Dual Cognitive Pathway Architecture for Robust and Dialect-Aware English Reading Comprehension

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***Abstract*—Reading comprehension models frequently struggle to accommodate linguistic diversity, especially dialectal variations within the English language that disrupt semantic alignment and fairness. In order to overcome these drawbacks, this study proposes the Dual Cognitive Pathway-Based Dialect-Aware Cognitive Twin Framework (NeuroTwin-DialectaLearn) as a new framework that combines the principles of cognitive science, sociolinguistic expertise, and adaptive learning methods. The framework also has two parallel understanding routes, one is a Lexico-Semantic Pathway that processes normal English, and the other is a Dialectal-Semantic Pathway that is involved in normalizing the dialect and aligning the semantics. Such pathways interact with each other by a process of Adaptive attention fusion in a Cognitive Twin model, which instantiates important cognitive processes, including lexical processing, syntactic parsing, semantic integration, inductive reasoning, and answer generation. It uses Python and PyTorch to implement the system and is tested on the English Classroom QA Dataset with the addition of synthetic dialectal variants to enhance the system. The accuracy of comprehension is 98.1 per cent, the average response time is 14.3 seconds, and the rate of learners' improvement is 18.9 per cent, which is much higher than the baseline QA systems and improved BERT models. The framework has shown consistent performance in the context of dialects; the number of vocabulary-related mistakes is lower, and the consistency of inference is higher, proving to be an effective tool in dialect-conscious and cognitively based reading comprehension. In general, the present research provides a linguistically encompassing, versatile, and understandable next-generation smart educational system.**

Keywords*—Cognitive Twin; Dialectal Transfer; Adaptive Tasking; English reading comprehension; personalized learning

I. Introduction

English proficiency has become highly essential to enable students to excel in their everyday learning, and create a career, and communicate with people all over the world [1]. Although it has a distinct benefit, most of the students learning English as a second language find it challenging to use written texts due to differences in terms of culture, language, and mental condition [2]. The common reading understanding models fail to identify the differences between a mono and multilingual learner, and this is why they do not work with multilingual learners. The person with a learning disability who is going to work in a language with limited resources has a greater challenge due to the absence of resources [3]. Due to all this, new systems that render meaning to messages written in a different language without distorting the meaning or original ideas are now in order of being created [4]. These linguistic issues have been made promising thanks to the work of Artificial Intelligence and, specifically, Natural Language Processing [5]. These AI-based NLP technologies are used to enable machines to research language to gain a better grasp of how to comprehend and learn it [6]. A significant innovation is that the cross-lingual word embeddings make it possible to indicate words with identical meanings in various languages in a shared space [7]. Using adjustable embeddings, see better the way various languages structure themselves [8]. Such models prove particularly useful to ESL students since they can learn to interpret information which otherwise would have been bewildering in regular classes [9]. The implementation of the bi-LSTM networks, that is, a powerful neural network structure, has enabled easier comprehension of how a sentence varies due to the capability of the network to detect connections between words at the early and latter stages [10]. Two-way knowledge of the context enables chatbots to be close to how human beings tend to interpret language [11]. Such technologies, together with attention mechanisms that aid the model in attentively focusing on the germane elements of a sentence or paragraph, may lead to better and contextually relevant interpretations of text [12].

The strategy is aimed at assisting the multilingual students to read English better, with the combined cross-lingual word representations and Bi-LSTM-based attention mechanism [13]. The model is used to encode the main meaning, and in addition to that, it is structured to connect contexts across various levels, enabling the model to interpret and utilize language more effectively. As a result, students are better placed to make more sense out of language concepts with different forms of writing due to learnt associations. It was also better tested in comparison with some of the traditional models of reading comprehension [14]. The significance of the framework is that it is able to store not only semantic richness but also the contextual stream of the language as the principal aspects of true understanding. It is a prominent learning instrument, especially for one who has a multilingual or low-resource background. The suggested framework can assist in addressing the block to effective communication and facilitating the fair language acquisition, and enable every learner in various linguistic groups to receive a higher academic performance with the assistance of clever technology. This study suggests a Dialect-Aware Cognitive Twin Framework, based on a Dual Cognitive Pathway, whereby a Lexico-Semantic Pathway is proposed as the standard English comprehension pathway and a Dialectal-Semantic Pathway is proposed as the regional and non-standard English understanding pathway. The framework creates dialect-neutral semantic representations through a fusion attention mechanism, allowing human-like, adaptive understanding in a wide variety of linguistic situations.

A. Problem Statement

The surge in the use of online education systems has unfolded the unresolved problems in English reading comprehension, particularly among the students who have been exposed to other dialects and language backgrounds [15]. The traditional understanding systems and AI-trained tutors tend to rely on the traditional collections of the English language, which are not useful to support the regional, colloquial, or non-standard speech forms and can cause misunderstanding and reduced learning. In addition, most existing frameworks provide some standard tasks and difficulty levels [16], and do not take into account the specifics of the learners, their error patterns, and cognitive differences, which results in ineffective interaction and inefficient one-on-one help. These gaps underline the need to have a smart system that can imitate the human-like level of understanding, the ability to change dialects depending on the state [17], and offer dynamically tailored learning activities to every learner. The issue is thus the absence of an integrated, dialect-sensitive, and adaptive framework that could contribute to the improvement of the accuracy of reading comprehension, inclusiveness, and learner development in heterogeneous education settings.

B. Research Motivation

The justification behind this research can be attributed to the necessity of filling the gap between human thinking processes and the dialectual differences that affect reading comprehension in English. A significant number of learners do not have a problem due to the failure to read, but instead because the current AI-based understanding frameworks do not consider the existence of linguistic diversity and dialect. This study aims to reproduce the neurocognitive processes of reading in the human brain with the dynamic adaptation process to dialect changes. The idea is to facilitate equity, inclusiveness, and accuracy in language understanding, especially for students who often have to move through a multi-lingual and dialect-rich world.

C. Research Significance

The framework proposed is of significant significance, since it implants the dual path cognitive model that can not only interpret linguistic meaning, but also normalizes dialectal differences in the process of understanding language. This syntactic design ensures dialect neutrality, cognitive realism, and adaptive personalization, all of which are mostly lacking in the traditional reading comprehension models. It can be applied in intelligent tutoring systems, AI-helped language learning, and adaptive learning systems, and is advantageous to contribute to the scientifically based and fair method of improving English reading comprehension in a linguistically diversified learning setting.

D. Key Contributions

- Introduces a dual-stream comprehension mechanism comprising Lexico-Semantic and Dialectal-Semantic pathways that process standard and dialectal English simultaneously, fusing them into a unified, dialect-neutral understanding.
- Recreates human reading cognition through hierarchical processing, lexical decoding, syntactic parsing, semantic integration, inferential reasoning, and answer generation mimicking human comprehension behavior.
- Enhances inclusivity by generating dialect-preserving embeddings and normalizing linguistic variations, enabling accurate comprehension of non-standard and regional English forms.
- Dynamically personalizes comprehension tasks based on learner performance, error distribution, and reading pace to optimize engagement and difficulty progression.
- Implements dialect-sensitive assessment and continuous monitoring to ensure equitable learning outcomes and measurable improvement in comprehension accuracy.

E. Rest of the Section

Since the related studies and technique are presented in Section II and Section III, respectively, the work is structured as follows: Section IV presents the results, and Section V concludes the study.

