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A Study on the Creation of Context and Motivation of Production-Oriented Approach to Literacy Teaching Supported by Multimodal AI Technology

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Abstract Multimodal AI technology provides a new opportunity for the application of the production-oriented approach (POA), especially in reading and writing teaching, AI can enhance the teaching effect and learning motivation by generating authentic communicative scenarios, production difficulty diagnosis and personalized feedback. This paper investigates the application of production-oriented approach (POA) supported by multimodal AI technology in English literacy teaching in colleges and universities. Through experimental comparisons, it explores how the AI-driven teaching mode motivates students' learning and enhances their writing ability. The experimental subjects were two classes (English 1 and English 2) in a college in city B. Class 1 was taught with the AI-supported POA method, and class 2 continued to use the traditional teaching method. Students' affective experience, cognitive level and behavioral tendency changes were assessed through qualitative and quantitative analyses of questionnaires and pre and post writing tests. The experimental results showed that the AI-assisted POA method significantly increased students' learning interest, confidence and writing performance. The students in the experimental group increased 13.57% and 14.07% in the scores of learning interest and confidence, respectively, while in the writing achievement, the mean value of the experimental group was 18.45, higher than that of the control group, which was 14.24, and the difference was significant ($p < 0.05$). The multimodal AI-based teaching model effectively improved students' writing ability and learning motivation, indicating that the combination of POA teaching method and AI technology has good educational potential.

Index Terms production-oriented approach, AI technology, learning motivation, literacy teaching, writing ability, teaching experiment

I. Introduction

Reading and writing teaching plays a crucial role in the development of students' language expression ability and literary literacy. Through reading and writing teaching, students can expand their vocabulary, improve their reading comprehension ability, and cultivate critical and creative thinking, so as to improve their comprehensive quality [1], [2]. At the same time, literacy teaching is also an important way to cultivate students' language expression ability and thinking ability. Through continuous reading and writing, students can improve their expression ability, enrich their thoughts, enhance their self-confidence, and cultivate critical thinking and creative thinking [3]-[5]. However, the current literacy teaching faces these many challenges, such as students' insufficient comprehension of texts and lack of writing skills. These challenges mainly stem from teachers' single teaching method and students' lack of learning motivation, etc. With the application of artificial intelligence, the production-oriented method supported by multimodal AI technology provides support to cope with these challenges [6]-[8].

The production-oriented approach is a student-centered teaching model that emphasizes the promotion of students' language proficiency through production activities in actual language use situations [9], [10]. The approach holds that students' language use and communicative competence can be effectively enhanced by designing challenging language production tasks [11]. Multimodal AI technology, on the other hand, refers to artificial intelligence technology that can process and integrate multiple modalities of information (e.g., text, image, speech, video, etc.), aiming to understand and generate information more comprehensively and accurately for more intelligent and natural human-computer interaction [12]-[14]. This technology can provide dynamic context construction and personalized feedback support for the above teaching methods by integrating images, text, video, etc. Dynamic learning context can effectively stimulate students' motivation to learn, while personalized feedback can be targeted for teaching, which can effectively improve the effect of literacy teaching.

This study investigates whether the multimodal AI-supported POA pedagogy can motivate students' learning in actual teaching and learning by means of comparative experiments, especially the effectiveness of its application in English reading and writing teaching. Through a teaching experiment with two classes, this paper will analyze how AI technology plays a role in the three aspects of motivating, enabling and evaluating, and assess its impact on students' motivation and writing ability.

II. AI-supported Context Creation for Literacy Teaching Based on the POA Method

The multimodal AI-enabled production-oriented approach (POA) aims to enhance the teaching effect of literacy teaching and students' learning experience by means of AI technology. This paper mainly combines generative AI technology to analyze the context creation of POA method applied to literacy teaching.

II. A. Production-oriented Approach

POA theory combines cognitive linguistics and communicative language pedagogy to promote the development of learners' language abilities through practical language tasks. It is based on the core teaching concepts of "learning center", "integration of learning and application", "cultural exchange" and "key competencies", and is supported by four teaching assumptions, namely, the production-driven hypothesis that asserts that language production is the key to improving language ability, the input-enabled hypothesis that emphasizes the importance of high-quality input, the selective learning hypothesis which advocates the selection of learning content according to production objectives, and the evaluation-based learning hypothesis which emphasizes the role of evaluation and feedback in the learning process. Together, these ideas and assumptions guide the teaching process, content selection, and goal setting.

