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# *Research on Personalized Feedback Mechanism of Blended Writing Teaching for English Majors Based on Learning Analytics Technology*

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***Abstract.*** With the in-depth development of educational informatization, the blended teaching model has become an important direction for the reform of English major writing teaching. However, the traditional writing feedback mechanism has problems such as delay, singularity and difficulty in personalization, which restrict the improvement of teaching effect. This paper aims to explore how to use learning analytics techniques to construct a data-driven personalized feedback mechanism to transform into a data-driven personalized feedback mechanism, elaborates on the multi-source data integration path and multimodal feedback strategy, and through teaching experiment comparison, it is found that This mechanism can significantly improve students' writing performance (especially in terms of content and logic dimensions), enhance learning engagement and self-efficacy, and provide strong support for teaching optimization.

***Keywords:*** Learning Analytics Techniques, Blended teaching, English Writing, Personalized feedback, Data-driven

## 1. Introduction

### 1.1. The content of the blended teaching model and its application advantages in English writing teaching

#### 1.1.1. The teaching concept of the deep integration of online self-study and offline interaction

The blended teaching model is based on constructivist and humanistic learning theories. It emphasizes that students, under the guidance of teachers, actively construct knowledge using online resources and deepen understanding and application through interactive activities such as collaboration, discussion, and presentation in the offline classroom. In English writing teaching, This idea is reflected in students completing tasks such as collecting writing materials, writing first drafts, and peer evaluation on the online platform, while the offline classroom focuses on in-depth analysis of writing skills, the cultivation of critical thinking ability, and the concentrated solution of

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individualized problems [1], thereby forming a spiral upward learning loop and transforming into a spiral upward learning loop.

#### 1.1.2. The core features of expanding teaching time and space and enriching teaching resources

The blended teaching model breaks the time and space limitations of the traditional classroom. Students can arrange their learning according to their own pace, repeatedly watch teaching videos and access digital resources, achieving personalized learning. For English writing, teachers can integrate a vast amount of high-quality model essays, writing tutorials, and theme-related audio and video materials on online platforms. It builds a three-dimensional writing resource library for students, effectively addressing the problems of scarce resources and slow updates in traditional teaching, and laying the foundation for high-quality language output.

### 1.2. An analysis of the current situation and predicaments of feedback in English writing teaching

#### 1.2.1. The problems of delay and singularity in traditional feedback mechanisms

Under the traditional teaching model, students usually have to wait for a long time to receive feedback from the teacher after completing the writing task. This delay has led to the students' thinking enthusiasm for writing has already faded, the motivation for revision has been insufficient, and the feedback effect has been greatly reduced. On the other hand, the feedback source is single, mainly relying on the teacher's correction, in the form of grammar correction and simple comments [2], There is a lack of attention to high-level writing skills such as the structure of the article, the logic of the content, and the power of the argument, and it is difficult to meet the needs of students' all-round development.

#### 1.2.2. Difficulties in implementing individualized instruction in the context of large class teaching

The writing courses of English majors in colleges and universities generally face the problem of a large number of students. Due to the limited energy of teachers, it is difficult for them to track the writing process of each student in detail, nor can they provide continuous and in-depth personalized guidance based on individual differences. Feedback often tends to be generalized and cannot precisely reach the "zone of proximal development" of students at different levels, resulting in students with weak foundations feeling that it is out of reach. Students who have spare capacity feel that their improvement is limited and that teaching is seriously lacking in specificity.

### 1.3. The necessity and feasibility of learning analytics techniques to empower personalized feedback

#### 1.3.1. The ability of learning analytics technology to collect, analyze and interpret data from the learning process

Learning analytics technology refers to the measurement, collection, analysis, and reporting of big data of learners and their learning environment, with the aim of understanding and optimizing the learning process and its occurrence environment. In the context of blended writing teaching, this

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technology can automatically capture all-round behavioral data of students on online platforms, Such as login frequency, video viewing duration and number of times, discussion board speech quality, document modification history, resource download records, etc. Shift to behavioral data collection [3].

#### 1.3.2. Provide technical support for achieving precise, forward-looking teaching interventions

Based on the results of the learning analysis, teachers can make a shift from experience-driven to data-driven. The system can automatically identify students who repeatedly make mistakes on specific grammar points, or whose participation in writing tasks suddenly drops, and alert teachers in advance. This enables teachers to implement forward-looking interventions to help students before problems accumulate or learning motivation is lost. Shifting feedback from "post-event remediation" to "process support" and "prospective prevention" has greatly enhanced the timeliness and effectiveness of teaching guidance and shifted it towards teaching guidance effectiveness.

