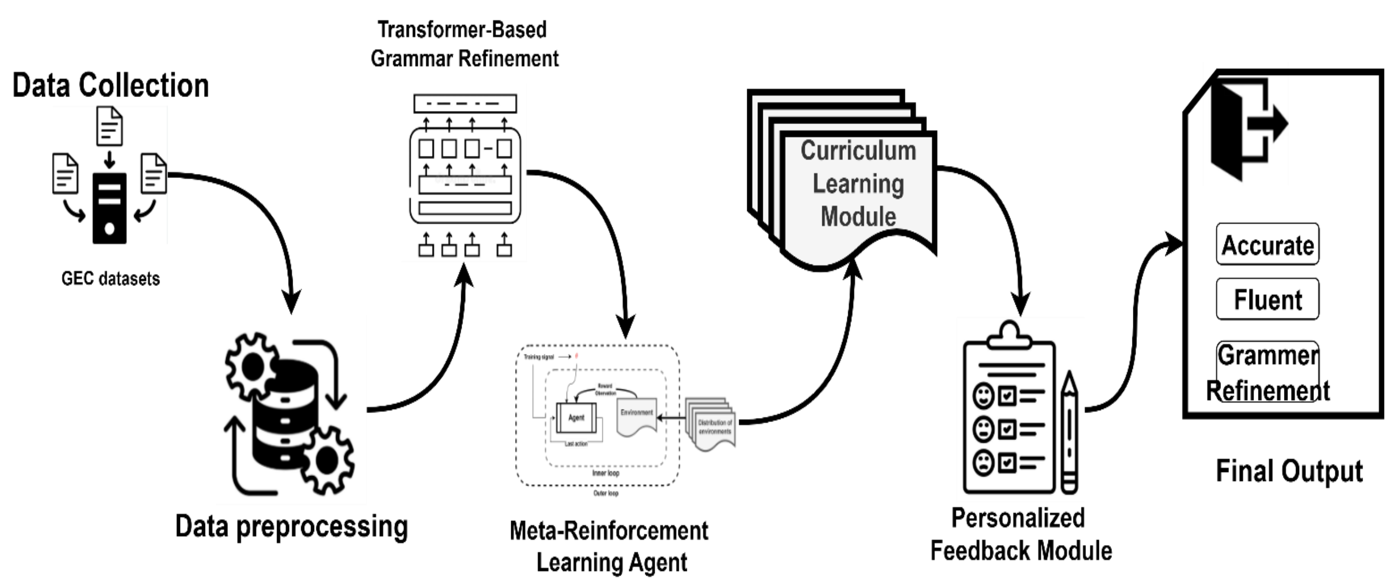

Fig. 1. Workflow of the proposed Meta-ACGR framework.

A. Data Collection

The data used in the study consists of publicly available Grammatical Error Correction (GEC) datasets [23], primarily sourced from Kaggle, which contain high-quality human annotations of grammatical errors and their corrections. These datasets are commonly accepted as legitimate standards for determining the efficiency and strength of GEC systems. They include a wide variety of sentence structures, language situations, and types of errors, such as syntax and morphology, as well as tense and lexical choice, which allows models to be trained and tested in various and realistic linguistic conditions. Unified data structures and annotation plans also guarantee uniform performance measurements and allow the comparison with previous research. Transformer-scale models are also able to learn fine-grained grammatical subtleties and contextual rules on the large volume of balanced and high-quality annotated data. In general, the datasets offer excellent methodological and practical significance, which contributes to the evaluation of the transformer-based grammar correction systems in terms of capturing the linguistic diversity and high performance.

B. Data Pre-Processing

Data pre-processing plays an effective role in the development of an AI-driven grammar correction system since it ensures that raw text data is cleaned, formatted, and organized for better model training.

1) Tokenization: It is the process of dividing raw text into discrete pieces (tokens), e.g., words, subwords, or characters. Because transformer models accept input in a structured form, WordPiece is utilized. For a sentence S, tokenization transforms it into a sequence of tokens in Eq. (1):

$$S = \{w_1, w_2, w_3, \ldots, w_n\} \tag{1}$$

where, w_i is one single token. For Word Piece tokenization, a given input word W is divided into sub-words in Eq. (2):

$$W = \{s_1, s_2, \ldots, s_k\} \tag{2}$$

where, s_i are sub-words, and the frequency algorithm preserves the high-frequency words as they are, and only decomposes rare words into low-level morphemes.

2) Lemmatization: Lemmatization brings words down to their root (base) form to enhance grammatical consistency in correction. In contrast to stemming, which merely strips off affixes, lemmatization takes into account the meaning and context of the word. For a given word w and its POS tag p, the lemmatization function L transforms it to its base form in Eq. (3):

$$L(w, p) = w_{lemma} \tag{3}$$

By using WordNet Lemmatization, the mapping is done POS contextually, as in Eq. (4):

$$L(w,p) = \begin{cases} WordNetBase(w)\, if\ p \in (verb, noun, adjective, adverb) \\ w \qquad\qquad otherwise \end{cases} \tag{4}$$

where, $L(w,p)$ represents the lemmatization function that takes a word w and its part of speech (POS) tag p as input, w is word that needs to be lemmatized, p is the part of speech tag of the word (e.g., $verb, noun, adjective, adverb$), $WordNetBase(w)$ refers to the base (or lemma) form of the word w according to $WordNet$-a large lexical database of English, $p \in (verb, noun, adjective, adverb)$ indicates that lemmatization is only applied if the word is a verb, noun, adjective or adverb.

