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Article

Biosensor assisted measurement of cognitive participation in English reading: A psychological perspective

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Abstract: Cognitive involvement in English reading is important for understanding and engagement. Traditional techniques of measuring cognitive participation frequently rely on individual evaluations that do not capture real-time physiological reactions. Recent developments in artificial intelligence (AI) and biosensor technology provide intriguing options to close this gap by offering a goal, real-time data. This work seeks to improve the evaluation of cognitive participation in reading in English by combining biosensor data analysis with modern AI algorithms. Participants completed English reading activities, and their electroencephalogram (EEG) and Galvanic Skin Response (GSR) signals were recorded. A median filter was used as a pre-processing to reduce noise. Discrete wavelet transform (DWT) was utilized to extract features to extract specific patterns from the biosensor signals. The new Dynamic White Shark Infused Residual Neural Network (DWS-IResNet) approach was used to model and forecast the level of cognitive participation. The proposed method is implemented using the Python platform. The algorithm used was trained and evaluated based on performance indicators such as accuracy. Using the features of simple, technical, analytical, and emotional, the proposed DWS-IResNet approach is compared with metrics between males and females. In simple features, the accuracy was 90% higher for females; in emotional features, the precision was 90% better for females; and in males and females, the percentage of emotion features was greater at 90% of recall and 90% of F1-score. The suggested technique demonstrates the efficacy of the AI-enhanced biosensor method for assessing cognitive engagement. This study demonstrates the possibility of AI-powered biosensor readings for real-time, accurate evaluation of cognitive involvement during reading.

Keywords: English reading; biosensor; physiological reactions; signals; Dynamic White Shark Infused Residual Neural Network (DWS-ResNet)

1. Introduction

The use of wearable biosensor technology (WBT) has dramatically increased in the last decade, as does its presence in classrooms. WBT refers to a class of portable scientific products designed to be intentionally damaged either unevenly or directly by a person and integrated with multiple sensors that will allow for the collection of physiological or bodily information. The WBT is frequently applied in instructive settings to improve student learning and investigate the results of its use [1]. WBTs are currently used to direct the design of enlightening programs, gather in sequence to guide how learners learn, make substance accessible, and assist teachers in considering those they teach. A teaching association and computation using virtual reality (VR) software with an educator in an invented environment is one of the earliest known applications of mobile devices in teaching. In addition to providing students and educators with access to learning resources depending on time and place, that knowledge ensures that important data is collected in various educational contexts for later study [2]. Learners would have an unhindered, non-restrictive educational setting. The use of WBTs in exercises for physiological feedback technologies and in sporting event acknowledgment, respectively, enhances students' athletic ability and overall health. It is well established that psychological concepts like emotion, cognitive demand, and attention are crucial to how a person learns [3].

To investigate presenters' discomfort while speaking, investigators have concentrated on a three-system model: psychological, emotional, and behavioral. Self-evaluation assessments, observer judgments of behaviors, and emotional excitement have all been used to measure each component. Language anxiety is common in the conventional English learning classroom. Communication tasks are developed by the instructional instructors based on their material for the class, rather than provided by the researcher, to maintain ecological reliability standards [4]. There is a need to create instructional resources that support foreign language teachers in a particular learning scenario, even if recent research has been focused on helping teachers become more adept at recognizing the emotional states of their students. Teachers can find it more difficult to recognize and comprehend their students' emotions if they speak various languages and come from diverse cultural backgrounds. A prevalent misunderstanding about digital markers is that they are merely a digital variation of traditional indicators of health, according to a recent response to the vagueness around their definitions [5].

Digital voice performance evaluations or cognitive assessments are examples of conventional biomarkers, but biofluid-based diagnostic tests should be considered traditional regardless of the type of instrument utilized. Adopting a more comprehensive strategy for data collection and analysis is becoming more and more crucial as modern technology and basic comprehension evolve. It is crucial to create the right environment for the clinical application of wearable and smart devices since they can significantly aid in the ongoing dynamic observation of indicators [6]. Additionally, taking into account an individual's multi-omics characteristics in conjunction with morphological and clinical data can help identify the best susceptibility and forecast the right biomarkers. One promising technique to enhance human productivity and overall health is completely immersive VR, which can enhance surroundings, education, instruction, and relaxation tasks in a secure, independent, and customized manner. Biosignals collected during encounters can greatly enhance user autonomy and allow the experience to be tailored to each user's unique traits [7]. Biological reactions are commonly described as biosignals. When these reactions vary, biological sensor devices capture and monitor the resulting chemical signals. With the seven applicability domains of education, military, medical science, psychology, athletics, travel and branding, and ergonomics, general-purpose answers are provided to the preceding points. Students' opinions of the instructional techniques and activities used in the classroom are typically closely related to their level of participation in the classroom. Effective reading instruction typically involves measuring engagement among learners [8].