POA theory adopts the "motivate-enable-evaluate" model to form a circular chain to achieve the objectives of the teaching unit. Each teaching unit is defined by an overall goal, which is further subdivided into a number of small production targets. These small goals are achieved through a micro-cycle of "motivate-enable-evaluate", which are independent but logically related to ensure the coherence and systematization of teaching. With the completion of these circular chains, the achievement of small goals one by one jointly promotes the achievement of big goals. The theoretical system of the production-oriented approach is shown in Figure 1. Through this structured and hierarchical teaching design, the POA theory system not only emphasizes the subjective position of learners in the teaching process, but also advocates promoting the all-round development of learners' abilities through practical production, providing an innovative and effective teaching model for literacy teaching education.

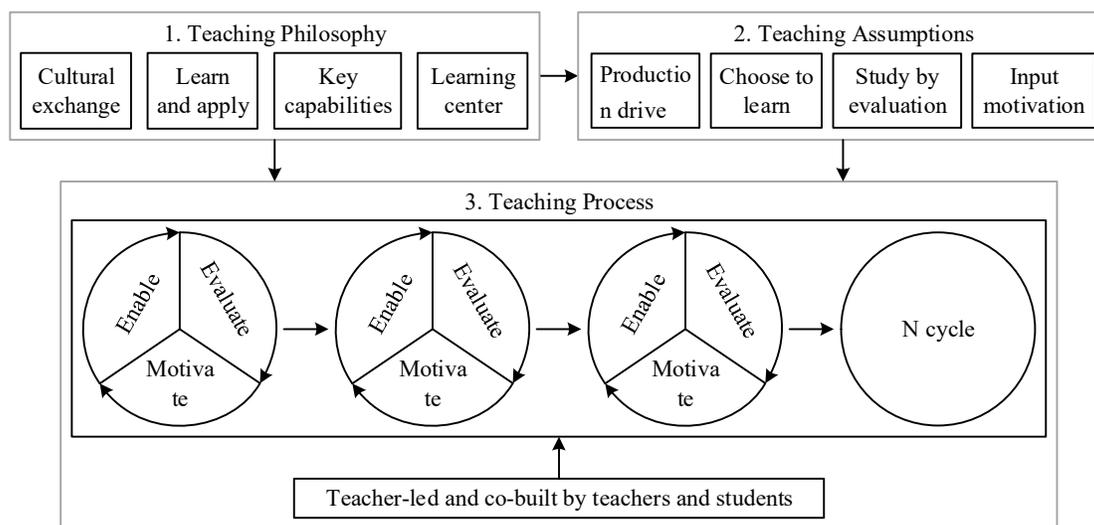


Figure 1: the theoretical system of the production-orientation method

II. B. Creating Contexts for Teaching Reading and Writing

The emergence of generative AI can provide powerful technical support for the implementation of POA in literacy teaching. It can effectively empower the creation of authentic communicative scenarios and the diagnosis of production difficulties required by POA, ensure the accuracy of input materials and the plurality of evaluations, and thus reduce the burden of teachers' teaching and improve the quality and efficiency of teaching.

II. B. 1) Motivating link

The POA-driven session consists of the following steps: the teacher first designs communicative scenarios and production tasks with communicative authenticity, cognitive challenge and production goal achievement. Then, students are guided to try the productions and recognize their own deficiencies through experiencing the difficulties and challenges of the tasks, so as to stimulate learning motivation and mobilize learning enthusiasm. Next, the teacher diagnoses students' difficulties in producing productions and explicitly states the teaching objectives and production tasks to enhance teaching accuracy. In this session, generative AI can support the analysis of teaching discourse, the creation of communication scenarios, the precise diagnosis of learning situation and the setting of teaching objectives by efficiently generating and analyzing multimodal corpus.

Specifically, firstly, teachers can use generative AI to comprehensively interpret the discourse and prepare for the creation of communication scenes. Then, with the help of the generative AI's text-to-diagram function, the teacher can generate illustrations for the story and utilize the AI digital human video creation platform to produce production task videos to enhance the intuition of the narrative and the realism of the scene. Subsequently, the students' pre-class productions and the evaluation criteria for that continuation task were inputted into the generative AI system and required to diagnose the students' typical problems according to the criteria. Finally, with the help of the generative AI, the teacher clarified the instructional objectives based on the instructional materials and the students' production difficulties in conjunction with the POA requirements.