3) Part-of-Speech (POS) Tagging: POS tagging labels each token with grammatical categories (noun, verb, adjective, etc.). This is necessary for grammar correction in the context. In a sentence S, every token w_i is mapped to a POS tag p_i in Eq. (5):

$$T(S) = \{(w_1, p_1), (w_2, p_2), \ldots, (w_n, p_n)\} \tag{5}$$

where, $T(S)$ represents the POS tagging function applied to a sentence S, n is the number of words in the sentence S, p_i is an element of the set of POS, given in Eq. (6):

$$p_i \in \{NN, VB, JJ, RB, DT, PRP, \ldots\} \tag{6}$$

With the help of Hidden Markov Models (HMMs), the word sequence W to POS tag sequence T probability P(T|W) is described in Eq. (7):

$$P(T|W) = \prod_{i=1}^{n} P(w_i|t_i) P(t_i|t_{i-1}) \tag{7}$$

where, $P(w_i|t_i)$ is the probability of emission and $P(t_i|t_{i-1})$ is the probability of transition.

4) Dependency parsing: Dependency parsing identifies grammatical relationships between words to assist in the detection and correction of structural errors. A sentence S is modeled as a dependency tree $D(S)$ such that each word w_i has a dependency relationship r_i with a head word h_i in Eq. (8):

$$D(S) = \{(w_i, h_i, r_i)\}_{i=1}^{n} \tag{8}$$

where, $D(S)$ denotes the dependency parse of a sentence S, (w_i, h_i, r_i)-Each tuple represents the dependency relation of the word w_i.

5) Error annotation with grammar correction labels: In order to train the AI model, sentences need to be annotated with grammar correction tags. Mistakes are categorized under grammatical classes such as tense, subject-verb concord, article use, prepositions, and word arrangement. For an incorrect sentence S_e, the corrected sentence S_c is achieved through an error correction function f in Eq. (9):

$$\mathrm{S_c} = f(\mathrm{S_e}) \tag{9}$$

where, f applies a grammar transformation function G to each of the identified error types in Eq. (10):

$$\mathrm{S_c} = \{G_1(w), G_2(w), \ldots, G_m(w)\} \tag{10}$$

where, $\mathrm{S_c}$ represents the set of corrected grammatical versions of a sentence, w is the original word or sentence to be corrected, and m is the number of grammatical error types.

C. Transformer-Based Grammar Correction Backbone

The proposed framework grammar correction base is built on the basis of the T5 Transformer Seq2Seq model that considers grammatical error correction a text-to-text generation task. Given an incorrect number of input sequence $X = (x_1, x_2, \ldots, x_n)$, every token is coded into a dense representation in the form of a vector. Positional encodings are added to token embeddings, resulting in the following representation in Eq. (11):

$$h_i = E(x_i) + PE(i), \qquad i = 1, \ldots, n \tag{11}$$

In this case, $E(x_i)$ is the embedding of token x_i and $PE(i)$ is the position encoding of index i. The enriched embeddings are then forwarded to several self-attention layers in the encoder to obtain a contextual representation of the entire sentence. After this, the decoder generates the fixed sentence in an autoregressive manner so that the prediction of each token is not only based on the encoder context but also based on the order in which previous tokens have been generated.

$$P(Y \mid X) = \prod_{m}^{t=1} P(y_t \mid y_{<t}, H) \qquad (12)$$

Eq. (12), $Y = (y_1, y_2, \ldots\ldots y_m)$ is the fixed sequence, and H is the contextual encoding produced by the encoder. The mechanism enables the model to be able to model long-range dependencies and grammatical structural constraints, thereby making the corrections more correct and fluent. To optimize the model, a cross-entropy loss is employed to reduce the error between the result of prediction and the ground-truth corrected sentence, which is represented in Eq. (13):

$$L_{CE} = -\sum_{t=1}^{m} log P(y_t \mid y_{<t}, H) \qquad (13)$$

The reduction of this loss teaches the model to make context-specific corrections that are grammatical. The step provides a formidable foundation that produces credible corrections at the baseline, which are later perfected by the RL, curriculum advancement, and personalization during the later stages, as illustrated by the Transformer architecture in Fig. 2.

