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Article

Enhancing the effectiveness of English grammar teaching through biomechanical feedback and deep learning algorithms

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Abstract: This study investigates the integration of biomechanical feedback—targeting posture, gestures, and articulation mechanics—with a Convolutional Neural Network (CNN) to improve the effectiveness of English grammar instruction. Traditional teaching methods frequently overlook the physical aspects of speech production, which are critical for both written and spoken language proficiency. In this study, 94 participants from China were divided into an Experimental Group (EG) receiving biomechanical feedback and a Control Group (CG) receiving traditional instruction. Key findings show that the EG demonstrated significant improvements in grammar accuracy (16.2%), sentence fluency (12.1%), and error reduction (12.3%) compared to the CG, with statistically significant differences ($p < 0.05$). The EG reported high satisfaction with the learning process, with 88.3% providing positive feedback on the overall experience. The CNN was instrumental in analyzing linguistic and biomechanical data, enabling personalized feedback that improved participant' speech clarity, pronunciation accuracy, and grammar retention. These results highlight the potential of integrating physical movement with AI-driven feedback to enhance grammar learning outcomes, offering a more comprehensive and engaging approach to language instruction.

Keywords: biomechanical feedback; articulation mechanics; convolutional neural network; grammar retention; posture; gestures

1. Introduction

Learning a new language, especially mastering its grammar, can be challenging for learners, particularly in English as a Second Language (ESL) [1,2]. Traditional grammar instruction often relies on written exercises and rote memorization, which may not fully engage learners or address the complexities of spoken language [3,4]. In recent years, research in educational neuroscience has highlighted the importance of integrating multimodal learning strategies—those that combine visual, auditory, and kinesthetic elements—in improving language acquisition outcomes [5–7]. Studies suggest that using physical movements, including gestures, posture, and articulation mechanics, can significantly enhance the cognitive and motor processes of language learning [8,9].

At the same time, advancements in artificial intelligence, particularly in deep learning, have made it possible to analyze and optimize complex learning behaviors, such as speech patterns, pronunciation, and grammatical accuracy [10,11]. Convolutional Neural Networks (CNNs), a class of deep learning models, have been widely used in fields like image and speech recognition, offering powerful tools to analyze linguistic data [12,13]. Combining biomechanical feedback and AI-driven algorithms presents an innovative approach to grammar instruction, enabling real-time, personalized feedback that addresses both the cognitive and physical aspects of language learning [14].

This study builds on these emerging trends by exploring the integration of biomechanical feedback—focusing on posture, gestures, and articulation mechanics—and a CNN-based Deep Learning (DL) algorithm to enhance the effectiveness of English grammar instruction. The research is motivated by the need to move beyond traditional methods and provide learners with a holistic approach that simultaneously engages their cognitive, linguistic, and physical faculties.

Despite the growing body of evidence supporting multimodal learning, few studies have explored the combined impact of biomechanical feedback and AI on grammar acquisition [15,16]. Traditional grammar instruction methods, while adequate to an extent, often fail to address the nuances of spoken language and the physical processes involved in speech production [17,18]. This gap in the literature highlights the need for a comprehensive solution that can enhance written and spoken grammar skills through real-time, actionable feedback.

Learners frequently struggle with specific grammatical constructs, such as verb conjugations, subject-verb agreement, and sentence formation, particularly when applied in spoken contexts [19]. Pronunciation errors, tense mistakes, and difficulties with sentence complexity further exacerbate these challenges [20,21]. Addressing these issues requires a method that not only provides linguistic feedback but also corrects the physical aspects of speech, such as articulation and posture, which can significantly influence grammar accuracy and fluency.

The primary objective of this study is to investigate the effectiveness of integrating biomechanical feedback with DL in improving English grammar instruction.

Specifically, the study aims to:

a) Assess how posture correction, gesture usage, and articulation mechanics influence grammar accuracy in written and spoken tasks.
b) Explore the impact of real-time biomechanical feedback on reducing common grammatical errors, such as tense mistakes, subject-verb agreement errors, and pronunciation inaccuracies.
c) Compare the performance of learners who receive traditional grammar instruction with those who receive biomechanical feedback using a CNN-based model to analyze and optimize learner outcomes.
d) Evaluate the participants' overall learning experience and satisfaction with the biomechanical feedback approach.

The following research questions guide the study:

- How does biomechanical feedback (including posture, gestures, and articulation mechanics) influence English grammar accuracy and fluency in written and spoken tasks?
- To what extent does the integration of a CNN-based DL improve the precision and effectiveness of grammar instruction?
- What are the differences in error reduction (e.g., tense mistakes, pronunciation errors) between learners receiving traditional instruction and those receiving biomechanical feedback?
- How do learners perceive the role of biomechanical feedback in their overall grammar learning experience?

This research offers a novel contribution to the field of language education by introducing an innovative teaching method that combines biomechanical feedback with cutting-edge AI. Integrating physical movement with DL provides a holistic solution to grammar instruction that addresses both the cognitive and physical challenges learners face. The findings from this study have the potential to revolutionize the way grammar is taught, particularly in ESL contexts, by providing more engaging, effective, and personalized learning experiences. The results of this study will be valuable for educators, curriculum designers, and policymakers seeking to improve language learning outcomes. Integrating biomechanical feedback into grammar instruction could pave the way for more interactive and dynamic teaching strategies that enhance linguistic skills and foster greater learner engagement and retention.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundations of biomechanics and deep learning in language instruction, highlighting key literature and methodologies relevant to the study. Section 3 details the Proposed ML model, and Section 4 presents the experimental design, including the apparatus and measurements used to capture linguistic and biomechanical data. Section 5 presents the study's results, comparing the grammar accuracy, fluency, and error reduction between the Experimental Group (EG) and Control Groups (CG). Finally, Section 6 concludes the paper with recommendations for future research and practical applications of the study’s results.

2. Biomechanics and language learning

2.1. Physical movements and language cognition

Language acquisition is a complex cognitive process that is influenced not only by auditory and visual input but also by physical movements. Gestures, posture, and articulation biomechanics are critical factors in learners' internalization of grammatical rules. Research has shown that using gestures during language learning aids memory retention by creating multimodal associations between physical actions and linguistic structures [22–25]. For example, pointing or making specific hand movements while learning subject-verb agreements or verb conjugations can help learners establish a concrete connection between abstract grammatical concepts and real-world actions. This physical engagement activates motor regions in the brain, which are closely linked to cognitive processes involved in language comprehension and production.

Posture also plays a significant role in cognitive load management during language learning [26–28]. A learner’s posture affects both the mechanics of speech production and the overall comfort during learning sessions. Slumped or misaligned posture may impede effective breathing, reducing vocal clarity and stamina during speech exercises. Conversely, an upright and balanced posture facilitates better breath control and articulation, which is crucial for accurate pronunciation and grammatical fluency. Moreover, body posture has been associated with cognitive alertness, where an open and attentive posture promotes focus and engagement, allowing for more efficient grammar learning.

Articulation biomechanics, such as tongue, lips, and jaw movement, are integral to producing grammatically correct speech. Subtle biomechanical adjustments during articulation—such as how learners position their tongue for different phonemes—can significantly affect their ability to speak with grammatical accuracy. This is particularly relevant for learners who struggle with English as a second language, where incorrect articulation patterns often lead to grammatical errors in spoken and written forms. Overall, incorporating an awareness of these physical movements into language cognition provides a holistic approach to mastering grammar, as it ties the internal processing of linguistic rules with external physical feedback [29,30].

