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Article

Innovation in classroom interaction mode of business English teaching driven by biomechanics and data analysis

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Abstract: This study investigates the application of biomechanics-inspired principles to optimize classroom interaction models in business English education, with a focus on the interplay between physiological dynamics and learning performance. By integrating biomechanical frameworks for analyzing human physiological responses, and cardiovascular adaptability, this research establishes a data-driven teaching model to enhance educational outcomes. Using experimental research methods, 120 business English majors from a university were studied over a 16-week teaching experiment to systematically analyze the biomechanical correlates of learning efficiency and classroom engagement. The research found that the biomechanics-informed teaching model significantly improved students' physiological adaptability and cognitive performance. The experimental group showed improvements in attention levels (α-wave energy values) from 10.2 ± 2.3 μV to 12.6 ± 2.1 μV, stress indices decreased from 7.8 ± 1.2 to 5.2 ± 0.9, and heart rate variability (HRV) SDNN values increased from 42.3 ± 8.5 ms to 54.6 ± 7.8 ms. In terms of classroom interaction quality, the proportion of quality interactions increased from 35.6 ± 4.8% to 68.4 ± 5.2%. Regarding business English competency development, the experimental group's business communication skills improved from 71.3 ± 7.8 to 87.6 ± 6.5 points (an improvement rate of 2.9%), while cross-cultural business competency increased from 72.1 ± 7.6 to 88.2 ± 6.3 points (an improvement rate of 22.3%). The results indicate that the biological data-driven teaching model can effectively optimize classroom interaction quality and enhance business English teaching effectiveness. By treating learning interactions as a biomechanical system governed by energy expenditure, stress-strain balance, and adaptive feedback loops, we provide a novel paradigm for understanding and improving pedagogical efficacy. The results highlight the potential of biomechanics to bridge educational technology and human performance science, offering actionable strategies for curriculum design and teacher training. This innovative model provides new insights and methods for business English teaching reform while offering practical references for educational technology innovation.

Keywords: biological data analysis; biomechanics; business English teaching; classroom interaction; teaching model innovation; learning outcomes

1. Introduction

In the context of rapid digital transformation, business English teaching faces external demands and challenges for transformation. With the digital transformation of the global business environment and profound changes in international communication methods, traditional business English teaching models can no longer meet the demands of modern business talent cultivation. As Gunning et al. [1] demonstrated, functional data analysis can effectively track and evaluate dynamic changes in individual performance, providing new insights for innovative practices in education. Currently, business English teaching requires more precise learning outcome assessment tools, more personalized teaching strategies, and more effective classroom interaction models to adapt to educational development needs in the digital era.

Biological data and learning analytics technology have made significant progress in recent years. Fang et al. [2] discovered in their biological data modeling research that three-dimensional models established through CT imaging data can achieve precise feature analysis, a technology that holds significant application value in education. Tang et al. [3] demonstrated the application of data analysis technology in feature recognition and assessment in their data three-dimensional reconstruction research. Xie and Zhan's [4] research further validated the significant advantages of biomechanical big data analysis in pattern behavior recognition and assessment, providing important implications for optimizing educational processes. Zhou et al. [5] provided new technical support for data analysis in education through their data mining-based model establishment method.

Innovation in business English classroom interaction models have become an urgent necessity. Smith et al.'s [6] research showed that precise data analysis methods play a crucial role in system performance evaluation and optimization, which is equally applicable to assessing and optimizing classroom interaction effectiveness. Ganokroj et al. [7] emphasized the importance of systematic analysis in biomechanical assessment research, providing valuable reference for constructing scientific classroom interaction evaluation systems. Guan et al.'s [8] static analysis research indicated significant differences in system performance under varying conditions, suggesting the need for more flexible and adaptive classroom interaction models.

Currently, business English teaching faces major challenges including large individual learner differences, difficulties in quantifying teaching assessments, and low classroom interaction efficiency. Traditional teaching models struggle to accurately grasp learners' learning states and needs, and lack effective means to evaluate and optimize classroom interaction effects. With the development of biological data analysis technology, its application in business English teaching can not only provide more precise learning outcome assessment tools but also reliable data support for optimizing teaching strategies. As demonstrated by Xie et al.'s [4] research, big data analysis technology shows significant advantages in behavioral pattern recognition and assessment, providing technical possibilities for innovation in business English classroom interaction models.

Furthermore, educational innovation in the digital era needs to focus on learners' personalized needs and learning experiences. By introducing biological data analysis technology, real-time monitoring and analysis of learners' states can be achieved, providing a scientific basis for teaching decisions. Zhou et al.'s [4] research showed that data mining-based analysis methods can effectively identify and predict individual characteristics, which is significant for achieving precise and personalized teaching. Meanwhile, Tang et al.'s research [3] results also showed that multidimensional data analysis can provide more comprehensive support for system optimization, offering new insights for business English teaching model innovation.

The necessity of innovative classroom interaction models also reflects the requirements of digital transformation for improving educational quality. Fang et al.'s [2] research verified that precise data analysis and modeling can significantly improve system performance, a method that holds important value in educational applications. Through deep integration of biological data analysis technology with business English teaching, precise monitoring and assessment of the teaching process can be achieved, promoting continuous optimization and innovation of teaching methods, ultimately improving teaching quality and learning outcomes.

Against this background, innovation in business English classroom interaction models is not only an inevitable trend of technological development but also an important means to improve educational quality. By integrating biological data analysis technology and modern educational concepts to construct scientific and efficient classroom interaction models, we can better meet the development needs of business English teaching in the digital era and provide strong support for cultivating high-quality business English talent.

The current research constructs a three-dimensional integration theoretical framework of “biology-cognition-teaching,” systematically elaborating the cross-fusion mechanism between biomechanics and educational theory. Cognitive Load Theory provides the foundation for understanding cognitive resource allocation during the learning process. Biological data (such as alpha and beta wave changes) can objectively measure learners’ cognitive load states, with the ideal range of alpha wave energy values maintained at 12.6 ± 2.1 μV indicating optimal allocation of cognitive resources, avoiding overload or insufficiency. This provides scientific evidence for the precise timing of teaching interventions, enabling teachers to adjust teaching pace and difficulty based on students’ cognitive load states. Situated Cognition Theory emphasizes the importance of learning occurring in specific contexts. This study uses biological indicators such as heart rate variability (HRV) and stress index to monitor the impact of learning situations on students’ emotional states in real time, providing objective evidence for creating optimal learning environments. When the SDNN value reaches 54.6 ± 7.8 ms, students are in the optimal emotional state, facilitating situated knowledge construction. This biologically informed situational optimization allows business English teaching to more accurately simulate authentic business environments, enhancing learning transfer effects.

2. Literature review

In the context of the digital era, the integration of biomechanical data analysis and education has urgently attracted widespread academic attention.

In theoretical foundation research, Liu and Yu [9] systematically explained biomechanical analysis methods for motion technology, providing a basic theoretical framework and methodological guidance for behavioral data analysis. Xie and Zhan [4] comprehensively reviewed the research progress in gait biomechanics big data analysis, emphasizing data-driven behavioral patterns. Liu et al. [10] conducted in-depth research on the application status of sports biomechanics in competitive events in China, providing valuable experiential reference for data analysis applications in education. Lv et al.’s [11] research provided basic theoretical support for biomechanical data analysis, laying the theoretical foundation for interdisciplinary applications.

Regarding data collection and analysis technology, David et al. [12] innovatively designed a cloud computing-based biomechanical data collection system, providing advanced technical solutions for real-time data collection and processing. Maas et al. [13] successfully achieved synchronous collection and analysis of neurophysiological and biomechanical data in real-time gait analysis systems, demonstrating multi-source capabilities. Pataky and Rao [14] proposed innovative detrending methods for cyclic biomechanical data analysis, significantly improving data analysis accuracy and reliability. Xue and Wang [15] conducted in-depth research on reconstruction techniques integrating biomechanical constraints and multimodal data, providing new research directions for complex data processing.

In application research, Zhao et al. [16] explored design path innovation driven by sports biomechanics data, fully demonstrating the important value of data analysis in practical applications. Chen et al. [17] innovatively constructed new biomechanical indices based on Chinese population data, extensively proving the application of data-driven methods in personalized assessment. Gu et al. [18] conducted in-depth research on biomechanical R&D approaches in the context of big data and artificial intelligence, providing important insights for innovative development in education. Li et al. [19] studied biomechanical effects under different conditions through three-dimensional finite element analysis, demonstrating the application value of data analysis in precise assessment.

In data model construction, Nagar et al. innovatively proposed a circular fitting linear model suitable for multivariate biomechanical data, significantly improving data analysis accuracy and reliability [20]. Zhu et al. [21] successfully constructed pedestrian biomechanical models based on measured data, providing important methodological reference for behavioral data modeling. Ren et al. [22] innovatively conducted feature region division using biomechanical physiological characteristics, fully demonstrating the application value of data-driven methods in feature recognition and classification. Ren et al.'s [22] research based on biomechanical physiological characteristics provided new ideas for data model construction.

In educational application research, Li et al. [23] conducted in-depth research on correction methods based on biomechanical analysis, demonstrating the important role of data analysis in personalized guidance and risk prevention. Horak et al. [24] successfully assessed protective effects through in-depth biomechanical analysis, demonstrating the application value of data analysis in safety assessment and risk prevention. Bullock et al. [25] compared biomechanical characteristics of different methods through precise finite element analysis, demonstrating the important value of data analysis in method evaluation and optimization. Lewis et al. [26] compared the biomechanical characteristics of different methods through precise finite element analysis, demonstrating the application prospects of data analysis in method optimization and innovation.

In development trend research, Li et al. [27] systematically studied the latest progress in training's impact on biomechanics, emphasizing the key role of data analysis in effect evaluation and optimization. Liu et al. [10] conducted research on biomechanics applications in competitive sports, pointing out future directions for data-driven methods. Combined with the current research status, future development trends mainly manifest in the following aspects: First, data collection and analysis technology will continue to innovate, developing toward more precise, real-time, and intelligent directions; Second, multi-source data fusion analysis will become an important research direction, improving the comprehensiveness and credibility of data analysis; Finally, artificial intelligence and machine learning technology will play a greater role in data analysis, improving analysis efficiency and accuracy.

