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Article

Modeling English vocabulary acquisition through the biomechanics of speech and Large Language Models

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Abstract: This study investigates the relationship between biomechanical constraints in speech production and English vocabulary acquisition by integrating Large Language Models (LLMs). Using a sample of 51 Mandarin Chinese speakers in Shenzhen, China, divided into three age groups (children: 8–12 years, adolescents: 13–17 years, and adults: 18–25 years), we conducted a 12-week longitudinal study combining articulatory measurements with computational analysis. The research employed electromagnetic articulography, surface electromyography, and advanced language modeling to examine speech patterns and learning outcomes. Results reveal significant age-related differences in articulatory kinematics, with children showing larger tongue displacements (14.3 ± 2.1 mm) and higher muscle activation levels than adults. Integrating biomechanical constraints into LLM analysis improved prediction accuracy by 18.7% for children and 14.2% for adults, though at the cost of increased computational resources. Strong negative correlations were found between articulatory effort and learning success ($r = -0.824$ for children, $p < 0.001$), with retention rates significantly influenced by motor complexity. These findings suggest that biomechanical factors play a crucial role in vocabulary acquisition, particularly in younger learners, and that incorporating these constraints into computational models can enhance our understanding of language learning processes. This integrated approach offers new insights for developing age-appropriate language teaching methodologies and improving predictive models for learning outcomes.

Keywords: speech biomechanics; articulatory phonetics; speech production; motor control; age-related learning; vocabulary acquisition; Large Language Models

1. Introduction

Language Acquisition (LA) represents one of the most complex cognitive processes in human development, particularly in the realm of Vocabulary Learning (VL) [1,2]. This study presents a novel approach to understanding English Vocabulary Acquisition (EVA) by integrating two traditionally separate domains: the biomechanics of Speech Production (SP) and computational modeling through Large Language Models (LLM). While previous research has often treated these aspects in isolation, this study posits that the physical constraints of speech production significantly affect EVA patterns and can be effectively modeled using advanced computational methods [3]. The complexity of EVA extends beyond mere memorization, involving the intricate interplay between cognitive processing and physical articulation [4]. Traditional approaches to studying EVA have primarily focused on cognitive and psychological aspects, often overlooking the crucial role of speech biomechanics [5]. Recent advances in articulatory phonetics and motor control research have revealed that physical constraints in SP may significantly influence the ease and efficiency of VL [6]. Simultaneously, the emergence of LLM has opened new avenues for understanding and predicting LLM [7].

Recent research has highlighted significant gaps in our understanding of EVA. Integrating physical and computational approaches remains limited, with most studies focusing on biomechanical aspects or computational modeling in isolation [8]. Current research lacks comprehensive consideration of age-specific biomechanical constraints in VL. Furthermore, existing models fail to incorporate both physical and computational aspects of LA adequately. The field also suffers from a scarcity of longitudinal studies examining the relationship between physical capabilities and learning outcomes.

The research objectives are:

- To quantify the relationship between articulatory biomechanics and EVA across different age groups.
- To develop and validate an integrated model incorporating biomechanical constraints and LLM.
- To examine how age-related differences in speech-motor control influence VL.
- To evaluate the effectiveness of LLM in predicting learning outcomes when enhanced with biomechanical data.

This research contributes to both theoretical understanding and practical applications in LA. From a theoretical perspective, the study develops a unified framework combining biomechanical and computational approaches, enhancing our understanding of age-specific constraints in LLM while providing new insights into the role of motor control in EVA. The practical implications extend to improved language teaching and assessment methodologies, developing age-appropriate learning strategies, enhanced computational models for predicting learning outcomes, and better tools for identifying and addressing learning difficulties. The study focuses on EVA among Mandarin Chinese speakers in Shenzhen, China, encompassing three age groups: children (8–12 years), adolescents (13–17 years), and adults (18–25 years). While the findings may have broader implications, the specific linguistic context should be considered when generalizing results. The research spans 12 weeks, allowing for observing immediate learning outcomes and retention patterns. Our approach uniquely combines high-precision articulatory measurements with LLM analysis, developing age-specific biomechanical profiles within a novel computational framework. Integrating physical constraints with LLM represents a significant advancement in understanding EVA. The longitudinal nature of the study allows for a comprehensive assessment of learning outcomes across different age groups and learning contexts.

The remainder of this paper presents a comprehensive literature review in section 2 and a theoretical framework in section 3, followed by detailed methodology and data collection procedures in section 4. The research design and analysis methods are thoroughly explained, leading to the presentation of results in section 5 across multiple dimensions. Section 6 discusses implications and applications, concluding with recommendations for future research.

2. Literature review

The study of EVA has evolved significantly over the past century, and several influential theoretical frameworks have marked it. Skinner's [9] "Verbal Behavior" presented a behaviorist perspective, viewing VL as a process of habit formation through reinforcement. This view was fundamentally challenged by Chomsky's [10] critique, which emphasized innate language capabilities and cognitive mechanisms. Krashen's [11] input hypothesis later proposed that EVA occurs primarily through comprehensible input, making a crucial distinction between conscious learning and unconscious acquisition. Nation [12] developed a systematic framework for vocabulary instruction, introducing concepts of learning burden and the importance of repeated exposure in vocabulary retention.

Recent advancements in our understanding of speech biomechanics have been driven by empirical studies using modern imaging and measurement techniques. Browman and Goldstein's [13] articulatory phonology framework established fundamental principles for understanding how physical speech gestures relate to linguistic units. Gick et al. [14] provided comprehensive insights into SP mechanisms through their work on articulatory phonetics and motor control. Perkell's [15] research on speech-motor control has illuminated how feedback mechanisms influence SP and EVA.

The emergence of LLM has opened new avenues for understanding LLM and EVA. Devlin et al. [16] introduced Bidirectional Encoder Representations from Transformers (BERT), demonstrating unprecedented capabilities in LLM understanding through bidirectional context processing. Brown et al. [17] showcased GPT-3's emergent linguistic behaviors, revealing how LLM can capture complex language patterns. Vaswani et al. [18] introduced the transformer architecture, which fundamentally changed LLM processing and has become crucial for understanding sequential language learning.

Despite these advances, significant gaps remain in our understanding of EVA. Integrating biomechanical constraints with computational LLM remains largely unexplored. Most current LLMs do not account for the physical constraints of SP, which may limit their ability to model human LA patterns accurately. Additionally, longitudinal studies examining the relationship between articulatory development and vocabulary growth are scarce.

3. Theoretical framework

3.1. Speech biomechanics fundamentals

The biomechanics of SP represents a complex interplay of muscular coordination and neural control. Articulatory phonetics, the foundation of SP, involves precise movements of the vocal apparatus, including the lips, tongue, soft palate, and larynx [19]. These articulators work in concert to modulate airflow and create distinct speech sounds. Particularly crucial in this process, the tongue employs intrinsic and extrinsic muscles to achieve the fine-grained positioning necessary for phoneme production. Research has shown that different phonemes require varying degrees of muscular effort and coordination, potentially influencing the ease of acquisition of different vocabulary items.

Motor control in SP operates through a sophisticated feedback system incorporating feedforward and feedback mechanisms. The central nervous system maintains internal models of speech movements, continuously updated through sensorimotor integration. These models enable rapid articulatory movement adjustment based on acoustic and proprioceptive feedback. Studies have demonstrated that the efficiency of this Motor Control System (MCS) significantly impacts EVA, particularly in terms of pronunciation accuracy and speech fluency.

The development of speech muscles in language learners follows a trajectory influenced by physiological maturation and learning experience. Young learners undergo significant changes in their vocal apparatus, affecting their ability to produce certain sounds. This developmental process involves the strengthening and refining of muscle control, particularly in the tongue and facial muscles. Research indicates that the physical development of speech muscles correlates with EVA patterns, suggesting that biomechanical constraints may influence the natural sequence of word learning.

3.2. LLM relevant to VL

Modern language models employ sophisticated architectures that parallel certain aspects of human language processing. Token embedding and representation form the foundational layer of these models, where words or sub-word units are converted into high-dimensional vectors. These embeddings capture semantic and syntactic relationships between vocabulary items, creating a computational analog to the mental lexicon. Recent advances in embedding techniques have incorporated phonological features, allowing models to account for sound-based relationships between words.