## 2. Construction of personalized feedback mechanism models based on learning analytics techniques

### 2.1. Core principles and framework design for mechanism construction

#### 2.1.1. Student-centered, data-driven, and feedback timeliness principles

The student-centered principle requires that feedback mechanisms be designed with the ultimate goal of promoting the development of students' writing skills and the improvement of their autonomous learning abilities. The data-driven principle ensures that feedback suggestions are not based on teachers' subjective impressions but are derived from an objective analysis of students' learning behaviors.

#### 2.1.2. "Data collection - analysis and diagnosis - personalized feedback - effect evaluation" closed-loop model

This model constitutes a continuously optimized loop system. The data collection layer is responsible for collecting various types of data from the blended teaching environment. The analysis and diagnosis layer uses learning analytics techniques and natural language processing techniques to analyze the data to identify students' learning status and needs. The personalized feedback layer [4], based on the diagnosis results, The effect evaluation layer assesses the effectiveness of the feedback by comparing the behavioral changes and performance of the students before and after the feedback, and feeds the evaluation results back to the data collection and analysis diagnosis layer to optimize the algorithm and strategy, thereby transforming the model from self-improvement to model self-improvement.

### 2.2. Paths for collecting and integrating multi-source heterogeneous writing data

#### 2.2.1. Online platform behavior data (such as video viewing, data downloading, draft submission)

Such data reflect students' learning engagement and learning paths, including the frequency and duration of students' visits to course modules, the completion rate and repeat viewing nodes of

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teaching videos, the download and reading time of relevant literature, the submission time and frequency of writing task drafts, etc., to transform into learning behavior data.

#### 2.2.2. Writing process data (such as revision trajectory, dwell time, resource invocation)

Process data directly reveals students' writing strategies and cognitive processes. By integrating text editors or specific plugins, It can record the student's revision trajectory during writing (such as adding or deleting content, adjusting word order), the time spent on different writing paragraphs or sentences, and the frequency of calling online dictionaries, grammar checking tools, or references during writing in turn to writing process data [5].

#### 2.2.3. Writing output data (such as language complexity, content relevance, structural logic)

The output data is the final composition text itself, which can be quantitatively analyzed using natural language processing techniques. Indicators include lexical complexity (such as lexical richness, proportion of advanced vocabulary), syntactic complexity (such as average sentence length, frequency of use of clauses), content relevance (the degree of conformity to the requirements of the topic), and assessment of the logical structure and coherence of the text through discourse analysis techniques. Such data provide a basis for objectively evaluating the quality of writing and shift to the evaluation of writing quality.

### 2.3. Learning analysis dimensions and the establishment of personalized feedback indicators

#### 2.3.1. Dimensions of learning behavior analysis: engagement, regularity, collaboration indicators

Engagement metrics include login frequency, task completion rate, depth of resource access, etc., which are used to identify students with insufficient learning engagement. Regularity metrics examine whether the time distribution of learning activities is balanced to avoid last-minute rush. Collaboration metrics focus on the quality of students' comments in discussion forums, the number and depth of comments on peers' homework, It reflects a shift in collaborative learning ability.

#### 2.3.2. Writing proficiency analysis dimensions: language accuracy, content richness, logical indicators

The language accuracy indicator is achieved through automatic grammar and spelling checks. The content richness can be measured by keyword coverage, the number of arguments, etc. The logic can be evaluated by text analysis tools for the use of conjunctions, transitions and connections between paragraphs. For students with persistently low language accuracy, the system can recommend targeted grammar exercises. For students with empty content, Push relevant reading materials to inspire thinking, and for students with confused logic, provide model essay structure analysis tools to shift towards improving writing skills.

#### 2.3.3. Dimensions of learning path analysis: mastery of knowledge, identification of weak points, indicators of development potential

By analyzing the behavior and output data of students in different knowledge units (such as argumentative writing, practical writing), the degree of their mastery of knowledge in each unit can

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be judged, and the weak points of knowledge (such as incorrect use of specific tenses) can be precisely identified. Further, by analyzing the attempt strategies of students to solve complex problems, their development potential can be evaluated accordingly, The system can plan personalized learning paths for students and recommend the next focus of learning to shift towards learning path planning.