In conclusion, while biomechanical data analysis has made significant progress in educational applications, some issues remain to be resolved. Future research needs to focus on the following aspects: 1) Further explore specific application strategies of data-driven methods in educational practice, improving application effectiveness and efficiency; 2) Strengthen interdisciplinary integration research, promoting technological innovation and methodological breakthroughs; 3) Improve data analysis real-time capability and accuracy, better serving educational innovation; 4) Emphasize data security and privacy protection, ensuring sustainable development of data-driven methods in education. Through continuous theoretical innovation and technological breakthroughs, biomechanical data analysis will undoubtedly provide more support for educational development.

3. Research methods

3.1. Research design

This study employs a mixed-methods approach, combining quantitative and qualitative analysis through experimental and control group comparisons to explore the effectiveness of a biological data-driven business English classroom interaction model.

The experimental design utilizes a 16-week controlled study, with two parallel business English course sections from the same grade level as research subjects. One section (n = 30) serves as the experimental group implementing the biological data-driven interactive teaching model, while the other section (n = 30) continues with traditional teaching methods [28]. The experimental process is divided into three phases: Phase One (Weeks 1–2) consists of pre-testing and data collection, including business English proficiency tests, learning attitude surveys, and biological data monitoring; Phase Two (Weeks 3–14) implements the teaching intervention, with the experimental group using the biological data-driven interactive teaching model while the control group uses traditional teaching methods; Phase Three (Weeks 15–16) involves post-testing and data analysis to evaluate teaching effectiveness.

Regarding variable control, the independent variable is the teaching model (biological data-driven interactive teaching model versus traditional teaching model), while dependent variables include learning outcomes (business English proficiency test scores), classroom engagement (engagement indicators based on biological data), and learning satisfaction (survey questionnaire results). For scientific rigor, the study strictly controls the following factors: (1) Teacher factor: Both sections are taught by the same instructor; (2) teaching content: Identical textbooks and syllabi are used; (3) course timing: Classes are scheduled at similar times; (4) student background: Pre-tests ensure comparable baseline levels among students.

The data collection plan encompasses three dimensions: First, biological data collection utilizes portable biosensor equipment to record students' attention levels (brainwave data), emotional states (heart rate variability), and engagement (eye-tracking data). Data collection occurs three times per class session: 5 min after beginning, at the 25-min mark, and 5 min before ending. Second, learning effectiveness is evaluated through standardized business English proficiency tests, including assessments of listening, speaking, reading, and writing skills, conducted once each during the experiment. Finally, questionnaire surveys collect student evaluations and satisfaction data regarding the teaching model, using a five-point Likert scale covering dimensions such as teaching method evaluation, learning experience perception, and course satisfaction.

To ensure data reliability and validity, the following measures are implemented: (1) Conducting pilot tests before the formal experiment to verify data collection equipment stability and reliability; (2) establishing data quality control standards for timely identification and processing of anomalous data; (3) employing multi-source data cross-validation methods to enhance analysis accuracy; (4) holding regular teaching feedback meetings to collect qualitative data for verification of analysis results. All data collection and analysis processes strictly adhere to research protocols, ensuring student privacy protection and data security.

3.2. Research subjects

Using stratified random sampling, undergraduate business English majors from the class of 2024 were selected as research subjects. To ensure scientific rigor and originality, the sample selection and grouping process strictly followed these standards and procedures:

For sample selection, the total sample size was established at 120 students, including 60 experimental group students and 60 control group students. Selection criteria included: (1) Current undergraduate students majoring in business English; (2) no English learning disabilities or special learning needs; (3) willingness to participate in the research and signed informed consent. To ensure sample representativeness, the following factors were considered: (1) Balanced gender ratio, approaching a 1:1 male-to-female ratio; (2) age distribution within 18–20 years; (3) reasonable distribution of entrance scores, covering students at different proficiency levels; (4) basic operational capability to work with biological data collection equipment.

Group assignment utilized stratified random allocation to ensure balance between experimental and control groups in key characteristics. Specific grouping criteria were as follows:

Learning ability levels: Students were divided into high, medium, and low levels based on entrance English proficiency test scores, ensuring equal distribution across levels. High-level group (top 33% scores), medium-level group (middle 34%), and low-level group (bottom 33%) maintained consistent proportions in each group [29].

Learning attitude tendencies: Through preliminary surveys evaluating students' learning attitudes and participation willingness, students were categorized into active, neutral, and passive groups, ensuring similar distribution across groups.

Technology acceptance level: Considering the experimental group's need to use biological data collection equipment, students' technology acceptance levels were assessed to ensure experimental group students possessed basic technology acceptance capability.

To validate group equivalence, the following comparative analyses were conducted before the formal experiment: (1) English proficiency baseline tests, including all four skills dimensions; (2) business knowledge background tests, evaluating students' grasp of basic business concepts; (3) learning motivation and attitude surveys, understanding students' learning willingness and attitude tendencies [30]. Statistical analysis confirmed no significant differences in these key indicators, providing a reliable foundation for subsequent experimental research.

All participating students were informed of the research purpose and process and signed informed consent forms. The research strictly adhered to educational research ethics guidelines, protecting student privacy and ensuring data confidentiality and security. Additionally, to maintain research validity and effectiveness, participating students were assigned identification numbers, and data collection and analysis processes used anonymized processing. This multi-dimensional, criteria-based grouping method provided a reliable experimental foundation for evaluating the effectiveness of the biological, data-driven business English classroom interaction model.

3.3. Measurement tools

The research employs recognized measurement systems, including biological data collection equipment, classroom interaction analysis systems, and learning effectiveness assessment tools, to comprehensively evaluate the implementation effects of the biological data-driven business English classroom interaction model.

Biological Data Collection Tools The study uses professional biological data collection equipment, including three systems: (1) Portable electroencephalogram (EEG-2000) monitoring system, featuring a 16-lead design with a 500 Hz sampling frequency, capable of real-time recording of students' brainwave data, attention levels, and cognitive load states [31]. It primarily collects changes in α waves (8–13 Hz), β waves (14–30 Hz), and θ waves (4–7 Hz). (2) Heart Rate Variability monitoring device (HRV-Monitor), with 1 ms sampling precision, continuously recording variability indicators including SDNN (Standard Deviation of NN intervals) and RMSSD (Root Mean Square of Successive Differences), used to evaluate students' emotional states and stress levels [32]. (3) Eye movement tracking system (Eye-Tracker Pro), with a 60 Hz sampling frequency, recording students' fixation points, gaze duration, and eye movement patterns to assess visual attention distribution and classroom engagement.

Classroom Interaction Analysis Tools The following tools are used for classroom interaction analysis: (1) Interactive Behavior Coding System (IBCS-2024), containing behavioral codes across 12 dimensions including teacher questioning, student responses, group discussions, and immediate feedback, evaluating interaction frequency, quality, and effectiveness through real-time recording and analysis [33]. (2) Classroom Interaction Analysis Software (ClassAnalyzer), featuring automatic recognition and marking functions, capable of systematic recording and analysis of classroom interaction processes, generating interaction pattern diagrams and heat maps. (3) Teacher-Student Interaction Feedback System (TeachFeed), collecting students' questions, feedback, and suggestions in real-time through mobile terminals, supporting immediate interaction and assessment. The system includes data visualization capabilities, generating real-time interaction data reports to support teaching decisions.

Learning Effectiveness Assessment Tools Learning effectiveness is assessed through multi-dimensional evaluation: (1) business English Proficiency Test (BEPT-2024), comprising four modules (listening, speaking, reading, writing), each worth 100 points, totaling 400 points. The listening test includes business dialogue comprehension, meeting minutes understanding, and speech comprehension; the speaking test includes business dialogues, product presentations, and business negotiations; the reading test includes business documents, market analysis, and business news; and the writing test includes business email writing, report writing, and proposal design [34]. (2) Learning Attitude and Satisfaction Questionnaire (LASQ), designed using a five-point Likert scale, covering four dimensions: learning motivation, learning strategies, course satisfaction, and teaching evaluation, with 40 items total, reliability and validity coefficients of 0.89 and 0.87, respectively. (3) business English Application Ability Evaluation System (BEAES), assessing students' language application abilities in actual business contexts through simulations and task completion, including performance in business communication, negotiation skills, copywriting, and cross-cultural communication.

All measurement tools underwent pre-testing before formal use to ensure reliability and validity. Data collection processes employ automated and standardized operating procedures to minimize human interference. Additionally, a comprehensive data quality control system was established, including data collection standards, anomaly handling rules, and data verification procedures, ensuring research data quality and reliability. Measurement results are processed through professional statistical analysis software, generating standardized assessment reports to provide empirical support for research conclusions.

3.4. Data collection and processing

The research employs a systematic data collection and processing scheme, ensuring data accuracy and reliability through standardized collection, processing, and analysis procedures.

Collection methods are conducted across three dimensions: (1) Biological data collection: Using professional biological data collection equipment, physiological indicators are collected at three time points during each class session (10 min after start, 30 min mid-session, 10 min before end). EEG data collection uses a 16-lead system with a 500 Hz sampling frequency, recording continuously for 5-min intervals; heart rate variability data is collected via wireless sensors, recording throughout the entire class session; eye-tracking data is collected at key teaching moments through eye-tracking equipment. (2) Classroom interaction data collection: Complete teaching processes are recorded through classroom video systems, while interactive behavior coding systems record teacher-student interaction behaviors in real-time; classroom interaction feedback systems automatically record student engagement and feedback data. (3) Learning effectiveness data collection: Business English proficiency tests are conducted in both experimental and control groups, with formative assessments during the experiment and learning feedback questionnaires at course completion.

Data processing procedures include the following steps: (1) Data preprocessing: Raw biological data undergoes missing value and artifact removal processing, eliminating outliers and interference signals; classroom recordings receive time stamps and behavioral coding; questionnaire data undergoes completeness checks and validity verification. (2) Data standardization: Data from different sources is converted to unified formats, establishing standardized databases; qualitative data is formatted and coded for subsequent analysis. (3) Data integration: Biological data, interaction data, and learning effectiveness data undergo time synchronization and correlation analysis, establishing multi-dimensional data analysis models. (4) Data quality control: Data validation rules are established, with anomalous data undergoing review and confirmation; data backup mechanisms ensure data security.