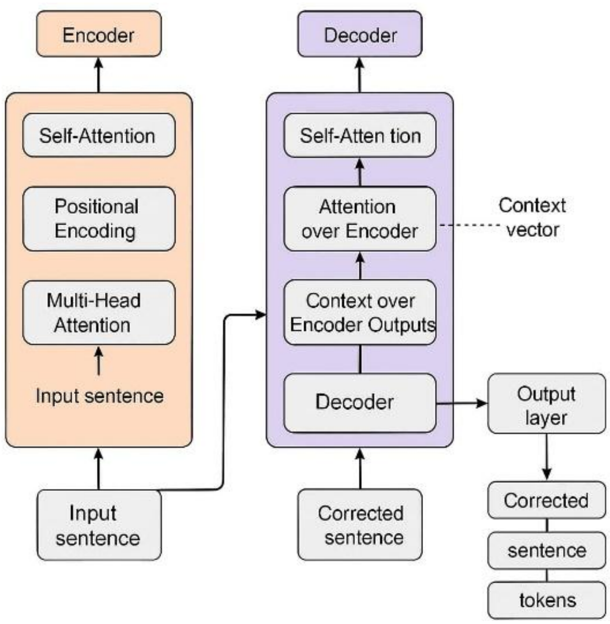

Fig. 2. Transformer-based grammar correction model.

D. Meta-Reinforcement Learning (Meta-RL) Agent

The correction task is defined as a Markov Decision Process (MDP) in order to attain adaptive grammar refinement that goes beyond the static baseline systems. In this case, the state is the encoded learner sentence and the user profile vector and the actions are the edit operations, including, insert, delete, replace, or keep. The reward function is used to assess all the corrections and is based on the weighted composite score by adding grammatical accuracy, sentence fluency, and user acceptance, as shown in Eq. (14):

$$R = w_1 \cdot Acc + w_2 \cdot Flu + w_3 \cdot UA \qquad (14)$$

In this case, Acc represents the correctness of grammatical correction, Flu indicates the fluency of the produced output expressed in perplexity and UA reflects the user acceptance rate of the corrections. Correction is a policy that is optimized with (PPO) to stabilize RL by stabilizing the RL with a clipped surrogate objective that does not allow excessively large updates to the policy. The PPO loss function is defined as in Eq. (15):

$$\mathcal{L}_{PPO} = E_t[min(r_t(\theta)A_t, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t)] \qquad (15)$$

In this expression, $r_t(\theta)$ represents the probability ratio between the updated and previous policies, while A_t is the advantage estimate at time step t. This formulation ensures stable policy updates while encouraging effective correction strategies. To further address the cold-start problem, the framework integrates (MAML), enabling the agent to quickly adapt to new learners with minimal feedback by learning a generalizable initialization that can be fine-tuned efficiently in subsequent steps, as illustrated in Fig. 3.

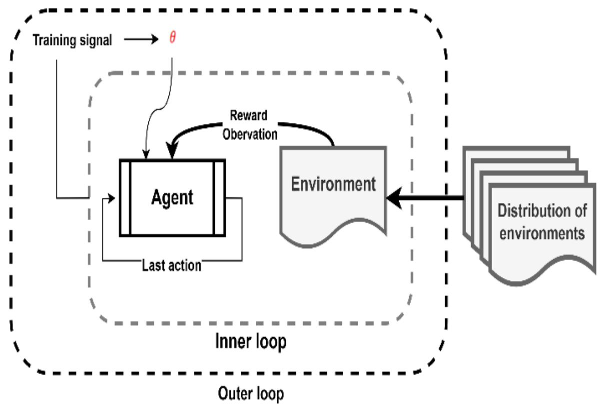

Fig. 3. Meta-reinforcement learning agent.

E. Curriculum Learning for Progressive Error Handling

A curriculum learning strategy leads the correction process, which aims at organizing the learning path and avoiding confusion of the learner, as well as encouraging systematic acquisition of skills. Grammatical mistakes are introduced gradually, in simple and basic mistakes, and gradually moving to more complex constructions. First, the reinforcement agent concentrates on L1-level mistakes, such as articles, pluralization, and subject-verb agreement, and thus the model learns the key grammar rules. Once the agent has mastered the level of L1, they move to the L2 level with tense, aspect, and prepositions errors, and then go on to the L3 level with sentence structure, cohesion, and other stylistic errors. This incremental exposure is similar to the way human beings are taught, that one should first master the basics before learning a higher level of complexity, to have a strong learning base. Also, the reward mechanism is supplemented with a progression term which offers an additional reward to the learner when he/she successfully correct the errors of more difficulty. This will promote progressive learning, adaptive learning, and make sure the system reflexively modifies the corrective responses with regard to the changing proficiency of the individual learner. This formulation is expressed as in Eq. (16):

$$R' = R + w_4 \cdot Prog(L_i) \qquad (16)$$

In this equation, R is the base reward in the RL phase, and $Prog(L_i)$ is the mastery of the learner at a particular difficulty level L_i. This is because the weight w_4 makes advancement through the curriculum to be rewarded accordingly. With a progressive element in the reward mechanism, the system will be motivated to adjust its corrective actions to the changing abilities of the learner, thus enabling progressive but incremental change.