2.2. Integrating biomechanics in grammar teaching

Integrating biomechanical feedback into traditional grammar teaching methods offers a novel approach to improving language acquisition outcomes. One practical method is posture correction, which can enhance spoken and written language skills. Instructors can encourage students to maintain a posture that supports optimal breathing and articulation. By using visual cues or digital feedback mechanisms, learners can become more aware of their postural alignment during speech exercises [31–34]. This approach not only improves vocal projection but also helps reduce fatigue during extended language learning sessions, ensuring sustained focus on grammar instruction.

Another effective integration method involves speaking exercises emphasizing the coordination of articulation biomechanics with grammatical accuracy. For example, instructors can guide students through slow-paced, exaggerated pronunciation drills focusing on the correct tongue, lips, and jaw placement when producing fundamental grammatical structures such as past tense endings (e.g., "-ed" sounds) or plural forms. By incorporating biomechanical feedback, learners can adjust their speech patterns in real-time, reducing common grammatical errors related to improper articulation. For instance, real-time audio or visual feedback can be provided through specialized software that monitors articulation and highlights areas where adjustments are needed to achieve accurate grammatical output.

Gesture alignment can also be a powerful tool in grammar instruction, especially for visual and kinesthetic learners. Teachers can design activities with specific gestures and grammatical rules or sentence structures. For example, raising a hand or making a motion that symbolizes adding something can be associated with using conjunctions in compound sentences. This physical representation of grammar rules helps create a multi-sensory learning environment, allowing students to internalize abstract grammatical concepts through repeated physical actions. Additionally, gesture-based activities can reinforce the syntactic structure of complex sentences, guiding learners through the logical flow of subject, verb, and object relationships.

3. Proposed deep learning algorithm

The proposed DL for enhancing English grammar teaching through biomechanical feedback is based on a CNN (**Figure 1**). CNN is highly effective for pattern recognition tasks, including language and gesture recognition, by learning spatial hierarchies of features from the input data. The model processes multimodal data, such as linguistic inputs (text) and biomechanical features (gesture or posture data). The CNN structure consists of multiple layers, including convolution, pooling, and Fully Connected (FC). These layers automatically extract relevant features from the input data, enabling the model to identify patterns associated with correct or incorrect grammar usage and biomechanical indicators.

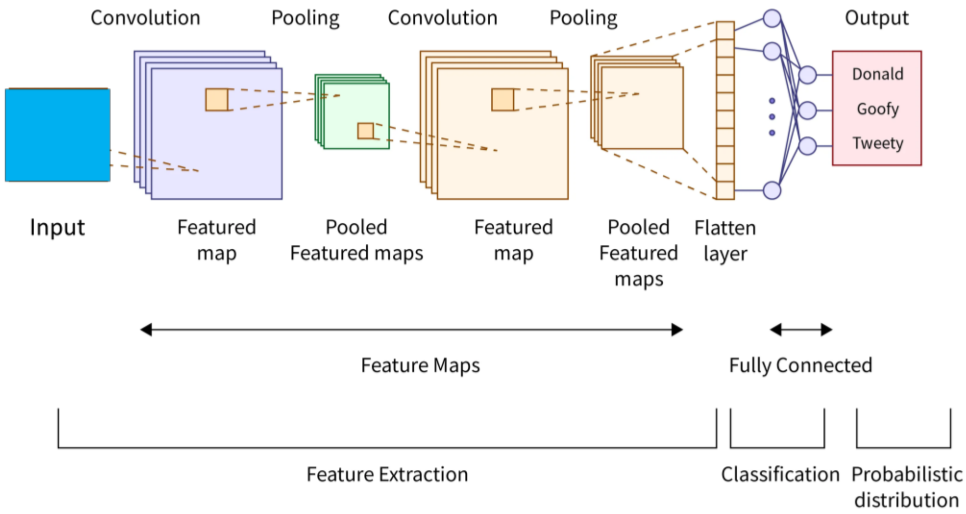

Figure 1. CNN Architecture.

The architecture consists of several key players: convolutional, pooling, flatten, and FC, each described by mathematical operations.

Convolutional Layer: The convolutional layer applies filters (or kernels) across the input to create feature maps. Mathematically, the convolution operation between the input X and a filter W is defined as:

$$S(i,j) = (X \times W)(i,j) = \sum_m \sum_n X(i+m, j+n)W(m,n)$$

where $X(i,j)$ is the input data at position (i,j), $W(m,n)$ is the filter/kernel applied over the region (m,n), $S(i,j)$ is the resulting feature map after the convolution. The convolution operation captures spatial hierarchies of features, such as edges or patterns related to grammar rules.

After the convolution, a non-linear activation function is applied to introduce non-linearity. The most common activation function used in CNN is the Rectified Linear Unit (ReLU), defined as:

$$f(x) = \text{Max}\,(0,x)$$

This ensures that the network can model complex patterns in the data by setting negative values to '0' and keeping positive values unchanged.

Pooling Layer: Pooling layers reduce the spatial dimensions of the feature maps, maintaining essential data while reducing computational complexity. Max Pooling is the most commonly used pooling operation, which selects the maximum value from a feature map region. Mathematically, max pooling over a region $\boldsymbol{R}$ is represented as:

$$P(i,j) = \underset{(m,n)\in R}{Max} S(m,n)$$

where $S(m,n)$ represents the input feature map values in the region R, $P(i,j)$ is the pooled feature map.

Flatten Layer: After the Feature Extraction phase (convolution + pooling), the 2D feature maps are flattened into a 1-D vector that can be fed into FC layers. This transformation is crucial for connecting the convolutional layers to the classification stage.

Let the feature map after pooling be F with dimensions $h \times w \times d$, where h and w are the height and width, and d is the depth (number of channels). The flatten operation reshapes this into a 1D vector f of length $h \times w \times d$.

Fully Connected Layer: The FC computes the final classification. It combines all features to make the final decision, mapping the flattened feature vector f into the output categories using a weight matrix W_{fc} and bias b_{fc}. The operation is given by:

$$z = W_{fc} \cdot f + b_{fc}$$

where W_{fc} is the weight matrix for the fully connected layer, f is the flattened feature vector, b_{fc} is the bias term, $\boldsymbol{z}$ is the resulting vector before activation.

SoftMax Activation for Output: For classification, the SoftMax function is applied to the output of the fully connected layer to convert the logits into probabilities. The SoftMax function is defined as:

$$Softmax\,(z_i) = \frac{e^{z_i}}{\sum_j \, e^{z_j}}$$

where $\boldsymbol{z_i}$ is the input to the SoftMax function (logits), and the output is a probability distribution over the classes (e.g., correct/incorrect grammar).

Training and Optimization: The CNN is trained using backpropagation and Stochastic Gradient Descent (SGD). The objective is to minimize the categorical cross-entropy loss function, which is suitable for multi-class classification problems:

$$L = -\sum_{i=1}^{N} y_i log\,(\hat{y}_i)$$

where N is the number of classes, y_i is the true label, $\hat{y}_i$ is the predicted probability for class i. The model's weights are updated iteratively using gradient descent, where the gradient of the loss concerning the weights is computed, and the weights are adjusted accordingly:

$$W_{t+1} = W_t - \eta \cdot \frac{\partial L}{\partial W_t}$$

where η is the learning rate, W_t are the weights at step t, $\frac{\partial L}{\partial W_t}$ is the gradient of the loss function concerning the weights.

4. Experimental design and data collection

4.1. Population

The study involved a total of 94 participants from various regions across China. The participants were selected based on their varying levels of English proficiency, ensuring a diverse representation of learners. This diversity allowed the study to capture the effectiveness of integrating biomechanical feedback and deep learning algorithms across different learner profiles, including beginners, intermediate learners, and advanced users.