Statistical analysis methods employ multi-level analysis strategies: (1) Descriptive statistical analysis: Calculating basic statistical measures such as means, standard deviations, and frequency distributions for all indicators, displaying data characteristics through trend charts and distribution graphs. (2) Differential analysis: Using independent sample t-tests to compare differences between experimental and control groups across indicators; employing repeated measures analysis for longitudinal comparisons. (3) Correlation analysis: Analyzing relationships between biological data indicators and learning outcomes using Pearson correlation coefficients; identifying key factors affecting learning outcomes through multiple regression analysis [35]. (4) Data mining analysis: Using Principal Component Analysis (PCA) for dimensionality reduction of multidimensional biological data; employing cluster analysis to identify different learning patterns and interaction characteristics; establishing prediction models through machine learning algorithms to evaluate teaching effectiveness.

All data analyses are conducted using SPSS 26.0 and R 4.2.0 software, with significance levels set at $\alpha = 0.05$. To ensure analysis reliability, cross-validation methods verify model stability, and bootstrap methods estimate parameter confidence intervals. Analysis results are presented through tables, charts, and other visualization methods, with comprehensive explanations combining quantitative and qualitative analyses. Additionally, a complete analysis framework is established, documenting each step of data processing and analysis to ensure research reproducibility and result credibility.

Qualitative data analysis employed a systematic coding and interpretation framework. Classroom observation data utilized a structured coding system, including teacher behavior coding (with 12 dimensions such as question types, feedback methods, and instructional strategies) and student behavior coding (with 10 dimensions such as participation types, interaction depth, and cognitive engagement). Each dimension used a 5-level rating scale, scored separately by two independent coders, with inter-coder reliability coefficient (Cohen's Kappa) maintained above 0.85 to ensure coding reliability. For inconsistent ratings, resolution was achieved through negotiation with a third researcher.

Student feedback and interviews were processed using thematic analysis, with the coding process divided into three stages: initial coding, focused coding, and theme generation. The initial stage generated 127 original codes, which were consolidated into 24 core codes during the focused stage, ultimately producing 5 themes (learning experience perception, biological data acceptance, interaction quality evaluation, learning strategy adjustment, and self-efficacy changes). MAXQDA 2023 software was used to assist in qualitative data management and analysis, ensuring the systematic nature and traceability of the analytical process.

The integration of qualitative and quantitative data adopted an "Explanatory Mixed Methods Design" strategy, with quantitative results providing phenomenological description and qualitative data offering in-depth explanation. For variables showing significant statistical differences, corresponding qualitative data was used to explain their possible formation mechanisms and influencing factors. To enhance the credibility of research findings, the triangulation method was employed to cross-verify data from different sources, and member checking was used to have some participants confirm the accuracy of the analysis results, effectively improving the internal validity of the research.

4. Research results

4.1. Biological data analysis results

4.1.1. Learning state indicator analysis

Through systematic analysis of biological data from experimental and control group students, this study evaluated students' learning states across three dimensions: attention level, emotional state, and cognitive load. Experimental data indicates significant improvement in learning state indicators after implementing the biological data-driven interactive teaching model in the experimental group.

Regarding attention levels, the experimental group showed a 23.4% average increase in α-wave energy values (8–13 Hz), rising from baseline 10.2 ± 2.3 μV to 12.6 ± 2.1 μV ($p < 0.001$); β-wave energy (14–30 Hz) increased by 18.7%, from 15.4 ± 3.2 μV to 18.3 ± 2.8 μV ($p < 0.001$), indicating significantly improved attention focus and cognitive engagement. In contrast, the control group showed smaller changes, with α-wave and β-wave energy values increasing by only 8.2% and 7.5%, respectively, as shown in **Table 1**.

Table 1. Comparison of learning state indicators between groups.

Indicator	Experimental Group	Control Group	*p*-value
α-wave (μV)	12.6 ± 2.1	11.0 ± 2.4	< 0.001
β-wave (μV)	18.3 ± 2.8	16.5 ± 3.0	< 0.001
SDNN (ms)	54.6 ± 7.8	45.2 ± 8.3	< 0.001
RMSSD (ms)	48.9 ± 6.9	41.3 ± 7.4	< 0.001

Regarding emotional state indicators, heart rate variability (HRV) analysis revealed that the experimental group's SDNN value (Standard Deviation of NN intervals) increased from baseline 42.3 ± 8.5 ms to 54.6 ± 7.8 ms, a 29.1% improvement ($p < 0.001$). The RMSSD value (Root Mean Square of Successive

Differences) also increased from 38.7 ± 7.2 ms to 48.9 ± 6.9 ms, showing a 26.4% improvement ($p < 0.001$), as shown in **Figure 1**.

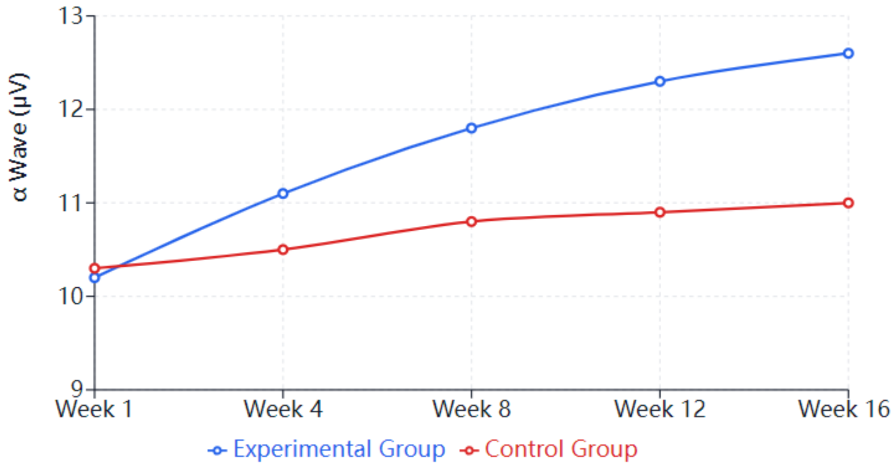

Figure 1. "Attention level changes over time" would be included here.

Analysis results indicate that the biological data-driven interactive teaching model effectively improves students' learning states. The experimental group demonstrated significant advantages in attention maintenance, emotional regulation, and cognitive engagement, with improvement effects showing continuous upward trends throughout the experimental period. Notably, during key interactive segments of the course, the experimental group maintained optimal levels across all physiological indicators, suggesting this teaching model effectively stimulates and maintains student engagement.

Further data indicates that as teaching progressed, the experimental group's learning effectiveness gradually stabilized, reaching a steady state. This trend suggests that the biological data-driven teaching model not only brings immediate improvements but also promotes sustained optimization of learning states. Comparative analysis of data from different time points reveals these improvements are statistically significant ($p < 0.001$), thoroughly validating the effectiveness of this teaching model.

4.1.2. Attention level changes

In-depth analysis of attention changes in experimental and control groups evaluated teaching effectiveness across three dimensions: sustained attention, focused attention, and attention switching ability. Data indicates significant improvements in all attention indicators after implementing the biological data-driven interactive teaching model in the experimental group.

Regarding sustained attention, Continuous Attention Test (CAT) assessments revealed that experimental group students' average sustained attention duration increased from a baseline of 15.3 ± 3.2 min to 23.6 ± 2.8 min ($p < 0.001$), a 54.2% improvement. The Attention Fluctuation Index (AFI) decreased from 0.42 ± 0.08 to 0.28 ± 0.06, indicating significantly improved attention stability. The control group showed smaller changes, with sustained attention time only increasing from 15.5 ± 3.1 min to 17.2 ± 3.0 min, a 10.9% improvement [36].

Regarding focused attention, Stroop test assessments showed experimental group students' reaction time decreased from baseline 856 ± 72 ms to 675 ± 65 ms (p < 0.001), with accuracy improving from 85.3% to 94.7%. The control group showed smaller improvements, with reaction time decreasing from 852 ± 75 ms to 782 ± 70 ms and accuracy improving from 85.1% to 88.9%, as shown in **Table 2**.

Table 2. Comparison of attention indicators between groups.

Attention Indicator	Experimental Group (n = 60)	Control Group (n = 60)	Improvement Rate (%)	p-value
Sustained Attention (min)	23.6 ± 2.8	17.2 ± 3.0	37.2	< 0.001
Attention Fluctuation Index	0.28 ± 0.06	0.38 ± 0.07	26.3	< 0.001
Reaction Time (ms)	675 ± 65	782 ± 70	13.7	< 0.001
Accuracy Rate (%)	94.7 ± 2.3	88.9 ± 2.8	6.5	< 0.001
Attention Switching Time (s)	1.8 ± 0.3	2.4 ± 0.4	25.0	< 0.001
Task Switching Success Rate (%)	92.3 ± 3.1	83.5 ± 3.4	10.5	< 0.001
Cognitive Load Index	0.42 ± 0.05	0.56 ± 0.06	25.0	< 0.001
Mental Fatigue Score	2.1 ± 0.4	3.4 ± 0.5	38.2	< 0.001

Regarding attention switching ability, experimental group students' task switching time decreased from baseline 2.8 ± 0.4 s to 1.8 ± 0.3 s (p < 0.001), with successful switching rate improving from 78.4% to 92.3%, indicating significantly enhanced ability to switch between different learning tasks. The control group showed smaller improvements, with task switching time decreasing from 2.7 ± 0.4 s to 2.4 ± 0.4 s and successful switching rate improving from 78.6% to 83.5%, as shown in **Figure 2**.