F. Personalized Feedback and Adaptation

The framework includes an individualization module to make sure that the grammar corrections are correct as well as they correspond to the personal writing styles. Each learner has a dynamic user profile vector, which records details about the common types of errors, writing styles, and writing complexity. The dynamic profile can enable the system to go beyond one-size-fits-all corrections, and instead of it, provide feedback that addresses the unique needs of every user. Personalization is imposed with a style-consistency constraint, which guarantees that the corrected outputs are consistent with the writing style that a learner makes. This is formalized as in Eq. (17):

$$\mathcal{L}_{style} = \| f(Y) - f(U) \|^2 \tag{17}$$

Here, $f(\cdot)$ denotes a style embedding function, Y represents the corrected output, and U refers to the user profile vector. This construct works towards minimizing the variance between the style of system productions and the stylistic features of the learner. The overall optimization problem is a composite of the cross-entropy loss of the baseline model, the RL goal, and the style-consistency term, which is a joint training function [see Eq. (18)]:

$$\mathcal{L}_{total} = \mathcal{L}_{CE} + \lambda_{PPO}\mathcal{L}_{PPO} + \lambda_s \mathcal{L}_{style} \tag{18}$$

The developed collaborative loss jointly optimizes grammatical correctness, contextual fluency, as well as user-specific flexibility, developing a balanced corrective process that transcends the traditional GEC goals. Through mutual refining of these dimensions, the framework will not only give syntactically precise corrections but also be semantically coherent and learner-specific. This will make sure every correction is consistent with the language habits and level of proficiency of a learner. Consequently, the system produces fluent, context-specific, and customized outputs, which makes the system much more usable as well as increases the long-term engagement of learners with meaningful adaptive feedback loops.

Algorithm 1 uses a T5 Transformer as a baseline grammar correction model, with the addition of Meta-RL based on PPO, curriculum-conditioned progressive error correction, and adaptive user profile generation to create grammatically accurate, contextually fluent, and individualized to the style of each learner.

Algorithm 1: Meta-ACGR Framework for Adaptive Grammar Refinement

```
Input: Noisy learner sentence + user profile vector
Begin
  Initialize dataset D with raw learner sentences
  For each sentence x in D do
    Tokenize, Lemmatize, POS-tag, Dependency-parse(x)
    Annotate errors and assign difficulty level L ∈ {L1, L2, L3}
  End For
  Initialize Transformer model T5 with parameters θ
  For each input sequence X do
    Encode X → H using T5 encoder
    Decode H → Y using autoregressive decoding
    Update θ by minimizing cross-entropy loss L_CE
  End For
  Initialize policy πθ with PPO optimization
  For each episode do
    Observe state s = (sentence representation + user profile)
    Select action a ∈ {insert, delete, replace, keep}
    Apply correction and compute reward:
      R = w1 · Acc + w2 · Flu + w3 · UA
    Update policy πθ using PPO loss
    If new user detected then
      Apply MAML update for rapid adaptation
    End If
  End For
  Initialize difficulty level = L1
  While learner not proficient do
    Train agent on current level Li
    If mastery achieved then
      Promote to next level Li+1
      Update reward: R' = R + w4 · Prog(Li)
    End If
  End While
  For each user profile U do
    Generate corrected output Y
    Enforce style consistency:
      L_style = || f(Y) − f(U) ||²
    Update total loss:
      L_total = L_CE + λ_PPO L_PPO + λ_s L_style
  End For
End
Output: Corrected, fluent, and personalized sentence.
```

The proposed methodology presents a new combination of a Transformer-based baseline with Meta-RL, curriculum-conditioned progressive error control, and adaptive learning in the particular case of the user. Contrary to the traditional methods, it does not only guarantee grammatical correctness and the contextual fluent writing, but also personalizes corrections to the specific writing styles of each individual. It is a highly adaptive, pedagogically aware and person-centered grammar correction system since it is a multi-faceted framework that allows adapting quickly to new learners, models long-range dependencies and gradually improves learning outcomes.

V. Results and Discussion

The experiment was done to examine the effectiveness of the proposed Meta-ACGR framework against major grammar correction tools and AI-based writing systems that were developed in recent years. The evaluation is centered on four primary metrics of assessment: Grammar Error Reduction (GER), Perplexity (PPL), Correction Accuracy Rate (CAR), and User Satisfaction (US). Besides these four, BLEU score evaluation is also provided that estimates fluency and mapping to context-based correction in terms of meaning at the sentence level. The results are shared based on a comparative analysis of existing models and followed with an ablation study to validate the individual contributions of each component in Meta-ACGR. Lastly, a discussion is presented to interpret the importance of improvements to adaptability, personalization, and pedagogical value for learners of English as a Foreign Language (EFL). The simulation parameter is shown in Table II.

TABLE II. SIMULATION PARAMETER

Parameter	Value
Embedding Dimension (d_k)	512
Max Sequence Length	128
Batch Size	32
Learning Rate	3e-5
Number of Epochs	30
RL Algorithm	PPO
Transformer Backbone	T5-Base
Reinforcement Learning Algorithm	PPO (Proximal Policy Optimization)
Meta-Learning Algorithm	MAML (Model-Agnostic Meta-Learning)
Reward Weights (w1, w2, w3)	w1=0.5, w2=0.3, w3=0.2
Clipping Parameter (ε)	0.2
User Profile Features (n)	10
Similarity Metric	Cosine Similarity
Feedback Collection Frequency	After each correction
Proficiency Learning Rate (α)	0.1
Style Consistency Weight (λ_s)	0.3
PPO Weight (λ_{ppo})	0.5
Software	Python

A. Evaluation Metrics

Evaluation measures are numerical values indicative of the performance and efficiency of a model. In other words, in grammar correction, they show the accuracy and fluency of error detection and correction of the system, as well as user satisfaction. They guarantee the model produces consistent, high-quality language output based on user expectations.