Reading is frequently a key component of children's growth and achievement, regardless of the setting of educational settings. It encourages critical thinking and fortifies the brain. Students who are proficient in comprehending text are also able to decipher written speech. Researchers can obtain useful information on students' psychological, mental, and behavioral states from three channels: audio, images, and video, and during certain educational events by using a computerized vision methodology [9]. Experts can track and assess how long students stay involved in a particular learning activity that was initially intended to teach anything using the data gathered from vision in computers. A number of the criteria used in these works, such as heart rate, cholesterol levels, posture, and sleep, to name a few, are pertinent to student participation. Additional investigators have set forth studies that concentrate on eye-tracking equipment to record students' focus to comprehend their participation in learning, as well as sensors and wearables that monitor students' physiology and behavior [10].

1.1. Aim of the study

The purpose of the study is to look into how students' mental engagement impacts their recall and understanding of English reading. It looks for important cognitive techniques that improve reading activity engagement. This study intends to provide ideas for improving English literacy instruction through the process of active thinking.

1.2. Contribution of the study

- **Teacher training:** Assists in training educators to recognize and encourage cognitive participation in students, leading to more effective English reading instruction.
- **Technology integration:** Supports the development of educational tools or digital platforms that enhance cognitive engagement in reading, using techniques like interactive exercises or adaptive feedback.
- **Promoting lifelong learning:** Encourages active cognitive participation, which can build stronger, lifelong reading habits and a positive attitude towards learning English.

1.3. Organization of the study

The remaining parts are separated as follows: Part 2 comprises the related work; Part 3 depicts the proposed methodology; Part 4 analyzes the study's results; Part 5 offers a discussion; and Part 6 concludes the study.

2. Related work

Conventional approaches for imparting Spanish vocabulary frequently rely mostly on student memory and teacher clarifications, both of which are limited by the passage of time and produce less-than-ideal learning results [11]. The use of bio-sensing technologies to improve the efficacy of teaching Spanish vocabulary was investigated in the investigation. For the design of the study, a thorough scientific architecture was created that covered the handling of data, corpus collecting, and experimental setup construction. With the possibility to transform conventional teaching methods and enhance student achievement in the context of Spanish language training, the research presented fresh viewpoints and ideas for using bio-sensing technologies in the classroom. Over the past ten years, wearable biosensor technological advances, or WBT, have become a game-changing instrument in education [12]. Following the criteria, a thorough and methodical search of the most important academic databases was carried out. Predetermined eligibility and exclusion criteria were used to choose pertinent studies. Significant results include the transition from theoretical investigation to real-world application to investigate mental processes, physiologic components, and the efficacy of instruction. Portable biosensors are having a major effect on education; they are a useful tool for learners and a valuable resource for teachers. One of the things that causes the most anxiety for English language learners, according to reports, is giving an address. According to research, teachers must become more cognizant of the emotions of learners to provide the right emotional and academic structuring to enhance their presentation skills [13]. The study aimed to determine the possibilities of using biosensor-based input from learners to assist educators in addressing the uncertainty and unpredictability of reading the students' state of emotions. These studies' contributions include the creation of guidelines for the use of biosensor-based suggestions, which help English language teachers detect various kinds and degrees of anxiety that their students experience when giving presentations.

In a large college lecture learning environment, the study used skin biosensors, specifically galvanic surface response, to quantify student attention in real time [14]. The study was carried out as part of a modification in an intermediate biology course where the conventional instructional methodology was used in one segment and active-learning techniques in the remaining ones. Although there were certain barriers to widespread adoption, the results show that GSR was an upward trend of instantaneous fashion student involvement in university classrooms, offering discipline-based instructors a fresh method to better gauge student interest. Cheap wearable smart gadgets have become more popular due to developments in electronic goods, nanotechnology, is among these technologies [15]. Because they need particular tools and competent workers, current techniques entail experimental testing afterwards obtaining blood in a clinical environment. It concluded by showcasing the core function, constraints, and opportunities of artificial intelligence (AI) in achieving by improving the current technology to support the creation and scientific adaptation of investigations.

There has been a lot of interest in the quick and precise identification of inflammatory signatures in bodily fluids, cells, and structures. However, despite being accurate and particular, many of the currently accessible approaches for the purpose involve expensive supplies and highly skilled human labor, and therefore do not meet the test period clarity, and point-of-care relevance requirements of today's clinic [16]. Particular focus was given to the techniques that take advantage of the important role that various materials have shown in recent years in the construction of analytical performance-enhanced electrical bio-sensing systems. In the study regarding human minds and actions, English was the most often used language. The majority of cognitive researchers speak English, as do the people they investigate. However, English differs from other languages in ways that impact the cognitive sciences overall and go much beyond communication studies [17]. Here, a growing corpus of data that demonstrates how the unique features that distinguish English and the language habits of its speakers tilt investigations and over-generalize findings about the behavior, brains, and mental ability of English participants to the entire species was examined.

The objective was to provide mitigation techniques that might assist in avoiding a few of these dangers.

