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Optimization Mechanism for Linking Digital Learning Analysis and Teaching Decisions in English Education

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Abstract This study addresses grammar correction tasks in English education by proposing the GET-MF model, which optimizes correction efficiency and adaptability through modular design. By integrating unsupervised clustering technology, personalized teaching strategies are developed. Using 100 English major students from a certain university as the research subjects, the effectiveness of digital English education is validated through the Global Competence Level Questionnaire and tests. The mean global competence score of the experimental group (4.02) was higher than that of the control group (3.74), and there was a significant difference in global competence between the two groups ($p=0.002$). The mean global competence score of low-level students in the experimental group (3.82) was lower than that of high-level students (4.04), and there was no significant difference in global competence between low-level and high-level students ($p > 0.05$). Additionally, there was no significant difference in the pre- and post-test scores of global competence among low-level students ($p > 0.05$), while there was a significant difference in the pre- and post-test scores of global competence among high-level students ($p = 0.002$).

Index Terms English education, GET-MF model, unsupervised clustering, grammar correction, personalized teaching

I. Introduction

The digital transformation of English education refers to the process of leveraging modern information technology to drive profound changes in English education models, educational content, teaching methods, and school management, with the aim of enhancing the quality and efficiency of English education [1]-[3]. As information technology continues to advance and educational demands grow, the digital transformation of education has become a critical task in educational reform [4], [5]. Accelerating the digital transformation of English education and continuously promoting the deep integration of information technology with educational governance and teaching practices is not only an urgent requirement for the high-quality development of English education but also an important manifestation of fulfilling the fundamental task of cultivating virtue and fostering talent [6]-[9].

The digital transformation of English education holds multiple significances, including the following key aspects: (1) Improving educational quality: Digital technologies can provide teachers with abundant teaching resources and diverse teaching methods, helping to stimulate students' interest and enthusiasm for learning, thereby enhancing teaching quality [10]-[12]. Additionally, digital technologies can enable personalized instruction to meet the diverse learning needs of students, promoting their comprehensive development [13], [14]. (2) Expanding educational resources: Digital technology can break through geographical, temporal, and spatial constraints, enabling high-quality educational resources to be disseminated and applied more widely [15], [16]. Students can access high-quality educational resources from around the world through the internet, broadening their knowledge and enhancing their overall competence [17], [18]. (3) Promoting educational equity: Digital technology can reduce educational costs, enabling more students to access high-quality education [19]. Especially in remote and impoverished areas, digital technology can help narrow the educational gaps between urban and rural areas and between the wealthy and the poor, thereby promoting educational equity [20], [21]. (4) Cultivating innovative talent: Digital technology provides students with abundant practical opportunities, helping to foster their innovative thinking and practical skills [22], [23]. In a digital environment, students can better leverage their creativity to contribute to societal development [24].

Literature [25] examines the advantages of educational digital transformation and analyzes reform strategies for university English education in the context of transformation, aiming to provide references for educators and stakeholders in the education sector. Literature [26] constructs an English multi-modal teaching system centered on the integration of multi-modal resources through promoting the application of multi-modal teaching models, optimizing teaching design, and improving the course evaluation system, aiming to promote students' comprehensive development in knowledge, skills, and abilities. Literature [27] examined datasets on students' and teachers' use and perceptions of digital tools, revealing that both groups use a limited number of digital technologies to complete primary assimilation tasks, and proposed recommendations to support broader use of technology for educational purposes. Literature [28] explores the digital transformation of foreign language teaching, emphasizing that it not only provides new opportunities and roles for teachers and students but also enables them to benefit from the digital transformation. It also highlights the promotional role of digital transformation in enhancing motivation for foreign language learning.

Literature [29] discusses the concepts of “creative thinking” and “creative thinking skills,” explores the possibilities of creative collaboration between teachers and students, and finally investigates the impact of corpus technology in an experimental design on the development of students' creativity, revealing that corpus technology plays an important role in enhancing students' creative thinking abilities and English learning efficiency. Literature [30] examines the impact of digital transformation on vocational English education in China, elucidating the positive effects of digitalization on teaching methods and educational quality, and revealing that the application of technologies such as online learning management systems and virtual reality enhances the interactivity and practicality of vocational English education. Literature [31] identifies issues in digital English teaching at the junior high school level, analyzes other unidentified problems through case studies, and communicates solutions based on data collected in this field.