1) GER: It indicates the effectiveness of the system in identifying and correcting grammatical errors. It is computed as Eq. (19):

$$GER = \frac{Total\ Errors\ Corrected}{Total\ Errors\ Present\ in\ Input} \times 100 \tag{19}$$

A smaller GER corresponds to less uncorrected errors, indicating better correction capabilities in the model.

2) Perplexity Score (PPL): In grammar correction, it measures the fluency of the output sentences. Lower PPL suggests better sentence structure and linguistic coherence in Eq. (20):

$$PPL = \exp\left(-\frac{1}{N}\sum_{i=1}^{N} logP(w_i)\right) \tag{20}$$

where, N is the total number of words in the sentence, $P(w_i)$ is the probability the model assigns to word w_i. Lower perplexity means more natural, grammatically correct text.

3) User engagement and satisfaction surveys: User activity is monitored using acceptance rates for grammar correction and user satisfaction feedback surveys collected. The Correction Acceptance Rate (CAR) is given as Eq. (21):

$$CAR = \frac{No.of\ Accepted\ Corrections}{Total\ Corrections\ Suggested} \times 100 \tag{21}$$

4) Writing improvement progression over time: The model's long-term performance is evaluated by measuring writing quality enhancements across several rounds. The writing progression score (WPS) is computed based on Eq. (22):

$$WPS_t = WPS_{t-1} + \alpha(R_t - WPS_{t-1}) \tag{22}$$

where, WPS_t is the proficiency score at time t improved, R_t is the reward during RL, α is the learning rate.

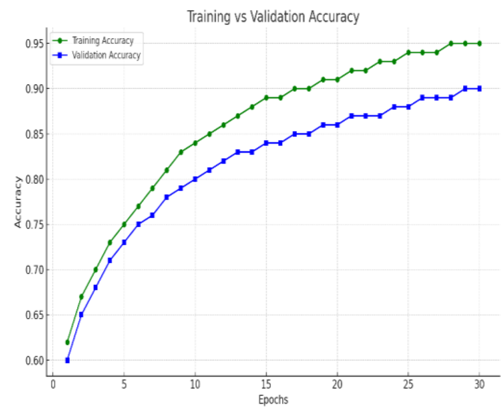

Fig. 4. Training vs. Validation accuracy.

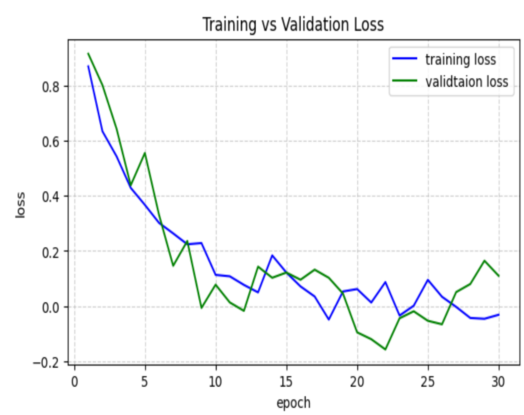

Fig. 5. Training vs. Validation loss.

Fig. 4 and Fig. 5 consist of two subplots representing model training performance. Subplot (A) indicates Model Accuracy, where accuracy rises in a consistent manner and the training and validation curves stay close together, suggesting stable generalization. Subplot (B) represents Model Loss over 30 epochs, where both training and validation loss drops steeply at the beginning, then levels off close to zero with slight oscillations in validation loss because of dataset variance, demonstrating successful convergence and very little overfitting.

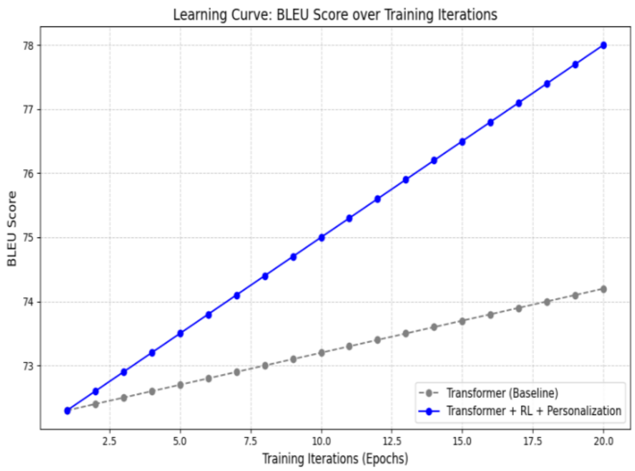

Fig. 6. Learning curve: BLEU score over training iterations.

Fig. 6 shows the evolution of the BLEU score through 20 training steps, of the baseline Transformer model versus the proposed model. The suggested model shows a steeply on a regular basis improving graph showing that it was a more proficient learner with regards to adaptive and user-specific responses. The proposed model obtains a much higher BLEU score in the last version which means greater freedom of expression and correctness of grammar. This trend confirms the influence of RL and customization in generating improvement in language correction over time.