II. B. 2) Enabling links

In the enabling link, generative AI can provide rich teaching materials and diversified teaching activity programs in content, language and structure facilitation to enhance the enabling effect according to students' needs.

In enabling content, the teacher first clarifies the core requirements of the instructional design: in response to the students' production difficulties, the teacher makes reasonable use of text analysis tools to sort out the plot and theme of the story. In terms of language enabling, teachers first allowed generative AI to carefully analyze the linguistic features of the original text in terms of multi-dimensional descriptions and rhetorical devices, and then designed language enabling activities that were highly relevant to the original text's themes, situations and contexts, in order to refine the content of the sequel and to enhance the sense of three-dimensionality of the narrative. In the production section, the teacher, assisted by the generative AI, decided to organize the story continuation activities in the form of writing circles, with students working in groups of four, responsible for the content, language and structure as well as the overall coordination.

II. B. 3) Evaluation sessions

In the evaluation session, generative AI can efficiently assess student production, help teachers select typical samples and generate targeted training materials, and at the same time can provide personalized feedback for each student, helping to tailor teaching to the student's needs.

Before the lesson, the teacher inputs the student production into the generative AI system and asks to diagnose typical problems based on the achievement of teaching objectives and select three typical samples, while giving reasons. Subsequently, the samples are quickly and manually reviewed and verified in conjunction with the teaching objectives and evaluation criteria, whereby a typical sample is finalized and labeled with the assistance of the AI for the evaluation focus on the official model of that continuation task.

In the lesson, the teacher first presented a typical sample and guided the students to independently correct it first, and then further refine the revisions through group collaboration. Eventually, the teacher and students collaborated to complete the revision of the typical sample.

At the end of the lesson, the teacher encourages students to think critically about the reasonableness of the machine evaluation through online and offline blended teaching. In the end, teachers and students voted for the "best story of the class" to promote the best demonstration. At the same time, teachers generate personalized learning materials for students with the help of AI, and carry out accurate improvement activities after class based on learning conditions.

III. Study Design

Based on the creation of POA-based reading and writing teaching scenarios supported by AI, this paper conducts experimental research based on the theoretical system of production-oriented method, aiming to explore whether the teaching mode of production-oriented method is more conducive to stimulating students' learning motivation than traditional teaching methods, and whether it can effectively improve students' writing ability through the teaching mode of "motivate-enable-evaluate".

III. A. Subjects of Study

The research subjects of this teaching experiment are two classes of English parallel classes in a university in City B, namely, English 1 and English 2, in which there are 48 students in Class 1 and 47 students in Class 2. From the examination scores of the placement test and the opening examination, the reading and subsequent writing and writing levels of the two classes are basically the same, and the scores are also basically the same in the writing pre-test conducted before the experiment.

III. B. Research Methodology

III. B. 1) Comparative experiments

In this study, the students participating in the experiment were divided into an experimental group and a control group, with class 1 being the experimental group, which was subjected to the teaching model of the AI-supported production-oriented method, and class 2 being the control group, which continued to use the traditional teaching method. The teaching experiment cycle was 16 weeks. After the experiment started, the teaching materials used, the teaching schedule, the number of composition practice and evaluation were kept the same in both classes, to maximize the exclusion of interfering variables in the experiment and to ensure the validity of the experiment.

The whole teaching experiment includes pre-test and post-test, and the data will be analyzed by both qualitative and quantitative methods to compare the differences between the experimental group and the control group in terms of learning motivation and writing ability.

III. B. 2) Questionnaires

Questionnaires were used to collect students' motivation for learning in literacy instruction. The learning motivation questionnaire in this study was designed to be divided into three dimensions: affective experience, behavioral tendency and cognitive level. The affective dimension includes learning interest and learning confidence; the cognitive level focuses on integrative motivation and instrumental motivation, and the behavioral tendency includes learning proactive performance, learning planning performance and learning cooperative performance. The pre-test and post-test questionnaires of the experiment used the same questionnaire, which was distributed and returned to the students of English 1 class.

