Adaptive Dyslexia Reading Intervention System Using Hybrid Readability Modeling, Error Classification, and Reinforcement Learning

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ABSTRACT:
Dyslexia is a type of learning disorder that occurs in individuals due to difficulties in reading fluency and comprehension. It can affect an individual's learning outcome in an important way. Therefore, early prediction and classification of dyslexia are very important to reduce its impact. In this context, this study suggests a data-driven model for early prediction and classification of dyslexia among individuals based on interaction data.. A hybrid feature vector consisting of 15 linguistic readability metrics and 384-dimensional Sentence BERT embeddings is employed for accurate readability score prediction (RMSE = 0.684, R^2 = 0.553). K-Means clustering is utilized for grouping reading passages into five different levels of difficulty based on K-Means clustering. Errors related to dyslexia, i.e., substitution, deletion, inversion, and transposition, are classified using orthographic features and a Random Forest classifier, achieving 98.03% accuracy for 1.44 million synthetic errors. Epsilon-Greedy Multi-Armed Bandit is employed for adaptive content delivery based on trends of learner performance. Simulations were conducted for accuracy improvement, and it was observed that the proposed adaptive reading intervention system consistently improves accuracy over a static approach, with an average improvement of +0.1648 over a static approach for five randomized simulation trials. Furthermore, error clustering identifies three cognitive sub-types for developing remediation plans for individuals with dyslexia. This holistic approach for individuals with dyslexia is a stepping stone for developing more accurate and effective intervention plans for individuals with dyslexia. The experimental results show better classification accuracy for learners with different levels of risk. Therefore, this model can be helpful in early prediction and classification of learners with dyslexia.

Keywords: Dyslexia Intervention, Adaptive Learning Systems, Readability Prediction, Error Classification, Reinforcement Learning.

INTRODUCTION

One of the most common neurodevelopmental disorders, dyslexia is defined as a difficulty with accurate and fluent reading and spelling [1]. It has been found that a significant number of children suffer from this disorder, with the figure estimated at 5-20% of the child population [1]. The disorder is also defined as the presence of persistent difficulties with accurate and/or fluent word recognition and decoding, resulting from a deficit in the development of these skills. The reading fluency of individuals with dyslexia is affected due to difficulties in phonological processing, slower decoding abilities, and difficulties in mapping graphemes to phonemes. [2].

Traditionally, structured and multi-sensory approaches are employed for remediation of dyslexia, but these methods are often labor-intensive and hard to scale. Recently, however, there have been efforts towards developing data-driven and AI-based solutions for dyslexic students. For instance, there are automatic readability measurement tools that use linguistic characteristics of texts to measure and estimate the complexity of texts [3]. Using deep learning techniques (such as transformer embeddings and graph-based neural networks), very accurate predictions of readability scores for educational texts have been made [4]. Further, there are learning technologies and devices that can adapt and present dyslexic students with alternative forms of learning material, based on their performance. Preliminary research suggests that these technologies have shown promising results for dyslexic students [5]. For example, there were marked improvements observed for dyslexic students who were exposed to an adaptive reading technology compared to those who were not [6]. Reinforcement learning algorithms (such as contextual multi-armed bandits) have been employed for optimizing learning gains for students [7]. Cognitive research on dyslexic populations suggests a large degree of variation and diversity among dyslexic students [8]. For neurocognitive subtyping research identified multiple subtypes of dyslexia, where predominantly phonological and visual-motor subtypes were identified among dyslexic readers [9].

However, most of these models focus on just one aspect of the problem. For example, while there are models for assessing the difficulty of texts, there may not be corresponding models for error detection and personalization. Similarly, while there are models for personalization, these may not incorporate fine-grained linguistic features for assessing the reading level. We propose a unified framework for addressing this problem, combining the strengths of hybrid models for assessing the difficulty of texts, automatic error detection and classification, cognitive profiling, and personalization using reinforcement learning. In this study, a unified framework of an adaptive dyslexia intervention system that includes readability modeling, error classification, and reinforcement learning-based personalization will be proposed. The proposed system will differ from existing systems, which have focused on particular components of an adaptive system, as it will provide an end-to-end solution for difficulty estimation, profiling, and personalization.

METHODOLOGY

The overall architecture of the proposed system for the adaptive dyslexia intervention system can be represented as shown in Figure 1. The proposed system incorporates hybrid readability modeling, error classification via machine learning, cognitive profiling, and adaptation via reinforcement learning. The proposed system incorporates all the above features in a unified pipeline.