This paper first proposes the GET-MF model, which breaks down the error correction task into error type prediction and specific modification execution. Unsupervised clustering technology is introduced to provide a basis for personalized teaching. A sample of 100 students majoring in English at a key university in City C, Province A, was selected as the research subjects, with a one-year teaching practice period established. Based on user behavior records from the teaching platform, cluster analysis was conducted to explore the learning styles and motivation types of the experimental group students. Combining questionnaire and test results on global competence levels from both groups of students, a systematic analysis was conducted on the impact of digital teaching on learners' global competence.

II. Digital-driven English grammar error correction and personalized teaching technology roadmap

In the context of global educational digital transformation, English education is undergoing a shift from traditional experience-driven to data-driven approaches. In traditional English instruction, grammar correction relies on manual feedback, which is inefficient and unable to meet personalized needs; the diverse characteristics of learners' styles and motivations also require teaching decisions to be more precisely tailored to individual needs. In this context, learning analytics, as a key technology connecting educational data with teaching practices, offers new pathways for optimizing teaching decisions by analyzing learner behavior data, cognitive characteristics, and emotional states.

This study focuses on two core issues in the digital transformation of English education: first, how to enhance the efficiency and adaptability of grammar correction through technological tools; second, how to achieve personalized optimization of teaching decisions based on learner characteristic analysis.

II. A. Overview of the GET-MF Model

This paper first redefines the task of automatic grammar correction. Given a sequence $x=(x_1,\cdots,x_n)$ containing grammatical errors, we want to modify it without changing its original meaning and restore it to a sequence $y=(y_1,\cdots,y_N)$ without altering its original meaning, where n and m may not be equal. For this purpose, we define an automatic grammar correction task as follows: given a sequence x containing grammatical errors, for each $x_i, i\in 1,\cdots,n$, output a combination $z_i=(e_1,w_i), e_i\in E, w_i\in V_{e_i}$, where e_i is the modification method corresponding to x_i, and w_i is the word corresponding to x_i and e_i.

Specifically, if e_i is to keep x_i unchanged or delete x_i, in this case we do not need to output any words, then $V_{ei}=\varnothing$; if e_i is to insert a word before x_i or replacing x_i with another word, then V_{ei} is all the words that can be used in that sequence.

Correspondingly, a grammar error correction model M is defined as:

$$M(x)=z=(z_1,\cdots,z_n)=((e_1,w_1),\cdots,(e_n,w_n)), e_i\in E, w_i\in V_{e_i} \tag{1}$$

Based on the above definition, we further divide the task of correcting grammatical errors into two tasks that can be completed sequentially and propose a modularized approach to the model, constructing GET and MF modules corresponding to the two tasks.

First, the GET module attempts to assign an error label e_i to each token in a text sequence $x = (x_1, \cdots, x_n)$, where $e_i \in E$. Unlike some studies that predict the error type for each token (e.g., verb tense, incorrect use of definite articles, or incorrect use of prepositions), we adopt an editing-label approach, aiming to predict the optimal modification method for each token. Here, we only propose whether modification is needed and what kind of modification is needed. For each token at each position, we output a feasible modification method e_i, which includes retention, replacement, insertion, deletion, etc. Therefore, the GET module is defined as:

$$GET(x) = e = (e_1, \cdots, e_n), e_i \in E \tag{2}$$

Second, the MF module modifies the original sentence after obtaining the editing label. There are two main types of modifications. The first type does not require any additional information and can be completed based on the label alone. The second type requires searching for the best word in a certain vocabulary after obtaining the label. For the second type, we propose using another masked language model or existing manually coded rules to predict the content that needs to be supplemented or replaced. Therefore, the MF module is defined as:

$$MF(x, e) = ze = (w_1, \cdots, w_n), w_i \in V_{e_i} \tag{3}$$

The basic structure of the GET-MF model is shown in Figure 1. We have divided the model into two modules: GET and MF. In the GET module, since the model only needs to predict the modifications required for each word, it simplifies the output space of a general grammar error correction model while ensuring no duplication or omission, enabling this module to focus more on the task during training and prediction. In the MF module, the words that the model can correct are no longer limited to the finite vocabulary defined during model design. The expansion of the vocabulary output by the module does not significantly impact the model's speed. Furthermore, for texts with different themes, the module's output word distribution can be adjusted through fine-tuning, enabling it to better adapt to syntax correction in various contextual settings.