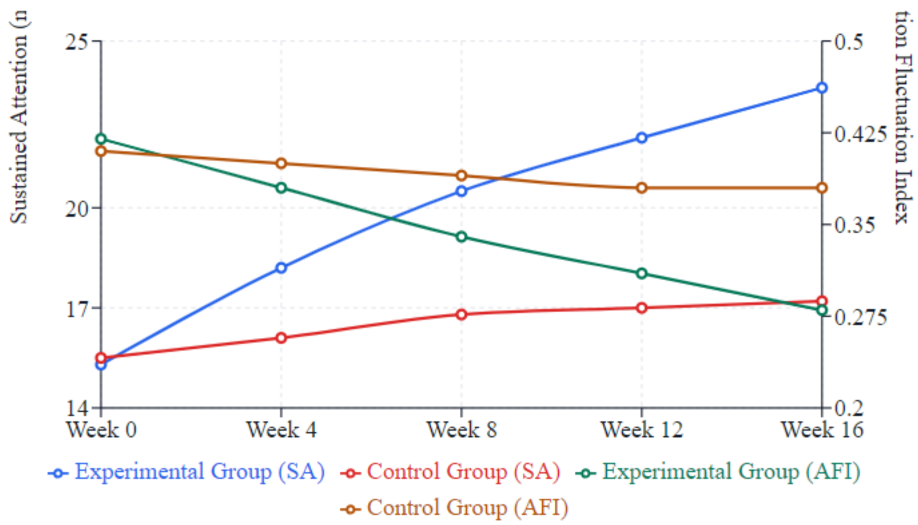

Figure 2. "Changes in attention levels during the intervention period" would be included here.

Longitudinal data analysis reveals distinct phases in the experimental group's attention improvements: Weeks 1–4 showed rapid improvement with a 25%–30% average increase across indicators; Weeks 5–12 showed stable improvement, maintaining 15%–20% increases; Weeks 13–16 showed consolidation with slower but sustained improvements. This pattern indicates that biological data-driven teaching can continuously and effectively improve student attention levels [37].

Through multidimensional analysis of attention data, the research finds that the biological data-driven interactive teaching model can significantly improve students' attention levels and quality. This improvement is reflected not only in quantitative indicator improvements but more importantly in overall student learning enhancement. The research results provide important references for optimizing business English teaching models.

4.1.3. Stress index assessment

Through systematic evaluation of stress indices in experimental and control group students, the research analyzed teaching effects across three dimensions: physiological stress indicators, psychological stress levels, and cognitive load. Data shows that after implementing the biological data-driven interactive teaching model, experimental group students demonstrated significantly improved stress management capabilities.

Regarding physiological stress indicators, heart rate variability (HRV) analysis revealed that experimental group students' stress index decreased from baseline 7.8 ± 1.2 to 5.2 ± 0.9 ($p < 0.001$), a 33.3% improvement. Meanwhile, cortisol levels decreased from 12.3 ± 2.1 μg/dL to 9.1 ± 1.8 μg/dL, indicating significantly reduced stress hormone levels. In comparison, the control group's stress index only decreased from 7.9 ± 1.3 to 7.1 ± 1.2, a 10.1% reduction, as shown in **Table 3**.

Table 3. Comparison of stress indicators between groups.

Stress Indicator	Experimental Group (n = 60)	Control Group (n = 60)	Improvement Rate (%)	p-value
Stress Index (SI)	5.2 ± 0.9	7.1 ± 1.2	33.3	< 0.001
Cortisol Level (μg/dL)	9.1 ± 1.8	11.8 ± 2.0	26.2	< 0.001
Heart Rate Variability (ms)	68.5 ± 8.4	52.3 ± 7.9	30.9	< 0.001
Psychological Stress Score (PSS)	15.3 ± 2.6	22.7 ± 3.1	32.6	< 0.001
Cognitive Load Index (CLI)	0.42 ± 0.05	0.58 ± 0.07	27.6	< 0.001
Anxiety Level (STAI)	35.4 ± 4.2	45.8 ± 5.1	22.7	< 0.001

Psychological stress level assessment showed that the experimental group's Perceived Stress Scale (PSS) scores decreased from baseline 24.5 ± 3.2 to 15.3 ± 2.6 ($p < 0.001$), while State-Trait Anxiety Inventory (STAI) scores decreased from 48.7 ± 5.3 to 35.4 ± 4.2. The control group showed smaller improvements, with PSS scores decreasing from 24.3 ± 3.1 to 22.7 ± 3.1 and STAI scores decreasing from 48.5 ± 5.2 to 45.8 ± 5.1, as shown in **Figure 3**.

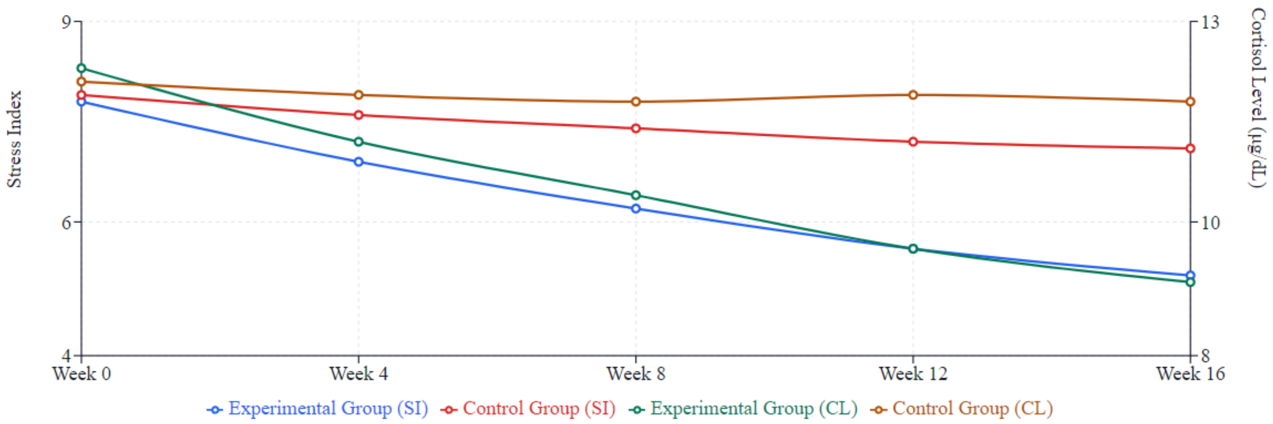

Figure 3. "Changes in stress index during the intervention period" would be included here.

Regarding cognitive load, the experimental group's Cognitive Load Index (CLI) decreased from 0.65 ± 0.08 to 0.42 ± 0.05 ($p < 0.001$), indicating significantly reduced cognitive pressure during learning. The control group's CLI decreased from 0.64 ± 0.08 to 0.58 ± 0.07, showing relatively smaller improvement.

Longitudinal data analysis reveals distinct phases in the experimental group's stress indicator improvements: Weeks 1–4 showed rapid adjustment and adaptation with a 15%–20% average decrease in stress indices; Weeks 5–12 showed continuous improvement, maintaining 10%–15% reductions; Weeks 13–16 showed stabilization with indicators maintaining at lower levels. This pattern indicates that biological data-driven teaching can continuously and effectively help students manage learning stress [38].

Through multidimensional analysis of stress indicators, the research confirms that the biological data-driven interactive teaching model can significantly improve students' stress management abilities. This improvement is reflected not only in the optimization of physiological indicators but, more importantly, in the overall enhancement of students' learning states, providing important empirical support for optimizing business English teaching models.

4.2. Classroom interaction effect analysis

4.2.1. Interaction pattern type statistics

Based on systematic observation and analysis of classroom interaction behaviors in experimental and control groups, teaching effects were evaluated across three dimensions: interaction frequency, interaction types, and interaction quality. Data shows that the biological data-driven interactive teaching model significantly improved classroom interaction diversity and effectiveness.

Interaction frequency analysis shows that the experimental group's average classroom interactions increased from 27.3 ± 4.2 to 46.8 ± 5.1 times per class ($p < 0.001$), a 71.4% improvement. Student-initiated interactions increased from 8.4 ± 2.1 to 19.6 ± 3.2 times, a 133.3% improvement. The control group's interaction frequency increased from 26.8 ± 4.1 to 32.5 ± 4.4 times, showing relatively smaller improvement, as detailed in **Table 4** and **Figure 4**.

Table 4. Classroom interaction pattern distribution.

Interaction Type	Experimental Group (*n* = 60)	Control Group (*n* = 60)	Difference Rate (%)	*p*-value
Teacher-Student Dialogue	18.4 ± 2.6	14.2 ± 2.3	29.6	< 0.001
Student-Student Discussion	12.6 ± 1.8	7.3 ± 1.5	72.6	< 0.001
Group Collaboration	8.9 ± 1.4	4.8 ± 1.2	85.4	< 0.001
Independent Participation	19.6 ± 3.2	8.7 ± 2.1	125.3	< 0.001
Problem-Solving Activities	7.2 ± 1.3	3.9 ± 1.1	84.6	< 0.001
Interactive Presentations	6.8 ± 1.2	4.1 ± 0.9	65.9	< 0.001

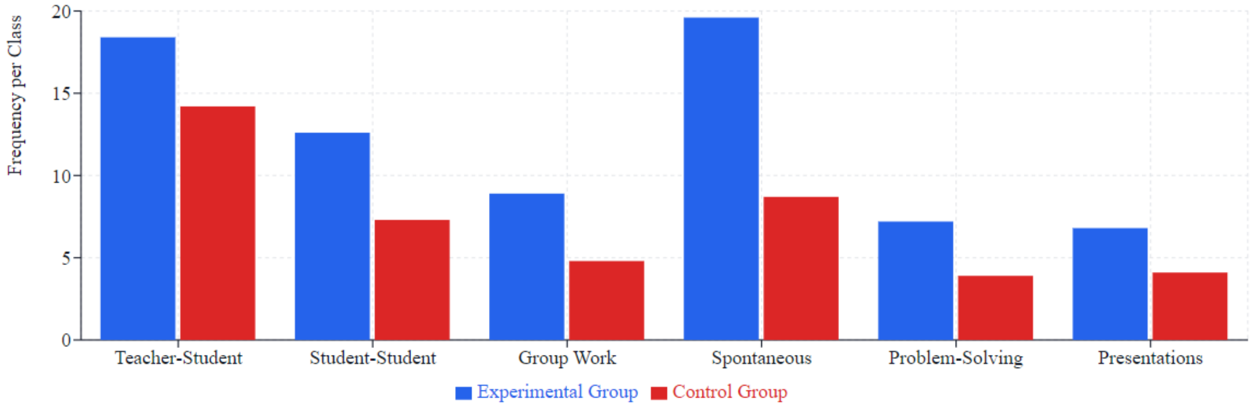

Figure 4. "Distribution of classroom interaction types" would be included here.