The participants were recruited from language institutes, universities, and corporate training programs, emphasizing learners with previous exposure to formal English grammar instruction. A balance was maintained between those with an academic focus on English and those learning the language for professional purposes. This ensured that the study's findings could be generalized across educational and professional contexts.

The age range of participants was between 18 to 40 years, with the majority falling within the 20–30 age group. Participants were divided evenly between genders, with approximately 52% male and 48% female learners. This distribution intentionally analyzed whether gender-specific differences in biomechanical feedback, particularly in posture or articulation, influenced the outcomes of the grammar teaching intervention.

Moreover, participants were categorized into two broad groups based on their baseline language competency:

1) Group A (n = 45): Learners at the beginner and lower-intermediate level of English proficiency, as determined by a standardized pre-test.
2) Group B (n = 49): Learners at the upper-intermediate and advanced proficiency levels were similarly assessed through pre-testing.

All participants underwent an initial orientation session where their biomechanical data related to posture, gesture, and articulation was recorded using specialized motion capture equipment. This baseline data was crucial for later comparison to track how integrating biomechanical feedback during grammar instruction affected their learning progression. Using biomechanical and linguistic performance data allowed the study to offer unique insights into the relationship between physical movements and grammar acquisition.

The geographic distribution of the participants spanned several provinces, including Beijing, Shanghai, Guangdong, and Hubei. This geographic diversity ensured that the study could account for regional differences in learning styles and access to English education, which may influence the teaching methods' effectiveness. The participants were all native Mandarin speakers, and most had learned English as a second language through traditional classroom settings, which provided a consistent baseline for assessing improvements in grammar accuracy and fluency throughout the intervention.

4.2. Apparatus and measurements

The apparatus used in this study served two primary purposes: capturing biomechanical feedback during English grammar instruction and collecting linguistic performance data. A combination of motion capture systems, audio recording devices, and specialized grammar evaluation software was employed to ensure a comprehensive analysis. These tools allowed for precisely measuring physical movements (such as gestures, posture, and articulation mechanics) and linguistic accuracy (including grammar correctness and fluency).

4.2.1. Biomechanical feedback apparatus

1) Motion Capture System: A high-resolution motion capture system was utilized to record the participants' physical movements during grammar instruction sessions. The system was equipped with multiple cameras and sensors to track posture, gestures, and articulation biomechanics in real-time. Key features of this system included:
   - Infrared Cameras: Positioned around the room to capture three-dimensional movement data, focusing on the participants' head, torso, arms, and hand movements.
   - Wearable Sensors: Placed on key points such as the shoulders, elbows, and wrists to accurately track posture and hand gestures. These sensors measured the angles and range of movement during different instructional activities.
   - Articulation Tracking: Additional sensors were positioned near the mouth and throat to capture detailed articulation movements, including lip and jaw positioning during speaking exercises. This allowed for an in-depth analysis of articulation biomechanics and their impact on grammar usage.
2) Posture Monitoring Devices: Small, portable posture correction devices were attached to the participants' upper back to monitor and provide feedback on their posture during seated and standing grammar exercises. These devices vibrated gently when the participant slouched or adopted a misaligned posture, encouraging real-time correction. The device data was logged for later analysis, focusing on how proper posture alignment impacted vocal clarity and grammar performance.

4.2.2. Linguistic performance apparatus

1) Audio Recording Devices: High-quality microphones were used to capture the participants' spoken grammar exercises, ensuring clear and accurate recordings for subsequent analysis. These recordings were essential for evaluating pronunciation, articulation, and grammar fluency. The audio data was processed using noise-canceling techniques to ensure that only the participants' speech was captured, eliminating background noise.
2) Grammar Analysis Software: The study utilized specialized grammar-checking software powered by natural language processing (NLP) algorithms to evaluate the participants' grammar accuracy. This software assessed both written and spoken grammar tasks, providing feedback on:
   - Grammatical Errors: Identifying and categorizing errors related to sentence structure, subject-verb agreement, verb tenses, and article usage.
   - Fluency: Measuring fluency in spoken and written responses, focusing on sentence complexity, word choice, and overall coherence.

4.2.3. Measurements

1) Biomechanical Data: The following biomechanical variables were measured throughout the study:
   - Posture Angles: Collected from the wearable sensors, measuring head tilt, shoulder alignment, and upper back curvature. These angles were tracked during grammar exercises to assess the relationship between posture and

speech production.

- Gesture Frequency and Amplitude: The motion capture system recorded hand gestures' frequency and amplitude (range of motion). These measurements were correlated with participants' ability to comprehend and express grammatical structures, such as verb conjugations or sentence formations.
- Articulation Metrics: Articulation data included lip movement distance, jaw angles, and tongue positioning during essential grammatical tasks (e.g., past tense pronunciations). These metrics were crucial for understanding how articulation mechanics influenced the accuracy of grammar usage.

2) Linguistic Performance Data: Linguistic measurements were captured through spoken and written tasks and evaluated using the grammar analysis software. Key linguistic metrics included:
   - Grammar Accuracy Rate: The percentage of grammatically correct sentences each participant produces in both written and spoken tasks.
   - Error Types: Categorization of errors into specific grammatical areas, such as tense mistakes, preposition misuse, and article omission.
   - Fluency Score: An aggregate score based on sentence length, complexity, and coherence, which helped assess the impact of biomechanical feedback on overall language fluency.
3) Combined Data Analysis: The study integrated biomechanical and linguistic data to analyze the interaction between physical movements and grammar acquisition. For instance, posture data was correlated with speech clarity and grammatical accuracy, while gesture metrics were linked to sentence complexity and fluency. Combining these datasets, the study aimed to identify how biomechanical feedback could enhance learning.

4.3. Study procedure

The study was conducted over 6 weeks, during which participants engaged in structured grammar instruction sessions designed to integrate biomechanical feedback and traditional teaching techniques. The study procedure was divided into three phases: initial assessment, intervention sessions, and post-intervention analysis. Each phase was carefully planned to ensure that the effects of biomechanical feedback on grammar learning could be effectively measured.

4.3.1. Initial assessment

At the outset, all 94 participants underwent a comprehensive baseline assessment to determine their initial English grammar proficiency and record their biomechanical data on posture, gestures, and articulation. The participants completed a standardized written and spoken grammar test, which assessed their ability to apply key grammatical structures, including verb tenses, subject-verb agreement, and sentence construction. Simultaneously, their biomechanical data was collected using the motion capture system, audio recording devices, and posture monitors. This initial assessment was crucial in establishing a baseline against which future progress could be measured, ensuring that grammar accuracy and fluency improvements could be linked to the biomechanical feedback intervention.

4.3.2. Intervention sessions

Following the initial assessment, participants were randomly assigned to one of two groups: a CG that received traditional grammar instruction and an EG that received grammar instruction enhanced with biomechanical feedback. Both EG and CG participated in five 90-minute grammar instruction sessions per week, with the content of the lessons focusing on grammar topics such as verb conjugation, sentence formation, and complex grammatical structures.

- EG Procedure: The participants in the EG were provided with real-time biomechanical feedback during the instruction sessions. Wearable posture monitors vibrated gently for correction when participants slouched or adopted poor postural habits. The motion capture system tracked their gestures, and a feedback screen displayed real-time suggestions for adjusting gestures in line with sentence structures. Articulation was monitored through sensors near the mouth, which provided instant feedback on lip and jaw positioning to improve pronunciation accuracy for complicated grammatical constructions, such as pluralization and past tense endings. The participants were encouraged to make biomechanical adjustments throughout the sessions, linking physical movement with grammatical learning.
- CG Procedure: The CG, in contrast, received identical grammar instruction content without any biomechanical feedback. They engaged in traditional learning methods such as written exercises, oral repetition, and group discussions. This group served as a baseline to compare the efficacy of the biomechanical feedback intervention.