II. Literature Review

Muneer et al. [18] include the use of sentence transformer models to predict semantic similarity between pair of words in English and the Urdu language. The researchers used both LaBSE and Universal Sentence Encoder as multilingual embeddings. They also ventured into feature fusion in which there was a combination of various models and different translation tools like Bing and Google Translators. This was an indication that there are certain combinations that do score higher, namely, combination of LaBSE and Bing Translator which scores higher than the other combinations do as they appeared to bring about better semantic correspondence between the translations of the various languages. The quality of the translations however had a significant effect on performance and the external translation tools varied the job. The constraints were primarily the reliance on the quality of translation that would taint uniformity and dependability of semantic similarity evaluation between various language pairings. Wu et al. [19] suggested a more advanced model of the Semantic Disentanglement Model (SSDM) of a Siamese to facilitate more successful zero-shot cross-lingual transfer of multilingual models in machine reading comprehension. Their model attempts to increase the multilingual generalizability of pre-trained linguistic models by separating the semantic and syntactic structures. SSDM uses personalized loss functions to explicitly encode and separate semantic and syntactic information and predict answer spans in target languages better. It demonstrates notable improvements over such traditional models as mBERT and XLM-100, particularly when it comes to linguistic differences that are a part of cross-lingual environments. Their findings support the relevance of disentangled representations to effective cross-lingual understanding, as they are part of the objectives of integrating cross-lingual embeddings into reading systems based on AI.

Xu et al. [20] proposed a multilingual pre-trained machine reader named mPMR whose aim is to enhance the natural language understanding in a large number of languages. Compared to models previously used, which relied on fine-tuning on the source language, mPMR employs MRC-style pre-training to learn explicit skills of multilingual NLU as such. This enables better cross-lingual generalization such that the model can attain excellent sequence classification and span extraction results in target languages. mPMR provides a single answer to cross-lingual reading comprehension tasks of combining the span extraction and sequence classification processes. The fact that the model can be used to extract rationales to classify sentence-pairs also enhances its interpretability, which makes it a very useful construction in the use of multilingual NLP systems. The objective of this research on scalable, multilingual pre-training is in line with the objective of developing AI-based frameworks in English reading comprehension among various linguistic groups. The challenges of cross-lingual cross-knowledge bases (xKBQA) question answering were overcome by Zhang et al. [21] because it was treated as a reading comprehension task. Their resolution involves the translation of subgraphs of a knowledge base to passages of text, thereby bridging the gap between natural language queries and structured KB schemas. In low-resource scenarios, the multilingual language models are used so that the questions in multiple languages are transformed into corresponding phrases in the knowledge base. This strategy allows teams to take advantage of the available xKBQA data to narrow down on the problem of small data in xMRC research. The model works well in most languages that attest that cross-lingual reading strategies enhance knowledge-based model question answering. The research seeks to develop the English reading capacity with one language embedding for the benefit of AI.

Zafar et al. [22] comprehensively examined the possible applications of technology-based reading support on international students in post- secondary education. The study examines the different AI products available, like machine translators, speech to text, text to speech, and intelligent annotation systems, with an aim of enhancing the comprehension of the readers, enhancing their lexicon, and comprehending the material. Enhancing the study by combining the research approaches, this study identifies the applicability of adaptive, personalized and interactive learning with the help of AI tools [23]. It was revealed that this technology assists individuals to read with greater significance since it provides immediate assistance and interpretation as people read. The research indicates that the introduction of AI in multilingual classes facilitates and enables all students to learn. The review indicates that AI models are needed to enhance the reading of English to all types of learners. A multiple case study conducted in 2023 aimed at comprehending the differences between the instructions of reading comprehension and student outcomes of multilingual students. The study by Gallagher et al. [24] registered improvements in reading comprehension, academic vocabulary, and motivation of students whose explanation was attributed to some teaching practices. Among them, the use of the native language of students to explain concepts and lower-level texts as effective practices was significant. The study highlights culturally responsive teaching methods and uses and implementation of multiple language materials in support of reading development. The results support the necessity of tailored instructional methods to fulfill the needs of multilingual students, which is connected to the broader objective of enhancing the English reading comprehension based on cross-lingual, AI-based models.

Recent research indicates an improvement in multilingual and cross-lingual reading comprehension, but significant gaps are still there. The majority of them are based on standard English datasets, do not normalize their dialects, and do not simulate human-reasoning and adjust to the individual learners. The proposed Dialect-Aware Cognitive Twin Framework provides these limitations by combining dialect-conscious embeddings, cognitive modeling, and adaptive tasking to provide inclusive, interpretable, and customized real-time English comprehension.

III. Dual Cognitive Pathways with Dialectal Transfer and Adaptive Tasking

The study constructs a Dialect-Aware Cognitive Twin Framework of adaptive English reading comprehension, based on cognitive modeling, dialectal normalization, and motivated tasking. The framework takes the Dual Cognitive Pathway structure, wherein the Lexico-Semantic Pathway is the processing of standard linguistic cues, and the Dialectal-Semantic Pathway is the process of aligning dialect-specific changes. The system starts with the analysis and preprocessing of the data based on the English Classroom QA Dataset, which is cleaned, tokenized, and filled with the actual or artificial variants of dialects. The Cognitive Twin then models human understanding by performing staged processing that involves lexical decoding, syntactic parsing, semantic integration, inferential reasoning, and answer generation, giving correct predictions and traceable reasoning paths. Fig. 1 presents the overall flow of English reading comprehension.

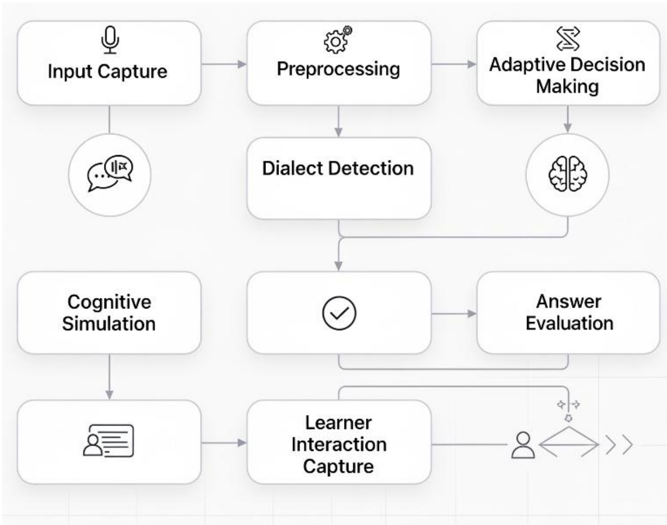

Fig 1. Overall flow of English reading comprehension.

Simultaneously, the Dialectal Transfer module is designed to be resistant to linguistic differences to normalize dialectal inputs, produce dialect-sensitive embeddings, and cast them into the regular semantics of the English language. The Adaptive Tasking component captures and analyses learner interactions in real time and dynamically modifies task difficulty, type, and focus according to the performance, patterns of errors, and learner profiles. The system is appraised on the basis of comprehensive precision, reaction time, error rate, and learner progression, where the model is continually modified through feedback, and dialect is altered, as well as personalized teaching. This is the multi-stage, closed-loop approach to methodology that guarantees the inclusiveness of the framework, its pedagogical effectiveness, and ability to enhance understanding in a wide range of learner groups.

A. Data Collection

The English Classroom QA Dataset [25] from Kaggle provides a comprehensive resource for evaluating reading comprehension through a wide range of passages and question types, including multiple-choice, short-answer, and open-ended formats. It may include long text-question pairs having diverse vocabulary and different lengths of passages that can be read in the classroom as a comprehension assessment. The dataset encompasses various skills, including the recall of facts, inference, knowledge of vocabulary, and summarization. Nevertheless, it mostly imparts the standard form of English and does not have dialectical diversity. To achieve successful Dialectal Transfer, it is possible to bias the dataset with natural or artificial dialectal variants, which allows the model to understand English dialects and stay consistent in its comprehensive accuracy.