## 3. Practical application and effect analysis of personalized feedback mechanism

### 3.1. Teaching experiment design and implementation process

This study conducted a one-semester teaching experiment in a writing course for the second-year English major at a university, aiming to shift from comparing the differences in teaching effects between personalized feedback mechanisms based on learning analysis techniques and traditional feedback models to comparing teaching effects.

#### 3.1.1. Subjects, duration and course content arrangement

Two parallel classes with no significant differences in entrance scores and previous writing skills were selected for the experiment. One was set as the experimental class (n=45) and the other as the control class (n=45). The experiment lasted for one semester (16 weeks), and both classes used the same textbook. The teaching content systematically covered writing knowledge and skills training in three core genres: narrative, expository, and argumentative. To ensure consistency of the teaching intervention variables, the teaching task for both classes was shifted from being undertaken by the same teacher with more than five years of teaching experience to teaching experiment design.

#### 3.1.2. The setting of the experimental group (applying the new mechanism) and the control group (traditional feedback)

The experimental class adopted the personalized feedback mechanism based on learning analysis technology constructed in this study. Teachers utilized online writing platforms integrated with learning analysis functions (such as the integrated environment of Moodle and iWrite) to assign writing tasks, release learning resources, and organize online discussion activities. The feedback session was strictly based on the learning analysis reports provided by the platform (such as learning behavior analysis, writing process data, text feature analysis), achieving an organic combination of system automatic feedback, teacher targeted manual feedback and system-recommended peer review to shift to the implementation of the feedback mechanism.

The control class adopts the conventional blended teaching process. The online platform is mainly used for course notification, distribution of teaching resources and assignment submission. The feedback session is mainly based on the teacher correcting the final submitted composition, focusing on grammar correction and content comments, lacking systematic collection and analysis of learning process data. There is also a shift from data-based personalized resource push or activity recommendation to the traditional feedback model.

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## 3.2. Feedback implementation cases supported by learning analytics technology

### 3.2.1. Personalized resource push and practice feedback for students with weak vocabulary foundations

The platform analyzed the text data of student A's previous compositions, calculated his vocabulary complexity indicators (such as vocabulary diversity index, proportion of academic vocabulary), found that this indicator was consistently below the class average, and there was a phenomenon of repeated use of high-frequency basic vocabulary. The system automatically triggered the intervention mechanism, The "Advanced Vocabulary replacement package" and contextualized exercises that are highly relevant to the current writing topic were pushed to the student. After the teacher reviewed the learning situation report generated by the platform, targeted guidance was given in the composition annotations. The platform data analysis shows that there is considerable room for improvement in vocabulary diversity, and the system has customized specific vocabulary exercises for you. Please focus on the usage of words such as' indispensable ', 'conventional', 'paradigm', and try to use them in your revision. This feedback mode closely links problem diagnosis with solutions, achieving a shift from precise empowerment to lexical feedback.

### 3.2.2. Feedback on model essay comparison analysis and reconstruction guidance for students with disordered logical structure

Student B's composition scored significantly lower in the structural logic analysis module of the platform. The system diagnosed that there was a lack of effective transitions and connections between paragraphs. Instead of using the general "unclear logic" comment, the teacher used the "model comparison" function of the platform to juxturalize student B's composition with a high-scoring model with a clear structure for comparison. And using the annotation tool to visually mark the transitional and topic sentences in the model text, the teacher's feedback clearly pointed out that please compare the model on the right and observe how it uses' However, this view neglects... 'at the end of the second paragraph. To make semantic transitions and naturally lead to the new argument of the third paragraph, it is suggested to imitate this method and add a transitional sentence between the second and third paragraphs of your article. This kind of feedback based on visual comparison enables students to intuitively understand the structural features of excellent texts and effectively guide them to make revisions and turn to logical feedback.

### 3.2.3. Progressive task setting and positive incentive feedback for students with writing anxiety

Analysis of platform behavior logs revealed that student C showed typical signs of writing anxiety by frequently logging into the platform before the task deadline, repeatedly checking the task requirements and related materials, but the submission time of the first draft was seriously delayed or needed to be urged multiple times. After the teacher received the learning status warning sent by the system, instead of simply urging, through the platform's task management function, This student was given a decomposed sub-task goal of submitting only a detailed writing outline in the first week, completing the introduction part in the second week, and completing the full text in the third week. At each sub-task stage, the teacher gave positive and encouraging comments and particularly affirmed the interim results.

