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A Hybrid Personalized Text Simplification Framework Leveraging the Deep Learning-based Transformer Model for Dyslexic Students

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ABSTRACT

This study proposes a hybrid personalized text simplification framework leveraging the deep learning-based Transformer model to generate simplified expository texts by addressing all sentence perspectives: semantic, syntactic, and lexical. This study targets dyslexic students due to its increasing population in the education context. Dyslexia is a learning disability characterized by reading deficiency and cognitive weakness. Thus, they need a more personalized learning experience i.e., personalized text simplification to support their classroom learning. Unfortunately, the current models of personalized text simplification can only address the syntactic and lexical perspectives of sentences, ignoring the semantic perspective. Other models employed text complexity classification at the beginning of the text simplification workflow with the intention to address the personalization element. Still, no mapping to the deficiencies of its intended users was made, and the semantic perspective of sentences remains under study. Therefore, this study is conducted to introduce hybrid methods to enhance the current personalization elements, as well as to accommodate generation of simplified expository texts at all sentence perspectives. An extensive literature was conducted using established online databases. The proposed hybrid framework is further divided into three distinct phases: Phase 1) two-phase personalization, Phase 2) multi-label text complexity classification, and Phase 3) explicit editing. It is expected that a successful implementation of the proposed hybrid personalized text simplification framework can accelerate the learning motivations of dyslexic students, hence increasing their academic achievements and reducing academic dropout rates.

1. Introduction

Technology in education enables students to learn or attain results more quickly and saves time according to Jaafar *et al.,* [1]. With the emergence of personalization, it becomes significant to blend personalization elements alongside these technology advancements. A study by Maghsudi *et al.,* [2] confirmed that incorporating the personalization elements into the text simplification model can

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provide a solid foundation for assisting students, particularly those with learning disabilities i.e., dyslexia, in comprehending expository texts in their school textbooks.

An ideal personalized text simplification must tackle both the personalization and text simplification at three (3) sentence perspectives: semantic, syntactic, and lexical. Personalization can be incorporated in two (2) approaches which are either extrinsic-intrinsic or by classifying the complexity of texts. Extrinsic approach reflects task-based protocols that require external user input which can be found in the study by Bingel [3]. His research requires the intended users to individually highlight words they have difficulty comprehending when lengthy paragraphs are shown. Despite the advantage of introducing individual personalization, its implementation can only address the lexical perspective of sentences. Intrinsic, on the other hand, refers to the internal collection of user preferences. This involves gathering topic preferences, aesthetic features, and expressive habits from the cache memory based on their historical inputs, as undertaken by Lin *et al.,* [4], and rewarding the user-provided style-related features, as implemented by Zhao [5].

Apart from the extrinsic-intrinsic personalization, classification of text complexity at the beginning of the text simplification workflow has been implemented by several studies, also with the aim to support personalization [6-11]. Each sentence is labelled either as *simple-to-read* or *difficult-to-read* based on scores measured by sentence comparisons. Unfortunately, with binary complexity classification, it is not enough to well support the diversity of dyslexic students since no two (2) dyslexic students are really alike. In addition, the complexity classification can only address the syntactic and lexical perspectives, while neglecting the semantic perspective of the sentences. Hence, insufficiency remains an open issue to be resolved as dyslexic students also have difficulty understanding the text structures that convey the semantic perspective of sentences.

This study also addresses the utilization of text simplification operations i.e., paraphrase, delete, split, and substitute at different sentence perspectives i.e., semantic, syntactic, and lexical to generate simplified texts. It is hypothesized that an effective personalized text simplification model should not be limited to a single simplification operation and the simplification operations should not be predetermined because the intended users, dyslexic students in this study, have varying levels of reading and cognitive deficiencies. Several studies have successfully generated simplified texts using their own proposed simplification operation [12-17]. However, their studies can only address the perspectives of sentences individually, either semantic or lexical. Again, the issue of insufficiency persists as the total sentence perspectives of semantic, syntactic, and lexical are still unable to be addressed simultaneously using appropriate simplification operations. This leads to another hypothesis that the most appropriate simplification operation to be performed is by combining multiple simplification operations with a content addition operation to balance the simplified texts.

It is perceived that the proposed personalized text simplification framework using the hybrid deep learning-based methods can enhance the existing text simplification models, by delivering a comprehensive personalization and text simplification at all the semantic, syntactic, and lexical sentence perspectives. Besides, the findings of this study are significant to the benefit of dyslexic students as it can be served as a personalized learning intervention to help them better comprehend the expository texts and thus, improve their academic achievement and reduce dropout rates.

1.1 Research Objectives

With regard to the above addressed issues, we found out that there is still a gap in previous studies related to both the personalization dan text simplification, where these two (2) important elements still insufficient to tackle all three (3) perspectives of the sentence simultaneously. Thus, the following research objectives are devised for this study:

i. RO1: To introduce a hybrid method by fusing two-phase extrinsic personalization with multi-label text complexity classification approaches for improved personalization elements.
ii. RO2: To introduce a hybrid method backboned by the Transformer model, capable of recommending the most accommodating multiple simplification operations, and able to tackle all sentence perspectives simultaneously.