III. C. Learning Motivation Evaluation Model

Through the questionnaire design, the evaluation index system of students' learning motivation stimulation in literacy teaching was determined, i.e., emotional experience, behavioral tendency and cognitive level were taken as the first-level indexes and subdivided into seven second-level indexes. Combined with the characteristics of comprehensive evaluation, binomial coefficient method was chosen as the subjective evaluation method, factor analysis method was chosen as the objective evaluation method, and the binomial coefficient method and factor analysis method were combined, and the distance function was used for the complementary advantages of the two to form the comprehensive evaluation method of learning motivation evaluation.

III. C. 1) Binomial coefficient method

Binomial coefficient method is based on the prioritization of indicators ranked by the decision maker, and the binomial coefficient is weighted and summed to determine the weight of indicators. Assuming that the decision makers are L experts, they analyze and qualitatively rank the N evaluation indicators in the comprehensive assessment index system of the situational awareness effect of smart distribution networks according to the degree of importance, and the detailed operation steps are as follows.

Step 1: The experts compare the evaluation indicators two by two, for the n th indicator, each of the L experts independently determines its importance in the order of V_m , and takes the average value of the ordering of the L experts to be a_n , which reflects its degree of importance, and the smaller the value is, the higher the degree of importance is. Its calculation formula is as follows:

$$a_n = \frac{1}{L} \sum_{m=1}^L V_m, n = 1, \dots, N \quad (1)$$

Step 2: According to the size of the average value of each indicator, a_n is reordered, and when there is a situation in which the indicators have the same order, the relevant indicators are reordered until there is no repetition, and the final order is determined. The indicator with the largest average value is ranked in the N th position, and the indicators with the smallest impact are placed on the right according to the principle of decreasing importance. The corresponding N indicators after a_n reordering are denoted by x_n in the following order:

$$x_1 > x_2 > \dots > x_N \quad (2)$$

Step 3: Following a symmetrical approach, the most important indicators are placed in the center, and the second most important indicators are arranged on either side of them, resulting in the following ranking:

$$x_N \leftarrow \dots x_2 \leftarrow x_1 \rightarrow x_3 \dots \rightarrow x_{N-1} \quad (3)$$

Step 4: Calculate the weight of each indicator using the binomial coefficient weighted sum method with the following formula:

$$\omega_i = C_{N-1}^{i-1} / 2^{N-1} \quad (4)$$

$$C_{(N-1)}^{(i-1)} = (N-1)! / \{(N-1-(i-1))!(i-1)!\} = (N-1)! / \{(N-i)!(i-1)!\} \quad (5)$$

where i denotes the position number of the indicator after it is arranged in a symmetric manner, and ω_i denotes the subjective weight corresponding to the indicator with position number i .

III. C. 2) Factor analysis

Factor analysis takes the degree of correlation between each variable as the point of extrusion, and the classification is based on the lowest degree of correlation, the original variables will be classified uniformly, so that the same class of variables will have a high degree of correlation between them, and then each class of such variables will be downgraded into a common factor, so as to divide a lot of different original variables into a small number of common factors, and reflect most of the original information.

Calculation steps:

The first step is to carry out the data consistency standardization step. The pre-collected and organized data sets are imported into the SPSS statistical analysis software platform, and the standardization of data indicators is carried out to achieve the consistency of different variables, thus effectively eliminating the barriers to data comparison that may be triggered by different units of the variables.

The second step is to test the data. Usually, before using factor analysis, it is necessary to do two tests on the data. One test is the KMO test, and the other test is the Bartlett's sphericity test. KMO is to test the degree of correlation between the initial variables, which is used to determine whether the initial data are suitable for factor analysis. Usually, if factor analysis is used, the KMO value should be greater than 0.5, and if it is greater than 0.5, the base variables selected in this case are not suitable for the factor analysis process. There is no fixed threshold for the Bartlett's test of sphericity, and the smaller the value tends to be, the more it indicates that the dataset is unsuitable for the implementation of factor analysis. In addition, according to the results of the statistical data analysis provided by SPSS, the P-value is below the threshold of 0.05, which indicates that there is a certain degree of independence between the variables.