4.3.3. Post-intervention analysis

After the 6-week intervention period, all participants underwent a post-intervention assessment, which mirrored the initial assessment. This assessment involved the same written and spoken grammar tests, allowing the researchers to evaluate any grammar accuracy, sentence complexity, and fluency improvements. In addition to linguistic testing, participants' biomechanical data was once again collected during the grammar exercises, enabling a comparison of their pre- and post-intervention physical movements. For the EG, particular attention was paid to whether improvements in posture, gestures, and articulation correlated with enhancements in grammar accuracy. For instance, participants who demonstrated better postural alignment and more precise articulation were expected to improve their complex grammatical structure use significantly. On the other hand, the CG's results were analyzed to determine whether improvements could be attributed solely to traditional teaching methods, thereby highlighting the additional value provided by biomechanical feedback.

4.3.4. Data collection and analysis

All sessions were recorded throughout the study, and biomechanical and linguistic data were continuously logged for further analysis. The research team employed statistical methods, including paired t-test and regression analysis, to assess the significance of improvements within and between groups. The results of this analysis provided insights into the direct impact of biomechanical feedback on grammar acquisition, with the aim of determining whether physical movement aids in learning complex grammatical rules.

5. Results

The results from **Table 1** and **Figure 2**, Grammar Accuracy Improvement, indicate a significant enhancement in the grammar performance of participants in the EG, who received biomechanical feedback, compared to the CG, who were taught using traditional methods. The pre-intervention accuracy rates across different grammatical structures were notably lower for both groups, highlighting the room for improvement in both written and spoken grammar tasks.

Table 1. Grammar accuracy improvement.

Grammatical structure	Pre-intervention accuracy (%)	Post-intervention accuracy (CG) (%)	Post-intervention accuracy (EG) (%)	Improvement (EG) (%)
Verb conjugations (written)	67.3	72.7	81.2	13.9
Verb conjugations (spoken)	58.6	64.2	76.9	18.3
Subject-verb agreement (written)	70.4	75.1	83.5	13.1
Subject-verb agreement (spoken)	61.9	67.6	79.4	17.5
Sentence formation (written)	65.2	71.8	84.6	19.4
Sentence formation (spoken)	59.8	65.5	80.2	20.4

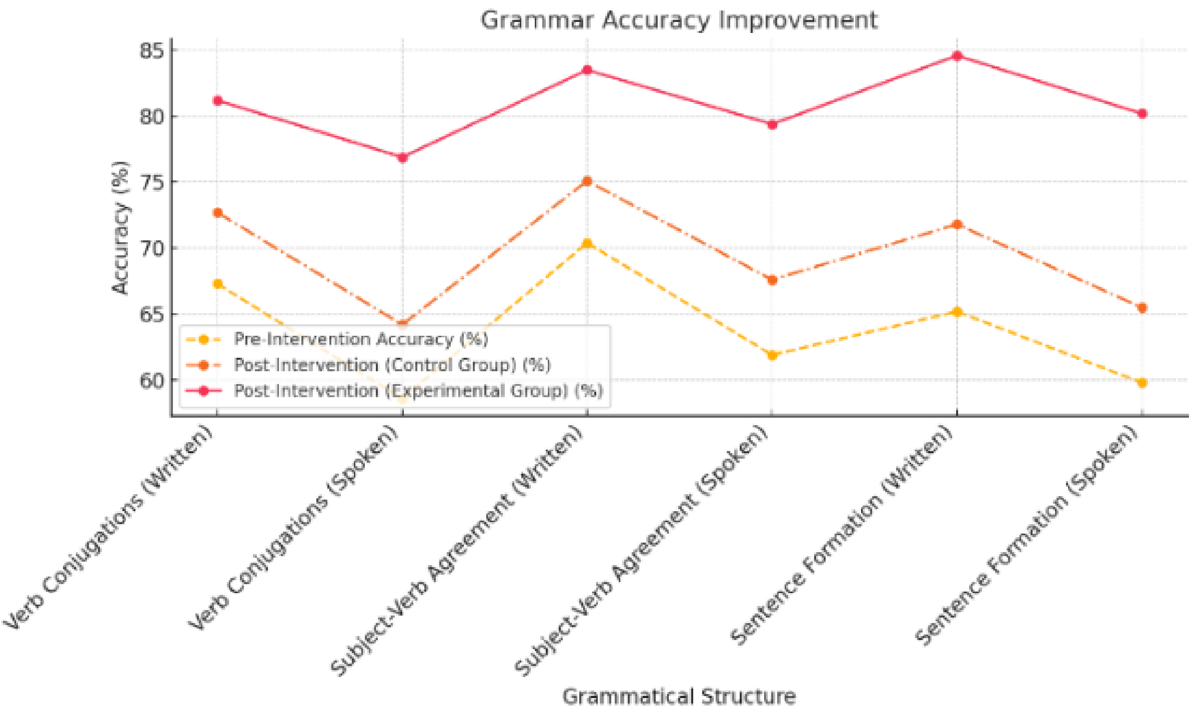

Figure 2. Grammar accuracy improvement.

For verb conjugations in written tasks, the pre-intervention accuracy was 67.3%, and participants in the EG showed a marked improvement to 81.2%, an increase of 13.9%. In contrast, the CG improved to 72.7%, demonstrating the additional advantage of biomechanical feedback. The spoken verb conjugation tasks showed an even more significant improvement, with the EG increasing from 58.6% to 76.9%, an impressive 18.3% improvement. This result suggests that the real-time feedback on posture and articulation biomechanics contributed significantly to enhancing spoken grammar accuracy, a task often more challenging than written grammar.

In subject-verb agreement, the EG increased from 70.4% to 83.5% for written tasks, reflecting a 13.1% improvement. The improvement was even higher for spoken tasks, rising from 61.9% to 79.4%, a 17.5% improvement. The CG, by comparison, showed a more modest improvement, suggesting that biomechanical feedback—mainly through posture correction and articulation adjustments—helped participants internalize the syntactic rules more effectively, especially in spoken grammar exercises where real-time physical feedback can play a critical role.

Sentence formation exhibited the highest improvement in written and spoken tasks in the EG. For written sentence formation, participants' accuracy improved from 65.2% to 84.6%, an increase of 19.4%. In spoken sentence formation, the improvement was even more pronounced, rising from 59.8% to 80.2%, representing a 20.4% increase. These results underscore the impact of integrating biomechanical feedback into teaching methods, as sentence formation requires a complex understanding of grammatical structure, and the physical cues provided through posture, gesture, and articulation feedback significantly enhanced the learners' ability to form coherent, grammatically accurate sentences.

Overall, the EG consistently outperformed the CG across all grammatical structures, with improvements ranging from 13.1% to 20.4%. These results demonstrate the effectiveness of biomechanical feedback in improving written and spoken grammar accuracy, with robust results in areas requiring precise articulation and syntactic understanding, such as verb conjugations and sentence formation.

Table 2. Fluency and sentence complexity.