2. Background of Study

This section is divided into four sub-sections that review previous literature on: 1) who are dyslexic students and what constitutes expository texts, 2) how personalization elements are incorporated into the text simplification model, 3) how text simplification operations are exploited to generate simplified texts, and 4) how deep learning-based models are employed in text simplification.

2.1 Dyslexic Students and Expository Texts

The focus demographic of interest in this study is dyslexic students at the primary school level. Dyslexia is a learning disability characterized by two primary components: 1) reading deficiency and 2) cognitive weakness, with the exception of visual, hearing, and motor disabilities as defined by Lindstrom [18]. With regard to reading deficiency and cognitive weakness, dyslexic students struggle to read and comprehend expository texts in school textbooks from semantic, syntactic, and lexical perspectives.

The semantic perspective is concerned with the organization of sentences, whereas the syntactic perspective is concerned with the grammatical principles of sentences. In contrast, the lexical perspective focuses on the vocabulary employed in sentences. Table 1 further depicts the semantic, syntactic, and lexical perspectives associated with expository texts, as well as the reading- and cognitive-related deficiencies reported by dyslexic students, which make comprehension of expository texts a challenge for them.

Table 1
Semantic, syntactic, and lexical perspectives of sentences and their relation to reading- and cognitive-related deficiencies of dyslexic students

Sentence Perspective	Definition	Reading- and Cognitive-related Deficiencies of Dyslexic Students	Reference
Semantic	• Semantic relates to how the sentences are organized. • There are five types of organizational structures in expository texts: compare and contrast, problem and solution, description, sequence, and cause and effect. • Each type of them is differentiated using the clue words i.e., *but*, *on the other hand*, and *different from* indicating the compare and contrast structure of expository texts.	Limited understanding of common text structure	Shankweiler *et al.,* [19], Watson *et al.,* [20], Graham and Bellert [21]
Syntactic	• Syntactic relates to the grammatical principles of sentences.	Immature understanding of syntactic principles	Shankweiler *et al.,* [19], Watson *et al.,* [20], Graham and Bellert [21], Bishop and Snowling [22]
Lexical	• Lexical relates to the vocabulary used in the sentences. • Expository texts include not only the vocabulary that represents important concepts but the scientific processes as well.	Vocabulary inadequacies due to only having a limited number of familiar words	Watson *et al.,* [20], Graham and Bellert [21], Padeliadu and Antoniou [23], Venable [24]

2.2 Incorporation of Personalization Elements into the Text Simplification Model
2.2.1 Extrinsic-intrinsic approach

The first work of personalized text simplification was conducted by Bingel [3], also known as an adaptive model. This work established an extrinsic personalization for addressing the lexical perspectives by learning from user feedback and behavioral data when users were required to identify and highlight every complex word in the lengthy paragraphs. This extrinsic personalization was encapsulated in loops and thus, extending the subsequent Eq. (1):

$$y = M_{D,H}(x, \pi) \tag{1}$$

where M is induced from a base dataset D and continuously updated from a history H of users' feedback. The output at the production time is conditioned on the input x and the explicit personalization of π.

As opposed to the extrinsic approach, the intrinsic personalization gathers user preferences indirectly by monitoring the user's computer usage activity. A study by Lin *et al.,* [4] has proposed an intrinsic cache-based module to be combined with the user-driven contrastive learning method to capture potential user traits from their historical inputs i.e., topic preferences, aesthetic features, and expressive habits. Furthermore, a study by Zhao [5] also leveraged intrinsic personalization by capturing the style-related features of the intended users. The reinforcement learning and the policy gradient methods were used to reward the user-provided style-related features. Nonetheless, because this method was incorporated at the very end of the text simplification workflow, there is an urgency to retrain the model each time the user information changes, thus, compromising the speed. Furthermore, it has been observed that the intrinsic personalization employed in both studies of Lin *et al.,* [4] and Zhao [5], was backboned by the deep learning-based Transformer model.

2.2.2 Text complexity classification approach

Some studies have embedded text complexity classification at the beginning of the text simplification workflow, also with the aim to support personalization, and address the diverse needs of the intended users. Following the reading and cognitive deficiencies of dyslexic students, complexity classification can be further subdivided into syntactic, lexical, and semantic perspectives. The classification methods for text complexity are often combined with Natural Language Processing (NLP) so that the essential linguistic features of the text may be identified for evaluation and then utilized to train the text simplification model.