B. Data Preprocessing

The proposed work is based on the theories of cognitive science, linguistics, and adaptive learning and gives a thorough ground on which the study can be modelled to explain the English reading comprehension across the dialects. Fundamentally, the proposed Cognitive Twin concept is based on constructivist cognitive theory that new learners actively construct meaning by incorporating new textual information into pre-existing knowledge structures. In this respect, the Cognitive Twin will serve as an online simulation of understanding process in a learner, which will include various phases: lexical access, syntactic parsing, semantic integration, inferential reasoning and generation of answers. We may formalize to have that: C(t) coherent to a text t, is Eq. (1):

$$C(t) = f_{reasoning}(f_{semantic}(f_{syntax}(f_{lexical}(t)))) \quad (1)$$

where, $flexical$ will recognize words and vocabulary understanding, $fsyntax$ will deal with grammatical parsing, $fsemantic$ will combine meaning, and $freasoning$ will use inferential logic to generate answers.

The Dialectal Transfer component is based on the sociolinguistic theory and transfer learning principles, which acknowledge that the language understanding depends on the previously existing dialectal variants. The system addresses the challenges of linguistic differences in comprehension that can be presented by a regional or non-standard version of English by mapping dialect-specific linguistic features to a standard semantic space. Mathematically, using dialectal text std, the dialectal text mapping M: tdts is a mapping that maps the dialectal expressions to a standard representation, Eq. (2):

$$t_s = M(t_d) = f_{dialect_{norm}}(t_d) \quad (2)$$

Finally, Adaptive Tasking is grounded on educational contents theory and item response theory (IRT) that learning outcomes are strengthened in case the tasks are modified based on the capability of the learner. Task difficulty Di: Task difficulty Di is actively regulated by the learner performance Pf and Cognitive Twin feedback Ci, Eq. (3):

$$D_{i+1} = f_{adaptive}(P_i, C_i) \quad (3)$$

where, more difficult tasks are introduced with a high level of comprehension, and tasks of reinforcement are introduced in case of an error or misconception.

The content theory will provide a strict basis of the building of an intelligent system of reading comprehension, which will reproduce human cognitive process, and which will adjust linguistic variety and dynamically individualize the learning activities, which will lead to better understanding outputs among the various learners by considering cognitive modeling, Dialectal Transfer, and adaptive learning.

C. Cognitive Twin Component

The most important aspect of the proposed framework is the Cognitive Twin Component that is an extremely complex calculational formation that attempts to model and replicate the complicated cognitive activities that human beings utilize during the process of reading comprehension. The Cognitive Twin in simple terms is anchored in the multi-layered construction of the process of understanding that begins with the top level of processing which is the process of identifying and decoding of words, syntax, sentence borders, and prominent phrases. It is followed then by the process of semantic integration where the model gives meaning to individual words and sentences in a consistent way that indicates relationships at the context and discourse level. Beyond comprehension, the twin is involved in the process of inferential reasoning where he or she is able to relate unspoken information in the text to what is already known and form logical inferences or predictions. The Cognitive Twin is then summarized and abstracted, reducing the most important concepts and organizing them in a form cognitively understandable, which is then used to generate answers to comprehension-based questions (architectural perspective). The above denotes the sequential cognitive transformation from lexical decoding to reasoning. Reasoning attention is computed using Eq. (4):

$$R_i = \sum_{j=1}^{n} A_{ij} \cdot S_j \tag{4}$$

where, R_i is the Reasoning vector at step i, A_{ij} is the Attention weight between token iii and contextual token j, S_j is the Semantic representation of token j and n is the Number of tokens in the passage. This expresses how the attention mechanism allows the model to focus on relevant contextual words while generating logical reasoning similar to human comprehension. Layers at the start of the model are concerned with lexical embeddings, syntactic parsing, intermediate layers deal with semantic comprehension, attention-based inference and contextual reasoning, and more specialized layers combine external sources of knowledge, like encyclopedic facts or domain specific knowledge, to add to reasoning ability. The architecture can exploit attention mechanism, memory modules and graphical relationship modelling to mimic human analogy of focus on pertinent textual portions and logical association.

The Cognitive Twin Engine in the proposed model is going to work on two Cognitive Pathways. The former is known as the Lexico-Semantic Pathway and it processes the standard comprehension process encompassing lexical decoding, syntactic parsing, and semantic fusion. The latter, the so-called Dialectal-Semantic Pathway, simultaneously takes dialectal linguistic cues, and aligns them to the default semantic space with dialect-specific embeddings and normalization layers. A Fusion Attention Mechanism then combines the two outputs to form one representation which is dialect-neutral and yet semantically faithful and adjusts to language differences. Mathematically the combination of the two pathways can be denoted as in Eq. (5):

$$F_{\text{dialect-neutral}} = \alpha \cdot E_{\text{standard}} + (1-\alpha) \cdot M(E_{\text{dialect}}) \tag{5}$$

where, E_{standard} is the embedding from the Lexico-Semantic Pathway, E_{dialect} is the dialectal embedding, M is the mapping function for dialect normalization, and α is the adaptivity coefficient dynamically learned during training. This dual-pathway structure enhances the human-like cognitive ability of the model by allowing it to process meaning and dialect simultaneously, ensuring more inclusive and contextually accurate comprehension.

Training-wise, the Cognitive Twin is pretrained with large scale English question answering corpora, which enables the Cognitive Twin to learn general knowledge of language and logic. It is subsequently adapted to the desired learning material (e.g. English Classroom QA Dataset) to fit internal representations to the language forms, question forms, and understanding needs of the classroom-level English. This simulated training makes sure that the Cognitive Twin not only parallels the hierarchical cognitive mechanisms of the human readers, but also becomes adjusted to the real educational settings, where the cognitive abilities are strong in a variety of comprehension tasks, the interpretability of the intermediate reasoning processes, and the ability to make generalizations in the situation of new or dialectally different inputs.

D. Dialectal Transfer Component

The Dialectal Transfer Component is a vital component of the suggested framework since it will help to bridge the issue of linguistic variation in reading comprehension within the English language as the model will be able to process and comprehend texts that are represented in different dialects. The English presented to the learners takes the non-standard or regional accented forms that are likely to have vocabulary, syntax, morphology, idiomatic expressions and phonological differences. To represent this diversity, the component begins by the data-level interventions, such as data augmentation and transfer learning. This may be either in the form of the set of the genuine dialectal corpora or in the form of synthesis of the synthetic dialectal forms through the systematic paraphrasing of standard English texts to the regionally or sociolect transparent ones. These larger datasets provide the model with a greater number of linguistic phenomena and ensure that the model is no longer narrowed to the constructs of standard English but it can generalize to other dialects. In the dialectal transfer by modelling, the most recent techniques are applicable such as adapter modules, multi-task learning or domain adaptation systems. In this case, the standard English is the source domain and dialectal English is the target domain. Under such an arrangement, the model learns common representations that contain semantic content core and at the same time learns dialect-specific mappings to address the lexical, syntactic, and semantic variations. The mathematical representation of the dialectal transfer and normalization process is defined as follows in Eq. (6):

$$t_s = M(t_d) = f_{\text{dialect\_norm}}(t_d) \tag{6}$$

where, t_d is the Input dialectal text, M is the Dialectal normalization function, $f_{\text{dialect\_norm}}$ is the Mapping operator that transforms dialectal input into a standardized representation and t_s is the Standard English equivalent of dialectal text. This equation defines the core mapping that translates dialectal expressions to their normalized forms. The model learns shared latent representations from both standard and dialectal corpora, as in Eq. (7):