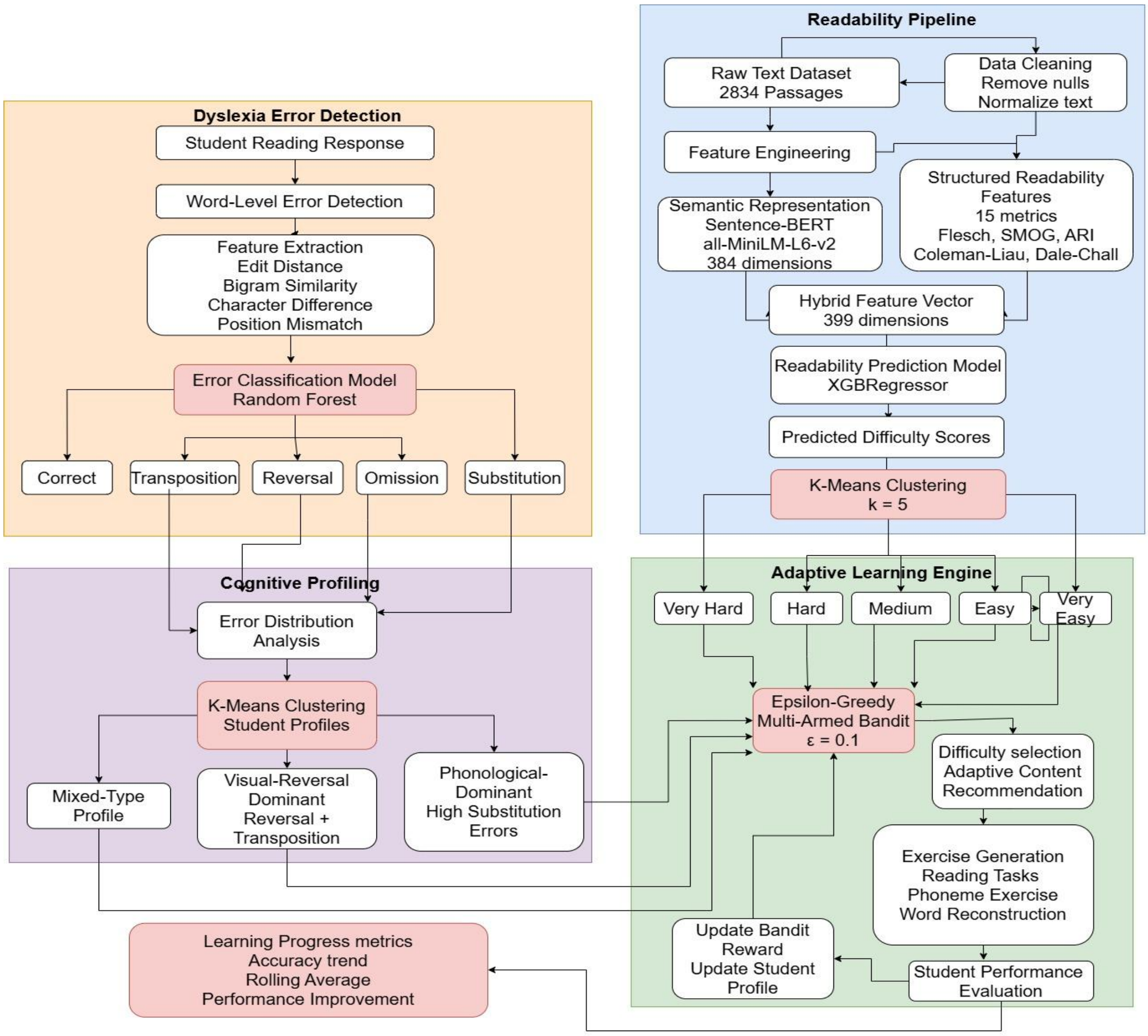

Figure 1. Architecture of the proposed adaptive dyslexia learning framework.

2.1 Dataset Description

This study employed a quantitative computational research design to design an adaptive reading intervention system to support individuals with dyslexia. The proposed framework incorporates various techniques from natural language processing, machine learning, clustering, and reinforcement learning to estimate the readability of text, identify dyslexia error patterns, and adapt the reading difficulty level. The dataset used in this study is represented as $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i is a textual excerpt and y_i is the readability score assigned by human annotators to the text excerpt. The overall system architecture has three major components: hybrid text difficulty modeling, dyslexia error classification, and adaptive difficulty personalization.