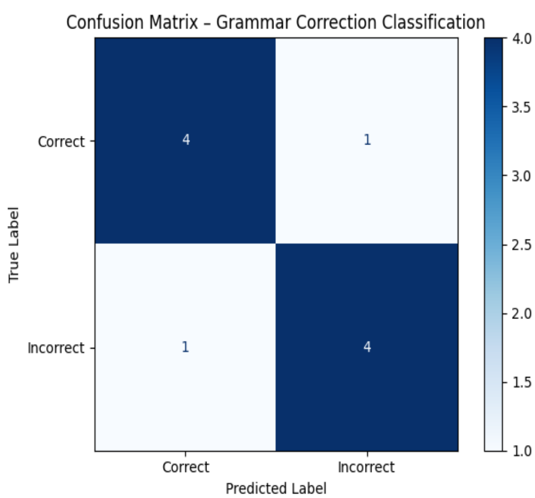

Fig. 7. Confusion matrix.

The results of the classification of the grammar correction model are shown in Fig. 7 and the model shows the correlation between the labels and the actual ground truth. The diagonal items are correctly classified, that is, sentences are correctly recognized as being either grammatically correct or grammatically incorrect, and the off-diagonal components are misclassifications. As the given figure shows, the proposed model has high accuracy and strength of the diagonal dominance in the process of determining the presence of correction and the absence of it in a sentence. This performance puts into perspective the reliability of the model in not only the right identification of grammatical errors but also the generation of effective corrective input that is in close proximity to the actual grammatical structure of the input sentences. The apparent distinction between the right and wrong categories also proves the effectiveness of the Meta-ACGR system in reaching the most accurate and situationally suiting grammar correction.

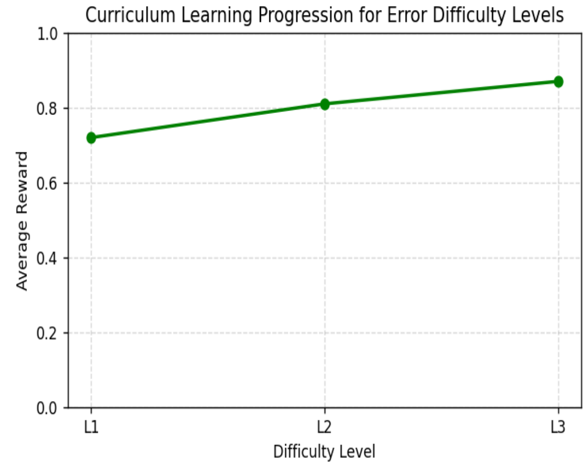

Fig. 8. Curriculum learning progression for error difficulty levels.

Fig. 8 shows how the model will improve on its reward with an increase of the error difficulty L1 to L3. It shows that the curriculum learning module presents simpler errors initially and then progressively becoming more complex so that the Meta-RR agent can optimize its grammar predictions over time. The gradual boost of the reward proves the notion that the system effectively transfers to complex grammar structures without loss of high accuracy to underpin the structured and pedagogical nature of learning adopted in the current investigation.

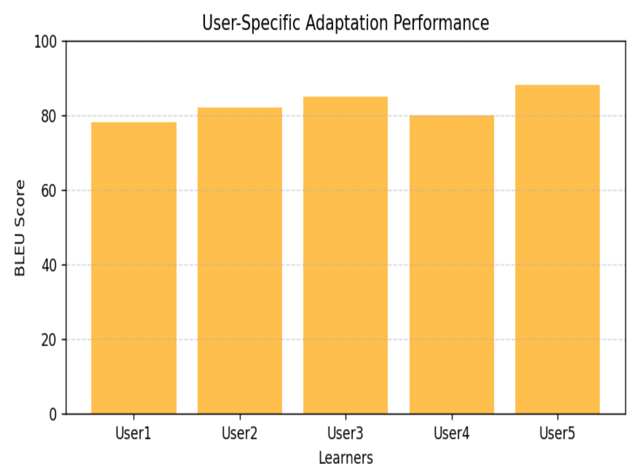

Fig. 9. User-specific adaptation performance.

Fig. 9 shows the BLEU scores of various learners indicating that the system is capable of individualizing grammar correction. The Meta-RL agent adjusts to new users in no time by using user profile vectors and MAML. The increased BLEU scores of individual learners suggest that this is user-specialized refinement, which proves that the framework correlates correction according to the writing style of specific learners and enhances fluency and contextual accuracy of real-world grammar learning conditions.