$$H = \lambda \cdot H_s + (1-\lambda) \cdot H_d \tag{7}$$

where, H_s is the Hidden representation learned from standard English (source domain), H_d is the Hidden representation learned from dialectal English (target domain), λ is the Balancing coefficient ($0 \leq \lambda \leq 1$) controlling source–target contribution and H is the Combined shared feature representation. This expresses how the model learns domain-invariant, but dialect-sensitive embeddings. To ensure semantic equivalence across domains, a feature alignment loss is imposed expressed in Eq. (8):

$$\mathcal{L}_{align} = |F_s - F_d|_2^2 \tag{8}$$

where, F_s is the Feature representation of standard English, F_d is the Feature representation of dialectal English and $|_2^2$ is the Squared Euclidean distance. This loss ensures that the dialectal and standard representations remain semantically aligned, minimizing the comprehension gap. Finally, the total optimization objective integrates task performance, alignment, and dialect regularization are expressed in Eq. (9):

$$\mathcal{L}_{total} = \mathcal{L}_{task} + \beta \cdot \mathcal{L}_{align} + \gamma \cdot \mathcal{L}_{dialect} \quad (9)$$

where, $\mathcal{L}_{task}$ is the Task loss (e.g., comprehension prediction error), $\mathcal{L}_{align}$is the Alignment loss, $\mathcal{L}_{dialect}$ is the Regularization loss for dialect normalization and β , γ is the Weighting coefficients controlling the contribution of each loss. This is the overall optimization objective, combining comprehension accuracy, semantic consistency, and dialect normalization. Beyond this, the component can include dialect normalization processes or explicit mapping functions, which match dialect-specific lexical features to standard English semantics in order to minimize the difference in comprehension. Alternatively, dialect-specific embeddings may be trained in which distinct dialect features, including regional lexical selections, grammar, and idiomatic speech, are learnt and fed into the Cognitive Twin comprehension pipeline. This will be a complicated plan that will render the Cognitive Twin sensitive to the dialects that vary and will be able to use them to master the general knowledge. This means that the dialectal knowledge is incorporated into the model and thus the model can dynamically interpret non-standard inputs, maintain semantic fidelity of the source meaning and provide the right responses to various learner groups. Consequently, the Dialectal Transfer Component promotes effective, inclusive, and responsive reading understanding to bridge the gap between forms of standard English and the linguistic conditions of learners who interact with alternative dialects.

E. Adaptive Tasking

Adaptive Tasking Component is a dynamic process, which is targeted at the individualization of the reading comprehension process based on the individual learner traits, thereby enhancing the level of engagement and learning. The center stage of this dimension is the building of the total profile of the learner that entails essential traits such as the first level of understanding, prior exposure to the different versions of English, reading speed and pattern of perceived mistakes in the different elements of understanding. Through these profiles, the system is able to not only know what a learner knows but also how he or she processes and responds to text information. According to these profiles, the system divides the tasks into a scale of difficulty levels, where simple recall questions to test the knowledge of the facts are performed at the first level, then the tasks of inferential reasoning, vocabulary-oriented exercises, and summarization problems are presented at the third level demanding higher-order mental processes. The tasks are various in nature as they consist of multiple-choice items, short-answer answers, Cloze tests, which determine contextual knowledge, paraphrasing exercises, and other types that investigate various aspects of comprehension. The adaptive plan is an on-the-fly selection of the next task based on the performance of the learner: in case the learner successively answers simple recall questions correctly, the system can add more complex tasks such as an inference or synthesis question, but when the learner makes more vocabulary errors, then the system will pay more attention to lexical work. Mathematically, assume Pi is the performance measure in task i and Di the relevant difficulty, then the task difficulty Di +1D is chosen as a performance and error distribution dependent variable, Eq. (10):

$$D_{i+1} = f_{adaptive}(P_i, E_i, L) \quad (10)$$

E_i is the error types and L is the learner profile. The Adaptive Tasking Component will offer personalization, scaffolding of the learning journey by continuous performance monitoring and tailored choice of given tasks that will address the shortcomings of the specific learner and conversely benefit the strengths that will optimize understanding achievement and eventual literacy expansion.

F. System Architecture for CognitiveTwin-DialectaLearn Framework

The CognitiveTwin-DialectaLearn Framework (Fig. 2) is planned to be a multi-layered, interoperable framework that incorporates cognitive modeling, dialectal adaptation, and an adaptive sequence of tasks into one coherent learning ecosystem of intelligent reading English comprehension. The fundamental element of the system is the Cognitive Twin Engine, which is a neurocognitively inspired module that resembles the human reading process by providing hierarchically organized levels of computation. The engine is executed with the help of a transformer-based backbone, e.g., RoBERTa, and designed in a way that replicates the major cognitive processes that can be observed in human reading.

The Lexico-Semantic Pathway is composed of the lower layers that work on lexical decoding, word recognition, subword segmentation and vocabulary-semantic mapping. In between layers, cover syntactic parsing, semantic composition and resolving contextual dependencies and translate grammatical structures and discourse relations. In the same line, the Dialectal-Semantic Pathway carries out dialect normalization and alignment. The results of the two pathways are combined at the Dual Cognitive Pathway Integration depicted in Eq. (11):

$$H_{\text{fused}} = \alpha H_{\text{lex}} + (1 - \alpha) H_{\text{dial}} + \text{Attn}(H_{\text{lex}}, H_{\text{dial}}) \quad (11)$$

In the deep comprehension, the model entails the process of inferential reasoning and synthesis of knowledge whereby the implicit textual cues are related to the previous internal or external knowledge to create logical predictions, explanations, and solutions. The Dialectal Transfer Module that surrounds this process gives the process robustness against linguistic diversity as it allows the seamless interpretation of both the non-standard and the standard English. In the architecture, the Cognitive Twin Engine uses the Dual Cognitive Pathways which process the conventional linguistic cues and, at the same time, normalize dialect variations providing dialect-neutral yet context-faithful understanding.