2.2 Participants and Sample

The study will employ the CommonLit Readability Prize dataset [10], which contains educational reading content with readability difficulty scores obtained from human evaluators. The definition of the dataset is given by $D = \{(x_i, y_i)\}_{\{i=1\}}^{N}$, where x_i represents the reading content, and y_i denotes the readability difficulty score associated with the content [11]. The dataset has 2800 reading excerpts, each with varying linguistic complexity obtained from literature and educational sources.

To ensure the quality of the dataset, some preprocessing steps are carried out before the commencement of the model training process. The steps include the deletion of samples with missing text entries $(x_i \neq \emptyset)$ and readability scores $(y_i \neq \emptyset)$, and the deletion of duplicate samples to avoid bias in the training process [12]. Following the preprocessing step, the clean dataset is split into the training and test datasets using the 80-20 ratio to allow the model to learn from the training samples and evaluate its generalization ability on the test samples.

2.3 Features engineering

For the implementation of the proposed framework, various computational tools and models based on machine learning have been utilized. For text processing and data manipulation, Python libraries Pandas and NumPy have been used [13]. For calculating the linguistic readability measures, the library TextStat has been utilized, which offers various readability measures such as Flesch Reading Ease, Flesch-Kincaid Grade Level, SMOG Index, Coleman-Liau Index, and Dale-Chall Score [14].

For the extraction of contextual semantic features, the sentence embedding technique has been utilized, where the Sentence-BERT (SBERT) model [15] has been used as the transformer model for the extraction of the sentence embedding representation $E_i = SBERT(x_i)$, where $E_i \in R^{384}$. For the prediction model, Extreme Gradient Boosting (XGBoost) has been utilized for estimating the readability scores, while the Random Forest classifier and XGBoost classifier have been utilized for the prediction of the type of error caused by dyslexia [16]. For the clustering of the difficulty scores, the K-Means clustering model has been utilized, while the Epsilon Greedy Multi-Armed Bandit model has been utilized for the adaptive difficulty selection [17][18].

2.4 Model development

The proposed system uses a multi-stage computational pipeline that includes text preprocessing, feature extraction, model training, clustering, and adaptive difficulty selection. First, all text passages were preprocessed to achieve uniformity. Then, a structured linguistic feature vector $S_i = [s_1, s_2, \dots, s_m]$ was extracted using readability measures and statistical text properties for each text passage x_i. These features include $AWL = \frac{\sum_{w \in x}|w|}{N_w}$, type–token ratio $TTR = \frac{\text{Unique Words}}{\text{Total Words}}$, and stopword density $SD = \frac{\text{Stopwords}}{\text{Total Words}}$ [19].

To incorporate semantic context, each text passage was encoded using the Sentence-BERT model to generate an embedding vector $E_i = SBERT(x_i)$ [13]. Finally, the hybrid representation was created by combining the extracted linguistic features and semantic embedding vectors $F_i = S_i \oplus E_i$ [20]. These hybrid feature vectors are represented in the feature matrix $X = [F_1, F_2, \dots, F_N]$, which was used to train a regression model to predict the readability scores.

The regression model was implemented using XGBoost [14], with the predictions computed as $\hat{y}_i = \sum_{k=1}^{K} f_k(F_i)$, with f_k denoting the decision trees in the model. It was trained to minimize the squared error loss function $L = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2$ [16]. Once the readability scores were predicted, K-Means clustering was used to cluster the texts based on their difficulty level, with five levels of difficulty determined by minimizing the clustering objective function

$J = \sum_{k=1}^{K} \sum_{x_i \in C_k} || x_i - \mu_k ||^2$, with the clusters corresponding to interpretable levels of difficulty ranging from Very Easy to Very Hard [21].

To find word pairs that are likely to be dyslexia-related word reading errors, pairs of words (w_o, w_r) consisting of the original word and the word as it is read by a student were examined using edit distance and character similarity features. The Levenshtein distance [18] $d(w_o, w_r)$between two words, the character difference $CDR = \frac{d(w_o,w_r)}{|w_o|}$ between two words, and the bigram similarity $Sim = \frac{|B(w_o) \cap B(w_r)|}{|B(w_o)|}$. These features have been used to train classification models that can recognize substitution, omission, reversal, and transposition types of errors.