Students must have a unique approach to learning English. Students can become more fluent in English if they employ suitable language-learning techniques. The study looked into how EFL students acquire languages and how that relates to their competence in the English language [18]. It used an afterward statistical analysis approach, gathering data from participants' most recent language ability score as well as their Language Education Inventory results. The utilization of language development strategies and the attainment of English competence were also significantly correlated. The studies using a cross-linguistic study approach were analyzed to survey the current data on the cognitive antecedents of reading in various layouts [19]. Understanding acquisition was found to be related to graphic symbol understanding, phonology, architectural perception, and rapid automated naming in all of the orthographic designs that were examined. Compared to the complex English pronunciation, it might not be as difficult, depending on data including systematically transparent orthographic structures, both alphabetical and non-alphabetic. The limitations of reading conceptions that were first created for alphabetic orthographic Foundations can be analytically evaluated with the use of cross-linguistic research methods. Article [20] examined the characteristics of the implication of national awareness in the kingdom of social and cultural interaction, and it addressed the most important problems in linguoculturalology and cognitive languages. The notions that are recognized in contemporary languages as elements of human awareness become clearer during the analysis for the benefit of those who preserve the body of information regarding specific global phenomena and aspects of national civilization. Representatives from the fields of psychological semantics discussed how a person's vocabulary perspective of the world reflects their contextual structure, incidents, and unique cultural backgrounds.

3. Methodology

A combination of techniques is used to examine cognitive involvement in English-consuming literature, integrating qualitative studies to document learners' reading encounters and tactics with test results to gauge mental involvement levels. Deep conversations and validated comprehension of text examinations are a few possible methods of gathering data. As illustrated in **Figure 1**, this approach provides a comprehensive understanding of the connection between cognitive engagement and English reading proficiency.

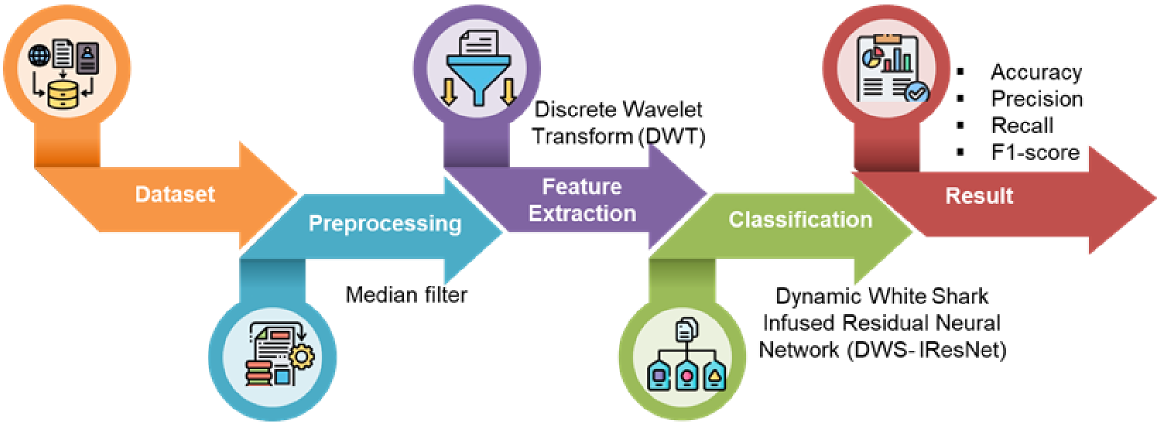

Figure 1. Detailed workflow of the research methodology.

3.1. Data collection

The dataset was collected from the open-source Kaggle website [21]. There are 50 participants asked to perform four different tasks as part of the study: simple, analytical, technical, and emotional. The main goal was to collect physiological data while reading in English, as they are important markers of cognitive engagement and emotional arousal. Electroencephalography (EEG) and Galvanic Skin Response (GSR) were the two physiological signal kinds that were gathered. Because variations in skin conductance are linked to different degrees of emotional arousal, GSR, which was captured by skin conductance sensors, offered insights into the individuals' emotional reactions. In contrast, EEG assessed cognitive involvement during reading by measuring brainwave activity. As they performed the reading exercises, those participating wore biosensors that recorded data. This data offers a useful dataset for comprehending the connection between task difficulty, emotional response, and cognitive processing it enables a thorough examination of how various task types affect emotional and cognitive states.

3.2. Data pre-processing using a median filter

To estimate cognitive involvement in English reading, biosensor data must be pre-processed using a filter with a median to level out noise and ensure clearer, more dependable signals. This procedure refines the accuracy of popularity forecasts by cantering on critical patterns in the data. The order-statistics filter or median filter, which computes levels of engagement by averaging relevant biosensors in sequence, can be adapted to predict a level of cognitive commitment in reading English. This filter measures a reader's intellectual confidence in the reading activity accurately through the ranking and analysis of sensor information as denoted in Equation (1). This process helps identify key trends concerning mental signals.

$$e'(w,z) = \underset{(t,s) \in T_{wz}}{median} \{h(t,s)\} \quad (1)$$

The average is calculated using the initial evaluation of attention to data. Some forms of randomness in biomedical capacity can be effectively reduced by median filtration. They improve the accuracy of predicting the degree of cognitive involvement in English reading by offering better noise elimination with noticeably less data distorting than a similar linear straightening filter. Before replacing the present amount with the average value in that set, every single interaction information value from the readings of the sensors is sorted numerically to get the median. When dealing with unpredictability in biosensor data, including reading spikes, median filters work well. This method increases confidence in predictability by reducing distortion and noise in the data, which is more relevant to the prediction of the level of cognitive assurance in the English language.