The current state of syntactic complexity classification is data-driven, with scores assigned after sentence comparisons, leading to binary classifications of '1' - *difficult-to-read* or '0' - *simple-to-read*, as conducted by Schicchi *et al.,* [7], Bosco *et al.,* [8], and Gasperin *et al.,* [9]. The part-of-speech tagger (NLP) was utilized to break down the sentences according to the syntax linguistic principles to fit the binary classification. Schicchi *et al.,* [7] and Bosco *et al.,* [8] employed an end-to-end deep learning-based Recurrent Neural Network model in their study, whereas Gasperin *et al.,* [9] adopted a more traditional rule-based strategy. Their implementation of binary classification is supported by a function defined by Garbacea *et al.,* [6], as illustrated in Eq. (2):

$$f : D \rightarrow \{0,1\} \quad (2)$$

such that *f(d)=1* belongs to *difficult-to-read* and *d* needs to be further simplified, and *f(d)=0* otherwise.

In the meantime, research on lexical complexity classification at the word level by Gooding and Tragut [10] and Balyan *et al.,* [11] has transformed the binary classification into a more thorough multi-class classification. The study by Gooding and Tragut [10] has classified the words into seven classes based on the English Common European Framework of Reference for Languages (CEFR), while the study by Balyan *et al.,* [11] has classified the words into four classes: easy, medium, difficult, and very difficult. In terms of methodologies, Gooding and Tragut [10] implemented the unsupervised active learning agglomerative clustering method, which performed the clustering from the bottom up, whereas Balyan *et al.,* [11] strongly utilized the Machine Learning approach coupled with the NLP. Both studies extracted similar word-level features: uncommon words, word familiarities, word frequencies, word imageabilities, the average number of syllables per word, and the average number of characters per word.

In a nutshell, incorporating comprehensive personalization elements into the text simplification model is still an open issue. Extrinsic personalization could only address dyslexic students' reading and cognitive deficiencies in terms of lexical perspective. On the other hand, the text complexity classification is performed solely on a data-driven basis, addressing only the dyslexic students' reading and cognitive deficiencies of syntactic and lexical perspectives, leaving the semantic perspective behind. As a result, in order to establish a comprehensive, resilient, and effective personalized text simplification model for dyslexic students, all three perspectives of semantic, syntactic, and lexical complexity classification should be combined and incorporated at the beginning of the text simplification workflow. Furthermore, the current study of text complexity classification should be extended so that the classification can go beyond the two classes of *difficult-to-read* and *simple-to-read* in order to support better personalization of dyslexic students.

2.3 Text Simplification Operations

A successful generation of simplified texts is influenced by the choice of its simplification operation that is closely related to the sentences' semantic, syntactic, and lexical perspectives. Currently, the text simplification model predominantly employs four simplification operations: 1) paraphrase 2) delete 3) split, and 4) substitute. The substitute operation is typically performed at the word level, while the others are at the sentence and document levels. Depending on their research concerns, some researchers concentrated on a single simplification operation, whereas others concentrated on multiple simplification operations.

2.3.1 Single simplification operation

In a single simplification operation, studies by Botarleanu *et al.,* [12] and Lin *et al.,* [13] have employed the paraphrase operation to address the semantic perspective of the sentences. The challenge of performing the paraphrase operation is to preserve the similar meanings and context of the original sentences without diminishing their coherence upon conversion from the original text into the simplified texts. An earlier study conducted by Botarleanu *et al.,* [12] leveraged the Neural Machine Translation using the Universal Transformer model to translate the original English text into its simplified version. A positional encoding is added to the sequence of word embeddings (NLP technique) so that it can uniquely identify each word position in the text. The resulting embeddings were then processed by the multi-head attention layer of the Universal Transformer model. On the other hand, a later study by Lin *et al.,* [13] leveraged the graph GRU to learn the coherence-aware relationship of sentences. The graph GRU is made up of a stack of L_g identical layers, each of which has a multi-head graph attention block, a GRU cell, and a normalization layer. The graph GRU is positioned within the Transformer model's encoder-decoder layer.

Aside from the paraphrase operation, the delete operation can be used as a single operation to accommodate the sentences' semantic perspective. A study by Zhong *et al.,* [14] proposed that, in addition to sentence length and content, contextual, discourse-level information influences sentence deletion. The average GloVe technique was used instead of positional encoding for word embeddings. Using the Newsela corpus, each sentence is placed in the rhetorical structure tree and treated as a discourse unit. The discourse relations were then used to identify the relationships between clauses and sentences i.e., contrast and causal. The logistic regression and feedforward neural networks were then used as classifiers to determine whether or not the words in the sentences should be deleted.