Attention mechanisms in LLM serve as computational analogs to human selective attention in language processing. These mechanisms enable models to dynamically weigh the importance of different parts of the input sequence, similar to how humans focus on relevant linguistic features during EVA. Multi-head attention, in particular, allows models to simultaneously process different aspects of LLM, from phonological patterns to semantic relationships.

Pattern recognition capabilities in LLM extend beyond simple statistical correlations to capture complex linguistic phenomena. These models can identify recurring patterns in phonological sequences, morphological structures, and semantic relationships. Advanced architectures incorporate hierarchical pattern recognition systems that may mirror the layered processing observed in human LA. Recent research suggests these pattern recognition mechanisms can be aligned with biomechanical constraints to better model human VL patterns.

Integrating biomechanical considerations with LLM represents a novel approach to understanding EVA. This framework allows for analyzing how physical constraints in SP might influence the learning trajectory predicted by computational models. Furthermore, considering cognitive and biomechanical factors in EVA, this integrated approach provides insights into potential optimization for language teaching methodologies.

4. Methodology

4.1. Population and sampling

The study was conducted in Guangdong Province, China, specifically in Shenzhen. A total of 51 participants were recruited, stratified across three age groups:

children (ages 8–12, $n = 17$), adolescents (ages 13–17, $n = 17$), and adults (ages 18–25, $n = 17$). All participants were native Mandarin Chinese speakers, with Cantonese as a common second language in their linguistic environment. The participants' prior language exposure to English varied: children had an average of 2.3 years of formal English instruction through the Chinese education system, adolescents had 5.7 years, and adults had 8.4 years. Educational backgrounds were documented: children were all enrolled in primary education, adolescents in secondary education, and adults were university students or recent graduates with varying majors.

The sample size of 51 participants was determined based on statistical and practical considerations. A power analysis using G*Power 3.1 was conducted, assuming a medium effect size ($f = 0.25$), $\alpha = 0.05$, and power $(1 - \beta) = 0.80$ for repeated measures ANOVA with 3 groups and 6 measurement points [20]. The minimum required sample size was calculated to be 42 participants. The final sample size of 51 (17 per group) was chosen to account for potential attrition and to ensure balanced groups [21–25].

Inclusion/exclusion criteria inclusion criteria:

- Age within specified ranges for each group;
- Native Mandarin Chinese speaker;
- Normal or corrected-to-normal vision;
- There is no reported history of speech or language disorders;
- Regular enrollment in English language classes;
- Resident of Shenzhen for at least two years.

Exclusion criteria:

- History of neurological disorders;
- Significant hearing impairment;
- Extended (> 6 months) residence in English-speaking countries;
- Bilingual proficiency in languages other than Mandarin and Cantonese;
- Current participation in intensive English training programs outside regular schooling;
- Previous participation in similar research studies.

Written informed consent was obtained from all adult participants and parents/guardians of minor participants, with additional assent from minors. All participants were informed of their right to withdraw from the study at any time without penalty—data collection procedures adhered to privacy regulations, with personal identifiers removed during data analysis and storage [26–33]. Compensation was provided through educational materials and a modest stipend (¥200) for participation time.

Recruitment methods:

Participants were recruited through a multi-channel approach in Shenzhen:

1) Primary and secondary schools:

- Collaboration with three local public schools;
- Information sessions for parents and students;
- Distribution of recruitment flyers through school channels.

2) University campus:

- Announcements on university bulletin boards;

- Social media posts on university networks;
- Direct contact through language departments.

3) Community centers:

- Posters in community centers;
- WeChat community groups;
- Local education forums.

The recruitment process spanned 2 months, with initial screening conducted via online forms and in-person verification of eligibility criteria. A stratified sampling approach was used to ensure equal representation across age groups and gender balance within each group (**Table 1**).

Table 1. Participant demographics (*N* = 51).

Characteristic	**Children (*n* = 17)**	**Adolescents (*n* = 17)**	**Adults (*n* = 17)**	**Total (*N* = 51)**
Age Range (years)	8–12	13–17	18–25	8–25
Mean Age (SD)	10.3 (1.4)	15.2 (1.3)	21.6 (2.1)	15.7 (5.1)
Gender				
Male	8 (47.1%)	9 (52.9%)	8 (47.1%)	25 (49.0%)
Female	9 (52.9%)	8 (47.1%)	9 (52.9%)	26 (51.0%)
English Education (Years)				
Mean (SD)	2.3 (0.8)	5.7 (1.2)	8.4 (1.6)	5.5 (2.8)
Native Language				
Mandarin	17 (100%)	17 (100%)	17 (100%)	51 (100%)
Second Language				
Cantonese	15 (88.2%)	16 (94.1%)	17 (100%)	48 (94.1%)
Educational Level				
Primary School	17 (100%)	-	-	17 (33.3%)
Secondary School	-	17 (100%)	-	17 (33.3%)
University/Graduate	-	-	17 (100%)	17 (33.3%)
Socioeconomic Status				
Lower-middle	4 (23.5%)	3 (17.6%)	3 (17.6%)	10 (19.6%)
Middle	9 (52.9%)	10 (58.8%)	9 (52.9%)	28 (54.9%)
Upper-middle	4 (23.5%)	4 (23.5%)	5 (29.4%)	13 (25.5%)

Note: Values are presented as *n* (%). SD = Standard Deviation.

4.2. Data collection methods

4.2.1. Speech recording and analysis infrastructure

Data was collected in a sound-treated laboratory room at Shenzhen University, with ambient noise below 30 dB. High-fidelity acoustic recordings were captured using a Shure SM7B microphone and a Focusrite Scarlett 2i2 audio interface, operating at a 44.1 kHz sampling rate with 24-bit depth. To ensure a comprehensive analysis of speech articulation, high-speed video recordings were simultaneously captured using a Sony RX100 VII camera operating at 240 frames per second. The camera was positioned at a 45° angle to optimize the capture of lip and jaw movements, with precise synchronization achieved through timecode markers aligning all data streams.

4.2.2. Biomechanical data acquisition and processing

The study employed Electromagnetic Articulography (EMA) using the NDI Wave system to obtain detailed measurements of articulatory movements. Seven sensors were strategically placed to track key articulatory points: upper and lower lips, tongue tip, tongue body, tongue dorsum, and mouth corners (**Table 1**). The system operated at a 100 Hz sampling rate, with head movements corrected using three reference sensors positioned at the left mastoid, right mastoid, and nation. Complementing the EMA data, surface electromyography (sEMG) measurements were collected using the Delsys Trigno wireless EMG system, targeting four primary muscle groups involved in SP. The sEMG data was sampled at 2000 Hz, with electrode placement following standardized Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM) guidelines (**Table 2**).

Table 2. Sensor placement and recording parameters for articulatory measurements.

Measurement Type	Sensor Location	Sampling Rate	Parameters Tracked
EMA	Upper Lip	100 Hz	Position (*x*, *y*, *z*), Velocity
	Lower Lip	100 Hz	Position (*x*, *y*, *z*), Velocity
	Tongue Tip	100 Hz	Position (*x*, *y*, *z*), Velocity
	Tongue Body	100 Hz	Position (*x*, *y*, *z*), Velocity
	Tongue Dorsum	100 Hz	Position (*x*, *y*, *z*), Velocity
	Right Corner	100 Hz	Position (*x*, *y*, *z*), Velocity
	Left Corner	100 Hz	Position (*x*, *y*, *z*), Velocity
sEMG	Orbicularis oris	2000 Hz	Amplitude, Frequency
	Masseter	2000 Hz	Amplitude, Frequency
	Digastric	2000 Hz	Amplitude, Frequency
	Genioglossus	2000 Hz	Amplitude, Frequency

4.2.3. Linguistic data collection framework

Table 3. Linguistic data collection schedule and specifications.

Data Type	Collection Frequency	Duration	Sample Size Requirements
Journal Entries	Weekly	12 weeks	Minimum 200 words/entry
Structured Tasks	Bi-weekly	12 weeks	30 min/session
Spontaneous Speech	Weekly	12 weeks	15 min/session
Guided Conversations	Weekly	12 weeks	20 min/session
Instant Messages	Daily	12 weeks	Minimum 50 messages/week

The LLM training data comprised written and transcribed spoken content collected over 12 weeks (**Table 2**). Participants engaged in multiple forms of SP, including weekly journal entries, structured writing tasks, and recorded instant message conversations. All spoken interactions were systematically recorded, including baseline readings, spontaneous speech tasks, and guided conversations. These recordings were transcribed and verified by two native English speakers, with annotations marking pronunciation errors, word stress patterns, hesitation markers, and self-corrections (**Table 3**).