3.3. Feature extraction using discrete wavelet transforms (DWT)

A kind of signal dispensation method called the DWT examines sensing data at several scales to recognize both high-frequency and a small-number element. It describes the analysis of time-frequency variability of cognitive engagement in detail; it helps make predictions about the cognitive link while learning English. One of the tools used for the prediction of the cognitive meeting in reading in English is the DWT which samples biosensors sequentially. The DWT gives high time resolution for high-frequency data and medium-frequency reconstruction for vibrations data as opposed to the uniform time resolution of the short-time Fourier Transform (STFT). This feature reflects human vision and is better suited to capture the energetic characteristics of mental attachment while reading, thus making more accurate estimations of cognitive participation more possible. A particularly useful technique for effectively determining the biosensor signals, DWT provides a beginner's model in both the temporal and regularity domains. Recording rapid fluctuations in thinking ability across several scales, is especially helpful for predicting cognitive interaction with English reading and allows for more precise estimates of mental connection during the studying processes denoted in Equation (2).

$$X(i,l) = \sum_i \sum_l w(l)\, w(l) 2^{-\frac{i}{2}} \Psi(2^{-i}m - l) \tag{2}$$

The Ψ, a time function with limited power and rapid decay, is used by the DWT to forecast cognitive appointments in English reading. A quick, pyramidal method associated with multiage filter banks can be used to effectively execute DWT analysis. This allows for the deep deconstruction of biosensor information to track the various levels of psychological involvement throughout reading, leading to more effective mental commitment prediction. With interval separation among filter centers, the DWT predicts cognitive engagement in English reading by acting. The signal can be examined at various frequencies with varying resolutions because each sub band includes half of the data points of the nearby captures the fluctuations of mental concentration during readings by breaking down the biological sensor data into both particular facts and coarse assumptions. To provide a thorough examination of cognitive engagement levels, this is accomplished by repeated high pass and low pass processing denoted in Equations (3) and (4).

$$z_{high}[l] = \sum_m w[m]\, h[2l - m] \tag{3}$$

$$z_{low}[l] = \sum_{m} w[m]\, g[2l - m] \tag{4}$$

The results of the high pass (g) and lowpass (h) filters, represented as $z[l]$ where $z_{high}[l]$, and $z_{low}[l]$ accordingly, are acquired after sub-sampling tasks by two to predict the degree of cognitive commitment in the English language. The number of generated coefficients of wavelets and the total quantity of input points are equal due to this reduction. They allow to preservation of the subtleties of mental involvement during the interpretation process, to efficiently analyze biological sensor information.

3.4. Forecast the level of cognitive participation in the English reading for Dynamic White Shark Infused Residual Neural Network (DWS-IResNet)

The DWS-IResNet improves the reliability of predictions by fusing the flexible search features of the WSO technique with the durability of residual networks. The system detects and predicts various degrees of mental involvement during reading assignments by analyzing accelerometer data and deriving patterns associated with mental engagement. More transparent information to be entered for a neural system is ensured by the hybrid method, which uses wavelet transform for removing features and suppression of noise. The approach provides a strong apparatus for tracking and predicting cognitive commitment in reading immediately.

3.4.1. Infused Residual Neural Network (IResNet)

The model (IResNet) was produced using deep learning (DL) that uses feature absorption and residual information to predict the degree of cognitive involvement in English reading. Using residual relationships and a multi-stream flow of knowledge to capture intricate cognitive operations and relationships throughout reading activities improves the accuracy of predictions.

The infused residual network, the structure's flexible unit, which is used to predict cognitive involvement in English reading, is made up of a broadly remaining block with identical states: A transient stream, which is a requirements convolutions layer, and an independent stream q, which contains identity convenience interactions. Though modified to represent the psychological dynamics that surround reading, the architecture is comparable to that of the original IResNet. Furthermore, the model's capacity to predict different degrees of cognitive involvement during listening to English is improved by the incorporation $\left(parametersX_{k.q\to q}\right)$ of information across the streams using two distinct sets of convolution filtering models, $(X_{k.s\to s})$ and $\left(X_{k.q\to s}, X_{k.s\to q}\right)$ as denoted in Equation (5).

$$q_{k+1} = \sigma\left(conv\left(q_k, X_{k.q\to q}\right) + conv\left(s_k, X_{k.s\to q}\right) + shortcut(q_k)\right)$$

$$s_{k+1} = \sigma\left(conv\left(q_k, X_{k.q\to s}\right) + conv\left(s_k, X_{k.s\to q}\right)\right) \tag{5}$$

Before sequential normalization and ReLU discontinuities are applied to calculating the block's production states, same-stream and cross-stream reactions are added together to predict the degree of cognitive involvement in English comprehension. While the altering distributes $s$analyzes data obtained from either the movement gradually, permitting the discarding of extra cognitive input, the residual stream *q* adheres to its IResNet architecture with shortcuts connectivity. The model's capability to examine intricate patterns of cognitive commencement during reading is enhanced by this hybrid construction. As illustrated in **Figure 2**, the shortcut connection is used as a practical character or as an extension to preserve relevant information in a graceful manner.