Measurement	Pre-intervention score	Post-intervention score (CG)	Post-intervention score (EG)	Improvement (EG)
Sentence length (words)	12.8	13.7	15.4	2.6
Sentence complexity (subordinate clauses)	1.5	1.8	2.3	0.8
Sentence coherence score (1–10)	6.2	6.9	8.2	2.0

Table 2 and **Figure 3** compare fluency and sentence complexity before and after the intervention. The results show that the EG, which received biomechanical feedback, demonstrated notable improvements in sentence construction, fluency, and coherence compared to the CG. In terms of sentence length, the EG increased from an average of 12.8 words per sentence pre-intervention to 15.4 words post-intervention, reflecting an improvement of 2.6 words. This increase indicates that participants in the EG could construct longer sentences, likely due to enhanced articulation, posture, and gesture alignment, which helped them confidently articulate more complex thoughts. The CG, on the other hand, only showed a slight improvement to 13.7 words per sentence.

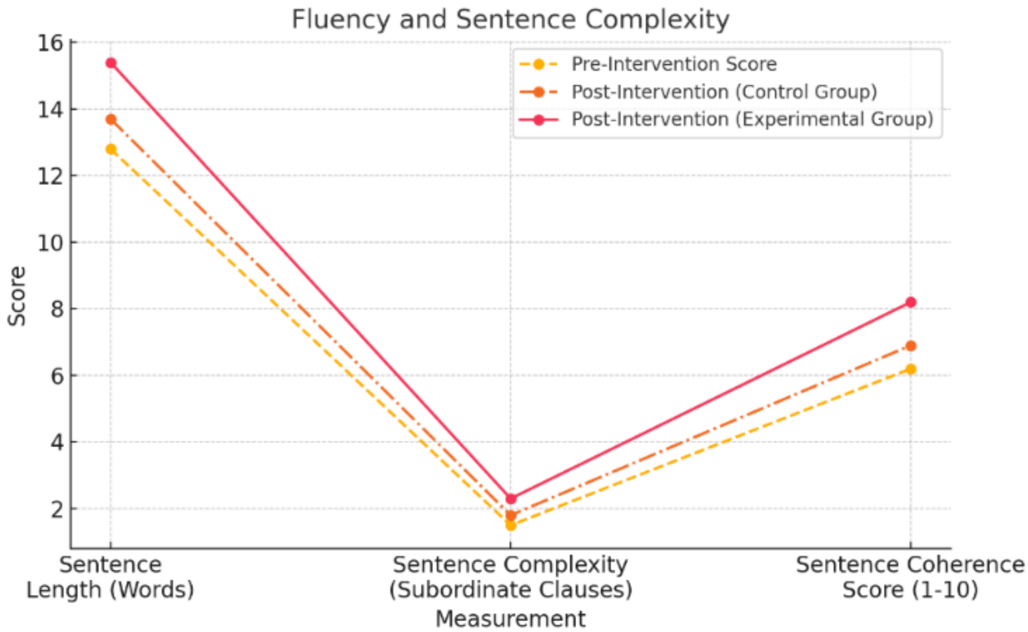

Figure 3. Fluency and sentence complexity.

Sentence complexity, measured using subordinate clauses, also improved significantly in the EG. Pre-intervention scores showed an average of 1.5 subordinate clauses per sentence, which increased to 2.3 post-intervention. The CG showed a more modest increase from 1.5 to 1.8, underscoring the role of biomechanical feedback in supporting the cognitive and motor coordination required to handle more grammatically complex sentences. The improvement of 0.8 in sentence complexity in the EG indicates a higher capacity to use complex grammatical structures. The sentence coherence score, evaluated on a scale of 1 to 10, improved substantially in the EG, rising from 6.2 to 8.2, an improvement of 2.0 points. This reflects a better logical flow and organization of ideas in participants' sentences. The CG only increased from 6.2 to 6.9, suggesting that traditional instruction was less effective at enhancing coherence. These results indicate that biomechanical feedback, mainly through improved posture and articulation, helped learners achieve greater fluency and coherence in their sentence construction.

Table 3. Posture correction and grammar (PCG) performance.

Measurement	Pre-intervention score	Post-intervention score (CG)	Post-intervention score (EG)	Improvement (EG)
Posture alignment improvement (%)	65.1	68.7	78.4	13.3
Spoken grammar accuracy (%)	59.3	63.2	76.8	17.5
Sentence duration (seconds)	12.4	12.8	14.1	1.7

Table 3 and **Figure 4** compare PCG performance between the EG and CG. The results highlight the significant impact of posture alignment and its correlation with enhanced grammar performance in the EG. Posture alignment improvement showed a marked increase in the EG, rising from 65.1% pre-intervention to 78.4% post-intervention, an improvement of 13.3%. This improvement suggests that participants in the EG, who received real-time feedback on their posture during grammar

instruction, were able to adopt better posture habits that likely contributed to their overall performance. In contrast, the CG showed only a minor improvement, from 65.1% to 68.7%, suggesting that traditional grammar instruction did not substantially influence physical posture.

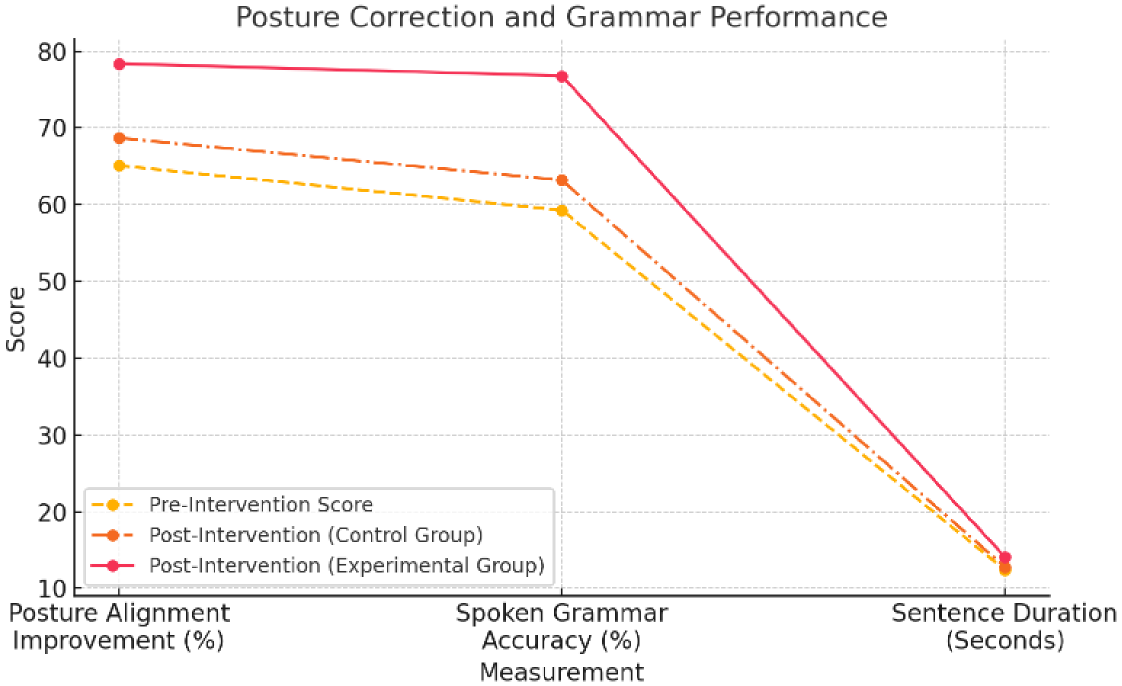

Figure 4. PCG performance.