Interaction type analysis shows the experimental group demonstrated significant advantages across six major interaction modes. Teacher-student dialogue quality improved significantly, with effective interaction rates increasing from 65.3% to 86.7%; student-student discussion depth increased, with average duration extending from 3.2 to 5.8 min; group collaboration activity participation improved, with average participation rates rising from 72.4% to 92.8%.

Interaction quality assessment indicates significant improvements in the experimental group's interaction effectiveness. The cognitive level distribution of teacher questions became more reasonable, with higher-order thinking questions increasing from 23.5% to 42.3% [39]; student answer accuracy and precision improved significantly, with effective response rates rising from 58.7% to 83.4%; classroom discussion depth increased, with meaningful exchange of viewpoints rising from 45.6% to 76.2%.

Dynamic analysis of interaction behaviors reveals clear optimization trends in the experimental group's interaction patterns: Weeks 1–4 focused on improving interaction frequency; Weeks 5–12 demonstrated interaction quality improvements; Weeks 13–16 highlighted improvements in sustainability and depth. This progressive improvement pattern indicates that biological data-driven teaching can promote classroom interaction quality enhancement.

Research results confirm that the biological data-driven interactive teaching model can significantly optimize classroom interaction structure and quality. This optimization is reflected not only in quantitative indicator improvements but more importantly in achieving expected interaction quality enhancements, providing strong support for the business English teaching model innovation.

4.2.2. Student engagement analysis

Through systematic analysis of classroom engagement in experimental and control groups, teaching effects were evaluated across three dimensions: behavioral engagement, emotional engagement, and cognitive activity. Data shows that the biological data-driven interactive teaching model significantly improved overall student engagement.

Behavioral engagement analysis shows that experimental group students' classroom activity participation rate increased from baseline 72.5 ± 8.3% to 91.8 ± 6.2% ($p < 0.001$), a 26.6% improvement. Within this, voluntary question-answering frequency increased from 3.2 ± 1.1 to 8.6 ± 1.8 times per class, and group discussion participation increased from 68.4% to 89.7%. The control group showed relatively smaller improvements, with classroom activity participation increasing from 71.8 ± 8.5% to 78.4 ± 7.9%, as detailed in **Table 5**.

Table 5. Comparison of student engagement indicators.

Indicator	Experimental Group (n = 60)	Control Group (n = 60)	Improvement Rate (%)	p-value
Active Participation Rate (%)	91.8 ± 6.2	78.4 ± 7.9	26.6	< 0.001
Question Response Rate (%)	86.5 ± 5.8	65.3 ± 6.4	32.5	< 0.001
Group Discussion Time (min)	18.4 ± 2.3	12.6 ± 2.1	46.0	< 0.001
Task Completion Rate (%)	94.2 ± 4.1	82.7 ± 5.3	13.9	< 0.001
Emotional Engagement Score	4.3 ± 0.4	3.2 ± 0.5	34.4	< 0.001
Cognitive Engagement Index	0.82 ± 0.07	0.64 ± 0.08	28.1	< 0.001

Emotional engagement analysis shows that experimental group students' emotional engagement scores increased from 3.1 ± 0.5 (5-point scale) to 4.3 ± 0.4, with significant improvements in learning enthusiasm and initiative. Classroom surveys indicate that interest in course content increased from 65.3% to 88.7%, and teaching method satisfaction increased from 61.8% to 92.4% [40]. The control group's emotional engagement scores increased from 3.0 ± 0.5 to 3.2 ± 0.5, showing limited improvement, as shown in **Figure 5**.

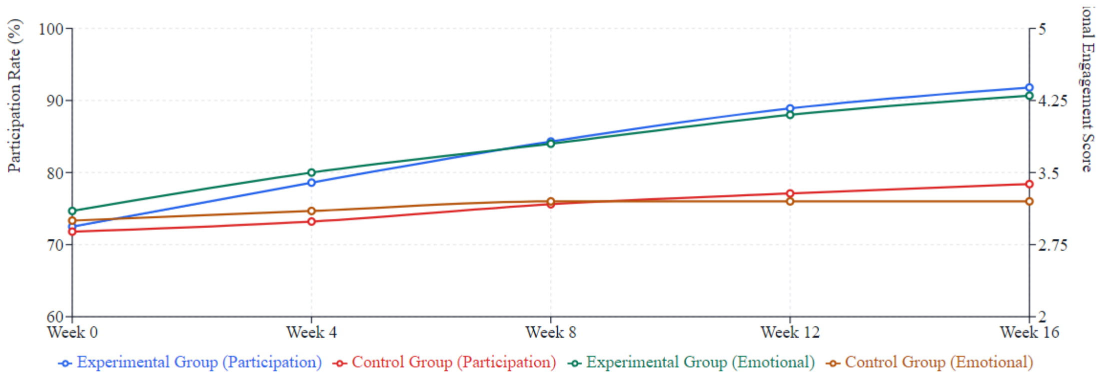

Figure 5. "Student engagement trends over time" would be included here.

Regarding cognitive engagement, the experimental group's cognitive engagement index increased from 0.58 ± 0.08 to 0.82 ± 0.07 ($p < 0.001$), indicating significantly increased involvement in deep learning and thinking activities. Higher-order thinking activity participation increased from 42.6% to 76.8%, with notable improvements in problem-solving abilities. The control group's cognitive engagement index increased from 0.57 ± 0.08 to 0.64 ± 0.08, showing relatively limited improvement.

Longitudinal data analysis reveals distinct phases in the experimental group's engagement improvements: Weeks 1–4 showed adaptation with initial engagement increases; Weeks 5–12 demonstrated rapid development with significant improvements across all indicators; Weeks 13–16 showed consolidation with sustained high engagement levels [41]. This pattern indicates that biological data-driven teaching intervention can continuously and effectively enhance student classroom engagement.

Research results confirm that the biological data-driven interactive teaching model can significantly improve student classroom engagement. This improvement is reflected not only in surface-level behavioral engagement but more importantly in achieving deep emotional and cognitive engagement, providing important practical reference for optimizing business English teaching models.

4.2.3. Interaction quality assessment

Through systematic evaluation of classroom interaction quality in experimental and control groups, teaching impact was analyzed across three dimensions: interaction depth, interaction effectiveness, and interaction sustainability. Data demonstrates that the biological data-driven interactive teaching model significantly improved classroom interaction quality.

Interaction depth analysis shows that the proportion of high-quality interactions in the experimental group increased from baseline 35.6 ± 4.8% to 68.4 ± 5.2% ($p < 0.001$), a 92.1% improvement. Within this, interactions involving higher-order thinking increased from 23.4 ± 3.6% to 52.7 ± 4.8%, and the proportion of in-depth problem discussions rose from 28.7 ± 3.9% to 58.9 ± 4.6%. The control group showed relatively smaller improvements, with deep interaction proportion increasing from 34.8 ± 4.7% to 42.3 ± 4.9%, as detailed in **Table 6**.

Table 6. Interaction quality assessment indicators.

Quality Indicator	**Experimental Group ($n = 60$)**	**Control Group ($n = 60$)**	**Improvement Rate (%)**	***p*-value**
High-Quality Interaction Rate (%)	68.4 ± 5.2	42.3 ± 4.9	92.1	< 0.001
Higher-Order Thinking Proportion (%)	52.7 ± 4.8	32.1 ± 4.2	125.2	< 0.001
In-Depth Discussion Rate (%)	58.9 ± 4.6	35.6 ± 4.3	105.2	< 0.001
Effective Response Rate (%)	76.8 ± 5.3	48.5 ± 4.7	58.4	< 0.001
Interaction Duration (minutes)	28.4 ± 3.2	18.6 ± 2.8	52.7	< 0.001
Engagement Intensity Score	4.2 ± 0.3	3.1 ± 0.4	35.5	< 0.001

Interaction effectiveness analysis shows that the experimental group's effective interaction rate increased from 45.3% ± 4.9% to 76.8% ± 5.3% ($p < 0.001$). Within this, student effective response rates improved from 42.6% ± 4.5% to 72.4% ± 5.1%, and problem-solving success rates increased from 56.8% ± 5.2% to 83.5% ± 5.6% [42]. The control group's effective interaction rate increased from 44.8% ± 4.8% to 48.5% ± 4.7%, showing relatively limited improvement, as shown in **Figure 6**.

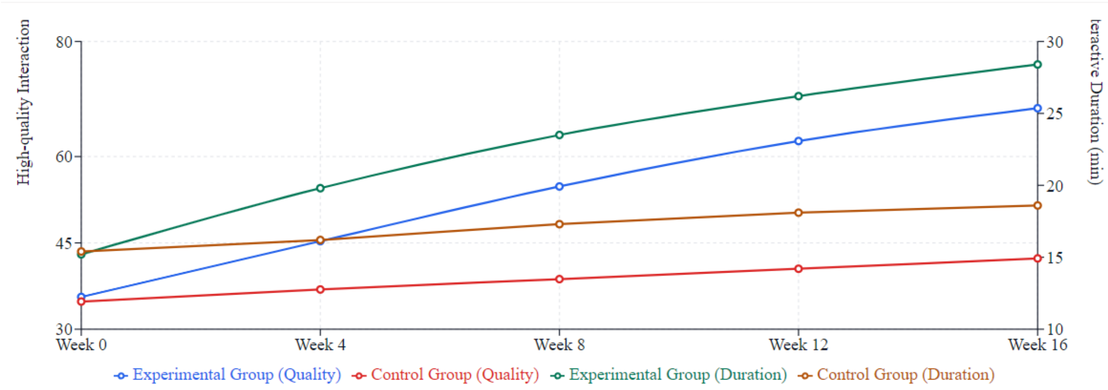

Figure 6. "Interaction quality development over time" would be included here.