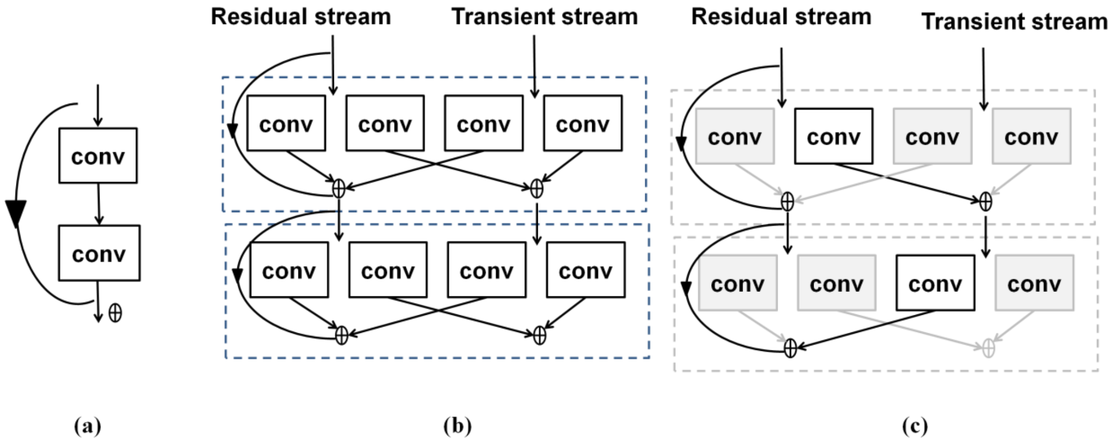

Figure 2. Structure of IResNet (**a**) ResNet prevent with two layers; (**b**) Two extended residual elements; (**c**) two generalizing blocks of residuals from a two-layer ResNet unit; and (**d**) RiR block in two layers.

The generalized residual block can adjust to a variety of behaviors of knowledge in predicting the degree of cognitive involvement in English reading by functioning as a single-layered IResNet block or as a standard. The algorithm can model the complexities of mental involvement with readings by emphasizing the homogeneous remainder block, which allows the network to reflect different levels of thought processes. This flexibility makes it possible to use a variety of learning techniques, whether they include basic or sophisticated data processing steps, to accurately forecast cognitive engagement. The network's ability to examine reading-related mental conditions can be improved by adapting the standardized outstanding block arrangement to other neural designs.

3.4.2. Dynamic White Shark (DWS)

The DWS algorithm had issues with limited explorations and slow convergence when predicting the level of cognitive support in English-consuming literature, which could make it more difficult to make precise predictions about mental involvement. A version of DWS that can overcome these limitations is available in the DWS. This DWS enables redesigns of relative orientations of white sharks that are the cognitive indices with greater efficiency to collect better interaction patterns. The forecasting of cognitive engagement while reading in English gets more precise and faster as a whole because of the demographic diversity that also encompasses its better use simultaneously.

Gaussian Barebones (GB) technique

The model's unpredictability can decrease throughout the evaluation stage of predicting cognitive involvement in English reading, which could result in exertion with validity and the rate of convergence. By avoiding quicker convergence to poor solutions and guaranteeing sustained progress resembling optimal projections, the GB method aids in choosing the best course for the psychological state. The addition of GB's permutation description increases the variety of the model's forecasts by repositioning the cognitive situations. The exactness and speed of predicting cognitive appointment during readability in English are greatly increased by this harmony between local removal and global investigation. The inadequate Particle Swarm Optimization (BBPSO) technique is the source of the GB technique, which is used to enhance the prediction of thinking engagement in English reading. In this technique, a variable Q governs the update of every individual's positioning. A normal distribution is used to update the person's position if the randomly generated frequency is less than Q if not, ideas of difference evolution are applied. This method improves the precision and quickness of predicting the cognitive level of involvement during readability in English by diversifying the projections of the model and striking a balance between regional exploration and international search as denoted in Equation (6).

$$x_{l.HA}^{i} = \begin{cases} H\left(\frac{\left(x_{hbest,l-1} + x_l^i\right)}{2}, \left|x_{hbest,l-1} - x_l^i\right|\right) if\ rand < Q \\ x_l^{i1} + q_4\left(x_l^{i2} - x_l^{i3}\right) otherwish \end{cases} \tag{6}$$

where the $x_{l.HA}^{i}$ denotes the international optimal solution thus far in the repetition $x_{hbest,l-1}$ is a random value with the interval [0,1]; and $\frac{\left(x_{hbest,l-1}+x_l^i\right)}{2}$, GB indicates the new location for the $x_{hbest,l-1} - x_l^i$ white shark using the GB method. It repetition l^{th}; i^1, , i^2 and i^3 consist of three people who were selected that differ from the electrical power personal, i.