Additionally, the substitute operation can also be performed as a single simplification operation. The substitute operation is typically utilized at the word level, where complex words are identified and substituted with more familiar words. Studies by both Lee and Yeung [15] and Bulté *et al.,* [16] have employed the lexical simplification pipeline which is further divided into four phases: 1) complex word identification 2) substitution generation 3) substitution selection, and 4) substitution ranking. With the concern of substituting complex words with non-complex words and at the same time, remaining semantic faithfulness within the context of surrounding sentences, Lee and Yeung [15] have proposed a novel two-step substitution ranking algorithm. The proposed algorithm ranks word substitution candidates based on their semantic proximity to the target words, and then the highest-ranked candidate is chosen as output to represent non-complex terms for the intended users. The study by Bulté *et al.,* [16] on the other hand, is more data-driven, utilizing the average age of acquisition of lemmas and word frequency methods to evaluate the words' difficulty level. The structured lexical semantic database is then used to generate word synonyms to reflect the identified complex words. In the meantime, Abualhaija *et al.,* [17] proposed a metaheuristic approach utilizing the D-Bees optimization algorithm that simulates swarm intelligence as an extrinsic evaluation in order to tackle word sense disambiguation in lexical simplification operation. It employed a top-down generation strategy in which the target complex words are first disambiguated with respect to the context of their surrounding sentences, and the D-Bees optimization algorithm is then used to recommend a list of non-complex word substitutions.

Finally, Garain *et al.,* [25] performed a single simplification operation utilizing a split operation. Instead of employing contemporary neural networks, they used a rule-based approach to simplify English sentences, which ranged from complex and compound words to simple syntactic sentences. They separated their model into two phases: 1) simplifying compound sentences with clauses joined by coordinating conjunctions, and 2) simplifying compound sentences with clauses connected by subordinating conjunctions. To construct the simplest sentences with no residual conjunctions, the syntactic parse trees were fully exploited recursively.

2.3.2 Multiple simplification operations

On the other hand, previous researchers have also undertaken multiple simplification operations in order to address multiple sentence perspectives simultaneously. A study by Niklaus *et al.,* [26] has integrated the split and paraphrase operations to address both the syntactic and lexical perspectives at the same time in their study. Their goal is to reduce the original sentences to a collection of minimal propositions, therefore a two-layered parse tree in the form of core facts and associated contexts was produced to preserve the coherence structure. Then, 35 hand-crafted grammar rules were used to accomplish two goals: 1) to split up and rephrase the original sentences into structurally simpler sentences, and 2) to establish a semantic hierarchy amongst them. Meanwhile, Cumbicus-Pineda *et al.,* [27] expanded the explicit edit-based method by incorporating the dependency tree's syntactic information and feeding it into the graph convolutional network (GCN). The GCN was supported by Long Short-Term Memory Networks (LSTM), which include an encoder, decoder, and interpreter modules, allowing it to learn and generate edit operations sequentially. The LSTM model was chosen because of its capacity to grasp long-distance syntactic relationships between words.

Additionally, Sharma and Goyal [28] were able to address the semantic and lexical perspectives simultaneously by employing the Neural Machine Translation (NMT) framework along with the 2-layer encoder-decoder model and Gated Recurring Unit. The NMT framework was opted for by the researchers due to its benefit to represent the sentences as a continuous space representation which can be leveraged for semantic similarity in case of paraphrasing. Zero-shot learning using a multi-pivot method was added to facilitate the adaption of anchor points sentence mapping during the learning of sentence translation i.e., from original to simplified sentences. Furthermore, lexical simplification was integrated at the end of the simplification workflow by using the “Treetagger” along with “treetaggerwrapper” to mark the complex words. External vocabulary resources were referenced during the word substitution operation.

In conclusion, an effective personalized text simplification model should not be restricted to a single simplification operation. This is due to the fact that a single simplification operation cannot address all three perspectives of the sentences. The prior study's methodology, which defined in advance the exact simplification operation to be conducted, rendered it ineffective for the intended users. In addition, the rule-based method necessitates a tremendous quantity of manpower because it involves an endless number of language experts. The multiple simplification operation, on the other hand, is a more promising area, albeit it still needs expansion. With the developments of the deep learning-based model, it is possible to extend the explicit edit-based approach and the NMT method so that a complete component of syntactic, semantic, and lexical perspectives may be incorporated into the personalized text simplification model. The summary of the literature on text simplification operations is shown in Table 2.

Table 2
A summary of text simplification operations

Level of Simplification Operation	Sentence Perspective	Type of Simplification Operation	Model	Method	Reference
Single	Semantic	Paraphrase	Universal Transformer model	Positional word embeddings and Neural Machine Translation	Botarleanu *et al.,* [12]
			Transformer model	Graph GRU	Lin *et al.,* [13]
		Delete	Feedforward neural networks	Average GloVe word embeddings and rhetorical structure tree	Zhong *et al.,* [14]
	Lexical	Substitute	Not specified	Two-step substitution ranking algorithm	Lee and Yeung [15]
			Not specified	The average age of acquisition of lemmas and word frequency, with the structured lexical semantic database as the external resource	Bulté *et al.,* [16]
			Not specified	D-Bees optimization algorithm	Abualhaija *et al.,* [17]
	Syntactic	Split	Not specified	Syntactic parse tree and rule-based approach	Garain *et al.,* [25]
Multiple	Syntactic and lexical	Split and paraphrase	Not specified	Two-layered parse tree and hand-crafted grammar rules	Niklaus *et al.,* [26]
	Syntactic	Edit-based (KEEP, REPLACE, DELETE)	LSTM model	Dependency tree and GCN	Cumbicus-Pineda *et al.,* [27]
	Semantic and lexical	Paraphrase and substitute	Recurrent Neural Network	Zero-shot learning with a multi-pivot method, NMT, and “Treetagger” for lexical simplification	Sharma and Goyal [28]