Finally, the adaptive selection of difficulty levels was incorporated using an Epsilon-Greedy Multi-Armed Bandit algorithm [15]. Each of the difficulty levels was represented as an arm, i.e., $A = \{a_1, a_2, a_3, a_4, a_5\}$. At each learning session t, the system selects the difficulty level based on the policy, i.e., $a_t = random(A)$ with probability ϵ, and $a_t = \arg\max Q(a)$ with probability $1 - \epsilon$, where $Q(a)$represents the expected reward of the difficulty level. Here, the reward is represented as the student's reading accuracy $r_t \in [0,1]$, and the value update is calculated as $Q(a) \leftarrow Q(a) + \frac{1}{N(a)}\left(r_t - Q(a)\right)$ [22]. This approach enables the system to dynamically adjust difficulty levels to maximize learning effectiveness.

2.7 Evaluation Metrics

The performance of the proposed system has been evaluated based on the standard evaluation criteria for machine learning models. For the proposed readability prediction model, the Root Mean Squared Error and coefficient of determination have been considered as the evaluation criteria for the accuracy and variation of the model predictions. For the proposed dyslexia error classification model, the model accuracy, precision, recall, and F1 score have been considered as the evaluation criteria for the accuracy of the model for different types of reading errors. The performance of the proposed adaptive learning system has been evaluated based on the trends of the proposed model and the static difficulty-based model for different learning sessions.

RESULTS

A baseline linear regression model and a standalone SBERT model were evaluated for comparison. The proposed hybrid model outperformed both baselines.

3.1 Dataset and Feature Representation

Readability dataset comprised 2,834 text instances with associated readability target scores. For each text instance, 15 structured readability features were computed. The features include Flesch Reading Ease, Flesch Kincaid Grade Level, SMOG Readability Formula, Automated Readability Index, Coleman Liau Index, Dale Chall score, character count, word count, sentence statistics, lexical diversity features, stopwords density feature, and average syllables per word feature.

To incorporate semantic features, Sentence BERT embeddings (all-MiniLM-L6-v2) were used to generate a vector representation for each text instance. The vector representation comprises 384 dimensions. The hybrid feature vector for each text instance comprises the 15 structured features and the 384-dimensional vector representation. Hence, the hybrid feature vector comprises 399 dimensions.

3.2 Readability Prediction Performance

A gradient boosting regression model (XGBRegressor) was used to predict the readability scores. The model used 500 estimators, a learning rate of 0.03, and a maximum depth of 7. The model was trained with an 80-20 split for training and testing.

Table 1 Readability Modeling and Difficulty Clustering Results

Component	Metric	Value
Dataset size	Total passages	2,834
Structured features	Linguistic metrics	15
SBERT embedding dimension	Contextual features	384
Hybrid feature dimension	Combined features	399
Regression model	XGBRegressor	–
Prediction RMSE	Test set	**0.684**
Prediction R^2	Test set	**0.553**
Clustering algorithm	K-Means	k = 5

The predicted scores were then categorized into five levels of difficulty using K-Means clustering. The table below summarizes the cluster means and distribution of the dataset across different levels of difficulty.

Table 2 Difficulty Level Distribution

Difficulty Level	Mean Score	Number of Passages
Level 0 (Very Easy)	−2.6427	392
Level 1 (Easy)	−1.6823	681
Level 2 (Medium)	−0.8636	801
Level 3 (Hard)	−0.1159	634
Level 4 (Very Hard)	0.6996	326

The clustering resulted in a balanced distribution of the dataset, allowing the adaptive system to pick passages based on their level of difficulty shown in Figure 2.

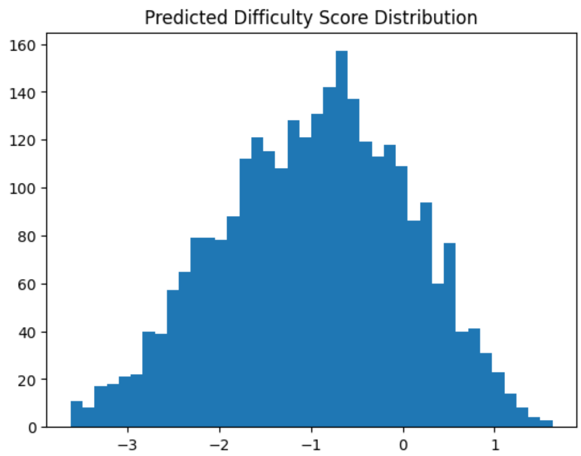

Figure 2. Distribution of predicted readability scores across the dataset.