Opposition-Based Learning (OBL) approach

By accelerating convergence and enhancing solution effectiveness, the OBL approach was first set forth by improving the prediction of cognitive engagement in English reading. Because every option has an equal probability of being better than the other, OBL improves the exploration process by taking into account both the present forecast and the alternative. To improve the model's capacity to predict levels of cognitive involvement, the most effective of the two inversion equations is chosen. The model's ability to predict cognitive activity during interpretation and writing tests is improved by this method. The inverse of an arbitrary number y in the interval $[b_1, b_2]$ can be expressed as denoted in Equation (7).

$$y^0 = b_1 + b_2 - y \tag{7}$$

If $o(y_1, y_2, \dots, y_i, \dots, y_c)$ is a location in a d-dimensional search environment where the $y_i \epsilon [b_{1,i}, b_{2,i}]$ eventually the reverse one $po(y_1^p, y_2^p, \dots, y_i^p, \dots, y_c^p)$ is represented by the relationship that follows denoted in Equation (8).

$$y_i^p = b_{1,i} + b_{2,i} - y_i \tag{8}$$

Although OBL offers advantages, new studies have established that OBL is more successful in enhancing the prediction of cognitive involvement in English literature. By taking into account the quasi-opposite solution, which improves forecast accuracy, OBL improves the model's effectiveness. The cognitive involvement model can be updated more effectively and accurately by utilizing the descriptions of quasi-opposite quantities and indications, which eventually enhances the model's aptitude to forecast understanding levels in talking. The quasi-opposite variable y^{rp} of an arbitrary value y in the search space $[b_1, b_2]$ can be expressed as follows in Equation (9).

$$y^{rp} = rand\left[\left(\frac{b_1 + b_2}{2}\right), (b_1 + b_2 - y)\right] \quad (9)$$

Likewise, $rpo(y_1^{rp}, y_2^{rp}, \ldots, y_i^{rp}, \ldots, y_c^{rp})$ the quasi-opposite position in Equation (10) is used to determine an exploring location with a d-dimensional difficulty.

$$y_i^{rp} = rand\left[\left(\frac{b_1 + b_2}{2}\right), (b_{1,i} + b_{2,i} - y_i)\right] \quad (10)$$

For the purpose of maintaining the people, the OBL technique can be applied both during the startup and development phases of a WSO methodology. It is possible to replace the result produced by the probabilistic barebones method used in the present investigation with a quasi-opposite answer. The hybrid DWS-IResNet algorithm is shown in Algorithm 1.

Algorithm 1 DWS-IResNet

```
Function DWS_IResNet (Input: data, Output: prediction)
   Initialize: IResNet
      layers = []
      weights = []
dynamic_factor = 0.5   adjustment factor
   If Input is not None:
layers.append(Input)
   Else:
      Return "Invalid Input"
      For each layer in range(1, N):
      If dynamic_factor > 0.5:
         Apply convolution(layer, weights, stride = 1)
         Apply Batch Normalization
         Apply Activation Function (ReLU)
      Else:
         Apply convolution(layer, weights, stride = 2)
         Apply Batch Normalization
         Apply Activation Function (LeakyReLU)
      If layer > 1:
residual = layers[−2]
layers[−1] += residual      For each weight in weights:
      If weight < threshold:
         Adjust weight using White Shark dynamic optimization
      Else:
         Maintain current weight
   Apply Fully Connected Layer to Final Layer
   If layers[−1] is valid:
prediction = Softmax(layers[−1])
   Else:
      Return "Error in Final Layer"
   If training_accuracy improves:
      Increase dynamic_factor by 0.1
   Else:
      Decrease dynamic_factor by 0.1
   Return prediction
End Function
```

To capture complex psychological features, the DWS-IResNet integrates dynamic grading and residual knowledge to forecast the level of mental involvement in English reading. This hybrid technique provides a model to generate metrics aspects such as Simple, Analytical, Technical, and Emotional involvement. One of the emotional elements regularly tends to obtain high scores due to its absolute significance during thinking participation. It is the complex architecture that can be utilized as a weapon for assessing emotional involvement with reading tasks because it not only strengthens weak cognitive links but also helps provide high expectations along a range of participant characteristics.

4. Result

The computer with the Intel Core i5 processor with 16 GB of RAM and 512 GB of SSD is part of the setup for the experiments. Python 3.8 is used for data analysis, and additional visual tracking technology is used to gauge reading involvement. Tools for monitoring cognitive reactions, attentiveness, and retention of information are used while individuals finish reading assignments. Both men and women were compared to the suggested approach (DWS-IResNet), which has the characteristics of being straightforward, analytical, technical, and emotional.

4.1. Accuracy

The percentage of precise forecasts the model makes when determining the degree of cognitive involvement during English reading tests is referred to as accuracy in this instance using DWS-IResNet techniques. It assesses the model's ability to detect users' involvement using psychological traits such as basic, technical, analytical, and emotional reactions. **Table 1** and **Figure 3** show that the "Simple" characteristic has the greatest accuracy for both males and females, at 90% for females and 85% for males. This implies that both genders succeed best when interacting with simple cognitive activities in English reading.

Table 1. Performance accuracy of DWS-IResNet across different feature categories.