Spoken grammar accuracy also improved significantly in the EG, increasing from 59.3% to 76.8%, a gain of 17.5%. This indicates a strong correlation between posture correction and improved articulation mechanics, leading to more precise and grammatically accurate speech. The CG, which did not receive biomechanical feedback, saw only a minor increase from 59.3% to 63.2%, further emphasizing the advantage of biomechanical feedback in enhancing spoken grammar performance. Lastly, sentence duration—the time taken to produce a sentence—showed a modest but meaningful improvement in the EG. The average sentence duration increased from 12.4 seconds pre-intervention to 14.1 seconds post-intervention, reflecting a 1.7-second improvement. This suggests that participants in the EG were more deliberate in their speech, taking the time to produce more precise, more accurate sentences due to better posture and articulation alignment. The CG only slightly increased sentence duration from 12.4 to 12.8 seconds.

Table 4. Gesture usage and grammatical understanding (GU).

Measurement	Pre-intervention score	Post-intervention score (CG)	Post-intervention score (EG)	Improvement (EG)
Gesture frequency (gestures per minute)	3.2	3.5	6.4	3.2
Correct use of gestures (%)	45.8	49.3	71.9	26.1
Grammar comprehension score (%)	57.6	62.1	80.3	22.7

Table 4 and **Figure 5** present the results of using gestures and their impact on GU. The EG, which received biomechanical feedback, including gesture guidance, demonstrated significant improvements across all measured aspects compared to the CG. Regarding gesture frequency, the EG showed a notable increase from 3.2 gestures per minute pre-intervention to 6.4 gestures per minute post-intervention, an improvement of 3.2 gestures per minute. This sharp increase suggests that the biomechanical feedback encouraged participants to use gestures more frequently during grammar tasks, reinforcing their understanding of grammatical concepts. In contrast, the CG only increased gesture frequency from 3.2 to 3.5 gestures per minute, indicating that traditional instruction had a minimal impact on gesture use.

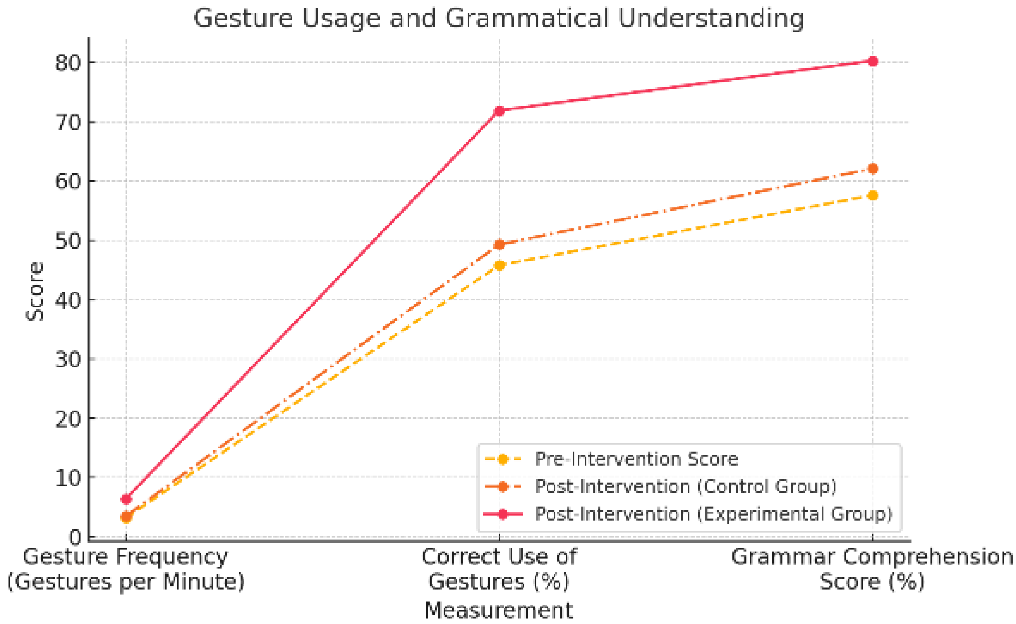

Figure 5. Gesture usage and GU.

The correct use of gestures also saw a remarkable improvement in the EG, rising from 45.8% to 71.9%, an increase of 26.1%. This significant improvement indicates that the real-time feedback on gesture alignment helped participants use gestures more purposefully and accurately to reinforce their GU. For example, pairing specific gestures with grammatical structures, such as using hand movements to represent verb conjugations or sentence connectors, likely helped participants internalize these concepts more effectively. In contrast, the CG showed only a modest improvement from 45.8% to 49.3%, underscoring the advantage of biomechanical feedback in guiding correct gesture use.

The grammar comprehension score improved significantly for the EG, rising from 57.6% pre-intervention to 80.3% post-intervention, reflecting an increase of 22.7%. This substantial gain suggests that using gestures and biomechanical feedback played a crucial role in enhancing participants' overall understanding of grammar. The CG, by comparison, only improved from 57.6% to 62.1%, further indicating that traditional instruction without gesture reinforcement was less effective in boosting grammar comprehension.

Table 5. Articulation mechanics and pronunciation.

Measurement	Pre-intervention score	Post-intervention score (CG)	Post-intervention score (EG)	Improvement (EG)
Lip movement precision (%)	58.4	61.9	76.4	18.0
Tongue placement accuracy (%)	61.2	64.1	79.6	18.4
Jaw movement stability (%)	57.5	60.2	75.1	17.6
Pronunciation accuracy (past tense endings) (%)	60.8	65.7	79.8	19.0
Pronunciation accuracy (pluralization) (%)	63.3	67.1	82.9	19.6
Pronunciation accuracy (word stress) (%)	59.6	64.5	80.4	20.8

Table 5 and **Figure 6** present a detailed analysis of articulation mechanics and their impact on pronunciation accuracy, focusing on lip, tongue, and jaw movements. The results highlight the substantial improvements in the EG, which received real-time biomechanical feedback to enhance articulation during grammar tasks. Regarding lip movement precision, the EG showed a significant increase from 58.4% pre-intervention to 76.4% post-intervention, representing an improvement of 18.0%. This suggests that the biomechanical feedback allowed participants to better CG and adjust their lip movements, which are crucial for accurately pronouncing specific sounds, especially in grammatically challenging forms like past tense endings and pluralizations. Conversely, the CG exhibited only a modest improvement from 58.4% to 61.9%, indicating that traditional instruction alone was less effective in enhancing lip movement precision.