3.3 Dyslexia Error Classification

To classify dyslexia-related error in reading, a supervised classifier was trained using artificially created error samples at the word level. The dataset had 1,440,385 samples, with each sample represented by 10 artificially created orthographic features based on edit distance, character difference, positional difference, and bigram similarity.

The classifier had five error types:

- correct response
- substitution error
- omission error
- reversal error
- transposition error

Table 3 Error Classification Performance (Random Forest)

Class	Precision	Recall	F1-Score	Support
Correct	0.91	1.00	0.95	57,616
Omission	1.00	1.00	1.00	57,615
Reversal	1.00	0.97	0.98	57,615
Substitution	1.00	0.96	0.98	57,616
Transposition	1.00	0.97	0.98	57,615
Overall Accuracy			**0.9803**	288,077

The classifier reported an accuracy of 98.03%, with macro-average and weighted-average F1 values of 0.98.

3.4 Adaptive Learning Evaluation

The adaptive learning mechanism was tested using a simulated learning scenario consisting of 40 sessions of readings. The adaptive learning mechanism was implemented using an Epsilon-Greedy Multi-Armed Bandit algorithm with Epsilon set to 0.1. The adaptive learning mechanism was compared with a baseline static system.

Table 4 Static vs Adaptive Learning Performance (Single Simulation)

Metric	Static System	Adaptive System
Mean Accuracy	0.6494	**0.8367**
Performance Trend	+0.00540	+0.00491
Final Rolling Accuracy	0.7350	**0.9150**

The adaptive learning mechanism reported significantly higher accuracy than the baseline static system.

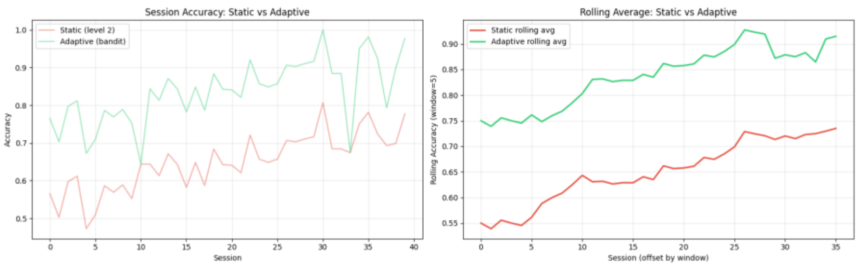

Figure 3. Session-level and Rolling average accuracy comparison.

3.5 Multi-Trial Evaluation

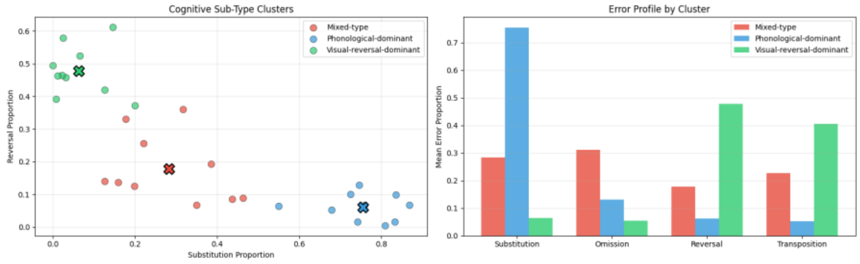

Figure 4. Cognitive profiling

The Figure 4 represents 30 students clustered into 3 profiles and to test the robustness of the experiment results, multiple independent trials of the experiment were carried out.

Table 5 Controlled Evaluation Across Trials

Trial	Static Accuracy	Adaptive Accuracy	Gain
Trial 1	0.6494	0.8167	+0.1673
Trial 2	0.6566	0.8460	+0.1894
Trial 3	0.6473	0.7423	+0.0950
Trial 4	0.6469	0.8469	+0.2000
Trial 5	0.6505	0.8230	+0.1725

Table 6 Aggregate Statistical Summary

Metric	Static	Adaptive
Mean accuracy	0.6501	**0.8150**
Standard deviation	0.0035	0.0383
Minimum accuracy	0.6469	0.7423
Maximum accuracy	0.6566	0.8469
Average improvement	–	**+0.1648**

Across all trials, the adaptive system consistently outperformed the static baseline. Also represented in the Figure 5.