Proposed [DWS-IResNet]		
Accuracy (%)		
Features	**Male**	**Female**
Simple	85	90
Analytical	80	85
Technical	75	80
Emotional	70	75

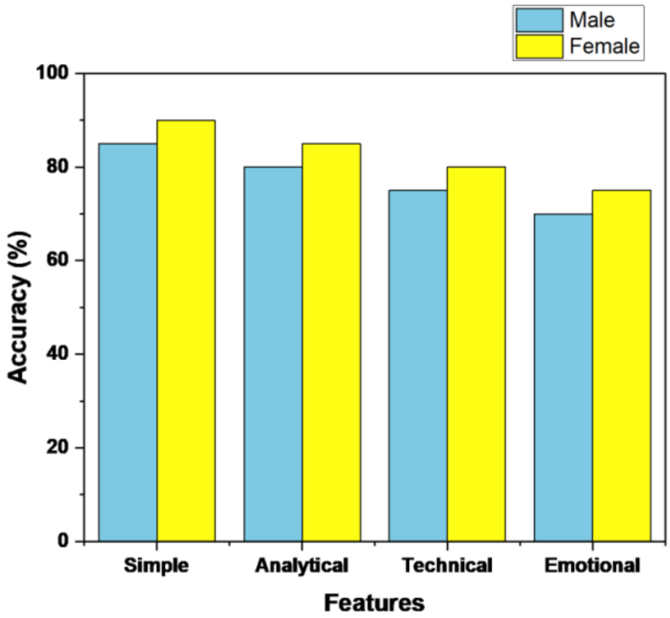

Figure 3. Accuracy result of DWS-IResNet across different various feature categories based on gender.

4.2. Precision

Regardless of all the situations when cognitive involvement was found to be occupied, precision is the percentage of genuine positive cases that involve proper cognitive involvement. It gauges how well cognitive engagement is estimated at the time of prediction using DWS-IResNet. When it comes to detecting cognitive activation throughout reading activities, greater precision means fewer incorrect results. **Table 2** and **Figure 4** show that the precision is 90% for females and 85% for males; the emotional feature has the highest precision for both genders. According to this, both types of cognitive involvement with comprehension of English are most strongly influenced by their feelings.

Table 2. Performance precision of DWS-IResNet across different feature categories.

Proposed [DWS-IResNet]		
Precision (%)		
Features	**Male**	**Female**
Simple	75	80
Analytical	70	75
Technical	60	65
Emotional	85	90

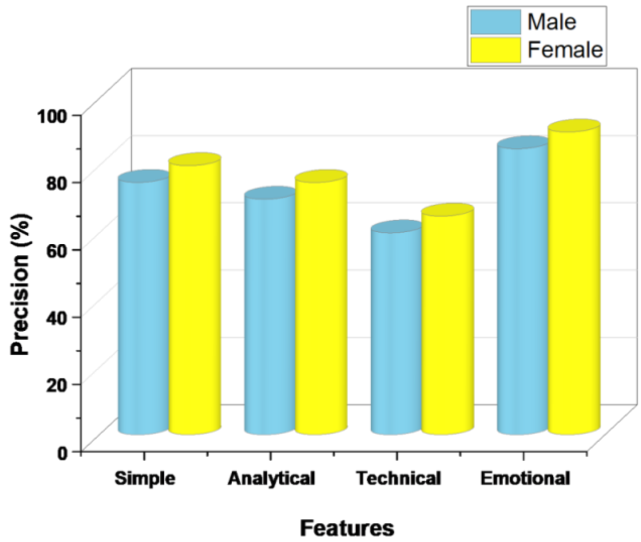

Figure 4. Precision of DWS-IResNet across different various feature categories by gender.

4.3. Recall

The capacity of a model to accurately identify every pertinent instance of cognitive activity in English comprehension, especially those linked to specific behavioral characteristics, is known as recall. Recall quantifies the extent to which the model represents user participation in this goal, particularly in areas like emotive or analytical participation. High recall reduces missed forecasts by guaranteeing that using the DWS-IResNet model detects the majority of instances of cognitive interaction. **Table 3** and **Figure 5** show that the emotional characteristic has the largest recall percentage for both males and females, at 90% for males and 87% for females. This suggests that emotional involvement in English reading was easier to recall than other cognitive qualities. This implies that both genders' memories may be more strongly impacted by emotional reactions to reading information.

Table 3. Performance recall of DWS-IResNet across different feature categories.

Proposed [DWS-IResNet]		
Recall (%)		
Features	**Male**	**Female**
Simple	85	88
Analytical	78	80
Technical	82	85
Emotional	90	87

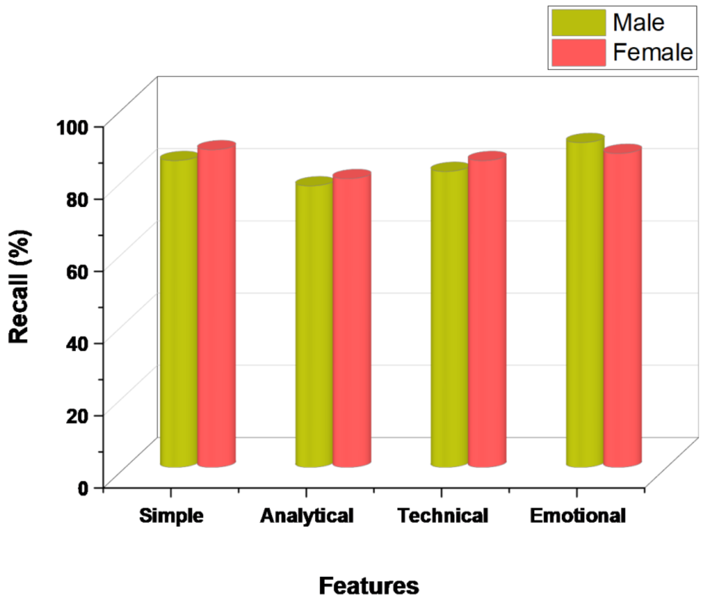

Figure 5. Recall of DWS-IResNet across different various feature categories.