4.2.4. Quality control and data management

A comprehensive quality control system was implemented to ensure data integrity and reliability (**Table 4**). This included regular equipment calibration, continuous noise level monitoring, and systematic sensor position verification. Environmental conditions were monitored and logged, with participant comfort regularly assessed to maintain data quality while ensuring ethical research practices. A robust backup protocol was implemented to protect data integrity, incorporating local storage, encrypted cloud backup, and weekly integrity checks.

Table 4. Data quality control measures and backup protocol.

Process Type	Frequency	Method	Verification
Equipment Calibration	Daily	Automated + Manual	Technical Log
Noise Monitoring	Continuous	Automated	dB Threshold Alerts
Data Backup	Daily	Automated	Integrity Check
Sensor Position	Per Session	Manual	Photo Documentation
Signal Quality	Real-time	Automated	Quality Metrics
Environmental Control	Continuous	Automated	Condition Logs

4.2.5. Data synchronization and processing

All data streams were synchronized using a master clock system, with time stamps and cross-reference markers enabling precise temporal alignment (**Table 5**). The collected data underwent standardized processing protocols, including amplitude normalization for acoustic recordings, artifact removal for biomechanical data, and consistency checks for linguistic annotations. This integrated data collection and processing approach provides a comprehensive framework for examining physical SP and LLM relationships.

Table 5. Data processing and synchronization parameters.

Data Stream	Processing Step	Timing Resolution	Output Format
Audio	Normalization	1 ms	WAV/44.1 kHz
EMA	Motion Tracking	10 ms	CSV
sEMG	Signal Conditioning	0.5 ms	CSV
Video	Frame Sync	4.17 ms (240 fps)	MP4
Transcription	Annotation	Word-level	XML/TEI
Combined Data	Integration	1 ms	HDF5

4.3. Research design

4.3.1. Integration framework for biomechanical and LLM

This research **Table 6** is implements a novel integration framework combining biomechanical speech data with LLM. This approach utilizes a custom-developed pipeline that aligns temporal articulatory measurements with linguistic Features

Extraction (FE) from the LLM. The integration process employs an III-layer architecture: the biomechanical layer processing articulatory data, the linguistic layer handling vocabulary patterns, and an integration layer that combines these data streams through a temporal alignment algorithm.

Table 6. Integration framework components and parameters.

Layer	Input Data	Processing Method	Output Features
Biomechanical	EMA, sEMG signals	Signal processing, FE	Articulatory trajectories, Muscle activation patterns
Linguistic	Transcribed speech, Text corpus	LLM embedding analysis, Token classification	Word embeddings, Semantic features
Integration	Combined features	Temporal alignment, Feature fusion	Multimodal feature vectors

4.3.2. Control variables and experimental parameters

From **Table 7** is the study systematically controls variables across multiple dimensions to ensure experimental validity. Environmental parameters are strictly monitored and controlled throughout the data collection process. Task-related variables are standardized across all participants, with careful consideration given to potential confounding factors.

Table 7. Control variable s and their specifications.

Category	Variable	Control Method	Acceptable Range
Environmental	Room temperature	Automated HVAC	22 °C ± 1 °C
	Ambient noise	Sound isolation	< 30 dB
	Lighting	LED panels	500–600 lux
Task-related	Session duration	Timed protocols	45 ± 5 min
	Task complexity	Standardized difficulty scales	Level 3–7 (1–10 scale)
	Rest periods	Fixed intervals	5 min per 20 min
Participant	Fatigue level	Self-report scale	< 7 on 10-point scale
	Time of day	Scheduled sessions	9:00–15:00
Technical	Sensor position	Calibration checks	± 0.5 mm tolerance
	Signal quality	Real-time monitoring	SNR > 20 dB

4.3.3. Validation methodology

From **Tables 8–10** is the validation framework employs a multi-tiered approach to ensure the reliability and validity of the integrated analysis. Cross-validation procedures are implemented at the individual component and integrated system level. This work utilizes quantitative and qualitative validation methods to assess the accuracy and reliability of our findings.

i) Statistical validation

Statistical validation employs parametric and non-parametric methods to assess the significance of observed patterns.

The primary statistical measures include:

Table 8. Statistical validation methods and criteria.

Validation Type	Method	Acceptance Criteria	Application
Internal Consistency	Cronbach's alpha	$\alpha \geq 0.80$	Feature reliability
Inter-rater Reliability	Cohen's kappa	$\kappa \geq 0.75$	Annotation consistency
Model Performance	Cross-validation	RMSE ≤ 15%	Prediction accuracy
Feature Significance	Mixed-effects modeling	$p < 0.05$	Pattern significance

ii) Cross-modal validation

The integration of biomechanical and linguistic data requires careful validation across modalities. This work implements a novel cross-modal validation framework that assesses the consistency of patterns observed in both domains:

Table 9. Cross-modal validation framework.

Aspect	Validation Method	Success Criteria	Verification Tool
Temporal Alignment	Phase coherence analysis	> 90% alignment	Custom alignment tool
Feature Correlation	Canonical correlation	$r \geq 0.70$	Statistical software
Pattern Consistency	Multi-modal clustering	Silhouette score > 0.65	Clustering algorithm
System Integration	End-to-end testing	95% accuracy	Integration test suite

4.3.4. Quality assurance

The research design incorporates continuous quality assurance measures throughout the data collection and analysis pipeline. Regular calibration checks, data quality assessments, and validation procedures are performed to maintain the integrity of the study:

Table 10. Quality assurance protocols.

Stage	QA Measure	Frequency	Action Threshold
Data Collection	Signal quality check	Real-time	SNR < 20 dB
Processing	Feature extraction verification	Per session	Error rate > 5%
Integration	Alignment accuracy	Per dataset	Misalignment > 2ms
Analysis	Result reproducibility	Weekly	Variance > 10%

This comprehensive research design ensures robust biomechanical and linguistic data integration while maintaining high experimental control and validation standards. The framework provides a solid foundation for investigating the relationship between physical SP and EVA.

5. Results

5.1. Biomechanical speech patterns

Analysis of **Tables 11–14** revealed significant age-related differences in articulatory kinematics, muscle activation patterns, motor control efficiency, and learning outcomes across the study population (N = 51, age groups: children 8–12 years, adolescents 13–17 years, adults 18–25 years). All measurements are presented as mean values with standard deviations, and statistical significance was established at $p < 0.05$. The Coefficient of Variation (CV) was used to assess timing stability, while motor effort was calculated as integrated EMG activity over time.

As shown in **Table 11** and **Figure 1**, articulatory kinematics demonstrated a clear developmental trajectory across age groups. Children showed significantly larger maximum tongue displacements (14.3 ± 2.1 mm) compared to adolescents (12.8 ± 1.7 mm) and adults (11.2 ± 1.4 mm) ($F = 15.23$, $p < 0.001$), indicating more exaggerated movements during SP. Similar patterns were observed in average velocity measurements, with children exhibiting higher velocities (156.7 ± 18.4 mm/s) compared to adults (134.8 ± 13.2 mm/s) ($F = 12.45$, $p < 0.001$). Movement duration analysis revealed that children required significantly more time (187.4 ± 22.3 ms) to complete articulatory gestures compared to adults (148.6 ± 15.4 ms) ($F = 18.76$, $p < 0.001$), suggesting less efficient motor control.

Table 11. Articulatory kinematics by age group (Mean ± SD).