2.4 Deep Learning-based Models in Text Simplification

Deep learning is a subset of machine learning, and artificial intelligence is now regarded as a core technology due to its ability to learn from data with greater accuracy. Its architecture is based on an encoder-decoder artificial neural network (ANN) with multiple hidden layers (*hidden layer = N* and N≥2). Sarker [29] stated in his study that deep learning-based models go through the same processing stages as machine learning models, which have three steps. The first step is data understanding and pre-processing, followed by model building and training, and finally, validation and interpretation which has been observed applicable in text simplification. Figure 1 depicts the three processing steps of deep learning-based models in more detail.

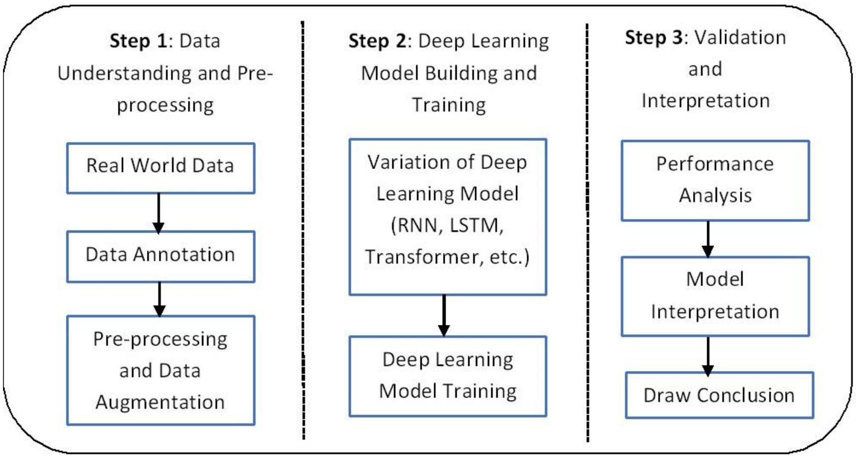

Fig. 1. Three processing steps of deep learning-based models

In text simplification, the deep learning-based model that was employed by Zhang and Lapata [30] is known as the Recurrent Neural Network (RNN). They considered the model to be an encoder-decoder agent that also possessed an attention mechanism, which was determined by applying the dot product function. Nevertheless, because of the model's limitations, particularly regarding understanding the long-term connections among the words in the sentences, other researchers have turned to using the LSTM model instead.

The LSTM model has gained widespread acceptance for its effectiveness in learning sequential data prediction in text simplification. Cumbicus-Pineda *et al.,* [27] employed the LSTM model with the encoder used to transform the input sequence x into a sequence of output, o_i, and hidden representations, h_i. Instead of putting the attention mechanism at the encoder layer, they put it at the decoder layer, coupled with a series of linear layers and activation functions to carry out better accuracy of prediction tasks.

In contrast to the LSTM model, the Transformer model has attracted more interest in text simplification since it does not require the input sentences to be processed in sequential order. Vaswani *et al.,* [31] remarked that by recognizing the context that gives meaning to each word in the input sentences. The Transformer model permits parallelization and a faster training period, providing it more advantages than the other models. With multi-head attention as opposed to single-head attention, the model is able to simultaneously attend to information from distinct representation subspaces at distinct places. Numerous researchers, including Lin *et al.,* [4], Zhao [5], Botarleanu *et al.,* [12], and Lin *et al.,* [13] have utilized the Transformer model in their studies.

3. Hybrid Personalized Text Simplification Framework

In light of earlier research, this study proposed a hybrid personalized text simplification framework, with the personalization elements addressing dyslexic students' reading and cognitive deficiencies. The hybrid framework is further separated into three phases to align with the two research objectives mentioned earlier. The first two phases are concerned with the first research question, while the third phase is concerned with the second research question. Figure 2 shows a more detailed representation of the proposed hybrid personalized text simplification framework.