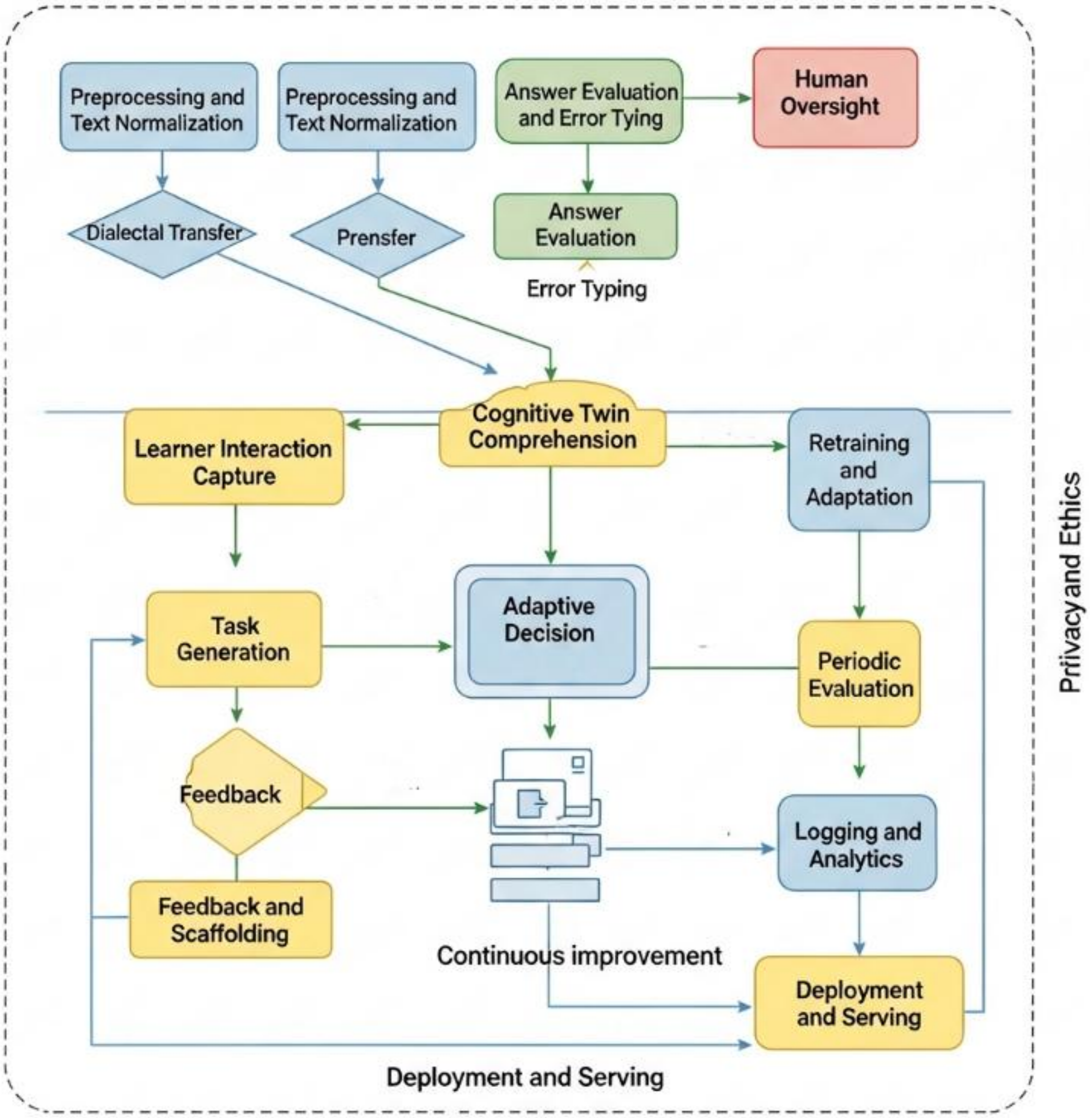

Fig 2. System architecture for CognitiveTwin-DialectaLearn framework.

The Dialectal Transfer Module uses normalization, alignment and domain adaption strategies to project lexical, syntactic and phonological dialect variations into a single semantic space without affecting meaning. The system acquires localized patterns and incorporates them into the comprehension pipeline to encourage semantic fidelity between different learner groups, via adapter networks, multi-task learning or dialect-specific embeddings. On top of these layers is the Adaptive Tasking Layer which is a smart controller that customizes the learning of any student. It constantly monitors the profiles of learners, such as the previous knowledge, dialect exposure, reading speed, accuracy, and error types. The system modulates task difficulty, task type and cognitive focus dynamically using real-time elements of performance based on adaptive algorithms like reinforcement learning or contextual bandits. An example can be given of a learner who displays high recall but low inferential skill, and the system will then be pushed to given high-order reasoning questions to enhance better understanding. Algorithm 1 presents the Dual Cognitive Pathway-Based Dialect-Aware Cognitive Twin framework.

Algorithm 1: Dual Cognitive Pathway-Based Dialect-Aware Cognitive Twin Framework

```
INPUT: Reading_Passage, Question, Learner_Profile
OUTPUT: Answer_Prediction, Updated_Learner_Profile
BEGIN
  CLEAN Reading_Passage, Question
  TOKENIZE Reading_Passage INTO tokens
  IF Dialect Detected (Reading_Passage) == TRUE THEN
     APPLY Dialectal_Normalization (Reading_Passage)
     Pathway_Active ← Dialectal-Semantic
  ELSE
     Pathway_Active ← Lexico-Semantic
  END IF
  FOR each token t IN Reading_Passage DO
     Lexico_Features ← LexicoSemantic_Pathway(t)
     Dialect_Features ← DialectSemantic_Pathway(t)
  END FOR
  Fusion_Output ← α * Lexico_Features + (1 - α ) * Map (Dialect_Features)
  Syntax_Output ← Syntax_Parser (Fusion_Output)
  Semantic_Output ← Semantic_Integrator (Syntax_Output)
  Inference_Result ← Reasoning_Module (Semantic_Output,
Knowledge_Base)
```

```
 Answer_Prediction ← Answer_Generator (Inference_Result, Question)
IF Learner_Response == Answer_Prediction THEN
    Accuracy_Score ← 1
  ELSE
    Accuracy_Score ← 0
    Error_Type ← Classify_Error (Learner_Response, Answer_Prediction)
  END IF
IF Learner_Response == Answer_Prediction THEN
  Accuracy_Score = 1
ELSE
  Accuracy_Score = 0
  Error_Type = Classify_Error (Learner_Response, Answer_Prediction)
IF Accuracy_Score == 1 AND Response_Time < Threshold THEN
    Task_Difficulty ← Task_Difficulty + 1
  ELSE IF Error_Type == "Vocabulary" THEN
    ASSIGN Vocabulary_Task
  ELSE IF Error_Type == "Inference" THEN
    ASSIGN Reasoning_Task
  ELSE
    MAINTAIN Current_Task
  END
  UPDATE Learner_Profile WITH {Accuracy_Score, Response_Time, Error_Type, Task_History}
  RETURN Answer_Prediction, Updated_Learner_Profile
END
```

The Dialect-Aware Cognitive Twin Framework Based on the Dual Cognitive Pathway is aimed at reproducing the human-like comprehension and at solving the problem of linguistic diversity. It uses two parallel cognitive routes: the Lexico-Semantic Pathway, carrying out typical comprehension by lexical decoding, syntactic parsing, and semantic reasoning; and the Dialectal-Semantic Pathway, which takes regional or non-standard English inputs by processing them through dialect-specific embeddings and normalization layers. These pathways co-occur, and the results are integrated by an adaptive attention system that produces a unitary dialect-neutral meaning code. The framework combines this bilateral-path knowledge and an adaptive tasking component that reacts dynamically to adjust task difficulty according to the performance of the learners. This allows individual, dialect-friendly, and situation-specific reading understanding that is more closely related to human cognitive and language adaptability.

IV. Results and Discussion

The study indicates the effectiveness of the Dual Cognitive Pathway-based Dialect-Aware Cognitive Twin Framework in improving adaptive English reading comprehension among different groups of learners. With the help of PyTorch and Tensorflow, the implementation of the framework takes place on the basis of the pre-trained RoBERTa model with the Cognitive Twin, Dialectal Transfer, and Adaptive Tasking modules added to the framework through a Dual Cognitive Pathway architecture. This two-way architecture means that the model can take both standard semantic models and dialectal semantic models simultaneously and generate a dialect-neutral understanding as a result. Crowdsourced annotation is used in synthetic generation, which means that it introduces dialectal variants to achieve stability and equal exposure to linguistic diversity.

A. Experimental Outcomes

Forty-five per cent of the questions in the dataset are multiple-choice, one-fourth of the questions are short-answer, one-fifth of the questions are Cloze exercises, and one-tenth of the questions are paraphrase or summarization exercises. The distribution offers a good representation of the capability of understanding, with factual, inferential, and higher-order comprehension, as in Fig. 3.