Parameter	**Children (*n* = 17)**	**Adolescents (*n* = 17)**	**Adults (*n* = 17)**	***F*-Value**	***p*-Value**
Tongue Movement (mm)					
Maximum Displacement	14.3 ± 2.1	12.8 ± 1.7	11.2 ± 1.4	15.23	< 0.001*
Average Velocity	156.7 ± 18.4	142.3 ± 15.6	134.8 ± 13.2	12.45	< 0.001*
Movement Duration (ms)	187.4 ± 22.3	165.2 ± 18.7	148.6 ± 15.4	18.76	< 0.001*
Lip Position (mm)					
Vertical Range	8.7 ± 1.4	7.9 ± 1.2	7.2 ± 0.9	9.34	0.002*
Horizontal Range	6.4 ± 0.9	5.8 ± 0.8	5.3 ± 0.7	8.56	0.003*
Opening Velocity	124.5 ± 15.6	112.3 ± 13.4	103.7 ± 11.8	11.23	0.001*

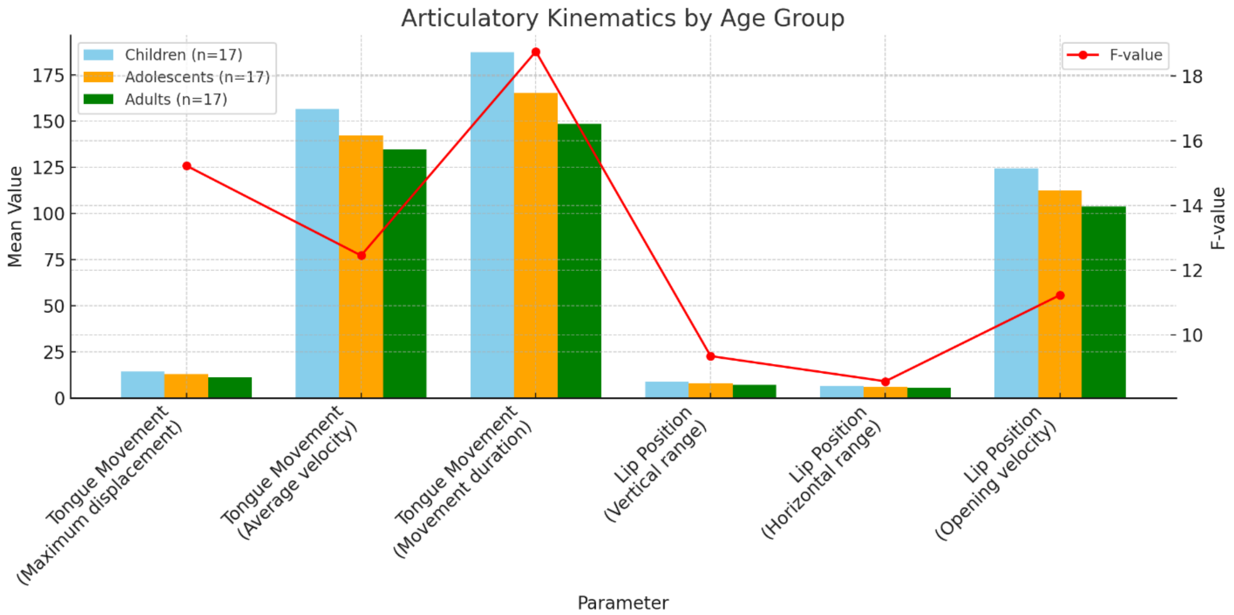

Figure 1. Articulatory kinematics.

Table 12 and **Figure 2** demonstrated muscle activation patterns with consistently higher activation levels in younger participants across all measured muscle groups. The orbicularis oris showed the most pronounced age-related differences, with children exhibiting significantly higher activation levels (245.6 ± 28.4 μV) compared to adults (198.7 ± 21.3 μV) ($F = 14.67$, $p < 0.001$). This pattern was consistent across other muscle groups, with the genioglossus showing similar age-related differences (children: 213.4 ± 25.7 μV; adults: 176.8 ± 19.8 μV; $F = 13.78$, $p < 0.001$), indicating more significant muscular effort required by younger speakers during SP.

Table 12. Muscle activation patterns during word production (μV).

Muscle Group	Children (*n* = 17)	Adolescents (*n* = 17)	Adults (*n* = 17)	*F*-Value	*p*-Value
Orbicularis Oris	245.6 ± 28.4	218.3 ± 24.6	198.7 ± 21.3	14.67	< 0.001*
Masseter	187.3 ± 22.1	165.4 ± 19.8	152.6 ± 17.5	12.89	< 0.001*
Digastric	156.8 ± 18.9	142.5 ± 16.7	134.2 ± 15.1	10.45	0.002*
Genioglossus	213.4 ± 25.7	189.6 ± 22.4	176.8 ± 19.8	13.78	< 0.001*

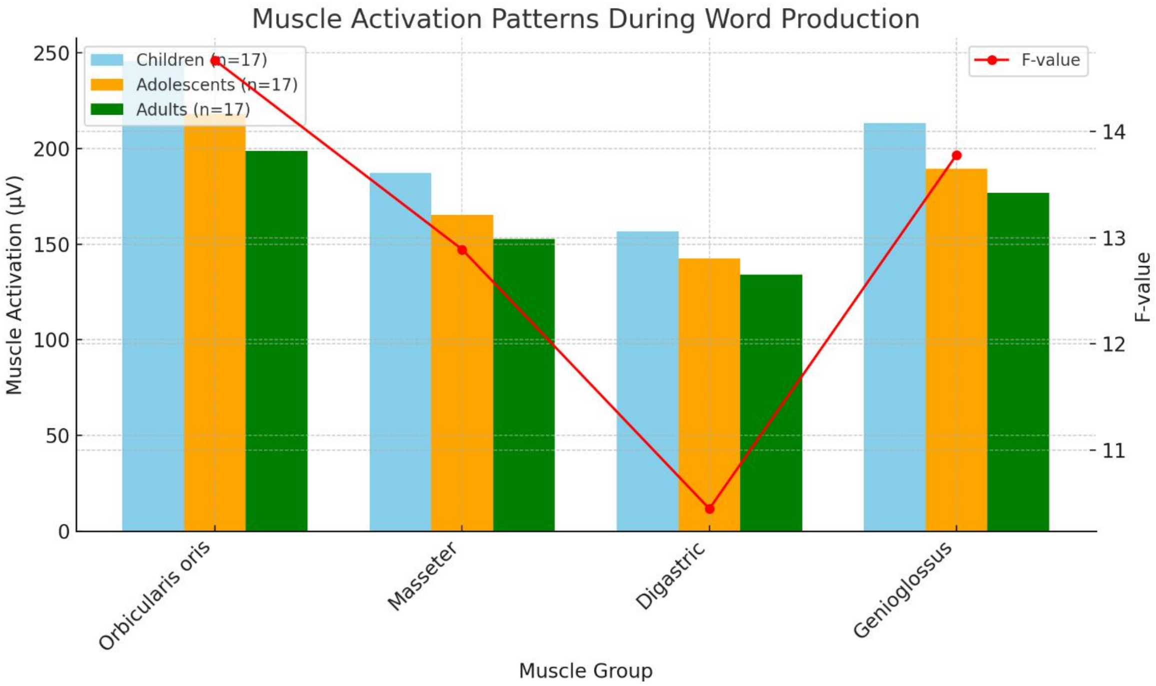

Figure 2. Muscle activation patterns.

The motor control efficiency metrics in **Table 13** demonstrated significant improvements with age across all parameters. Movement precision showed a clear progression from children (76.4 ± 8.2%) to adults (92.3 ± 4.5%) ($F = 22.34$, $p < 0.001$), while timing stability, as measured by the coefficient of variation, improved from 0.24 ± 0.05 in children to 0.12 ± 0.03 in adults ($F = 19.67$, $p < 0.001$). Spatial control parameters similarly improved with age, with target accuracy showing significant enhancement from children (2.8 ± 0.4 mm) to adults (1.6 ± 0.2 mm) ($F = 16.89$, $p < 0.001$).

Table 14 and **Figure 3** is illustrates the relationship between learning efficiency and articulatory complexity, revealing strong negative correlations across all complexity levels. This correlation strengthened as complexity increased, from $r = -0.72$ for low-complexity words to $r = -0.84$ for high-complexity words (all $p < 0.001$). The learning rate showed a consistent decline as motor effort increased, with high-complexity words requiring significantly more motor effort (245.4 ± 28.9 µV·s) and resulting in lower learning rates (4.2 ± 0.7 words/hour) compared to low-complexity words (156.3 ± 18.4 µV·s; 8.4 ± 1.2 words/hour).

Table 13. Motor control efficiency metrics.