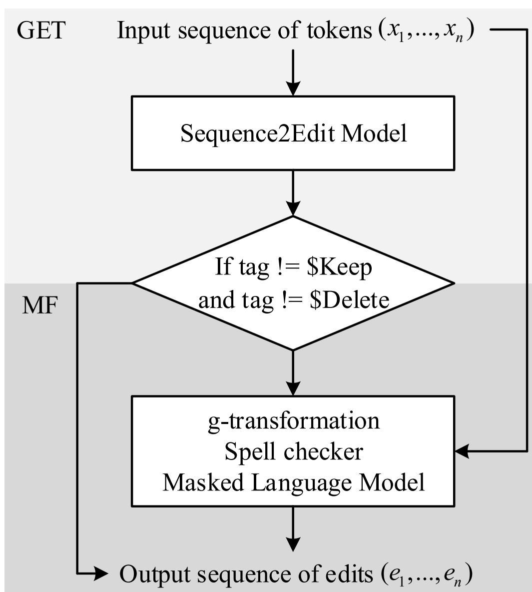


Figure 1: Schematic diagram of the GET-MF model structure

II. B. Unsupervised clustering techniques

II. B. 1) Fuzzy C-means clustering algorithm

The Fuzzy C-Means Clustering Algorithm (FCM) is a type of soft clustering method. The FCM algorithm assumes that the dataset contains n samples, which can be represented as $X = (x_1, x_2, \cdots, x_n)$. Under the specified constraints, the FCM algorithm combines an optimization objective function to calculate the membership degree of each sample to each cluster center. Based on the membership values, the algorithm can automatically determine the category to which each sample belongs, thereby achieving automatic classification of the samples. The objective function of the FCM algorithm is shown in Formula (4), and the constraints are shown in Formula (5).

$$O_m(U, C) = \sum_{i=1}^{c} \sum_{j=1}^{n} U_{ij}^m D^2(x_j, C_i) \tag{4}$$

$$\sum_{i=1}^{c} U_{ij} = 1; \forall j \tag{5}$$

where U_{ij} denotes the membership degree of the j th sample in the C_i th cluster, m denotes the fuzzy degree of the algorithm, and D denotes the distance between the sample and the cluster center, which is generally calculated using the Euclidean distance.

The steps of the fuzzy C-means clustering algorithm are as follows:

(1) Randomly initialize the cluster centers C_i, given the maximum number of iterations L, the number of clusters K, and the allowed error value ε;

(2) Use equation (6) to calculate the distance D between the sample and the cluster center;

$$D^2(x_j, C_i) = \| x_j - C_i \|^2 \tag{6}$$

(3) Use equation (7) to calculate membership degree U_{ij};

$$U_{ij} = \frac{(D(x_j, C_i))^{-1/(m-1)}}{\sum_{k=1}^{c} (D(x_j, C_i))^{-1/(m-1)}} \tag{7}$$

(4) Update cluster center C_i using formula (8);

$$C_i = \sum_{j=1}^{n} U_{ij}^m x_j \Big/ \sum_{j=1}^{n} U_{ij}^m \tag{8}$$

(5) Repeat steps 2 to 4 until the difference between the latest cluster center value C_{new} and the old cluster center value C_{old} is less than ε or the number of iterations reaches the maximum iteration count.

The core steps of the Fuzzy C-Means clustering algorithm involve continuously iterating to update the cluster center C_i and optimize the objective function. Due to its low time complexity, this algorithm has been widely adopted. However, the FCM algorithm still has several limitations, primarily as follows:

(1) The number of clusters K in the FCM clustering algorithm must be determined in advance. Different values of K can lead to significant differences in clustering results, and multiple experiments may be required to determine the optimal K.

(2) The FCM clustering algorithm is sensitive to noise and outliers, which can significantly impact clustering results.

(3) The FCM clustering algorithm is sensitive to initial cluster centers, which can lead to the objective function converging locally and failing to reach the global optimal solution.

II. B. 2) K-means clustering algorithm

The K-means clustering algorithm plays a significant role in big data mining technology. As a divisive hard clustering algorithm, the K-means algorithm stands out among other clustering algorithms due to its excellent performance and simple underlying principles, earning widespread recognition and application in both industrial and research fields. The basic principle of this algorithm is to divide the samples in a dataset into K clusters such that each sample belongs to the nearest cluster center, and each cluster center is the mean of all samples belonging to that cluster. In the K-means algorithm, the Euclidean distance formula is a commonly used distance measurement method for calculating the similarity or distance between any two sample points in a dataset. Let the dataset D contain n sample points, i.e., $D = \{x_1, x_2, \ldots, x_n\}$, where each sample point x_i is a multidimensional feature vector. The Euclidean distance formula between any two sample points x_p and x_q is calculated as follows:

$$d(x_p, x_q) = \sqrt{\sum_{i=1}^{m} (x_{pi} - x_{qi})^2} \tag{9}$$

where $x_p = \{x_{p1}, x_{p2}, \cdots, x_{pm}\}; x_q = x_{q1}, x_{q2}, \cdots, x_{qm}$; m is the dimension of the sample elements.