4.4. F1-score

The F1-score balances memory and precision to find how well a model predicts cognitive engagement in reading English. It is especially helpful for analyzing how well the DWS-IResNet model performs in locating pertinent characteristics, like technical analytical, or interpersonal involvement. A larger F1 score in a cognitive involvement environment means it is possible to better predict how the respondent will react to the reads based on multiple psychological factors. As highlighted in **Table 4** and **Figure 6**, the emotion characteristic was the one with the highest F1 scores for both male subjects at 88% and female subjects at 90%, therefore showing that emotional involvement most significantly enhances cognitive involvement in reading in the English language. The technique DWS-IResNet successfully traps these mental signals and improves reliability with predictions for both genders.

Table 4. Performance F1-score of DWS-IResNet across different feature categories.

Proposed [DWS-IResNet]		
F1-score (%)		
Features	**Male**	**Female**
Simple	85	82
Analytical	78	80
Technical	80	75
Emotional	88	90

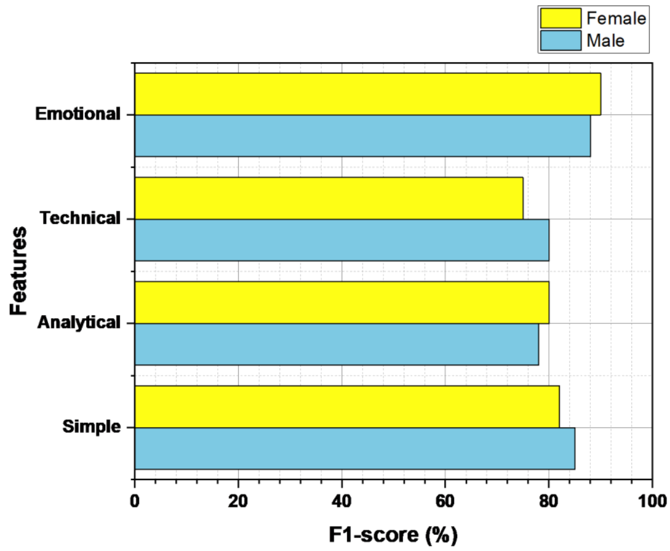

Figure 6. F1-score of DWS-IResNet across different various feature categories.

5. Discussion

The English reading with clear gender-based differences, the results show that the DWS-IResNet approach well captures mental processes in English reading across several parameters. The emotional feature had the highest F1 scores, recall, accuracy, and precision for both males and females, which inferred that emotional participation was an important component of cognitive participation during learning. Female respondents scored excellently on analytical and emotional involvement elements, but men were much stronger on the simpler and more technical elements of the model. In general, the results show that although the emotional dimensions have a strong influence on reading ability for both sexes, the model's ability to predict engagement varies with several cognitive profiles, and in this case, the method applied as DWS-IResNet has proven effective in resolving these mental components. To quantify mental participation and emotional response during comprehension of English tasks, the proposed DWS-IResNet technique integrates biosensor data, namely Galvanic Skin Response (GSR) and Electroencephalography (EEG), improving on the existing features are Simple, Analytical, Technical, and Emotional. DWS-IResNet offers a more thorough psychological viewpoint by gathering real-time physiological information, providing an improved comprehension of how participants mentally and emotionally engage with various reading tasks, in contrast to traditional models that focus on task classifications. The model overcomes the drawbacks of existing approaches that mostly depended on task classification by incorporating these biosensor signals and providing a more profound psychological on the execution of tasks. This method improves the model's capacity to capture the entire range of psychological reactions during English reading operations by enabling more precise and dynamic evaluations of both physical excitement and cognitive interaction.

6. Conclusion

This study highlights the importance of cognitive engagement in enhancing

English reading abilities from a psychological standpoint. The study shows that engaged thought participation greatly enhances the reading results by concentrating on cognitive variables like retention, focus, and conceptualization. This realization emphasizes the necessity of instructional approaches that promote intense, long-term reading interaction, especially for students in bilingual settings or those who struggle with comprehending the text. The suggested DWS-IResNet techniques compared the F1-score, recall, accuracy, and precision using the features of simple, technical, analytical, and emotional between both males and females. The accuracy achieved a higher 90% for females in simple features, precision performed better and achieved 90% for females in emotional features, and 90% of recall, and 90% of F1-score achieved a higher percentage of emotion features in males and females. Future investigations into customized and adaptable learning strategies can shed light on how to best adjust cognitive methods of participation to the requirements of different students. The measurement and support of cognitive involvement may be improved by using cutting-edge technology like visual tracking, real-time evaluation mechanisms, and artificial intelligence-based learning platforms. They can be able to learn more about how emotions support successful English language acquisition if they extend this study to examine other cognitive abilities, such as essential reasoning and problem-solving, in connection to literature.

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