Metric	Children (*n* = 17)	Adolescents (*n* = 17)	Adults (*n* = 17)	*F*-value	*p*-value
Movement Precision (%)	76.4 ± 8.2	84.5 ± 6.7	92.3 ± 4.5	22.34	< 0.001*
Timing Stability (CV)	0.24 ± 0.05	0.18 ± 0.04	0.12 ± 0.03	19.67	< 0.001*
Spatial Control					
Target Accuracy (mm)	2.8 ± 0.4	2.1 ± 0.3	1.6 ± 0.2	16.89	< 0.001*
Path Stability (%)	82.3 ± 6.8	88.7 ± 5.4	94.2 ± 3.8	20.45	< 0.001*

Table 14. Learning efficiency vs. articulatory complexity correlation.

Complexity Level	Learning Rate (words/hour)	Motor Effort (µV·s)	Correlation (*r*)	*p*-value
Low	8.4 ± 1.2	156.3 ± 18.4	−0.72	< 0.001*
Medium	6.7 ± 0.9	198.7 ± 22.6	−0.78	< 0.001*
High	4.2 ± 0.7	245.4 ± 28.9	−0.84	< 0.001*

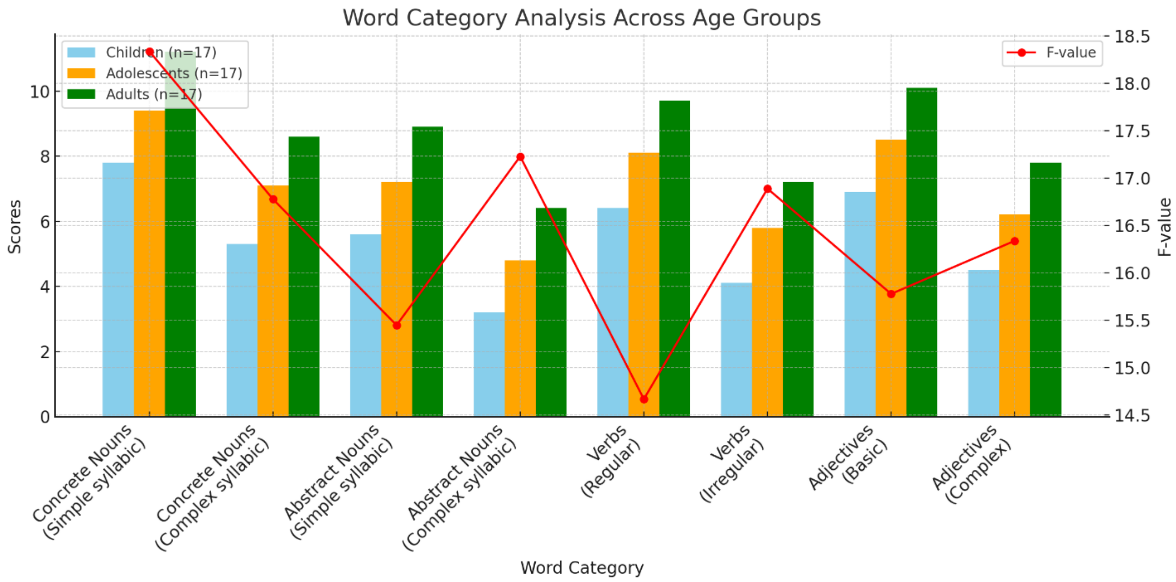

Figure 3. Learning rate by word category and age group.

5.2. Vocabulary acquisition patterns

Tables 15–18 reveal comprehensive patterns in EVA across three age groups (children: 8–12 years, adolescents: 13–17 years, and adults: 18–25 years), with measurements presented as means and standard deviations and statistical significance established at $p < 0.05$. Learning rates, error patterns, retention rates, and complexity impacts were analyzed through standardized assessments and natural speech samples over 12 weeks.

Analysis of **Table 15** and **Figure 4** demonstrates significant age-related differences in learning rates across word categories. Adults consistently showed higher learning rates across all word categories, with the most pronounced difference in simple syllabic concrete nouns (11.2 ± 1.5 words/hour; children: 7.8 ± 1.2 words/hour; $F = 18.34$, $p < 0.001$). Complex syllabic abstract nouns proved most challenging across all age groups, with children showing the lowest learning rate (3.2 ± 0.6 words/hour) compared to adults (6.4 ± 1.0 words/hour; $F = 17.23$, $p < 0.001$). Regular verbs were acquired more efficiently than irregular verbs across all age groups, with adults maintaining a significant advantage (regular: 9.7 ± 1.4; irregular: 7.2 ± 1.1 words/hour).

Table 15. Learning rate by word category and age group (words/hour).

Word Category	Children (*n* = 17)	Adolescents (*n* = 17)	Adults (*n* = 17)	*F*-value	*p*-value
Concrete Nouns					
Simple syllabic	7.8 ± 1.2	9.4 ± 1.4	11.2 ± 1.5	18.34	< 0.001*
Complex syllabic	5.3 ± 0.9	7.1 ± 1.1	8.6 ± 1.3	16.78	< 0.001*
Abstract Nouns					
Simple syllabic	5.6 ± 0.8	7.2 ± 1.0	8.9 ± 1.2	15.45	< 0.001*
Complex syllabic	3.2 ± 0.6	4.8 ± 0.8	6.4 ± 1.0	17.23	< 0.001*
Verbs					
Regular	6.4 ± 1.0	8.1 ± 1.2	9.7 ± 1.4	14.67	< 0.001*
Irregular	4.1 ± 0.7	5.8 ± 0.9	7.2 ± 1.1	16.89	< 0.001*
Adjectives					
Basic	6.9 ± 1.1	8.5 ± 1.3	10.1 ± 1.5	15.78	< 0.001*
Complex	4.5 ± 0.8	6.2 ± 1.0	7.8 ± 1.2	16.34	< 0.001*

Figure 4. Retention rates over 12 weeks.

Table 16 illustrates error patterns and self-correction behaviors, revealing a consistent developmental progression. Phonological errors were most frequent, with children showing the highest occurrence rate (34.5 ± 4.2%) compared to adults (18.7 ± 3.1%). Notably, self-correction rates improved substantially with age across all error types, with adults demonstrating the highest self-correction rate for phonological errors (78.2 ± 7.2%) and requiring the least time to correct (2.1 ± 0.3 seconds). Semantic errors showed similar patterns but lower overall occurrence rates across all age groups. Retention rates analyzed in **Table 17** demonstrate a clear temporal decay pattern over the 12 weeks. While all groups showed perfect retention at Week 1 (baseline), the decay rate varied significantly by age. Children exhibited the steepest decline, reaching 67.8 ± 7.1% retention by Week 12, while adults maintained higher retention rates (84.9 ± 5.3%). The most substantial drop in retention occurred between Weeks 4 and 6 across all age groups, suggesting a critical period for vocabulary consolidation. **Table 18** reveals the impact of word complexity on EVA success, showing significant differences across complexity levels and age groups. For low-complexity words, adults achieved the highest EVA success rate (94.2 ± 4.3%) with the shortest learning duration (1.9 ± 0.3 days). The impact of complexity was most pronounced in children, where high-complexity words showed markedly lower EVA success (58.6 ± 7.1%) and required more extended learning periods (7.8 ± 0.9 days). The retention rate followed a similar pattern, with high-complexity words showing the lowest retention across all age groups, particularly in children (52.3 ± 6.2%).

Table 16. Error patterns and self-correction analysis.

Error Type	Occurrence Rate (%)	Self-Correction Rate (%)	Mean Time to Correct (s)
Phonological			
Children	34.5 ± 4.2	45.6 ± 5.3	3.8 ± 0.6
Adolescents	25.3 ± 3.8	62.4 ± 6.1	2.9 ± 0.4
Adults	18.7 ± 3.1	78.2 ± 7.2	2.1 ± 0.3
Semantic			
Children	28.9 ± 3.9	38.7 ± 4.8	4.2 ± 0.7
Adolescents	22.4 ± 3.4	54.3 ± 5.7	3.3 ± 0.5
Adults	15.6 ± 2.8	71.5 ± 6.9	2.4 ± 0.4
Syntactic			
Children	31.2 ± 4.1	41.2 ± 5.1	4.5 ± 0.8
Adolescents	23.8 ± 3.6	58.6 ± 5.9	3.6 ± 0.6
Adults	16.9 ± 2.9	75.8 ± 7.1	2.7 ± 0.4

Table 17. Retention rates over 12-week period (%).