The K-means clustering algorithm process is as follows:

(1) Randomly initialize the number of clusters K and the cluster centers, with the maximum number of iterations set to N;

(2) Calculate the Euclidean distance d between each sample and the cluster center using formula (9), and assign each sample to the nearest cluster center, making it a member of that cluster center;

(3) Calculate the mean of the samples in each cluster and update the cluster center;

(4) Repeat steps 2 and 3 until the cluster centers no longer change.

The advantages of the K-means algorithm are its fast convergence and good clustering results, making it suitable for clustering large-scale datasets. However, the traditional K-means clustering algorithm has the disadvantage that the number of clusters K must be set manually. If the value of K and the clustering centers are selected randomly, the accuracy and scientific validity of the clustering results cannot be guaranteed. Therefore, the optimal value of K should be determined based on the data itself. The commonly used method for determining the number of clusters K is the elbow method. During the K-means clustering process, the algorithm divides the data. As the value of K increases, the degree of data division also increases, while the sum of squared errors (SSE value) decreases. In the plot of the relationship between the SSE value and the K value, the following trends can be observed: as the K value approaches the actual number of clusters, the fluctuation in the SSE value significantly increases; when the K value exactly equals the actual number of clusters, further increases in the K value result in a gradually flattening trend in the SSE value. The optimal value of K is determined based on the relationship between the SSE value and K value. The SSE formula is as follows:

$$SSE = \sum_{i=1}^{K}\sum_{j=1}^{r_i}(x_j - v_i)^2 \tag{10}$$

In equation (10), K is the number of clusters; r_i is the number of sample elements in the i th cluster; x_j is a sample element in the i th cluster; v_i is the mean value of all sample elements in the i th cluster.

III. Research on the Practice of Digital English Education

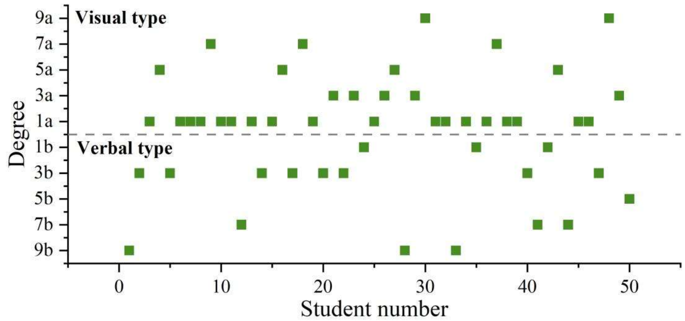
III. A. Data Sources

The research data for this paper is sourced from the teaching platform discussed herein. The platform employs the GET-MF model as its grammar correction model, providing registered users with a diverse range of multilingual dictionaries, primarily English dictionaries, supplemented by dictionaries in Japanese, Korean, German, and other less commonly used languages. The platform integrates design elements from games into traditional vocabulary learning scenarios, using gamified forms such as level-based challenges, competitive play, and team-based activities to stimulate user interest and enhance engagement. Users complete the registration process under the guidance of the platform's login interface and begin a vocabulary assessment. The system's algorithm estimates the user's initial vocabulary size based on their performance in the assessment, helping them identify their current proficiency level: Before starting vocabulary learning, users must select one or more vocabulary books as textbooks. Each vocabulary book is divided into several levels based on the number of words, and users must master the vocabulary in the current level to unlock the next level. The process of learning vocabulary is referred to as “leveling up.” After completing a round of leveling up, users can compete with randomly matched opponents or their friends to test their current learning outcomes. Additionally, users can decide whether to review previously learned words or check their rankings on the leaderboard based on their needs. Every learning session on the platform leaves corresponding usage records, and these real historical behavioral data form the research dataset for this study.