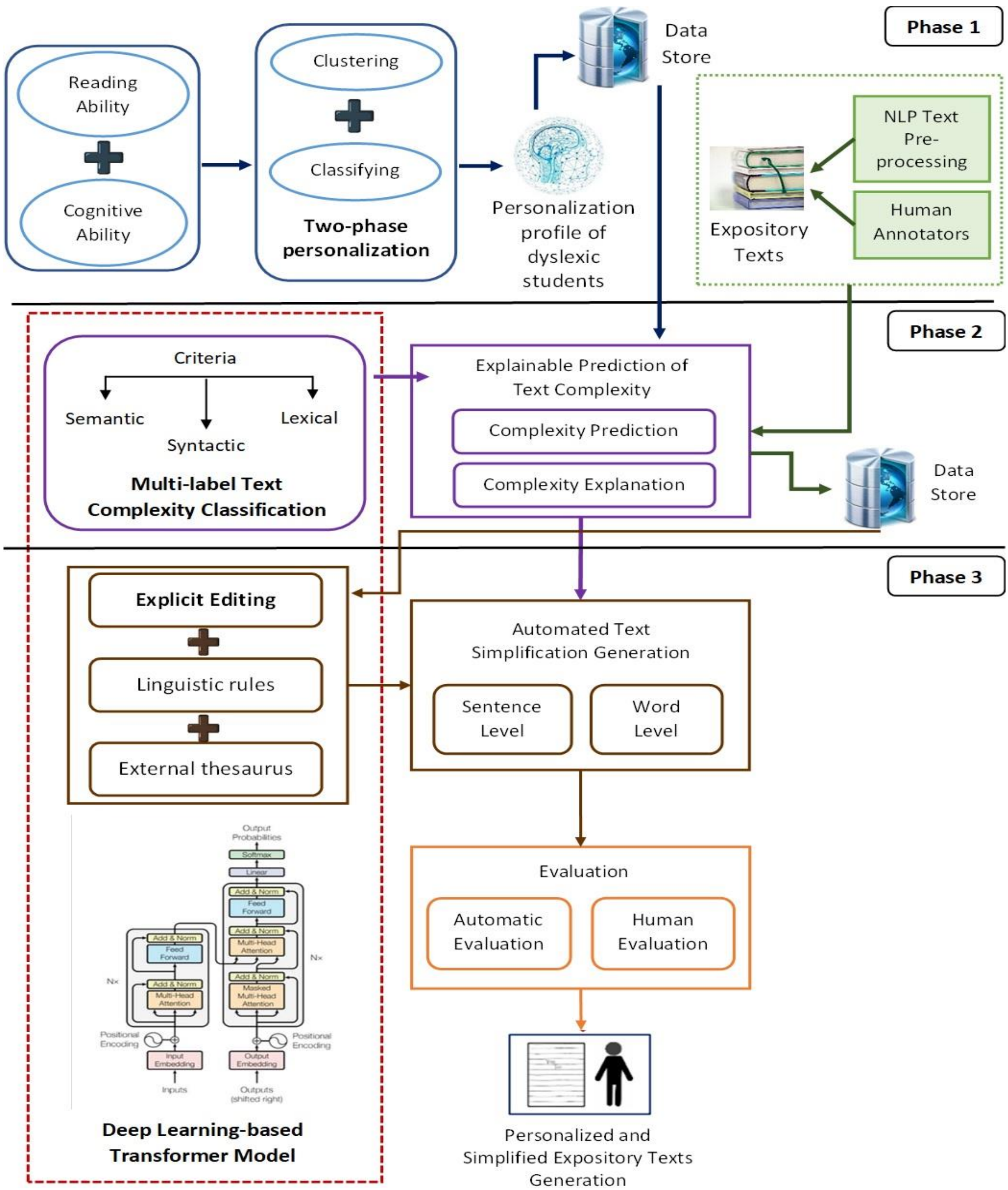

Fig. 2. The proposed hybrid personalized text simplification framework leveraging the deep learning-based Transformer model for dyslexic students

RO1: To introduce a hybrid method by fusing two-phase extrinsic personalization with multi-label text complexity classification approaches for improved personalization elements.

The hybrid framework's phases 1 and 2 are integrated to respond to the first research objective. The primary goal of phase 1 is to capture dyslexic students' personalization by addressing both their reading and cognitive deficiencies. As a result, the extrinsic personalization elements are added by collecting their answers externally from the standardized assessment battery. We screened and retrieved only the most important features from the numerous and lengthy assessments available for dyslexic students. Following the studies of Capin *et al.,* [32], Loizou and Laouris [33], and UNESCO's global proficiency framework for reading, the six most essential cognitive traits, and the three most important reading features have been determined. To indicate a more accurate personalization of dyslexic students, it is hypothesized that their classification should go beyond the binary classification of *have-dyslexic* or *no-dyslexic*. As a result, this study proposed a two-phase personalization strategy, in which the clustering approach is used first to train the model, followed by the classification approach. Unsupervised agglomerative clustering with a bottom-up hierarchical method is proposed for clustering. The dendrogram obtained by the squared Euclidean distance matrix is then used to understand the heterogeneity of dyslexic students. After training the model, the linear classification method is proposed to identify the corresponding personalized profile of each dyslexic student. Figure 3 depicts the sequential pipeline for developing personalized profiles for dyslexic students.