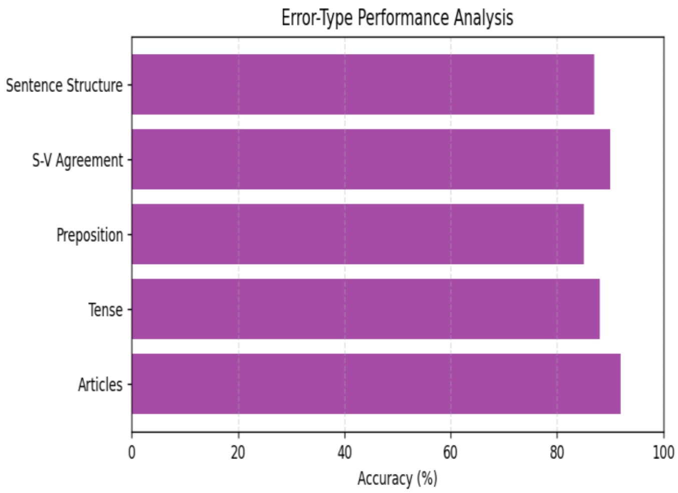

Fig. 10. Error-type performance analysis.

Fig. 10 illustrates the accuracy of the model for the different types of grammatical errors, including articles, tense, prepositions, subject-verb agreement, and sentence structure. The evidence shows that curriculum learning and attention mechanisms provide the model room to focus on different error types. The accuracy, which was consistently high, indicates that the framework could adapt the refinement of sentences, managing both simple and complex grammatical dependencies, while also addressing the study's goal of developing context-sensitive, adaptive refinement of grammar.

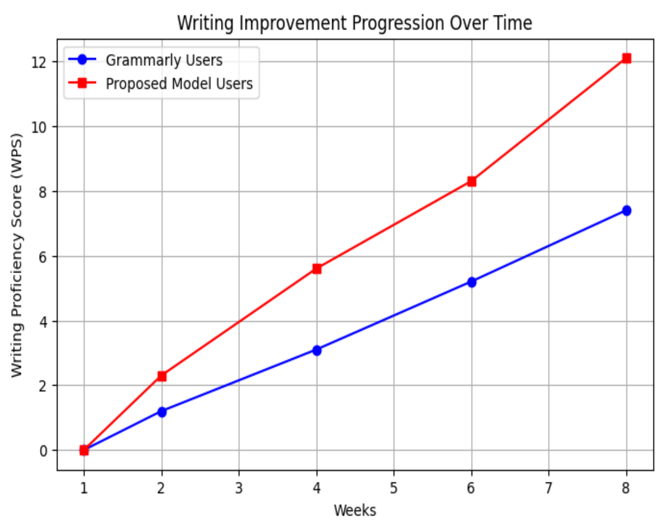

Fig. 11. Writing improvement progression.

Fig. 11 shows the effect of grammar-checking software on user writing skill after eight weeks, with Grammarly (control group) compared to the ACGR framework (test group). The Writing Progression Score (WPS) reveals that users of ACGR showed quicker and more significant improvement, with a WPS of 12.1, while users of Grammarly reached only 7.4. This performance gap emphasizes the strength of ACGR's adaptive feedback, personalization based on RL, and context-sensitive grammar correction. The findings verify the model's capacity for ongoing learning and extended skill improvement, making it a better long-term solution for the improvement of writing compared to traditional grammar-checking models.

B. Ablation Analysis

An ablation study has been performed to assess the contribution of each individual component within the Meta-ACGR framework. To demonstrate through the deliberate ablation of modules how the impact of Meta-RL, curriculum progression, and personalization have improved each of accuracy, fluency, and user satisfaction in language generation beyond the T5 baseline.

TABLE III. ABLATION STUDY

Model Variant	BLEU Score ↑	Perplexity (PPL) ↓	Accuracy (%) ↑	User Satisfaction (%) ↑
Full Model (T5 + Meta-RL + Curriculum + Personalization)	82.7	18.6	91.2	88.5
T5 + Meta-RL + Personalization	78.9	21.3	87.5	79.2
T5 + Meta-RL + Curriculum	77.4	22.0	86.1	73.8
Baseline T5 only	74.6	24.1	83.4	70.3

Table III displays the results of the ablation study of the proposed Meta-ACGR framework. The results indicate the addition of Meta-RL, Curriculum Learning, and Personalization having significant improvements in BLEU score, perplexity, and accuracy and user satisfaction, compared to the baseline T5 model.

C. Cross-Domain and Linguistic Variation

TABLE IV. PERFORMANCE ACROSS LANGUAGE VARIANTS AND DOMAINS

Language Variant / Domain	Accuracy (%)	BLEU Score	Perplexity (PPL)	User Satisfaction (%)
American English (Formal)	91.4	83.2	17.9	89.0
British English (Academic)	89.8	81.7	18.7	85.6
Indian English (Professional)	87.3	79.2	20.1	82.4
Informal/Casual Domain	84.6	76.9	21.5	78.2

Table IV shows the cross-language, cross-domain performance flexibility of the model to varied variation within the assortment of English and writing situations. American English (Formal) has the best performance rate (91.4), BLEU score (83.2), and most of the texts are characterized by high precision in standardized and structured documents. Although the model continues to perform well in both British and Indian English, there is a small decrease in the level of accuracy and fluency when dealing with informal and ESL contexts, indicating the greater fluctuation in the grammar and tone. These results indicate that as the model is highly transferable, the future improvements such as domain specialized fine-tuning or dialect adaptation might further enhance non-standard conditions performance.