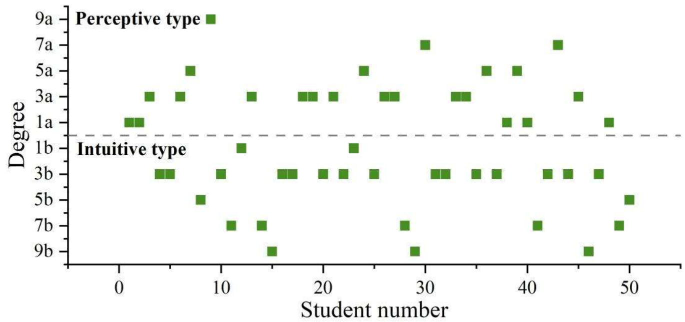
This study selected 100 students from the English major at a key university in City C, Province A as the research subjects. Among them, 50 students used the teaching platform described in this paper and employed clustering technology to achieve personalized teaching, forming the experimental group. The remaining 50 students received conventional instruction and were designated as the control group. English learning data from the experimental group in 2024 was collected. To address issues such as missing or invalid values caused by online data upload anomalies, such data must first be cleaned and supplemented before analysis. After data cleaning, Min-Max normalization is performed to ensure consistent units of measurement, facilitating subsequent data analysis and comparison.

III. B. Learning Style Analysis

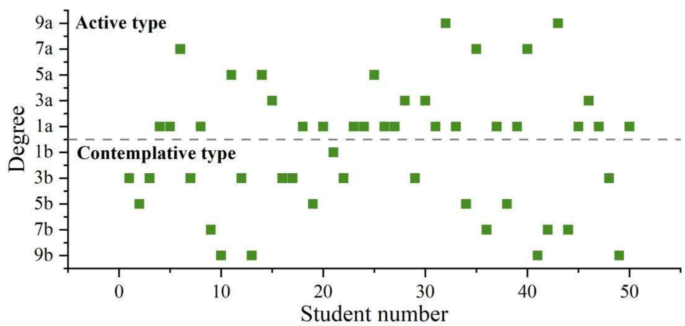
To understand students' learning style preferences and types, we visualized the learning style preferences of each student in the experimental group using experimental data. The distribution results of learning styles across four dimensions are shown in Figure 2 (a–d). The format of numbers combined with letters on the vertical axis represents learning style types and their degrees. Points above the central axis tend toward the previous type of style within that dimension, while points below the central axis tend toward the subsequent type of style within that dimension. The farther a point is from the central axis, the more unbalanced it is. To present each student's style type as intuitively as possible, the horizontal axis represents the student's ID number, with the ID number increasing from bottom to top. Based on the statistical results, in the information input dimension, visual types are more common than verbal types. In the information perception dimension, intuitive types are more common than perceptive types. In the information processing dimension, active types are more common than reflective types. In the information understanding dimension, holistic types are predominant. Holistic learning styles tend toward visual, intuitive, active, and holistic types, but in all four dimensions, balanced types are the most common.



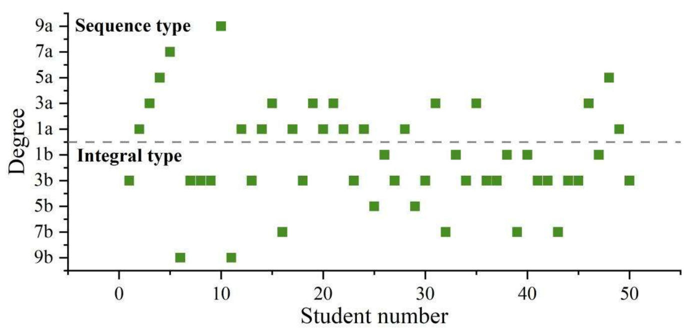
(a)Information input dimension



(b)Information perception dimension



(c)Information processing dimension



(d)Information understanding dimension

Figure 2: Visualization results of learning styles

III. C. Analysis of Motivation Types

III. C. 1) Motivational factors

The nine variables in learning motivation include seven motivational factors and two motivational outcomes. In addition to the three factors in the second language self-system—ideal self, should self, and second language learning experience—several other closely related factors have been incorporated. Upon examining the data characteristics of the experimental group, it was found that the data carried by each category of samples followed a discernible pattern. Referring to the classification numbers from previous studies, the optimal number of classifications for student learning motivation was determined to be five, and these were represented using a backbone diagram. Next, K-means clustering was performed. The initially determined classification number of five was input into the clustering statistical program for all samples. After 15 iterations, the mean values of various motivational factors for the five categories of learners (with a maximum score of 5 points) were obtained, as shown in Table 1. The first category of students exhibited generally low motivation, with scores for most factors being the lowest among the five categories. Additionally, except for instrumental motivation, the scores for other motivational factors were below the critical threshold ($M < 3$). In contrast, the fifth category of students exhibits the strongest motivation, with scores for all motivational factors nearly reaching the peak among all categories of learners, indicating that they possess clear self-identity, enjoy the language learning process, have strong cultural interests, and also exhibit strong instrumental motivation. The second category of students has moderate scores for learning experience and instrumental motivation. The third category of students showed a steady increase in scores for most motivational factors compared to the first two groups, with their combined distribution pattern most closely resembling that of the fifth category. The fourth category of students exhibited two opposing traits: they scored high in ideal self, learning experience-promoting instrumental motivation, and cultural attitude, but their should self and preventive instrumental motivation scores were the lowest among all learners.