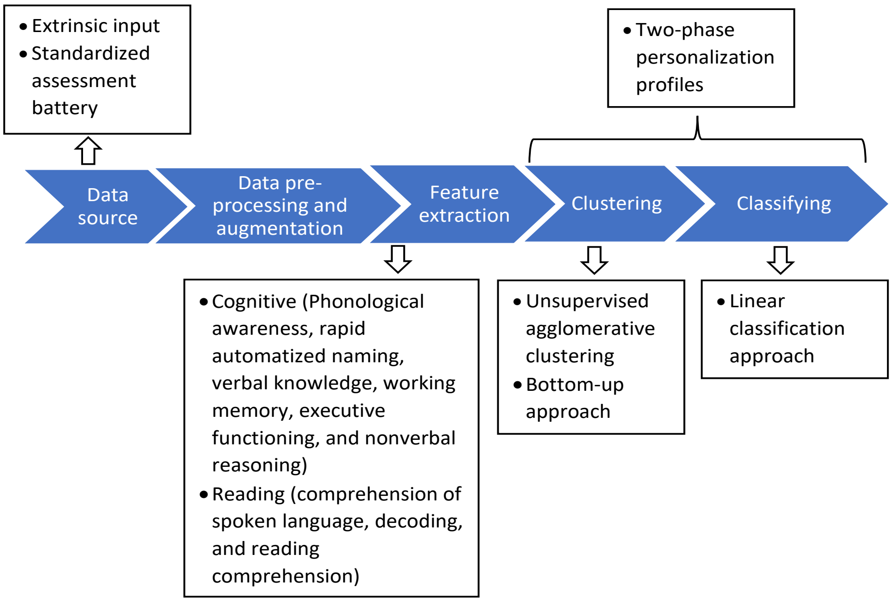

Fig. 3. The sequential pipeline of two-phase personalization profiles for dyslexic students

To add value to dyslexic students' personalization elements, the personalization profiles generated at the end of phase 1 would be combined with the text complexity classification in phase 2. The primary goal of phase 2 is to predict which sentences and words dyslexic students would struggle to understand based on their personalization profiles. This phase makes use of multi-label text complexity classification, as well as NLP pre-processing and human annotations. The multi-label classification method is chosen by evaluating a circumstance where a certain text appears simple to student A but difficult to student B. Furthermore, a multimodal embedding method is proposed to address complexity classification in terms of semantic, syntactic, and lexical perspectives simultaneously, replicating the research of Gargiulo *et al.,* [34]. The dependency tree and part-of-speech embeddings are used for the syntactic complexity classification, along with the linguistic rules, while word embeddings are used to address the semantic complexity classification, as studied by Chandrasekaran and Mago [35], and also to address the lexical complexity. Prior to the complexity classification, fundamental NLP pre-processing operations such as lower casing, stop word filtering, and tokenization is performed. Aside from that, the data annotation task is assigned to linguistic experts who are frequently involved in teaching students with learning disabilities. Figure 4 depicts the sequential pipeline for classifying multi-label text complexity.

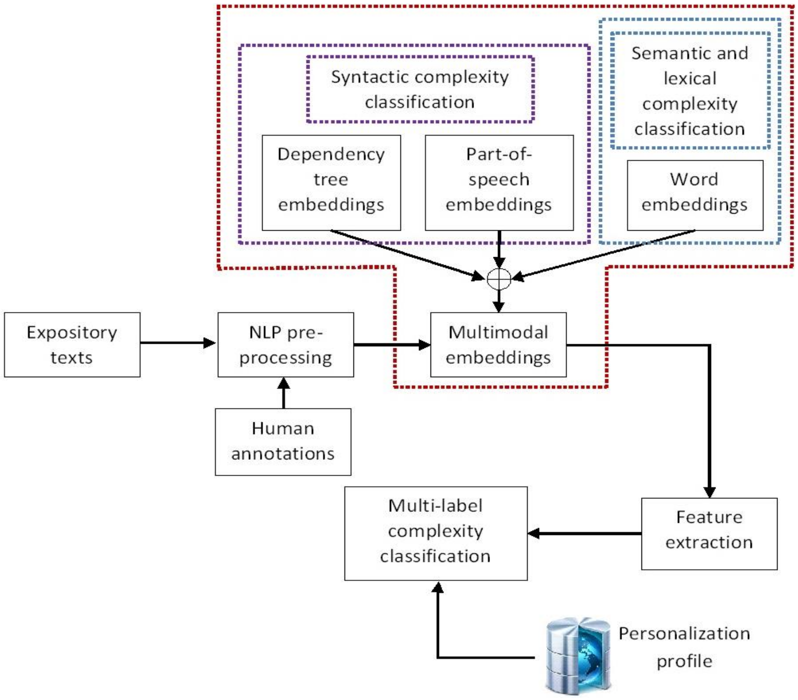

Fig. 4. The sequential pipeline for multi-label text complexity classification addressing semantic, syntactic, and lexical perspectives of the sentences simultaneously

RO2: To introduce a hybrid method backboned by the Transformer model, capable of recommending the most accommodating multiple simplification operations, and able to tackle all sentence perspectives simultaneously.