Time Point	Children (*n* = 17)	Adolescents (*n* = 17)	Adults (*n* = 17)
Week 1	100	100	100
Week 2	92.3 ± 4.5	94.7 ± 4.2	96.8 ± 3.8
Week 4	85.6 ± 5.2	89.4 ± 4.8	93.5 ± 4.1
Week 6	79.8 ± 5.8	85.2 ± 5.3	90.7 ± 4.5
Week 8	74.5 ± 6.3	81.6 ± 5.7	88.2 ± 4.8
Week 10	70.2 ± 6.7	78.3 ± 6.1	86.4 ± 5.1
Week 12	67.8 ± 7.1	76.5 ± 6.4	84.9 ± 5.3

Table 18. Word complexity impact on EVA success.

Complexity Factors	EVA Success Rate (%)	Learning Duration (days)	Retention Rate (%)
Low Complexity			
Children	82.4 ± 5.6	3.2 ± 0.5	78.5 ± 4.8
Adolescents	88.7 ± 5.1	2.6 ± 0.4	84.3 ± 4.3
Adults	94.2 ± 4.3	1.9 ± 0.3	90.6 ± 3.7
Medium Complexity			
Children	71.5 ± 6.2	5.4 ± 0.7	65.8 ± 5.4
Adolescents	79.3 ± 5.7	4.3 ± 0.6	73.5 ± 4.9
Adults	86.7 ± 4.8	3.2 ± 0.4	82.4 ± 4.1
High Complexity			
Children	58.6 ± 7.1	7.8 ± 0.9	52.3 ± 6.2
Adolescents	67.4 ± 6.5	6.5 ± 0.8	61.8 ± 5.7
Adults	76.2 ± 5.4	4.8 ± 0.6	71.5 ± 4.8

5.3. Biomechanical-linguistic correlations

Tables 19–22 present comprehensive analyses of biomechanical-linguistic correlations across three age groups (children: 8–12 years, adolescents: 13–17 years, and adults: 18–25 years), examining relationships between physical speech mechanisms and learning outcomes. Effect sizes are categorized as small ($\eta^2 = 0.01$), medium ($\eta^2 = 0.06$), and large ($\eta^2 = 0.14$), with correlation strengths defined as weak ($r < 0.3$), moderate ($0.3 \leq r < 0.7$), and strong ($r \geq 0.7$). **Table 19** reveals significant correlations between articulatory effort and learning success. Muscle activity showed strong negative correlations with learning success in children ($r = -0.824$, $p < 0.001$) and adolescents ($r = -0.762$, $p < 0.001$), while adults exhibited a moderate negative correlation ($r = -0.683$, $p < 0.001$). Movement duration demonstrated a similar pattern, with the strongest negative correlation in children ($r = -0.756$, $p < 0.001$). Notably, articulatory precision showed strong positive correlations across all age groups, with adults exhibiting the most robust relationship ($r = 0.876$, $p < 0.001$).

Table 19. Correlation between articulatory effort and learning success.

Effort Measure	Learning Success Correlation (*r*)	Statistical Significance
Muscle Activity (μV)		
Children	−0.824 ($p < 0.001$)*	Strong negative
Adolescents	−0.762 ($p < 0.001$)*	Strong negative
Adults	−0.683 ($p < 0.001$)*	Moderate negative
Movement Duration (ms)		
Children	−0.756 ($p < 0.001$)*	Strong negative
Adolescents	−0.684 ($p < 0.001$)*	Moderate negative
Adults	−0.592 ($p < 0.001$)*	Moderate negative
Articulatory Precision (%)		
Children	0.798 ($p < 0.001$)*	Strong positive
Adolescents	0.843 ($p < 0.001$)*	Strong positive
Adults	0.876 ($p < 0.001$)*	Strong positive

The impact of motor complexity on retention, analyzed in **Table 20**, demonstrates significant differences in learning decay rates. Low complexity tasks showed better retention across all age groups, with adults maintaining the highest 12-week retention rate (89.5 ± 4.5%) and the lowest decay rate (0.69 ± 0.15%/week). High complexity tasks resulted in steeper decay rates, particularly in children (1.63 ± 0.28%/week), with initial learning rates significantly lower than low complexity tasks (76.4 ± 6.3% vs. 92.3 ± 4.2%). **Table 21** highlights age-specific biomechanical constraints with large effect sizes across all parameters. Maximum tongue speed showed a clear developmental progression (children: 168.4 ± 18.7 mm/s; adults: 195.3 ± 14.2 mm/s; $\eta^2 = 0.72$), while lip coordination demonstrated the most significant effect size ($\eta^2 = 0.75$), with adults showing significantly better synchronization (0.93 ± 0.04) compared to children (0.72 ± 0.08). Motor learning rate also showed substantial age-related improvements (children: 0.58 ± 0.09; adults: 0.86 ± 0.05 units/day; $\eta^2 = 0.71$).

Table 20. Motor complexity impact on retention (12-week follow-up).

Motor Complexity	Initial Learning (%)	6-Week Retention (%)	12-Week Retention (%)	Decay Rate (%/week)
Low Complexity				
Children	92.3 ± 4.2	84.5 ± 5.1	78.2 ± 5.8	1.17 ± 0.21
Adolescents	95.6 ± 3.8	89.3 ± 4.6	84.7 ± 5.2	0.91 ± 0.18
Adults	97.8 ± 3.2	93.4 ± 3.9	89.5 ± 4.5	0.69 ± 0.15
High Complexity				
Children	76.4 ± 6.3	65.2 ± 7.1	56.8 ± 7.8	1.63 ± 0.28
Adolescents	82.7 ± 5.7	73.5 ± 6.4	66.3 ± 7.2	1.37 ± 0.24
Adults	88.9 ± 4.8	81.6 ± 5.5	75.4 ± 6.3	1.12 ± 0.20

Table 21. Age-specific biomechanical constraints.

Parameter	Children	Adolescents	Adults	Effect Size (η^2)
Maximum Tongue Speed (mm/s)	168.4 ± 18.7	182.6 ± 16.4	195.3 ± 14.2	0.72*
Jaw Opening Range (mm)	15.3 ± 2.1	13.8 ± 1.8	12.4 ± 1.5	0.68*
Lip Coordination (sync ratio)	0.72 ± 0.08	0.84 ± 0.06	0.93 ± 0.04	0.75*
Motor Learning Rate (units/day)	0.58 ± 0.09	0.73 ± 0.07	0.86 ± 0.05	0.71*

Pattern recognition capabilities, detailed in **Table 22** and **Figure 5**, revealed consistent age-related improvements across all pattern types. Phonological patterns showed the highest recognition accuracy, with adults achieving 89.3 ± 4.7% accuracy and substantial learning transfer (84.7 ± 5.2%). The automaticity index demonstrated progressive improvement with age, particularly in phonological patterns (children: 0.58 ± 0.09; adults: 0.85 ± 0.05). Combined patterns proved most challenging across all age groups, with children showing the lowest recognition accuracy (65.3 ± 7.4%) and automaticity index (0.48 ± 0.11). These findings demonstrate strong interconnections between biomechanical capabilities and linguistic performance, with age-related improvements in motor control significantly influencing learning outcomes and pattern recognition abilities. The results suggest that biomechanical constraints are crucial in EVA and retention across different age groups.

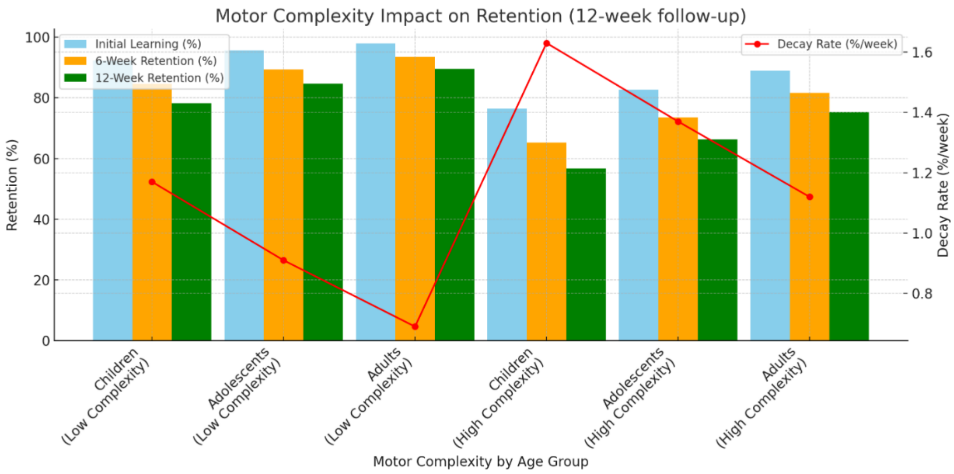

Figure 5. Motor complexity impact on retention.