Table 1: Means of various motivational factors of the five types of learners

	The first category	The second category	The third category	The fourth category	The fifth category
Ideal self	2.68	3.12	3.72	4.66	4.72
Should be self	2.82	3.26	3.70	2.78	3.98
Second language learning experience	2.60	3.48	3.78	4.68	4.66
Facilitative instrumental motivation	2.94	3.44	3.92	4.18	4.74
Preventive instrumental motivation	3.28	3.52	4.24	3.18	4.24
Family influence	2.78	3.28	3.54	3.04	4.12
Cultural attitude	2.02	3.16	3.04	4.24	4.18

Since cluster analysis is merely an exploratory analytical method, to verify whether the intergroup differences in the cluster results are indeed heterogeneous, a one-way analysis of variance (ANOVA) was subsequently conducted to test the intergroup differences among the five categories of students for each motivational factor. The test results are shown in Table 2, where "**" indicates $p < 0.01$ and "*" indicates $p < 0.05$. For the ideal self variable, the intergroup differences were 1 < 2 < 3 < 4, 5 ($F = 134.87$, $p = 0.004$), indicating that there were significant differences between all groups except for the fourth and fifth categories. For the should self variable, the intergroup differences were significant, with 4 < 1 < 2 < 5 < 3 ($F = 457.49$, $p = 0.001$). In terms of second language learning experience, the group differences were 1<3, 2<4, 5 ($F=98.58$, $p=0.003$). There were no significant differences between the third and second groups, nor between the fourth and fifth groups, but there were significant differences between the remaining groups. In terms of the promotional and preventive tool dimensions, the group differences were 1<2<4, 3<5 ($F=592.62$, $p=0.001$) and 4<1<2<3,5 ($F=90.34$, $p=0.001$), respectively, indicating significant differences between groups. In terms of family influence, 1<4<2<3<5 ($F=91.49$, $p=0.023$), with group differences showing marginal significance. In terms of cultural attitudes, the differences were 1<3<2<5,4 ($F=335.24$, $p=0.001$), with the exception of the fifth group, which showed no significant difference from the fourth group, while the remaining groups showed significant differences. The above analysis indicates that the five categories of students exhibit significant differences across various motivational factors, confirming the reliability of the cluster analysis results.

Table 2: Results of the difference test between groups

	The first category	The second category	The third category	The fourth category	The fifth category	Post Hoc(Turkey)	F value
Ideal self	2.68	3.12	3.72	4.66	4.72	1<2<3<4,5	134.87**
Should be self	2.82	3.26	3.70	2.78	3.98	4<1<2<5<3	457.49**
Second language learning experience	2.60	3.48	3.78	4.68	4.66	1<3,2<4,5	98.58**

Facilitative instrumental motivation	2.94	3.44	3.92	4.18	4.74	1<2<4,3<5	592.62**
Preventive instrumental motivation	3.28	3.52	4.24	3.18	4.24	4<1<2<3,5	90.34**
Family influence	2.78	3.28	3.54	3.04	4.12	1<4<2<3<5	91.49*
Cultural attitude	2.02	3.16	3.04	4.24	4.18	1<3<2<5,4	335.24**