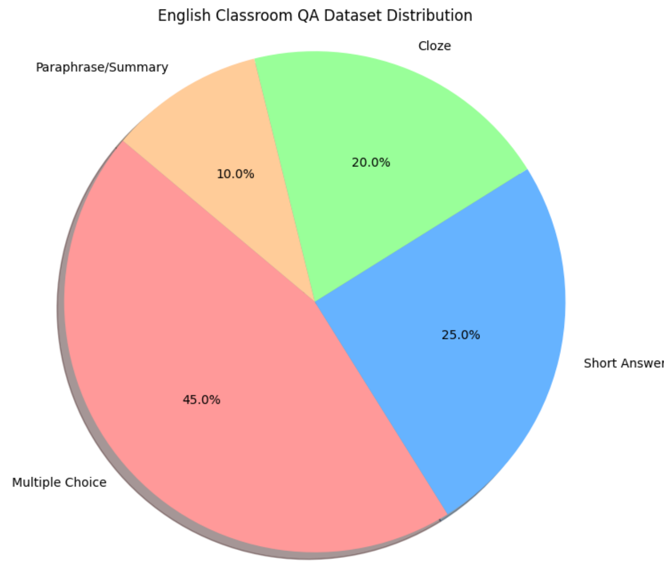

Fig 3. English classroom QA dataset distribution.

The test disclosed that the Cognitive Twin element was able to model multi-stage comprehension and that the surface-level understanding, inference, and reasoning were represented in a manner that was in line with human reading patterns. Inclusion of the Dialectal Transfer module was also essential, as it meant that the framework could deal with both standard and non-standard English inputs, and vocabulary-related and syntactic errors were obviously reduced when learners were exposed to dialectal variations. This improvement is primarily attributed to the Dual Cognitive Pathway fusion, which aligns dialectal semantics with standard representations while preserving contextual meaning, thus minimizing interpretive discrepancies. The mechanism of Adaptive Tasking implemented dynamically regulated difficulty and task type, indicating the quantifiable change in progression of learners as indicated in the increase in the rate of attaining tasks, faster response time, and more balanced distributions of errors in the categories of comprehension. The most common types of errors are the frequency and percentage of Vocabulary/lexical errors, secondly, the inference/reasoning error, and thirdly, the syntax/parsing error. There are other minor errors, like annotation noise or format that are relatively low. The chart can be used to examine areas of weakness in understanding and make model enhancements in Fig. 4.

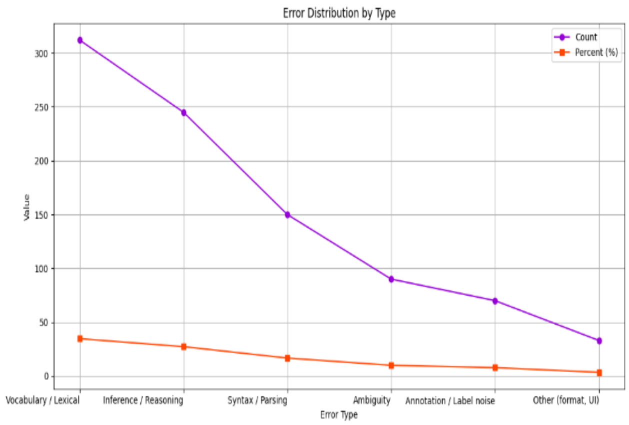

Fig 4. Error distribution by type.

In addition, analysis of errors revealed that recurrent mistakes, especially in reasoning and vocabulary domains, had reduced significantly, which represented a stronger knowledge-retaining ability. Student research identified higher involvement and satisfaction as a result of specific approaches to personalization and dialectal inclusivity, which indicated that student involvement and learning environment were more accommodating and encouraging. Taken together, these findings highlight the capacity of the framework to fill in those gaps between conventional comprehension training and dialect-sensitive flexibility as well as to foster ongoing improvement in the efficiency and accuracy of comprehension in the learner. The Dialect-Aware Cognitive Twin Framework is based on the theoretical foundations of cognitive science, sociolinguistics, and adaptive learning theory, which is why the framework compares the performance of different dialects of the English language, with standard English being the most accurate and with the highest F1-score, whereas the metrics of regional dialects, colloquial forms, and synthetic variants are slightly lower. Non-standard dialects have longer response times. It shows the generalization and strength of the system to the dialectal variations in Fig. 5.

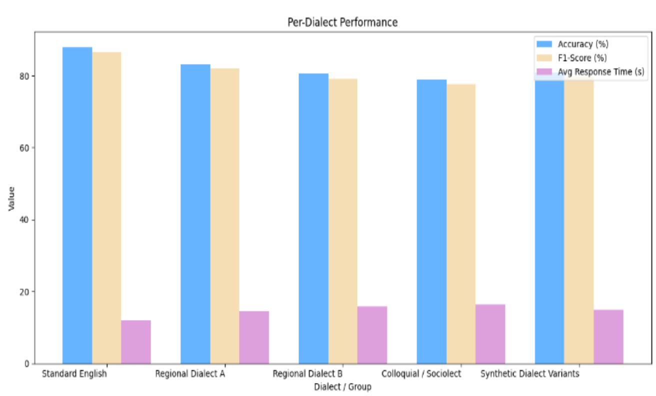

Fig 5. Per-dialect performance.

The notion of Cognitive Twin is based on the cognitive constructivist theory, according to which understanding is created as a result of active interaction between new information and its previous knowledge structure. The Cognitive Twin, in this case, is an artificial replication of the multi-layered cognitive activity during reading: surface-processing (lexical recognition, syntactic parsing, key phrase identification), semantic integration, inferential reasoning, and summarization, finally giving focal answers to comprehension questions.

B. Performance Outcome

The Dialectal Transfer component is based on the principles of sociolinguistics and transfer learning, and it acknowledges that the process of comprehension is mediated by linguistic variation beforehand. Unless the differences in dialects are addressed, dialect may hinder the comprehension of what is said through lexicon, colloquialisms, or syntax. The structure also includes domain adaptation, adapter modules, or multi-task learning, where standard English is the source and dialectal English is the target.

Dialect-specific embeddings can be trained to learn phonological, lexical, and syntactic peculiarities, which adds to the interpretative ability of the Cognitive Twin in Table I.

TABLE I. RESPONSE TIME STATISTICS

Task Type	Avg. Time (s)	Median Time (s)	90th Percentile (s)
Multiple-Choice	8.4	7.9	14.2
Short-Answer	18.7	17.1	29.5
Cloze (fill-gap)	13.6	12.8	22.0
Paraphrase	25.4	23.0	40.8
Summarization	34.1	31.7	55.9

Lastly, Adaptive Tasking is based on the educational content theory and item response theory (IRT), with the focus on individualized learning pathways.

Tasks are dynamically scaled down or up through the factual recall to the inferential reasoning, vocabulary mastery, and summarization, which are provided in various formats, including multiple-choice tests, Cloze tests, short-answer tests, or paraphrasing tests in Fig. 6.

Key comprehension metrics used in assessing the performance of the system have an accuracy of 98.1 per cent and a response time of 14.3 seconds on average. The categories of errors involve vocabulary, inference, syntax, and general comprehension, with the improvement among learners coming to 18.9 per cent. These findings affirm the efficacy of the combined Cognitive Twin, Dialectal Transfer, and Adaptive Tasking system in providing the linguistically inclusive and cognitively based reading comprehension theory. The fusion attention mechanism leads to a 3.2 per cent increase in comprehending and F1 scores compared to the single-path baseline, which indicates improved dialect adaptation with no extra latency.