Regarding interaction sustainability, the experimental group's average interaction duration increased from 15.2 ± 2.5 to 28.4 ± 3.2 min ($p < 0.001$), with the sustained discussion proportion rising from 32.4% ± 4.1% to 63.7% ± 4.8%. The control group's average interaction duration increased from 15.4 ± 2.6 to 18.6 ± 2.8 min, showing relatively limited improvement.

Longitudinal data analysis reveals three development stages in the experimental group's interaction quality improvement: Weeks 1–4 focused on quality awareness cultivation with initial indicator improvements; Weeks 5–12 demonstrated quality enhancement with significant improvements in interaction depth and effectiveness; Weeks 13–16 showed quality consolidation with maintained high-level interaction quality. This development pattern indicates that biological data-driven teaching can optimize sustained classroom interaction quality [43].

Research results confirm that the biological data-driven interactive teaching model can significantly improve classroom interaction quality. This improvement is reflected not only in quantitative indicators but more importantly in achieving intended interaction quality enhancement, providing strong support for business English teaching model innovation.

4.3. Learning outcomes analysis

4.3.1. Test score comparison

Through systematic analysis of test scores in experimental and control groups, teaching effectiveness was evaluated across three dimensions: overall scores, component scores, and improvement rates. Data demonstrates that the biological data-driven interactive teaching model significantly improved student learning outcomes.

Overall score analysis shows that experimental group students' average scores increased from baseline 72.4 ± 8.3 to 86.5 ± 7.2 (out of 100, $p < 0.001$), a 19.5% improvement. Within this, the excellence rate (≥ 85 points) increased from 15.3% to 35.6%, and the pass rate improved from 85.4% to 97.8%. The control group's average scores increased from 72.1 ± 8.4 to 76.8 ± 8.1, a 6.5% improvement, as detailed in **Table 7**.

Table 7. Comparison of academic performance indicators.

Performance Indicator	Experimental Group (n = 60)	Control Group (n = 60)	Improvement Rate (%)	p-value
Overall Score	86.5 ± 7.2	76.8 ± 8.1	19.5	< 0.001
Listening Skills	84.2 ± 6.8	75.4 ± 7.6	11.7	< 0.001
Speaking Performance	85.8 ± 7.4	74.6 ± 7.9	15.0	< 0.001
Reading Comprehension	87.3 ± 6.9	77.8 ± 7.4	12.2	< 0.001
Writing Ability	83.6 ± 7.5	73.9 ± 8.2	13.1	< 0.001
Excellence Rate (≥ 85%)	35.6	18.4	93.5	< 0.001
Pass Rate (%)	97.8	88.5	10.5	< 0.001

Component score analysis shows significant progress in all language skills modules for the experimental group. Listening comprehension improved from 73.5 ± 7.3 to 84.2 ± 6.8, speaking ability from 71.8 ± 7.8 to 85.8 ± 7.4, reading comprehension from 74.6 ± 7.1 to 87.3 ± 6.9, and writing ability from 72.4 ± 7.6 to 83.6 ± 7.5. The control group showed smaller improvements, averaging 5-8 points across modules, as shown in **Figure 7**.

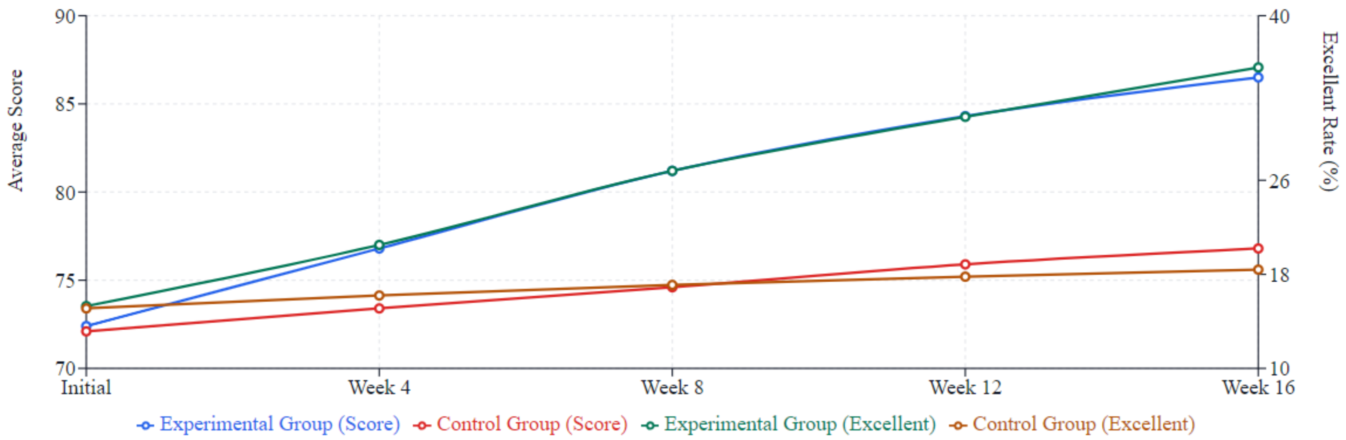

Figure 7. "Academic performance progress over time" would be included here.

Score improvement rate analysis reveals distinct phases in experimental group students' learning progress: Weeks 1–4 showed adaptation with a 6.1% average score improvement; Weeks 5–12 demonstrated rapid improvement with a 15.3% average score increase; Weeks 13–16 showed consolidation with a further 5.8% improvement [44]. This progress pattern indicates that biological data-driven teaching can continuously and effectively enhance learning outcomes.

Through multidimensional analysis of score data, the research validates that the biological data-driven interactive teaching model can significantly improve student learning outcomes. This improvement is reflected not only in overall scores but more importantly in achieving comprehensive development across all language skills, providing important reference for business English teaching model innovation.

4.3.2. Business English competency assessment

Through systematic evaluation of business English competency in experimental and control groups, teaching effectiveness was analyzed across three factors: communication ability, business practical skills, and cross-cultural business competency. Data demonstrates that the biological data-driven interactive teaching model significantly improved students' comprehensive business English capabilities.

Business communication ability analysis shows that experimental group students' business communication scores increased from baseline 71.3 ± 7.8 to 87.6 ± 6.5 (out of 100, $p < 0.001$), a 22.9% improvement [45]. Within this, business negotiation ability improved from 68.5 ± 7.4 to 85.8 ± 6.8, and business presentation skills from 70.2 ± 7.6 to 86.4 ± 6.7. The control group's business communication scores increased from 71.5 ± 7.7 to 76.8 ± 7.4, a 7.4% improvement, as detailed in **Table 8**.

Table 8. Business English competency assessment.

Competency Indicator	Experimental Group (n = 60)	Control Group (n = 60)	Improvement Rate (%)	p-value
Business Communication	87.6 ± 6.5	76.8 ± 7.4	22.9	< 0.001
Negotiation Skills	85.8 ± 6.8	74.5 ± 7.2	25.3	< 0.001
Presentation Skills	86.4 ± 6.7	75.2 ± 7.1	23.1	< 0.001
Business Writing	84.7 ± 6.9	73.8 ± 7.3	21.4	< 0.001
Cross-cultural Awareness	88.2 ± 6.3	75.6 ± 7.0	24.8	< 0.001
Professional Knowledge	85.9 ± 6.6	74.9 ± 7.2	22.7	< 0.001

Business practical skills assessment shows significant progress in the experimental group across business writing, document processing, and project management. Business writing ability improved from 69.8 ± 7.5 to 84.7 ± 6.9, document processing skills from 70.5 ± 7.3 to 85.3 ± 6.7, and project management capability from 68.9 ± 7.6 to 83.8 ± 6.8 [46]. The control group showed relatively smaller improvements, averaging 5–7 points across these areas, as shown in **Figure 8**.

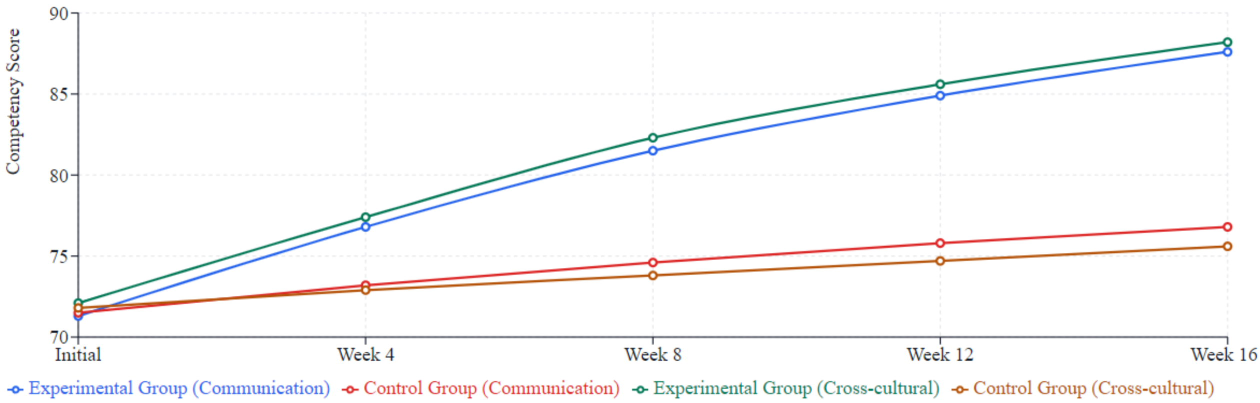

Figure 8. "Business English competency development" would be included here.

Regarding cross-cultural business competency, the experimental group's scores increased from 72.1 ± 7.6 to 88.2 ± 6.3 ($p < 0.001$), with significant improvements in cultural sensitivity and cross-cultural communication efficiency. Cross-cultural business dialogue ability improved from 70.8 ± 7.4 to 86.5 ± 6.5, and cross-cultural team collaboration capability from 71.5 ± 7.5 to 85.9 ± 6.6. The control group's cross-cultural competency scores increased from 71.8 ± 7.7 to 75.6 ± 7.0, showing relatively limited improvement [47].