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### 3.3. Data-driven assessment of the mechanism's application effect

#### 3.3.1. Comparative analysis of writing scores before and after tests

Before the experiment, a pre-test composition assessment (with a full score of 100 points) was conducted for the two classes. The independent sample t-test was used to analyze the scores. The results showed that there was no significant difference in the composition scores between the two classes ($t(88)=0.45, p=0.652>0.05$), indicating that the experimental group and the control group were at the same level at the beginning of the experiment. After one semester of teaching intervention, The post-test was conducted and the independent sample t-test was performed again. The results showed that the average composition score of the experimental class was significantly higher than that of the control class ($t(88)=2.89, p=0.005<0.01$). To further explore the details of the differences, the composition sub-item scores were analyzed (see Table 1), and it was found that in high-level writing skills such as logic and content richness, The advantages of the experimental class were more prominent, and the analysis of the scores was turned.

Table 1. Comparison of post-test composition scores between experimental classes and control classes (M±SD)

| Scoring dimensions | Experimental class (n=45) | Control class (n=45) | t value | p value |
|---|---|---|---|---|
| Language accuracy (30 points) | 25.2±2.1 | 24.8±2.4 | 1.12 | 0.266 |
| Content richness (35 points) | 28.9±3.2 | 26.3±3.8 | 3.56 | 0.001 * * |
| Logical structure (35 points) | 29.5±2.8 | 26.8±3.5 | 4.01 | 0.000 * * * |
| Total score (100 points) | 83.6±5.7 | 77.9±7.2 | 2.89 | 0.005 * * |

Note :$p<0.05, p<0.01, p<0.001$

#### 3.3.2. Analysis of changes in students' learning behavior and engagement

The log data generated by the teaching platform throughout the semester was mined and analyzed. The comparison of key indicators is shown in Table 2. The data indicates that the students in the experimental class significantly outperformed the control class in all indicators representing the depth of learning engagement. The students in the experimental class visited the platform more frequently, not only completing basic tasks but also being more active in resource exploration and interactive discussions. The number of essay revisions was also significantly higher than that of the control class, reflecting a stronger autonomous learning and a more refined writing attitude towards behavioral analysis.

Table 2. Comparison of platform learning behavior data between experimental class and control class (M±SD)

| Behavioral indicators | Experimental class (n=45) | Control class (n=45) | t value | p value |
|---|---|---|---|---|
| Average weekly logins | 5.8±1.5 | 4.2±1.8 | 4.67 | 0.000 * * * |
| Task point completion rate (%) | 96.5±3.2 | 88.3±10.1 | 5.12 | 0.000 * * * |
| Average access depth of resources (pages/times) | 8.5±2.1 | 5.7±2.6 | 5.89 | 0.000 * * * |
| Average number of posts in the discussion area | 12.3±4.5 | 7.8±5.2 | 4.45 | 0.000 * * * |
| Average number of revisions per essay | 3.5±1.2 | 1.8±0.9 | 7.81 | 0.000 * * * |

To measure the extent of learning progress, the GainScore, which is the difference between the post-test score and the pre-test score, is used as a formula:

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$$G = Post - test - Pre - test \tag{1}$$

Here, G represents the gain score, Post-test represents the post-test score, and Pre-test represents the transition from the pre-test score to the gain score calculation.

## 4. Closing remarks

This study systematically constructs and validates a personalized feedback mechanism for English major blended writing instruction based on learning analytics techniques. Practice shows that this mechanism, through data-driven precision diagnosis and multimodal feedback strategies, effectively improves students' writing skills, learning engagement and self-efficacy. It not only breaks the predicament of traditional feedback, It has also enabled the transformation of teaching from experience-oriented to data-evidence-based, providing strong support for the reform of English writing teaching.

## References

[1] Feng Xueqi, Zhang Yan. Research on Blended Teaching Model Based on Feedback Principle [J]. Shanxi Youth, 2025, (18): 12-15.
[2] Liu Ying. The Blended Model Helps Students Improve Their English Writing Literacy [J]. English Illustrated (High School Edition), 2025, (15): 43-45.
[3] Fu Lin. The Application of Blended Teaching in English Writing Teaching in Secondary Vocational Schools [J]. Students, Parents and Society, 2025, (15): 84-86.
[4] Wang C. Research on the Blended Teaching Model of Professional English and Writing Course for Postgraduate Students [J]. Chemical Engineering Management, 2025, (09): 25-28..
[5] Sun Xinxin, Hu Jingjing. Research on the Application of Blended Teaching Model in the Teaching of English Writing in Senior High School [J]. Overseas English, 2025, (05): 151-153.