Phase 3 of the hybrid framework is a continuation of the previous two phases, with the hypothesis that an effective personalized text simplification model should not be restricted to a single simplification operation. As a result, an explicit editing method based on the work of Dong *et al.,* [36] is proposed, but with a mapping to multi-labeled text complexity to address the personalized profiles of dyslexic students. Two connecting modules, the programmer and interpreter modules, are inserted within the deep learning-based model's encoder-decoder layer to replicate human editors who may execute simultaneous deletion, splitting, and other operations to shorten and simplify long and complex texts. The programmer module can learn to predict the edit operation, i.e., ADD, DELETE, or KEEP, on the original sentences by infusing multi-labeled text complexity information into the latent representation. The edit operations are then carried out by the interpreter module, which generates the simplified sentences. The scoring functions used by Kumar *et al.,* [37] are thought to be added to assist the programmer module in formulating edit operation predictions. The cosine similarity, f_{cos}, and entity score, f_{entity} can address semantic preservation measures, whilst the length, f_{len} score is related to the inverse of the phrase length. Furthermore, linguistic rules are included to respond to the paraphrase operation to retain the coherence of the simplified sentences. An external thesaurus is integrated to aid in the generation of candidate words for replacing the identified complex words. The content addition operation is performed as the final simplification step at the end of the edit operation, leveraging the pre-trained language models, i.e., the BERT model, to provide the contextual specificity to facilitate the elaboration generation, as undertaken by Srikanth and Li [38].

To facilitate the implementation of hybrid methods, the Transformer model is specified as the deep learning-based model. The Transformer model has been regarded as the first transduction model whose architecture is based purely on an attention mechanism. This model is capable of producing results of a higher quality than sequence-to-sequence models even without the use of any convolution. Each encoder layer consists of a multi-head self-attention mechanism and a fully connected feed-forward network. Additionally, the decoder consists of six similar layers, each with an additional sublayer. The additional sublayer's purpose is to perform multi-head attention over the encoder stack's output. Figure 5 displays the Transformer model's architecture and the multi-head attention mechanism in further detail. Note that the V, K, and Q in the scaled dot-product attention mechanism resemble vector representations of dimension values, dimension keys, and queries.

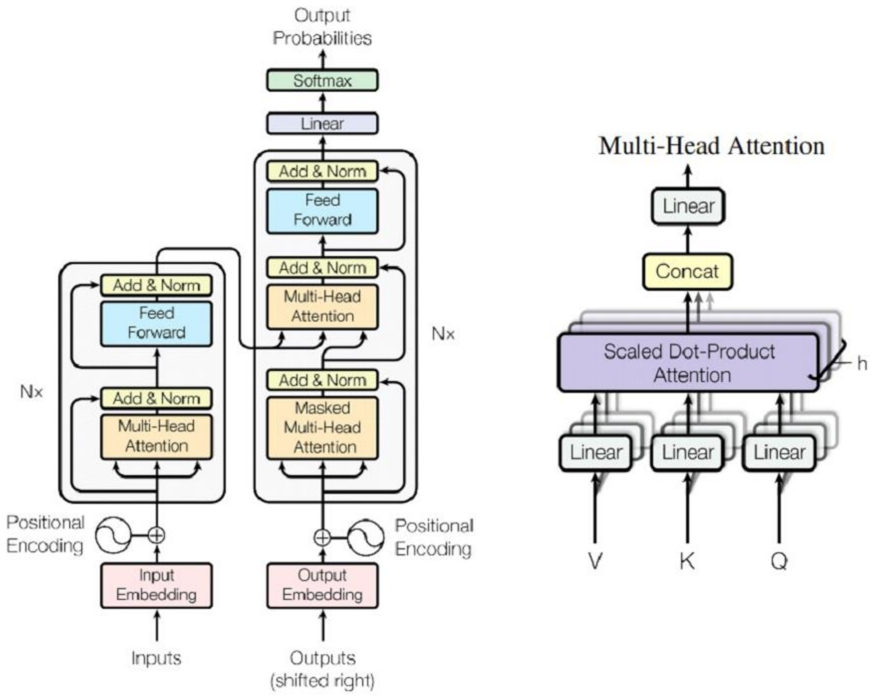

Fig. 5. The Transformer model architecture (left) and the multi-head attention mechanism (right)

4. Conclusion and Future Works

In conclusion, this study highlighted the integration of two-phase personalization, multi-label text complexity classification, and explicit editing as the comprehensive hybrid methods in the personalized text simplification framework, which is backboned by the deep learning-based Transformer model. In future work, an empirical study will be carried out in accordance with the proposed hybrid framework and will be benchmarked with the existing state-of-the-art text simplification models. The TensorFlow platform of deep learning, as well as the Python programming language, will be employed. The proposed hybrid framework will also be tested on actual dyslexic students to assure its usefulness in their classroom learning.

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