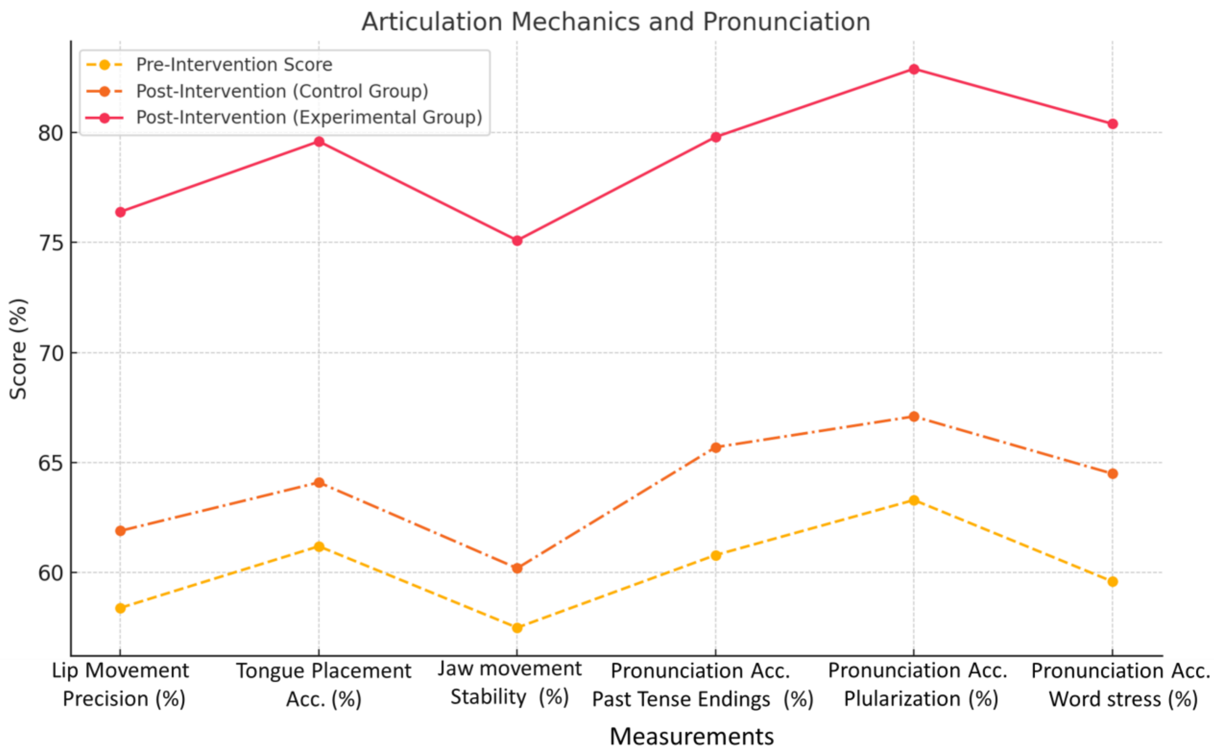

Figure 6. Articulation mechanics and pronunciation.

Tongue placement accuracy also markedly improved in the EG, increasing from

61.2% to 79.6%, a gain of 18.4%. This improvement reflects the participants' ability to position their tongues better to produce more precise and grammatically accurate speech, especially for complex grammatical forms like past tense verbs and word stress. The CG's improvement was minor, increasing from 61.2% to 64.1%, further emphasizing the added benefit of biomechanical feedback in refining articulation mechanics. Jaw movement stability, another key factor in accurate speech production, improved significantly for the EG, rising from 57.5% to 75.1%, an improvement of 17.6%. This improvement suggests that real-time feedback helped participants maintain more controlled and consistent jaw movements, leading to better pronunciation and overall grammar performance. The CG only improved from 57.5% to 60.2%, indicating that traditional methods were less effective in addressing jaw movement stability.

When focusing on specific pronunciation tasks, the EG's pronunciation accuracy for past tense endings increased from 60.8% to 79.8%, an improvement of 19.0%. This suggests that biomechanical feedback, mainly through articulation adjustment, helped participants master grammatically complex forms such as the "-ed" ending in past tense verbs, which often require precise articulation. In comparison, the CG only improved from 60.8% to 65.7%. For pluralization, the EG's pronunciation accuracy improved from 63.3% to 82.9%, reflecting a gain of 19.6%. This highlights how biomechanical feedback on articulation mechanics contributed to a better understanding and application of plural forms, where articulating sounds like "s" and "es" can be challenging for learners. The CG's improvement was more modest, increasing from 63.3% to 67.1%.

Finally, word stress pronunciation accuracy saw the most significant improvement in the EG, increasing from 59.6% to 80.4%, an improvement of 20.8%. Word stress is a critical aspect of pronunciation in English, and the significant improvement in the EG underscores the effectiveness of biomechanical feedback in helping participants better manage stress patterns in their speech, leading to more accurate and fluent pronunciation. The CG, by contrast, only improved from 59.6% to 64.5%.

Table 6. Error types and reduction.

Error type	Pre-intervention error rate (%)	Post-intervention error rate (CG) (%)	Post-intervention error rate (EG) (%)	Error reduction (EG) (%)
Tense mistakes (%)	21.4	18.7	10.9	10.5
Preposition misuse (%)	18.9	16.5	9.7	9.2
Pronunciation errors (%)	24.6	21.2	11.6	13.0
Subject-verb agreement Errors (%)	16.5	14.8	8.2	8.3
Article omission (%)	19.8	17.5	9.1	10.7

Table 6 presents a detailed comparison of error types and reduction between the pre- and post-intervention periods, highlighting the effectiveness of biomechanical feedback in reducing common grammatical and pronunciation errors in the EG. For tense mistakes, the EG showed a substantial error reduction from 21.4% pre-intervention to 10.9% post-intervention, marking an improvement of 10.5%. This

significant reduction in tense mistakes suggests that the biomechanical feedback helped learners internalize verb conjugations more effectively, particularly in spoken grammar tasks. The CG, in contrast, saw a more modest reduction from 21.4% to 18.7%.

Regarding preposition misuse, the EG reduced errors from 18.9% to 9.7%, reflecting a 9.2% reduction. This is another area where the EG outperformed the CG, which only reduced errors to 16.5%. This indicates that real-time physical feedback, especially regarding gesture alignment, may have helped reinforce the correct use of prepositions, a common area of difficulty in language learning. Pronunciation errors were significantly reduced in the EG, dropping from 24.6% to 11.6%, an improvement of 13.0%. The CG, on the other hand, reduced errors only to 21.2%. This result underscores the effectiveness of biomechanical feedback, particularly in improving articulation mechanics, which directly impacted pronunciation accuracy in grammatically complex forms like past tense endings and pluralizations.

For subject-verb agreement errors, the EG reduced errors from 16.5% to 8.2%, an improvement of 8.3%. This reduction suggests that posture correction and gesture feedback helped participants better understand syntactic structures in both spoken and written tasks. The CG's error reduction was minor, decreasing to 14.8% post-intervention. Finally, article omission errors saw a notable reduction in the EG, from 19.8% to 9.1%, an improvement of 10.7%. This significant reduction indicates that the biomechanical feedback likely helped learners pay more attention to minor grammatical elements, such as articles, often overlooked in both written and spoken language. The CG reduced errors to 17.5%, reflecting a less pronounced improvement.

Table 7. Comparison between EG and CG.

Performance metric	**CG improvement (%)**	**EG improvement (%)**	***t*-test, *p*-value**
Grammar accuracy (overall)	6.1	16.2	0.002
Fluency (sentence length and complexity)	4.2	12.1	0.015
Posture alignment	3.6	13.3	0.008
Gesture-based grammar comprehension	4.7	22.7	0.001
Articulation mechanics (pronunciation)	4.4	19.2	0.003
Error reduction (overall)	5.0	12.3	0.012

Table 7 provides a statistical comparison of performance improvements between the EG and CG across various metrics, using t-tests to evaluate the significance of the differences between the two groups. The results highlight the clear advantage of biomechanical feedback over traditional instruction methods. For overall grammar accuracy, the EG improved by 16.2%, significantly higher than the 6.1% improvement in the CG. The t-test *p*-value of 0.002 confirms that this difference is statistically significant, indicating that the biomechanical feedback provided a measurable and substantial benefit in improving grammar accuracy. In terms of fluency—measured by sentence length and complexity—the EG improved by 12.1%, compared to only 4.2% in the CG. The p-value of 0.015 demonstrates that this difference is statistically significant, showing that the real-time feedback significantly enhanced the EG's fluency and ability to form more complex sentences. Posture alignment improved by

13.3% in the EG, compared to just 3.6% in the CG. The *p*-value of 0.008 further emphasizes that the EG's improved posture significantly affected their grammar learning outcomes, particularly in spoken tasks.