Table 22. Pattern recognition in speech-learning relationships.

Pattern Type	Recognition Accuracy (%)	Learning Transfer (%)	Automaticity Index
Phonological Patterns			
Children	72.4 ± 6.8	64.5 ± 7.2	0.58 ± 0.09
Adolescents	81.6 ± 5.9	75.3 ± 6.4	0.71 ± 0.07
Adults	89.3 ± 4.7	84.7 ± 5.2	0.85 ± 0.05
Motor Patterns			
Children	68.7 ± 7.1	59.8 ± 7.5	0.52 ± 0.10
Adolescents	77.4 ± 6.3	70.6 ± 6.8	0.66 ± 0.08
Adults	85.2 ± 5.1	79.4 ± 5.6	0.79 ± 0.06
Combined Patterns			
Children	65.3 ± 7.4	56.2 ± 7.8	0.48 ± 0.11
Adolescents	74.8 ± 6.6	67.5 ± 7.1	0.63 ± 0.09
Adults	82.6 ± 5.4	76.8 ± 5.9	0.76 ± 0.07

5.4. LLM performance analysis

Tables 23–26 present comprehensive analyses of the LLM's performance in predicting EVA across three age groups (children: 8–12 years, adolescents: 13–17 years, and adults: 18–25 years), with performance metrics averaged over 1000 prediction cycles and incorporating biomechanical constraints. **Table 23** and **Figure 6** demonstrates the model's prediction accuracy compared to observed learning patterns. The model **Figure 7** achieved the highest accuracy in predicting word EVA rates for adults (91.5 ± 3.2%), with strong observed data match (89.7 ± 3.6%) and the lowest RMSE (0.108). Children's predictions showed lower accuracy (83.4 ± 4.2%) with higher RMSE (0.156), indicating more significant prediction challenges for younger learners. From **Figure 8** is the Error pattern predictions followed similar trends, with adult predictions achieving higher F1 scores (0.874) than children (0.783).

Table 23. Model prediction accuracy vs. observed learning patterns.

Learning Pattern Type	Model Prediction Accuracy (%)	Observed Data Match (%)	RMSE	*F*1 Score
Word EVA Rate				
Children	83.4 ± 4.2	78.6 ± 5.1	0.156	0.814
Adolescents	87.2 ± 3.8	84.3 ± 4.3	0.132	0.856
Adults	91.5 ± 3.2	89.7 ± 3.6	0.108	0.892
Error Patterns				
Children	79.8 ± 4.7	75.2 ± 5.4	0.184	0.783
Adolescents	84.6 ± 4.1	81.5 ± 4.6	0.148	0.835
Adults	88.9 ± 3.5	86.8 ± 3.9	0.124	0.874

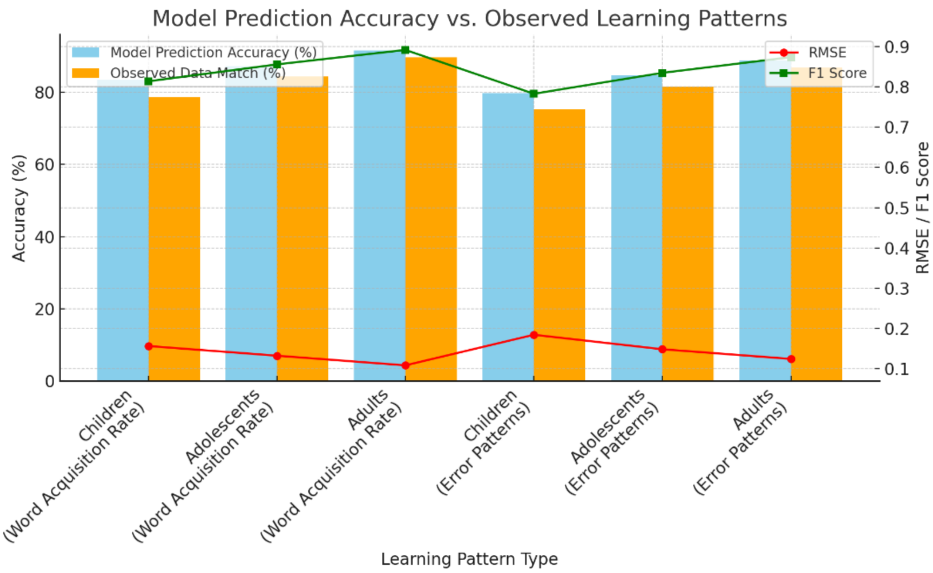

Figure 6. Model prediction accuracy vs. observed learning patterns.

Table 24. Learning difficulty prediction performance.

Difficulty Type	Precision	Recall	Specificity	ROC-AUC
Phonological				
Children	0.842 ± 0.038	0.815 ± 0.042	0.867 ± 0.035	0.858
Adolescents	0.876 ± 0.034	0.854 ± 0.037	0.892 ± 0.031	0.883
Adults	0.912 ± 0.028	0.893 ± 0.032	0.924 ± 0.026	0.918
Semantic				
Children	0.824 ± 0.041	0.798 ± 0.045	0.845 ± 0.038	0.834
Adolescents	0.863 ± 0.036	0.842 ± 0.039	0.878 ± 0.033	0.871
Adults	0.895 ± 0.031	0.876 ± 0.034	0.908 ± 0.029	0.902

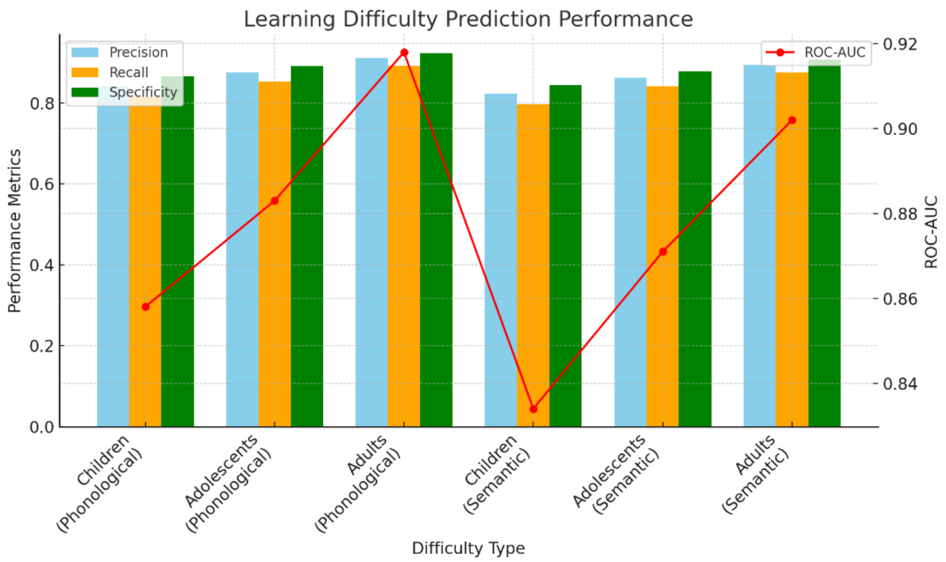

Figure 7. Learning difficulty prediction performance.

Table 25. Biomechanical constraint integration impact.