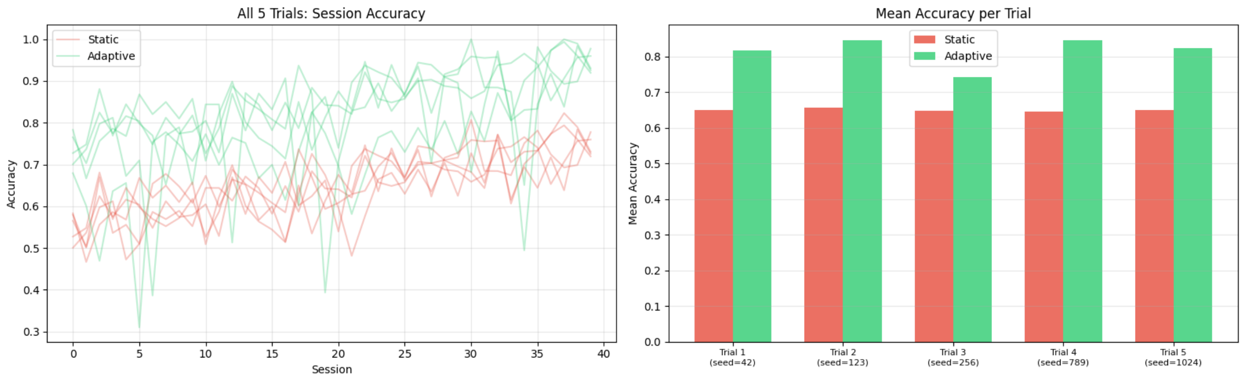

Figure 5. Session accuracy and mean accuracy per trail

DISCUSSION

The results show the effectiveness of integrating readability modeling, error classification, and adaptive learning in a unified framework for dyslexia-oriented reading assistance.

The proposed hybrid readability model was based on a 399-dimensional feature representation, including linguistic readability metrics and Sentence BERT embeddings. The model was able to achieve an RMSE of 0.684 and R^2 of 0.553. This shows that the proposed hybrid readability model can capture the variability in the readability of text. By clustering the scores into five levels of difficulty, the proposed model can create a structured hierarchy of reading passages, which can be useful in an adaptive learning framework. The dyslexia-oriented error classification component was able to achieve 98.03% accuracy on 1.44 million data points of generated error data. It was able to achieve perfect precision and recall on omission-type errors. It was also able to achieve high F1-scores of 0.98 on substitution, reversal, and transposition-type errors.

The adaptive learning evaluation revealed significant improvement compared to the static baseline. In the simulation experiment, accuracy increased on average from 0.6494 to 0.8367, and the final rolling accuracy reached 0.9150. The multi-trial evaluation of the adaptive learning system revealed its robustness. The adaptive approach reached 0.8150 in terms of accuracy on average after five trials, compared to 0.6501 for the static approach, resulting in a total improvement of 0.1648 on average. The cognitive profiles revealed three different learner types: the phonologically dominant learner with high substitution error rates of 75.5%, the visual reversal learner with high reversal and transposition error rates of 47.8% and 40.5%, and the mixed type learner with equal error distributions.

The improvement of the adaptive learning system's performance can be explained by the dynamic control of the difficulty levels, which is consistent with the zone of proximal development theory.

CONCLUSION

This study outlines a new approach for adaptive reading intervention in dyslexia treatment by developing a framework that leverages readability modeling, error classification, and personalization via reinforcement learning. The suggested system has considerable possibilities for practical use in digital learning systems and assistive technologies for dyslexic learners. The hybrid readability model showed impressive performance in predicting readability (RMSE of 0.684 and R^2 of 0.553). The five empirical difficulty levels of the model's output also showed potential for tiered content adaptation.

The dyslexia error classification model, trained on 1.44 million samples, showed impressive performance with a high accuracy of 98.03%, especially in omission and reversal errors. This shows that the model is able to generalize and learn from different error patterns through its design of orthographic features.

The adaptive learning framework using Epsilon-Greedy Bandit significantly outperforms the baseline on both single and multiple trial evaluations, improving accuracy from 0.6501 to 0.8150 on average. The final simulated learner also reached a rolling accuracy of 0.9150. Additionally, three dominant cognitive profiles of students were identified, enabling error-weighted remediation strategies based on individual profiles.

The study relies on simulated learning scenarios and artificially produced error sets. Further tests are necessary to assess the system's effectiveness with real dyslexic learners.

The ethical implications of the system are related to data privacy, fairness of the adaptive suggestions, and avoidance of learning bias.

Future directions of this study should be on its deployment and testing on human subjects and classroom settings to assess its long-term effects.

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