III. C. 2) Comparison between promotion-oriented groups and prevention-oriented groups

Regulatory focus types can provide validation for the conceptual framework within the second language self-system, so it is necessary to conduct between-group difference tests on students with different regulatory focus types. Since the ideal self is closely related to promotion orientation and the should self is closely related to prevention orientation, a common method in motivational psychology research was used to group students based on regulatory focus. Specifically, the ideal self score was subtracted from the should self score. If the difference was positive, it indicated that the student's ideal self was stronger, making them a promotion-oriented learner; if the difference was negative, it indicated that the student's should self was stronger, making them a prevention-oriented learner. All students were categorized into 31 promotion-oriented learners and 19 prevention-oriented learners based on their regulatory focus orientation. The results of the independent samples t-tests for all variables are shown in Table 3. In terms of the four variables—ideal self ($t = 4.98$, $p = 0.004$), second language learning experience ($t = 9.06$, $p = 0.001$), promotion-oriented instrumental motivation ($t = 1.78$, $p = 0.026$), and cultural attitude ($t = 20.58$, $p = 0.002$), the promotion-oriented group scored significantly higher than the prevention-oriented group, with all differences being statistically significant. However, in terms of self-concept ($t = -7.92$, $p = 0.003$), preventive instrumental motivation ($t = -9.09$, $p = 0.002$), and family influence, the latter group scored higher than the former. The between-group difference in family influence was not significant ($t = -2.06$, $p > 0.05$). Additionally, the promotion-oriented group scored significantly higher than the prevention-oriented group on motivational behavior ($t = 5.29$, $p = 0.002$), but significantly lower on language anxiety ($t = -8.28$, $p = 0.003$), indicating that promotion-oriented individuals exhibit superior motivational and emotional qualities overall compared to prevention-oriented individuals. The t-test results suggest that the classification of students' focus orientations has psychological validity.

Table 3: Results of independent sample t-tests

	Promoting orientation group		Preventive orientation group		t value
	M	SD	M	SD	
Ideal self	4.14	0.56	3.88	0.52	4.98**
Should be self	3.26	0.41	3.94	0.49	-7.92**
Second language learning experience	4.22	0.38	3.42	0.41	9.06**
Facilitative instrumental motivation	4.32	0.55	4.18	0.62	1.78*
Preventive instrumental motivation	3.96	0.67	4.20	0.71	-9.09**
Family influence	3.12	0.49	3.24	0.53	-2.06
Cultural attitude	3.86	0.72	2.34	0.76	20.58**
Motivational behavior	4.26	0.58	3.86	0.63	5.29**
Language anxiety	3.02	0.77	3.28	0.81	-8.28**

III. D. Optimization of Teaching Decisions

The Global Competence Level Survey Questionnaire was designed by experts and distributed at the end of the second semester of 2024, with a 100% response rate. The test content was based on the concept of global competence and utilized language knowledge, listening, speaking, reading, and writing question types to assess students' performance across various dimensions. The tests were conducted at the beginning of the first semester and at the end of the second semester of 2024. The questionnaire and test data were analyzed using SPSS 25.0.

III. D. 1) Students' Global Competence Levels in Digital English Teaching

To test the effectiveness of cultivating global competence through digital English teaching, this study conducted an independent samples t-test on the questionnaire data, with the results visualized in Figure 3. The results show that the mean global competence score of the experimental group (4.02) was higher than that of the control group (3.74), and there was a significant difference between the two groups ($p=0.002$). This indicates that students who underwent digital English instruction demonstrated overall better global competence than those who did not, suggesting that digital English instruction is relatively effective in cultivating global competence.

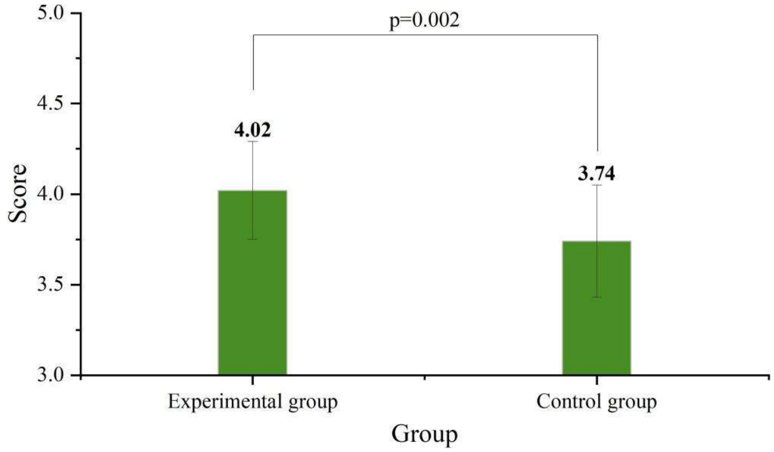


Figure 3: Results of the independent sample t-test for global competency levels

III. D. 2) Effects of ability development on low-level and high-level students

To verify whether there are significant differences in the perception of global competence among students of different proficiency levels in the experimental group under digital English instruction, this study conducted an independent samples t-test on the questionnaire and test data, with the results shown in Figure 4. It was found that the mean global competence score for low-level students (3.82) was lower than that for high-level students (4.04), and there was no significant difference between the global competence levels of low-level and high-level students ($p > 0.05$). This indicates that high-level students perceive and recognize the cultivation of global competence to a greater extent, but overall, there is little difference in the perceived cultivation of global competence between low-level and high-level students. Additionally, there was no significant difference in the pre- and post-test scores for global competence among low-performing students ($p > 0.05$), while there was a significant difference in the pre- and post-test scores for global competence among high-performing students ($p = 0.002$). The post-test mean score for high-performing students (85.6) was nearly 10 points higher than the pre-test mean score (77.76), indicating that the cultivation of global competence was more effective among high-performing students.