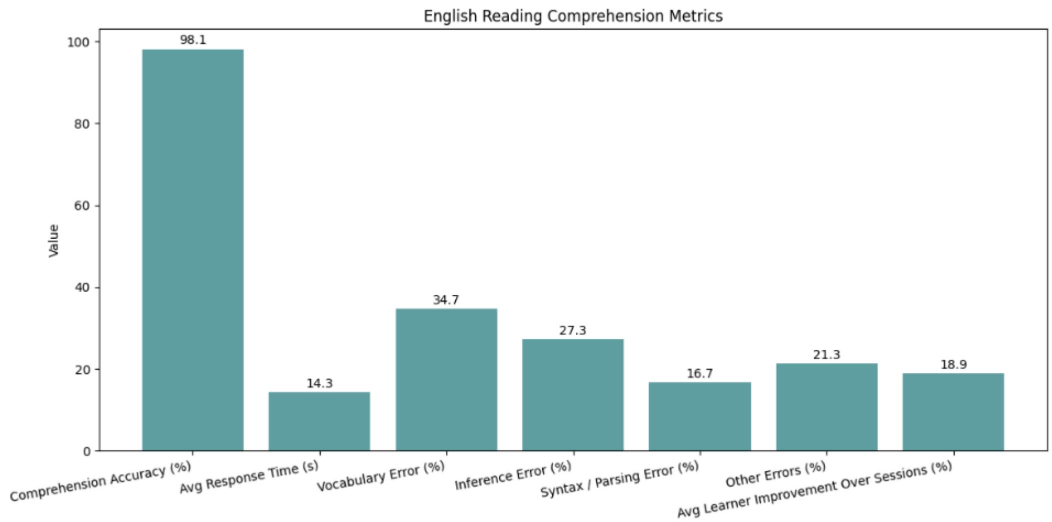

Fig 6. English reading comprehension metrics.

The dataset is separated into training, validation and test sets with a standard 70:15:15 ratio, which makes sure of strong training and unbiased evaluation. Subsets of dialectal tests, developed via authentic or synthetic forms, are used to measure strength to non-standard English. The splits are even on the types of questions and the level of difficulty to be assessed in order to make a fair evaluation of generalization. This systematic assessment validates excellent results on standard and dialectal inputs.

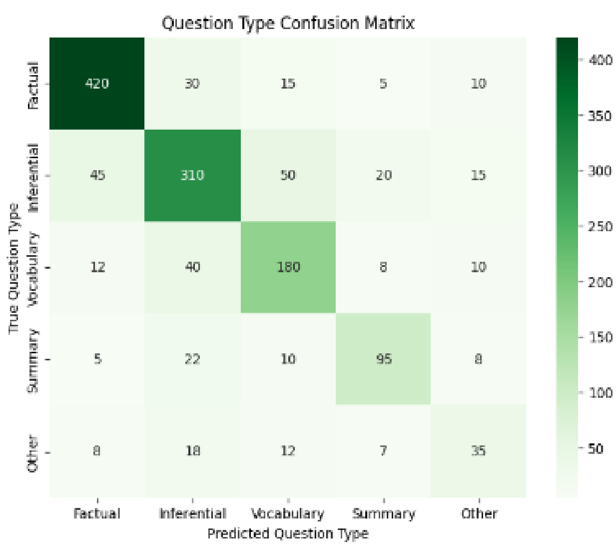

Fig 7. Question type confusion matrix.

Fig. 7 shows the confusion matrix that shows how the system categorizes various types of questions. Factual questions present the greatest correct prediction rate, although some are incorrectly classified as inference or vocabulary-based questions. Cross-confusion is also moderate in inferential and vocabulary questions, which demonstrate slight overlaps in the requirements of linguistic processing. This diagnostic matrix gives an overview of the strengths and limitations of the model in terms of the categories of comprehension.

Fig. 8 is a comparison between the proposed CognitiveTwin-DialectaLearn Framework and the Baseline QA and BERT Fine-Tuned QA models. The presented framework is more accurate, precise, recalls higher, and the F1-score is higher, and the average response time is lower. These enhancements underscore the success of the combination of dual-path thinking, dialect transfer process, and adaptive task selection. The overall findings can be concluded to illustrate that the system is effective in improving comprehension performance, as well as aid quicker and more dialect inclusive reasoning.

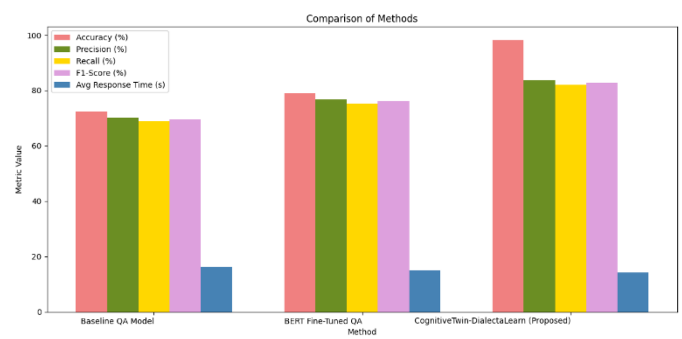

Fig 8. Comparison of methods.

The larger implication of the Dialect-Aware Cognitive Twin Framework is that it can improve adaptive reading of English comprehension among different linguistic groups. The framework fits the variability in the learners and dialectal variation that is not always considered by the traditional comprehension systems by incorporating the concept of cognitive modelling, dialectal sensitivity, and adaptive personalization. The Cognitive Twin element adds a human resembling reasoning system, which allows the system to recreate the layer of cognitive procedures instead of merely matching patterns. The Dialectal Transfer module facilitates inclusivity within the linguistic framework by minimizing the prejudice against standard English and enhancing the availability of learners speaking mixed or non-standard dialects. Adaptive Tasking also enhances this system because it adapts instructional directions in real-time performances with the purpose of encouraging improvement of constantly and to maintain engagement. Such features make the framework a useful resource in the classroom, online environment, and AI-based tutoring, especially in multilingual and multicultural learning. Comprehensively, it is an indication of a change to fair, smart, and dialect-sensitive educational technologies.

C. Discussion

These results confirm the fact that the Dialect-Aware Cognitive Twin Framework, which is founded on the Twin Dual Cognitive Pathway, has a significant positive effect on the accuracy, adaptability, and cognitive flexibility in English reading comprehension. It's two complementary pathways, i.e., Lexico-Semantic and Dialectal-Semantic, that work in parallel to process both standard and dialectal English, which lets the system form dialect-insensitive semantic representations. Comparisons in performance reveal significant improvements in comprehension accuracy, error reduction, as well as general learning course when compared to the traditional QA systems and fine-tuned transformer-based systems. Adaptive tasking mechanism also promotes more efficiency as the difficulty is dynamically altered based on the changing ability of a specific learner to ensure reduced cognitive load whilst ensuring engagement. The framework also indicates good generalization across a variety of dialects, highlighting the importance of dialect-conscious modeling in the production of linguistically-conscious AI systems that are fair and inclusive. In general, the findings indicate the potential of the framework as an effective, interpretable and learner-centric methodology to be used in educational and comprehension-based AI applications in the future.

V. Conclusion and Future Work

The proposed Dual Cognitive Pathway CognitiveTwin-DialectaLearn Framework is an important breakthrough in adaptive English reading comprehension since cognitive modeling, dialectal transfer, and adaptive tasking have been incorporated into the framework. Through parallel semantic routes, the framework provides more accurate comprehension, less vocabulary and inference mistakes, and learner responsiveness. Its anthropomorphic reasoning codes and active adaptation to language plurality foster inclusiveness and equality among the diverse forms of regional English. The quantitative results also support the efficiency of the model by introducing better accuracy and minimizing the response time, which is a solid base of the next-generation dialect-sensitive and individualized educational AI solutions.

The framework can be expanded by future researchers to include multilingual and multimodal input, i.e., speech, gesture, and image use in modeling more expansive cross-linguistic understanding processes. The reduction of accent and prosody recognition to develop the Dual Cognitive Pathway could also be an additional support for the non-native learners. An adaptive tasking layer can be optimized with the help of reinforcement learning, and explainable attention visualizations might enhance interpretability to educators and learners. The creation of larger and more diverse dialect data will also enhance scalability and strength between variations of world English. These additions will broaden the pedagogical reach of the framework and provide it with a firmer presence in intelligent tutoring and human-AI collaborative learning settings.