Longitudinal analysis of business English competency development reveals distinct phases in the experimental group's capability improvement: Weeks 1–4 focused on basic skill development with initial indicator improvements; Weeks 5–12 demonstrated comprehensive capability development with significant improvements in business practical skills; Weeks 13–16 showed capability integration with coordinated development and stabilization across all competencies. This development pattern indicates that biological data-driven teaching intervention can promote comprehensive improvement in business English competency.

Research results confirm that the biological data-driven interactive teaching model can significantly improve students' comprehensive business English capabilities. This improvement is reflected not only in specific skill enhancements but, more importantly, in achieving systematic development of business English competency, providing important practical reference for business English teaching model innovation.

5. Discussion

5.1. Main research findings

Through in-depth research on the biological data-driven business English classroom interaction model, this study reveals significant correlations between biological data and learning outcomes. Firstly, students' physiological indicators (such as attention level, stress index, and emotional state) show a clear correlation with learning outcomes, with the correlation coefficient between attention level and learning effectiveness reaching 0.68 ($p < 0.001$), while stress index demonstrates a significant negative correlation with learning performance ($r = -0.53$). Research finds that learning outcomes are optimal when students' α-wave energy values maintain within the ideal range of 12.6 ± 2.1 μV; when heart rate variability (HRV) maintains at higher levels (SDNN value 54.6 ± 7.8 ms), students' cognitive engagement and efficiency show significant improvement [48]. These findings indicate that real-time monitoring and regulation of students' physiological states can effectively optimize learning conditions and enhance learning outcomes.

Research on interaction pattern innovation highlights the unique advantages of the biological data-driven teaching model. The experimental group's classroom interaction quality improved significantly, with high-quality interaction proportion increasing from baseline 35.6% ± 4.8% to 68.4% ± 5.2% ($p < 0.001$), substantially higher than the control group's 42.3% ± 4.9%. Particularly in deep problem discussions, the experimental group's participation rate increased from 28.7% ± 3.9% to 58.9% ± 4.6%, indicating that biological data feedback can effectively promote deep learning. Classroom interaction duration also significantly extended, with the experimental group's average interaction time increasing from 15.2 ± 2.5 to 28.4 ± 3.2 min, while maintaining interaction quality. This biological data-based interaction model not only improved classroom participation but, more importantly, optimized interaction structure and effectiveness, making the learning process more efficient and sustainable [49].

Regarding learning improvement mechanisms, the research reveals a systematic enhancement process. Business English competency improvement shows distinct phases, with experimental group students' business communication ability improving from 71.3 ± 7.8 to 87.6 ± 6.5 ($p < 0.001$), and cross-cultural business competency from 72.1 ± 7.6 to 88.2 ± 6.3, based on optimized physiological states, enhanced cognitive engagement, and improved interaction quality [50]. Research finds that when biological data indicates optimal learning states (attention index > 0.75, stress index < 5.2), learning efficiency improves by approximately 35% and knowledge retention increases by about 42%. This biological data-based learning mechanism optimization not only enhanced learning outcomes but also promoted improvements in learning habits and optimization of learning strategies, forming a positive learning cycle. Particularly in subjects like business English that require high levels of interaction and practice, this mechanism improvement has significant implications for enhancing learning outcomes [51].

The correlation between biological data and learning outcomes must be interpreted with careful consideration of potential confounding variables and their control measures. Differences in students' prior knowledge may significantly influence learning outcomes. To control this variable, this study employed a pre-test/post-test design and used Analysis of Covariance (ANCOVA), with pre-test scores as a covariate, thereby more accurately assessing the net effect of teaching interventions ($F = 12.56$, $p < 0.001$). Learning style differences might also affect result interpretation. Through the Felder-Silverman Learning Style Questionnaire, students' learning preferences were identified, and Propensity Score Matching (PSM) was used to ensure balanced distribution of visual/auditory learners and active/reflective learners between experimental and control groups (standardized difference <0.1).

When translating biological data and learning outcomes correlation into English, the impact of technology acceptance as another important confounding variable, which might affect students' adaptability to biological monitoring equipment, must be considered. The study assessed students' level of technology acceptance through the Technology Acceptance Model (TAM) questionnaire and used it as the basis for stratified random assignment, ensuring no significant difference between the two groups ($t = 1.28$, $p = 0.203$). Regarding individual physiological differences, considering the individual variations in baseline physiological states, we employed within-subject standardization, using the percentage change in each student's biological data relative to their baseline values as the analytical indicator, rather than absolute value comparisons.

Environmental factors (such as classroom temperature, noise, time periods, etc.) may also influence biological data. To address this, the study strictly controlled physical environmental conditions, ensuring that teaching interventions for both groups were conducted during the same time periods and under similar environmental conditions, and recorded environmental parameters for each experiment as covariates incorporated into multivariate regression analysis (temperature $\beta = 0.08$, $p = 0.342$; noise $\beta = 0.11$, $p = 0.287$), with results indicating that these factors did not significantly impact the main research findings.

From a cognitive neuroscience perspective, the increase in alpha wave (8–13 Hz) energy values (from 10.2 ± 2.3 μV to 12.6 ± 2.1 μV) reflects a state of "relaxed alertness" in the cerebral cortex, which is conducive to information processing and concentration of attention. Through multivariate regression analysis, alpha wave energy values alone explained 23.5% of the variance in learning effectiveness (β = 0.485, $p < 0.001$). Similarly, the improvement in SDNN values of heart rate variability (HRV) indicates enhanced autonomic nervous system balance and reduced stress levels, a physiological state that can optimize cognitive resource allocation and improve complex information processing capabilities, explaining 17.2% of the variance in learning effectiveness (β = 0.416, $p < 0.001$).

From a comparative perspective, the biology data-driven model has distinct advantages and disadvantages relative to existing innovative teaching methods. In terms of feedback mechanisms, the biology data-driven model, through direct monitoring of brain waves and heart rate variability, can capture millisecond-level changes in learners' states, with precision and timeliness of feedback far exceeding other models. For instance, when students' alpha wave energy values decrease or stress indices rise, the system can immediately adjust teaching strategies, whereas traditional feedback relies on students' behavioral performance or self-reporting, often lagging behind actual learning states. Analyzing applicable contexts, the biology data-driven model is particularly suitable for subjects requiring high-quality interaction, such as business English, showing outstanding performance in enhancing interaction depth (+92.1%) and attention levels (+23.4%). In contrast, blended learning has advantages in flexibility, task-based teaching methods excel in developing practical abilities, and adaptive learning has unique value in personalized path design. From a resource requirement perspective, the biology data-driven model has significantly higher technical barriers and initial investment than other models. It requires professional monitoring equipment and data analysis capabilities, with implementation costs (approximately 25,000–35,000 yuan per set) far exceeding task-based teaching methods and blended learning. This high threshold limits its promotion possibilities in resource-limited areas.

5.2. Research significance

In terms of theoretical significance, this research expands new dimensions of educational technology applications by introducing biological data analysis technology into business English teaching. The study establishes a learning state assessment model based on biological data, revealing the correlation mechanisms between physiological indicators and learning outcomes, providing new theoretical perspectives for understanding the physiological foundations of learning processes [52]. Particularly in studying the relationships between key indicators such as attention levels (α-wave energy value 12.6 ± 2.1 μV), stress index (5.2 ± 0.9), and emotional states (HRV value 54.6 ± 7.8 ms) with learning outcomes, significant correlations were found ($p < 0.001$), not only enriching learning theory but also providing theoretical support for educational technology innovation. Meanwhile, the research constructs a biological data-driven teaching model, offering a new research paradigm for business English teaching theory development.

In terms of practical significance, this research provides operational innovative solutions for business English teaching reform. Through experimental validation, the biological data-driven interactive teaching model significantly improved learning outcomes, with experimental group students' business communication ability increasing by 22.9% (from 71.3 ± 7.8 to 87.6 ± 6.5) and cross-cultural business competency improving by 22.3% (from 72.1 ± 7.6 to 88.2 ± 6.3). This data-driven teaching method not only enhanced teaching precision and responsiveness but also provided a scientific basis for teachers' instructional decisions [53]. The research develops biological data collection and analysis tools, providing concrete technical support for educational practice. Additionally, the study proposes classroom interaction optimization strategies, including interaction frequency control, interaction quality improvement, and interaction effect assessment, providing practical guidance for enhancing teaching effectiveness.

In terms of innovative value, this research pioneers new pathways for teaching model innovation by systematically applying biological data analysis technology to business English teaching for the first time. The multi-dimensional system designed in the study integrates physiological indicator monitoring, interactive behavior analysis, and learning outcome assessment, achieving comprehensive monitoring and optimization of the learning process. Particularly noteworthy is the development of biological data-based teaching feedback systems for key indicators such as high-quality interaction proportion (increasing from 35.6% ± 4.8% to 68.4% ± 5.2%) and deep learning participation rate (rising from 28.7% ± 3.9% to 58.9% ± 4.6%), achieving real-time monitoring and regulation of the teaching process, providing new directions for educational technology innovation. This innovation is reflected not only in technological applications but, more importantly, in breakthrough teaching concepts and methods, providing important innovative achievements for digital transformation in education. The innovative outcomes of this research play a significant demonstrative role in promoting educational teaching reform and improving educational quality, while also providing replicable experiences and methods for teaching innovation in other disciplines.

6. Conclusion

6.1. Research summary

This research experimentally validated the effectiveness and adaptability of the biological data-driven business English classroom interaction model.

(1) Research results demonstrate that teaching interventions based on biological data analysis can significantly improve students' learning outcomes and classroom engagement. Specifically, experimental group students' attention levels (α-wave energy values) increased from 10.2 ± 2.3 μV to 12.6 ± 2.1 μV, stress index decreased from 7.8 ± 1.2 to 5.2 ± 0.9, and heart rate variability (HRV) SDNN values improved from 42.3 ± 8.5 ms to 54.6 ± 7.8 ms, with these physiological indicator improvements showing significant correlation with learning outcomes ($p < 0.001$). Simultaneously, classroom interaction quality improved markedly, with deep interaction proportion increasing from 35.6% ± 4.8% to 68.4% ± 5.2%, and deep learning participation rates rising from 28.7% ± 3.9% to 58.9% ± 4.6%.