D. Qualitative Output Evaluation

TABLE V. GRAMMAR CORRECTION OUTPUTS

Original Sentence	Corrected by Proposed Model
She don't has any idea about the plan.	She doesn't have any idea about the plan.
He go to office everyday by bus.	He goes to the office every day by bus.
This are the example we was talking.	These are the examples we were talking about.
She enjoy to play with her cat.	She enjoys playing with her cat.
They has complete the task successfully.	They have successfully completed the task.

Table V shows a qualitative analysis of the grammar correction results produced by the proposed Meta-ACGR model. The examples supply the fact that the model is capable of correctly recognizing and correcting different grammatical mistakes, such as the subject verb agreement, tense consistency, use of articles, and prepositional accuracy. The remedied sentences have better grammatical accuracy, contextual fluency, and natural expression demonstrating the suitability of the model in generating human-like, coherent, and linguistically accurate outputs.

E. Comparative Evaluation of Grammar Correction Performance

TABLE VI. COMPARATIVE PERFORMANCE WITH EXISTING GRAMMAR CHECKERS

Model	GER ↑	PPL ↓	CAR ↑	US (1-5) ↑
Grammarly [24]	61.2%	85.4	78.3%	4.1
Language Tool [25]	57.6%	92.1	72.8%	3.8
ChatGPT [17]	65.4%	81.2	81.2%	4.3
Proposed Model	72.5%	68.9	89.1%	4.7

Table VI provides the comparative analysis of four well-known language correction systems, namely Grammar, LanguageTool, ChatGPT and the Proposed Meta-ACGR Model depending on the main performance indicators, such as Grammatical Error Reduction (GER), Perplexity (PPL), Correction Accuracy Rate (CAR) and User Satisfaction (US). The Proposed Model is again superior to any of the baseline systems in that GER (72.5%), PPL (68.9), CAR (89.1%), and US score (4.7), it has the best ability to reduce grammatical errors, sentence fluency, and provide contextual appropriate corrections. Although ChatGPT shows a competitive advantage, especially in CAR (81.2%) and US (4.3), Grammarly is mediocre but has problems with the fluency rate. LanguageTool, on the contrary, has the lowest results in all measures. In general, the results demonstrate that the Proposed Meta-ACGR model generates the most balanced and successful grammar refinement results and provides a more reliable and preferred correction tool by end users.

F. Discussion

The comparative analysis shows clearly, the superiority of the suggested Meta-ACGR framework over the traditional AI-assisted writing tools in all the key performance indicators. Meta-Reinforcement Learning (Meta-RL) and Curriculum Learning resulted in a significantly reduced perplexity, a higher number of grammatical errors, and a more natural contextual fluency. In addition, the addition of customized feedback modification boosted the learner satisfaction and encouraged the learner to continue the engagement with the system because of the individualized error patterns. In contrast to the traditional software like Grammarly and LanguageTool, which typically focus on the surface level grammatical errors, Meta-ACGR shows the dynamic flexibility to the specific profiles of learner providing progressive correction of errors and feedback according to the writing style and level of proficiency. This flexibility is important in that, the process of correction changes with the student, which promotes a more profound linguistic comprehension. Altogether, the findings testify to the pedagogical success of the Meta-ACGR in EFL learning as the new stage of the existence of the static correction system and the newly developed iterative and learner-centered refinement one, which preconditions the next generation of adaptive AI-based learning technologies. Nevertheless, this research also has some limitations. This assessment was based on a contained set of data and a small sample of learners, which might not completely reflect the diversity of EFL writing situations in the real world. Also, comparison towards the traditional tools was credited to selected measures of performance and the overall trends of user behavior were not considered. Future research should overcome such limitations in an effort to enhance generalizability.

VI. CONCLUSION AND FUTURE WORK

The work presented suggested that the Meta-ACGR (Meta-Reinforcement Learning Adaptive Curriculum Grammar Refinement) framework can bring about quantifiable domain-level improvements by establishing a direct correlation between each technical characteristic and ESL learning outcomes. Transformer-based T5 backbones allow proper understanding of the context and minimizing the perplexity as well as addressing complex grammar constructions with deeper errors. The Meta-Reinforcement Learning agent is a PPO and MAML optimized agent that dynamically tailors corrections to individual learner profiles, producing contextual fluent feedback. Curriculum facilitates the correction process into single to complex errors, which leads to the improvement of grammatical accuracy and long-term language proficiency. Meta-ACGR has a stronger level of learner engagement, satisfaction, and adaptability with enhanced features as compared to the classic tools like Grammarly and LanguageTool, providing the learner with an iterative process of refining the tool as well as learners having a more personalized approach to it. Overall, these results make Meta-ACGR an important contribution to adaptive, personalized grammar correction, which offers both methodological and pedagogical novelty in ESL teaching. The Meta-ACGR framework will be broadened in three main directions in the future research. To start with, it will be deployed in large classes to determine its practicality and usability in relation to a wide variety of learners. Second, multimodal extensions, such as speech and handwriting analysis will be investigated in an attempt to expand its applicability to other language learning modalities. Lastly, explainable AI (XAI) mechanisms will be explored to increase transparency, interpretability, and trust between learners and educators. All these innovations in combination are geared towards creating more adaptive, effective, and learner-centric AI education technologies.

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