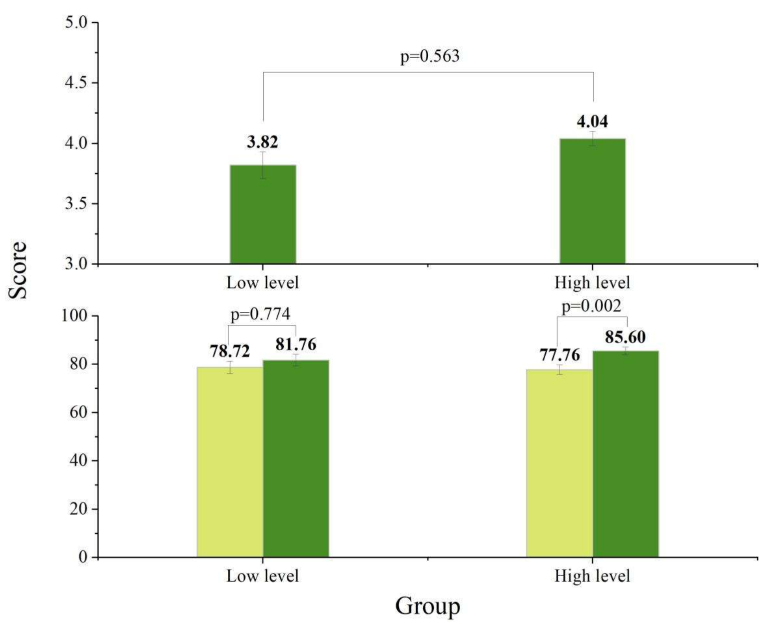


Figure 4: Independent sample t-test results of questionnaire and test data

III. D. 3) Teaching effectiveness of each sub-competency of global competence

To further understand the specific changes in the various sub-components of global competence among low-performing and high-performing students in the pre- and post-tests, this study analyzed the pre- and post-test data. The results of the various sub-components of global competence are shown in Table 4. The improvements in international understanding and cross-cultural communication skills were more pronounced for both low-performing and high-performing students in the pre- and post-tests, with mean differences of -1.08, -3.54, and -2.20, -0.32, respectively. Among these, the improvement in international understanding was more significant for high-performing students compared to low-performing students, as evidenced by the significant difference in test scores between the pre- and post-tests for high-performing students (p=0.002). In terms of intercultural communication skills, the improvement among low-level students was more pronounced, with significant differences in pre- and post-test scores (p=0.001). Additionally, overall, the teaching effects on the other two components of global competence were not significant, with only high-level students showing some improvement in cognitive analytical skills (mean difference -1.28) and reflective action skills (mean difference -2.70).

Table 4: Results of various capabilities of Global Competence

Group	Cognitive analytical ability		International understanding		Cross-cultural communication skills		Reflective action ability	
	Low level	High level	Low level	High level	Low level	High level	Low level	High level
Pre-test	20.18	20.58	19.04	18.94	19.28	20.86	20.22	17.38
Post-test	20.12	21.86	20.12	22.48	21.48	21.18	20.04	20.08
Mean difference	0.06	-1.28	-1.08	-3.54	-2.20	-0.32	0.18	-2.70
Significance	0.993	0.219	0.773	0.002	0.001	0.187	0.208	0.003

IV. Conclusion

This study designed a digital-driven English grammar error correction and personalized teaching technology framework, and explored its practical effectiveness through a controlled experiment.

The mean global competence score of the experimental group students (4.02) was higher than that of the control group students (3.74), and there was a significant difference between the two groups in terms of global competence (p=0.002). The mean global competence score of low-level students in the experimental group (3.82) was lower than that of high-level students (4.04), and there was no significant difference in global competence between low-level and high-level students (p > 0.05). Additionally, there was no significant difference in the pre- and post-test scores of global competence for low-level students (p > 0.05), while there was a significant difference in the pre- and post-test scores of global competence for high-level students (p = 0.002) . In terms of individual competencies, both low-level and high-level students showed significant improvements in international understanding and cross-cultural communication skills between the pre- and post-tests, with mean differences of -1.08, -3.54, and -2.20, -0.32, respectively.

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