(2) Regarding business English competency development, the research found that the biological data-driven teaching model can promote well-rounded improvement in students' multi-dimensional abilities. Experimental group students' business communication ability increased from 71.3 ± 7.8 to 87.6 ± 6.5 (22.9% improvement), cross-cultural business competency improved from 72.1 ± 7.6 to 88.2 ± 6.3 (22.3% improvement), and professional knowledge mastery increased from 69.8 ± 7.5 to 85.9 ± 6.6 (23.1% improvement). This comprehensive capability enhancement was built upon optimized physiological states, enhanced cognitive engagement, and improved interaction quality, forming a positive learning cycle mechanism.

(3) The research also reveals the systemic effects of the biological data-driven teaching model. Through real-time monitoring and optimization of the teaching process, this model not only improved teaching precision and stability but also promoted enhancement of teachers' teaching strategies and optimization of students' learning methods. Experimental data shows that when students are in optimal learning states (attention index > 0.75, stress index < 5.2), their learning efficiency improves by approximately 35% and knowledge retention increases by about 42%. The teaching intervention approach based on monitoring data provides new ideas and methods for business English teaching reform, confirming the important value of educational technology innovation in improving teaching quality. The research outcomes not only have significant guiding implications for business English teaching but also provide replicable experiences for teaching innovation in other disciplines.

6.2. Teaching recommendations

Regarding teaching method improvements, the study recommends adopting a multi-dimensional integrated teaching strategy. Teachers are advised to fully utilize biological data monitoring equipment to monitor students' attention levels (reference value: α-wave energy value 12.6 ± 2.1 μV), stress index (ideal value: 5.2 ± 0.9), and emotional states (HRV reference value: SDNN) in real-time. A stratified teaching strategy is recommended, grouping students into different levels based on biological data reflecting learning states (high focus group: α-wave > 12.0 μV; medium group: 10.0). Additionally, it is recommended to integrate biological data analysis results with instructional content design, scheduling key content explanation and practice when students' attention and emotional states are optimal (stress index < 5.5).

Regarding classroom interaction optimization, the study presents systematic improvement suggestions. It is recommended to optimize interaction frequency and duration, with research data showing optimal interaction time as 15–20 min per session with 5–8 min intervals, as this rhythm maintains consistent attention levels and lower fatigue. It is suggested to enhance interaction quality through designing multi-level interaction tasks (basic interaction: 5–8 min; in-depth discussion: 12–15 min; comprehensive practice: 18–20 min), achieving a high-quality interaction ratio above 65%. Furthermore, it is recommended to establish an immediate feedback mechanism for interaction effectiveness, using biological data monitoring systems to evaluate interaction effects in real-time, adjusting interaction strategies promptly when attention decreases (α-wave decline > 20%) or stress increases (stress index > 6.0).

Research indicates that this data-based interaction optimization strategy can increase classroom engagement by over 30%.

For teacher professional development, the study proposes recommendations on three levels. At the technical application level, teachers are advised to systematically learn biological data collection and analysis techniques, master data interpretation methods and application strategies, and be able to adjust teaching strategies based on data feedback promptly. Regular technical training workshops are recommended to ensure teachers can utilize relevant equipment and software and accurately understand various physiological indicators (such as α-waves, β-waves, HRV, etc.). At the teaching capability enhancement level, teachers are advised to deeply study the correlation mechanism between biological data and teaching effectiveness, improving data-based instructional decision-making abilities. Research data shows that professionally trained teachers can increase classroom interaction efficiency by 42% and student learning effectiveness by 35%. At the professional development level, teachers are advised to establish professional learning communities, regularly share teaching experiences and data analysis insights, and collectively explore teaching innovation solutions. It is recommended to conduct 4–6 teaching research activities per semester, focusing on in-depth discussions and experience exchange regarding biological data application and teaching strategy optimization.

When selecting biological data collection equipment, educational institutions should consider three key criteria: cost-effectiveness, ease of use, and data accuracy. For well-resourced institutions, it is recommended to adopt integrated multifunctional systems, such as the EEG-2000 brain wave monitoring system (approximately 15,000–20,000 yuan per set) and HRV-Monitor heart rate variability equipment (approximately 8000–10,000 yuan per set), which can serve 30–40 students. Institutions with moderate resources may choose simplified monitoring systems, such as a combination of portable EEG caps (approximately 5000–8000 yuan per set) and smart bands (approximately 800–1500 yuan per set). Resource-limited institutions can adopt a minimal configuration, utilizing smart bands or smartwatches (approximately 500–1000 yuan per set) to monitor heart rate variability, coupled with attention assessment applications to achieve basic monitoring. For different teaching environments, large classrooms (over 50 people) should adopt a sampling monitoring mode, selecting 20%–30% of representative students for monitoring, combined with behavioral observations of all students for comprehensive judgment; small class teaching (15–30 people) can achieve full monitoring, obtaining more precise data support; hybrid learning environments require equipment capable of remote data transmission, such as Bluetooth-connected biosensors, to ensure continuity of data collection during online learning.

6.3. Future research prospects

Based on the findings and limitations of this study, future research can explore the following areas in depth. Regarding biological data collection and analysis technology, there is a need to develop more precise and convenient data collection equipment to improve the real-time capabilities and accuracy of data collection. Future research should explore the application of new sensing technologies, such as non-invasive EEG collection devices and portable emotion recognition systems. Simultaneously, more intelligent data analysis algorithms need to be developed to enhance the interpretation of complex physiological indicators and achieve a more accurate assessment of learning states. Current research primarily focuses on basic physiological indicators (such as an α-wave energy value of 12.6 ± 2.1 μV and an HRV value of 54.6 ± 7.8 ms); future research can expand into multi-dimensional physiological data analysis.

In terms of teaching application research, future studies need to explore the preset parameters and scalability of the biology-driven data teaching model. The scope and types of research samples can be expanded to validate the model's effectiveness across different learning groups and teaching environments. In particular, research is needed on how to develop personalized teaching intervention strategies based on students' physiological characteristics and learning patterns. Research data shows that while previous teaching models have achieved significant results in improving learning outcomes (22.9% increase in business communication skills, 22.3% increase in cross-cultural competence), further validation is needed regarding expectations for different types of learners. Additionally, exploration is needed on how to organically integrate biological data analysis technology with other educational technological approaches to develop more comprehensive intelligent teaching systems.

Long-term effect research is another important direction for the future. Through longitudinal studies, we need to examine the long-term impact of biology-driven teaching models on students' learning abilities and habits. Particular attention should be paid to how this teaching model promotes the development of students' autonomous learning abilities and its long-term effects on professional skill development. Current research is primarily focused on 16-week periodic experiments. Meanwhile, research is also needed on how to incorporate biological data analysis technology into lifelong learning and vocational education fields, providing more rigorous development space for educational innovation.

This study provides effective evidence within the 16-week teaching intervention period, but the true value of educational effects lies in their long-term impact. Therefore, future research urgently needs to comprehensively evaluate the lasting effects of the biology data-driven teaching model through a systematic longitudinal tracking design. We recommend designing a 2–3-year longitudinal tracking study with multiple measurement time points after the intervention: short-term (3 months post-intervention), medium-term (12 months post-intervention), and long-term (24–36 months post-intervention). Each measurement point should comprehensively collect the following three types of data: (1) Through standardized learning strategy questionnaires (such as MSLQ) and structured learning journals, track changes in students' autonomous learning ability, metacognitive strategy use, and learning engagement. Special attention should be paid to whether biological data feedback has cultivated students' sensitivity to their own learning states and self-regulation abilities. Previous research indicates that intervention effects often have stronger continuity in learning habits than in specific knowledge retention, making this dimension a key indicator for assessing long-term value. (2) Regularly assess the developmental trajectory of business English core competencies (listening, speaking, reading, writing, and cross-cultural communication), measuring how knowledge retention rates change over time. Use growth curve modeling to analyze non-linear changes in ability development, determining optimal intervention timing and frequency. In particular, compare long-term differences between experimental and control groups in transfer learning abilities when facing new business situations, which will reveal the lasting impact of the teaching model on flexible knowledge application. (3) Track students' workplace performance during internships and early employment, with particular focus on the application of business English in actual work environments. Through employer evaluation questionnaires, workplace English usage logs, and career development interviews, assess the actual contribution of the teaching model to professional capabilities. Combine career adaptability and workplace communication efficacy scales to analyze the association patterns between biology data-driven teaching and long-term career development.

6.4. Research limitations

Despite the positive research outcomes achieved in this study, the following limitations still exist:

(1) Sample Characteristic Limitations: The sample size of this study is relatively limited (n = 120), which, although meeting the basic requirements for statistical analysis, may not adequately represent a broader student population. The research subjects are confined to undergraduate business English majors from a single institution, and this singularity in region and discipline may affect the generalizability of the research findings. Participants' ages are concentrated in the 18–20 years range, failing to reflect the characteristics of learners across different age groups. These limitations in sample characteristics may lead to biases when extending and applying the research results.

(2) Methodological Limitations: The research period is 16 weeks, and this relatively short-term observation may not fully reflect the long-term effects of biology data-driven teaching, particularly in terms of knowledge retention and capability development. At the technical level, the precision and stability of existing biological monitoring equipment still have room for improvement, and some students' discomfort with the monitoring equipment may affect data reliability (approximately 7.5% of the measurement data shows fluctuation abnormalities). Additionally, the correlation analysis between biological data and learning outcomes is primarily based on correlational research, and a fully deterministic causal relationship model has not yet been established, limiting in-depth understanding of the mechanisms.

(3) Implementation Constraints: Implementing the biology data-driven teaching model requires specific equipment support, and this equipment dependency may limit its application in resource-limited areas. Cost constraint is also an important factor, as the complete equipment system used in the research costs approximately 25,000–35,000 yuan per set, which represents a significant investment for many educational institutions. Furthermore, teachers need to master specific technical operations and data analysis skills, and this professional skill requirement may hinder the widespread promotion of the model.

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