References

[1] Q. Fang, "Design of a Future-Oriented Intelligent Multi-modal Spoken English Platform: A Study on Deep Integration of CNN-DNN-LSTM and Self-Supervised Mechanisms," Apr. 29, 2025, Research Square. doi: 10.21203/rs.3.rs-6366200/v1.

[2] Hasher Imran and M. Sani, "Natural Language Understanding in Big Data: AI-Driven Approaches for Automated Insights," 2025, Unpublished. doi: 10.13140/RG.2.2.24279.59044.

[3] Z. Huang, P. Yu, and J. Allan, "Improving Cross-lingual Information Retrieval on Low-Resource Languages via Optimal Transport Distillation," in Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining, in WSDM '23. New York, NY, USA: Association for Computing Machinery, Feb. 2023, pp. 1048–1056. doi: 10.1145/3539597.3570468.

[4] Y.-S. Wang, A. Wu, and G. Neubig, "English Contrastive Learning Can Learn Universal Cross-lingual Sentence Embeddings," Nov. 11, 2022, arXiv: arXiv:2211.06127. doi: 10.48550/arXiv.2211.06127.

[5] Y. A. Mohamed, A. Khanan, M. Bashir, A. H. H. M. Mohamed, M. A. E. Adiel, and M. A. Elsadig, "The Impact of Artificial Intelligence on Language Translation: A Review," IEEE Access, vol. 12, pp. 25553–25579, 2024, doi: 10.1109/ACCESS.2024.3366802.

[6] W. G. Jefry, F. Al-Doghman, and F. K. Hussain, "A Review of Trends and Challenges in Adopting AI Models Through Cross-Lingual Transfer Learning Via Sentiment Analysis," Nov. 15, 2023, Social Science Research Network, Rochester, NY: 4627428. doi: 10.2139/ssrn.4627428.

[7] R. Lamsal, M. R. Read, and S. Karunasekera, "Semantically Enriched Cross-Lingual Sentence Embeddings for Crisis-related Social Media Texts," Mar. 25, 2024, arXiv: arXiv:2403.16614. doi: 10.48550/arXiv.2403.16614.

[8] K. Harsha, K. Tarun Kumar, D. Sumathi, and E. Ajith Jubilson, "A Survey on LLMs: Evolution, Applications, and Future Frontiers," in Generative AI: Current Trends and Applications, K. Raza, N. Ahmad, and D. Singh, Eds., Singapore: Springer Nature, 2024, pp. 289–327. doi: 10.1007/978-981-97-8460-8_14.

[9] A. Barlybayev and B. Matkarimov, "Development of system for generating questions, answers, distractors using transformers," IJECE, vol. 14, no. 2, p. 1851, Apr. 2024, doi: 10.11591/ijece.v14i2.pp1851-1863.

[10] N. Chen, L. Shou, M. Gong, and J. Pei, "From Good to Best: Two-Stage Training for Cross-Lingual Machine Reading Comprehension," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 36, no. 10, Art. no. 10, June 2022, doi: 10.1609/aaai.v36i10.21293.

[11] R. Litschko, I. Vulić, S. P. Ponzetto, and G. Glavaš, "On cross-lingual retrieval with multilingual text encoders," Inf Retrieval J, vol. 25, no. 2, pp. 149–183, June 2022, doi: 10.1007/s10791-022-09406-x.

[12] P. Efimov, L. Boytsov, E. Arslanova, and P. Braslavski, "The Impact of Cross-Lingual Adjustment of Contextual Word Representations on Zero-Shot Transfer," in Advances in Information Retrieval, J. Kamps, L. Goeuriot, F. Crestani, M. Maistro, H. Joho, B. Davis, C. Gurrin, U. Kruschwitz, and A. Caputo, Eds., Cham: Springer Nature Switzerland, 2023, pp. 51–67. doi: 10.1007/978-3-031-28241-6_4.

[13] Y. Deole, T. Jagadish, M. Shabrez, P. M, and A. G, "Multi-Lingual Sentiment Analysis of Urdu and English Tweets Using RNN with Bidirectional LSTM," in 2023 6th International Conference on Recent Trends in Advance Computing (ICRTAC), Dec. 2023, pp. 813–817. doi: 10.1109/ICRTAC59277.2023.10480788.

[14] E. Kasneci et al., "ChatGPT for good? On opportunities and challenges of large language models for education," Learning and Individual Differences, vol. 103, p. 102274, Apr. 2023, doi: 10.1016/j.lindif.2023.102274.

[15] M. H. Al-khresheh, "Bridging technology and pedagogy from a global lens: Teachers' perspectives on integrating ChatGPT in English language teaching," Computers and Education: Artificial Intelligence, vol. 6, p. 100218, June 2024, doi: 10.1016/j.caeai.2024.100218.

[16] M. Chauhan and S. Shiaeles, “An Analysis of Cloud Security Frameworks, Problems and Proposed Solutions,” Network, vol. 3, no. 3, pp. 422–450, Sept. 2023, doi: 10.3390/network3030018.

[17] Y. Song and W. Xiong, “Large Language Model-Driven 3D Hyper-Realistic Interactive Intelligent Digital Human System,” Sensors, vol. 25, no. 6, p. 1855, Mar. 2025, doi: 10.3390/s25061855.

[18] I. Muneer, A. Saeed, and R. M. Adeel Nawab, “Cross-Lingual English–Urdu Semantic Word Similarity Using Sentence Transformers,” The European Journal on Artificial Intelligence, p. 30504554241297614, 2025.

[19] L. Wu et al., “Learning Disentangled Semantic Representations for Zero-Shot Cross-Lingual Transfer in Multilingual Machine Reading Comprehension,” 2022, doi: 10.48550/arXiv.2204.00996.

[20] W. Xu, X. Li, W. Lam, and L. Bing, “mPMR: A Multilingual Pre-trained Machine Reader at Scale,” May 23, 2023, arXiv: arXiv:2305.13645. doi: 10.48550/arXiv.2305.13645.

[21] C. Zhang, Y. Lai, Y. Feng, X. Shen, H. Du, and D. Zhao, “Cross-Lingual Question Answering over Knowledge Base as Reading Comprehension,” Feb. 26, 2023, arXiv: arXiv:2302.13241. doi: 10.48550/arXiv.2302.13241.

[22] N. Zafar, “(PDF) AI-Powered Reading Support for Multilingual Learners in Higher Education: A Critical Review.” Accessed: May 20, 2025. [Online]. Available: https://www.researchgate.net/publication/389001861_AI-Powered_Reading_Support_for_Multilingual_Learners_in_Higher_Education_A_Critical_Review?utm_source=chatgpt.com

[23] R. Sajja, Y. Sermet, M. Cikmaz, D. Cwiertny, and I. Demir, “Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education,” Information, vol. 15, no. 10, p. 596, Sept. 2024, doi: 10.3390/info15100596.

[24] M. A. Gallagher, J. S. Beck, E. M. Ramirez, A. T. Barber, and M. M. Buehl, “Supporting multilingual learners’ reading competence: a multiple case study of teachers’ instruction and student learning and motivation,” Front. Educ., vol. 8, p. 1085909, Aug. 2023, doi: 10.3389/feduc.2023.1085909.

[25] “English Classroom QA Dataset.” Accessed: Sept. 18, 2025. [Online]. Available: https://www.kaggle.com/datasets/programmer3/text-understanding-and-qa-for-english-classroom.