The EG showed a substantial improvement in gesture-based grammar comprehension, with a 22.7% increase compared to 4.7% in the CG. The *p*-value of 0.001 highlights the highly significant impact of gesture-based feedback on the participant's ability to understand and apply grammatical concepts. For articulation mechanics, which focused on pronunciation accuracy, the EG improved by 19.2%, while the CG only saw an improvement of 4.4%. The *p*-value of 0.003 confirms that this difference is statistically significant, demonstrating the importance of biomechanical feedback in refining articulation and improving pronunciation accuracy. Finally, the overall error reduction was more pronounced in the EG, with a 12.3% improvement, compared to a 5.0% improvement in the CG. The *p*-value of 0.012 indicates that this difference is statistically significant, further validating the effectiveness of biomechanical feedback in reducing common grammatical errors.

Table 8. Participant feedback and learning experience.

Feedback aspect	Positive feedback (EG) (%)	Neutral feedback (EG) (%)	Negative feedback (EG) (%)
Posture impact on speech clarity (%)	82.4	12.8	4.8
Gesture helpfulness (%)	75.9	17.6	6.5
Articulation feedback effectiveness (%)	84.1	10.5	5.4
Improved grammar retention (%)	79.6	13.2	7.2
Overall learning satisfaction (%)	88.3	9.4	2.3

Table 8 provides an overview of the EG participants' feedback regarding their learning experience with biomechanical feedback. The feedback is categorized into positive, neutral, and negative responses, reflecting how the participants perceived various aspects of the intervention, such as posture correction, gesture-based learning, articulation feedback, grammar retention, and overall satisfaction. Regarding the impact of posture on speech clarity, 82.4% of participants provided positive feedback, indicating that improved posture significantly enhanced their ability to articulate words clearly. Only 12.8% gave neutral feedback, and a slight 4.8% expressed negative opinions. This suggests that most participants recognized the value of posture correction in improving their spoken grammar accuracy and fluency.

Regarding the helpfulness of gestures, 75.9% of participants responded positively, indicating that they used gestures to reinforce grammatical concepts effectively. A smaller portion, 17.6%, provided neutral feedback, while 6.5% had negative opinions. This reflects a robust overall acceptance of gesture-based learning as a valuable tool for enhancing grammar comprehension and sentence formation, though a minority may have found it less applicable to their learning style. The effectiveness of articulation feedback received the highest positive feedback, with 84.1% of participants expressing satisfaction. This indicates that most learners found real-time articulation adjustments—such as feedback on lip, tongue, and jaw movements—crucial in improving pronunciation and grammar accuracy. 10.5% gave neutral feedback, and only 5.4% reported a negative experience, further highlighting the importance of articulation-focused feedback in language learning.

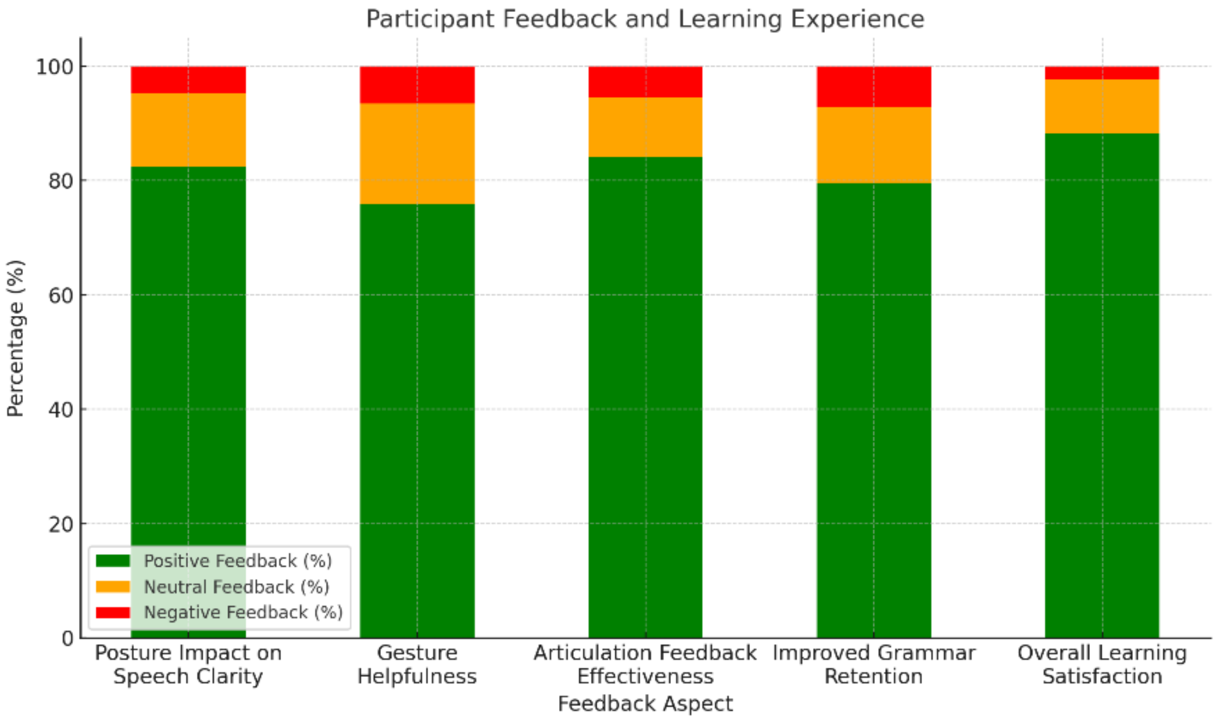

Figure 7. Participant feedback and learning experience.

Regarding improved grammar retention, 79.6% of participants felt that biomechanical feedback helped them retain grammatical structures more effectively. This positive feedback suggests that integrating physical movements (posture, gestures, articulation) into grammar instruction had a lasting impact on participants' ability to remember and apply grammar rules. 13.2% provided neutral feedback, and 7.2% expressed negative opinions, indicating that while most found the approach beneficial, a small segment may have preferred traditional learning methods. Finally, the participants' overall learning satisfaction with the biomechanical feedback-based approach was overwhelmingly positive, with 88.3% of respondents expressing high satisfaction levels. Only 9.4% were neutral, and a mere 2.3% expressed dissatisfaction. This strong positive feedback underscores the effectiveness of combining biomechanical feedback with grammar instruction, enhancing most participants' learning experience and overall outcomes.

6. Conclusion and future work

The results of this study highlight the substantial benefits of integrating biomechanical feedback with deep learning algorithms in English grammar instruction. Participants in the EG, who received real-time feedback on their posture, gestures, and articulation mechanics, exhibited significantly improved grammar accuracy, fluency, and error reduction compared to the CG. Using a CNN-based model allowed for precise linguistic and biomechanical data analysis, providing learners with targeted feedback that addressed both cognitive and physical dimensions of language learning. The findings underscore the importance of considering physical factors such as posture and articulation in grammar instruction, particularly in spoken tasks where these factors directly influence speech clarity and pronunciation. The significant reduction in common grammatical errors, including tense mistakes, preposition misuse, and pronunciation errors, further validates the effectiveness of biomechanical feedback in improving language acquisition outcomes.

Moreover, the overwhelmingly positive participant feedback on the learning experience suggests that this approach not only improves performance but also enhances engagement and retention. In conclusion, this study offers a compelling case for adopting biomechanical feedback and AI in language education. This integrated approach can potentially transform traditional grammar teaching methods, particularly in ESL contexts, by addressing both the cognitive and physical challenges that learners face. Future research should explore the scalability of this model across different languages and learning environments, as well as its long-term impact on language retention and fluency. Applying AI-driven feedback in education is a promising avenue for creating more interactive, personalized, and compelling learning experiences.

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