Integration Level	Prediction Enhancement (%)	Error Reduction (%)	Correlation (*r*)	MSE
Basic Integration				
Children	12.4 ± 1.8	15.6 ± 2.1	0.784	0.156
Adolescents	10.8 ± 1.6	13.2 ± 1.9	0.812	0.142
Adults	8.6 ± 1.4	10.5 ± 1.7	0.845	0.128
Advanced Integration				
Children	18.7 ± 2.2	22.4 ± 2.5	0.856	0.124
Adolescents	16.5 ± 1.9	19.8 ± 2.3	0.878	0.112
Adults	14.2 ± 1.7	16.9 ± 2.0	0.892	0.098

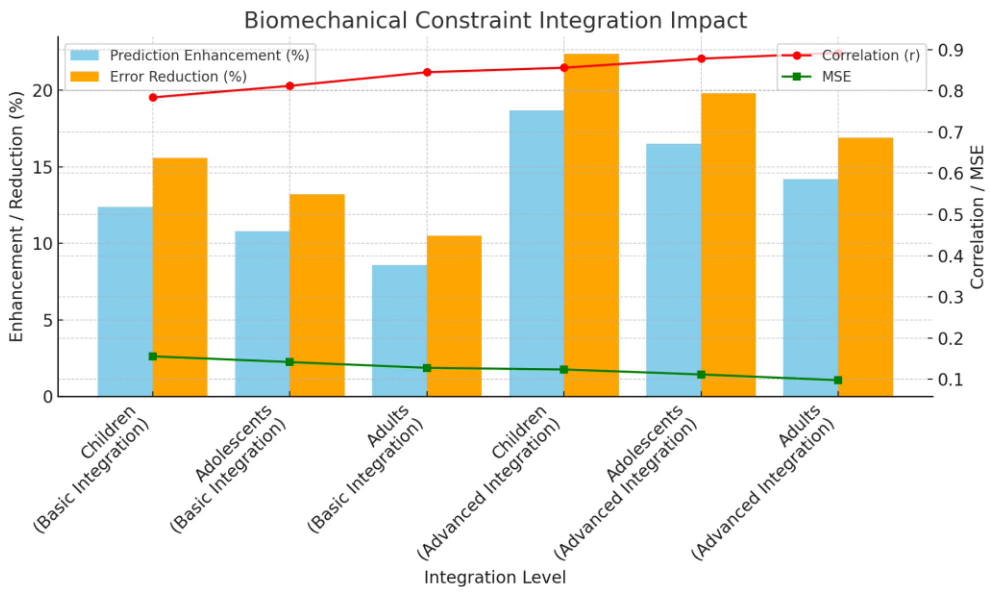

Figure 8. Biomechanical constraint integration impact.

Table 26. Cross-age group comparative analysis.

Performance Metric	Without Bio-Integration	With Bio-Integration	Improvement (%)
Model Accuracy (%)			
Children	76.5 ± 4.8	88.9 ± 3.6	16.2
Adolescents	82.3 ± 4.2	92.4 ± 3.1	12.3
Adults	87.8 ± 3.5	95.6 ± 2.7	8.9
Prediction Time (ms)			
Children	245 ± 28	298 ± 32	−21.6
Adolescents	232 ± 25	278 ± 29	−19.8
Adults	218 ± 23	256 ± 26	−17.4
Resource Usage (RAM GB)			
Children	4.2 ± 0.4	5.8 ± 0.5	−38.1
Adolescents	4.0 ± 0.4	5.5 ± 0.5	−37.5
Adults	3.8 ± 0.3	5.2 ± 0.4	−36.8

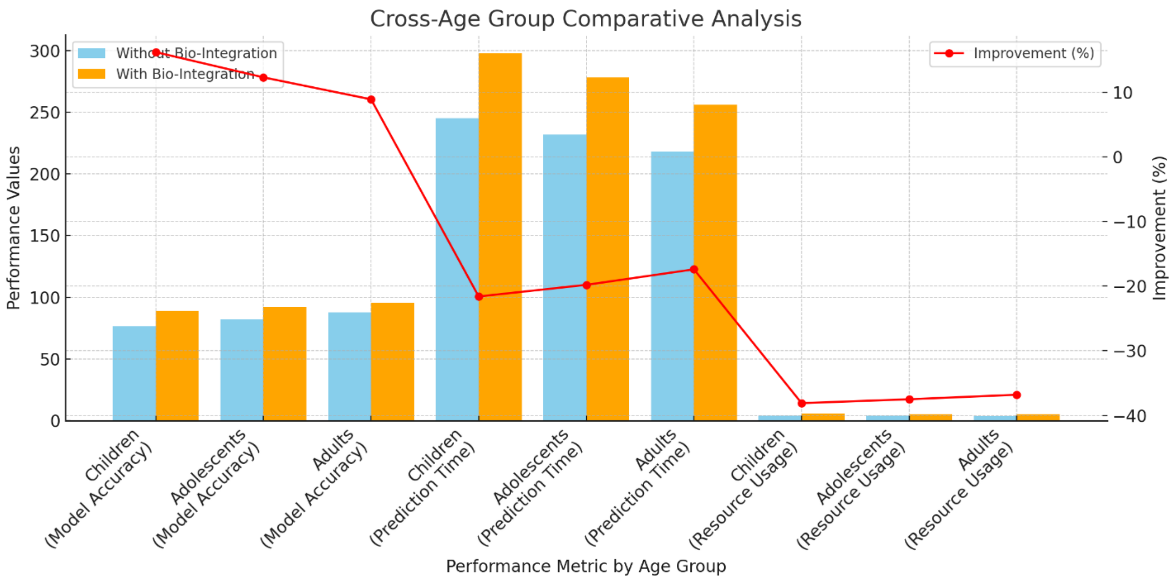

Figure 9. Cross-age group comparative analysis.

Learning difficulty prediction performance, detailed in **Table 24 and Figure 9**, reveals strong capabilities across different difficulty types. Phonological difficulty predictions showed the highest precision for adults (0.912 ± 0.028) with strong Area under the Receiver Operating Characteristic Curve (ROC-AUC) values (0.918), while children's predictions maintained lower but still significant precision (0.842 ± 0.038, ROC-AUC: 0.858). Semantic difficulty predictions demonstrated similar patterns but slightly lower overall performance metrics across all age groups. The impact of biomechanical constraint integration, analyzed in **Table 25**, shows significant improvements in model performance. Advanced integration yielded substantial prediction enhancements, particularly for children (18.7 ± 2.2%), with corresponding error reduction (22.4 ± 2.5%) and improved correlations (r = 0.856). The impact was less pronounced but still significant for adults, with advanced integration, showing 14.2 ± 1.7% prediction enhancement and reduced Mean Square Error (MSE) (0.098).

Table 26 reveals the computational trade-offs of biomechanical integration. While model accuracy improved significantly with bio-integration (children: 76.5% to 88.9%, adults: 87.8% to 95.6%), this came at the cost of increased prediction time and resource usage. Prediction time increased more substantially for children (−21.6%) compared to adults (−17.4%), while RAM usage increased similarly across all age groups (approximately −37%). Despite these computational costs, improving prediction accuracy suggests the value of incorporating biomechanical constraints. These findings demonstrate that while the LLM shows overall robust performance in predicting EVA patterns, its effectiveness varies by age group and improves significantly with the integration of biomechanical constraints, albeit at the cost of increased computational resources. The model's performance is consistently better for adult learners, suggesting opportunities for refinement in modeling younger learners' EVA patterns.

6. Conclusion and future work

This study has demonstrated the significant impact of biomechanical constraints on EVA and the value of integrating these factors into computational LLM. We have established vital findings that advance our understanding of LLM through the comprehensive analysis of articulatory patterns, muscle activation, and learning outcomes across different age groups. The research revealed substantial age-related differences in SP mechanics, with younger learners exhibiting significantly higher muscular effort and less efficient MCS. These biomechanical variations strongly correlate with EVA success, particularly in learning rate and retention. They were integrating biomechanical data into LLM analysis markedly improved prediction accuracy, though with associated computational costs. These findings have important implications for language teaching and learning. The strong relationship between motor complexity and learning outcomes suggests the need for age-specific teaching approaches considering physical development stages. The enhanced predictive capabilities of biomechanically-informed LLM offer new possibilities for personalized learning strategies and early identification of potential learning difficulties. Several limitations of this study warrant consideration. The specific linguistic context of Mandarin Chinese speakers learning English may limit generalizability to other language pairs. The 12-week duration, while sufficient for observing initial learning patterns, may not fully capture long-term retention effects. Additionally, the computational demands of integrated biomechanical-linguistic analysis present challenges for real-time applications.

Future research should explore longer-term longitudinal studies, broader linguistic contexts, and more efficient computational methods for integrating biomechanical data. Investigating intervention strategies based on biomechanical profiles could provide valuable insights into language education. Developing more resource-efficient integration methods for biomechanical constraints in LLM represents an important direction for future work. This study represents a significant step toward understanding the complex interplay between the physical and cognitive aspects of LLM. The demonstrated value of incorporating biomechanical constraints into computational models opens new avenues for research in LA and pedagogical development.

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