In the third step, the factor variables are constructed assuming that $X = (X_1, X_2, \dots, X_p)$ is an observable random variable with mean vector $E(x) = 0$ and covariance matrix $Cov(x) = \Sigma$, with covariance matrix Σ equal to the correlation matrix R . $F = (F_1, F_2, \dots, F_m)$ is an integrable vector with mean vector $E(F) = 0$ and the components of the vector are independent of each other. $E = (e_1, e_2, \dots, e_p)$ is independent of F , $E(e) = 0$, and the components of the vector are independent of each other. Then the following equation represents the factor model:

$$\begin{aligned} X_1 &= a_{11}F_1 + a_{12}F_2 + \dots + a_{1m}F_m + e_1 \\ X_2 &= a_{21}F_1 + a_{22}F_2 + \dots + a_{2m}F_m + e_2 \\ &\vdots \\ X_p &= a_{p1}F_1 + a_{p2}F_2 + \dots + a_{pm}F_m + e_p \end{aligned} \quad (6)$$

Step 4: Identify the common factors and perform the factor rotation operation. In the process of passing the factor rotation operation, first, the table of eigenvalues and cumulative contribution of eigenvalues is referred to. Then, identify the common factors based on the initial eigenvalues and total contributions. Finally, the orthogonal rotation technique is applied to transform the factors to obtain the rotated composition matrix. This matrix clearly reveals the extent to which each variable contributes to the public factors, which greatly facilitates the process of analyzing the information content of each factor.

Step 5: Evaluate factor scores and overall scores. This process involves using the factor score coefficients and standardized initial variables to determine the scores of the public factors, and then calculating the overall composite score based on the public factor scores and the proportion of variance contributed by each factor.

III. C. 3) Evaluation of portfolio empowerment

In this paper, the distance function pathway is selected to implement the combination of empowerment. In this method, the core lies in the establishment of the subjective and objective dimensions of the weight coefficients. These coefficients directly determine the proportion of the distribution of the combination of weights calculated based on the distance function. Evaluation of the binomial coefficient of the weight obtained as $W_i \times$, the factor analysis of the weight results of $W_i \times$, set the distance function of the two kinds of evaluation of the empowerment as: $d = (W_i \times, W_i \times \times)$ whose expression is:

$$d(W_i^*, W_i^{**}) = \left[\frac{1}{2} \sum_{i=1}^n (W_i^* - W_i^{**})^2 \right]^{\frac{1}{2}} \quad (7)$$

The binomial coefficient method and the factor analysis method are linearly weighted to obtain w , which is the value of the combination weights taken, and the expression is:

$$W_i = \alpha W_i^* + \beta W_i^{**} \quad (8)$$

where α, β is the weight assignment coefficient. $\alpha + \beta = 1$.

In order to ensure that a variety of assignment weight difference degree and allocation coefficients are consistent, set the distance function and allocation coefficients to take equal, its expression is:

$$d(W_i^*, W_i^{**}) = (\alpha - \beta)^2 \quad (9)$$

$$\alpha + \beta = 1 \quad (10)$$

$$\alpha = \sqrt{\frac{1}{2} \sum_{i=1}^n (W_i^* - W_i^{**})^2} + \frac{1}{2} \quad (11)$$

In summary, this paper in the selection of the combination of the assignment of the method of linear weighting. The subjective weights and objective weights are weighted and calculated, while realizing the complementary advantages of the two methods and balanced by the dynamic adjustment of multi-objective weights to enhance the persuasive power of the evaluation results, and the state combination of evaluation methods are as follows:

$$\omega_i = \alpha_{va} S_i + (1 - \alpha_{va}) Q_i \quad (12)$$

Here, α_{va} - the dynamic combination factor, by dynamically adjusting the size of its value to achieve a dynamic balance between subjective and objective. S_i - the subjective weight of the i th indicator. Q_i --the objective weight of the i th indicator.

IV. Results and Discussion

IV. A. Learning Motivation Evaluation

The questionnaire survey and the learning motivation stimulation evaluation model were used to observe the changes in students' motivation towards literacy learning before and after the literacy teaching experiment with AI technology support and production-oriented method. Students' attitudes were divided into three main dimensions, namely: affective experience, cognitive level and behavioral tendency.

IV. A. 1) Stimulating students' emotional learning experiences

Emotional experience includes learning interest and learning confidence, and the evaluation results of learning emotional experience are shown in Figure 2. After the teaching experiment, the evaluation scores of learning interest and learning confidence of 48 experimental students were 3.85 and 3.73, which were 13.57% and 14.07% higher than before the experiment. On the whole, through the literacy teaching experiment supported by AI technology and production-oriented method, students' motivation to learn literacy changed positively with greater learning interest and confidence.

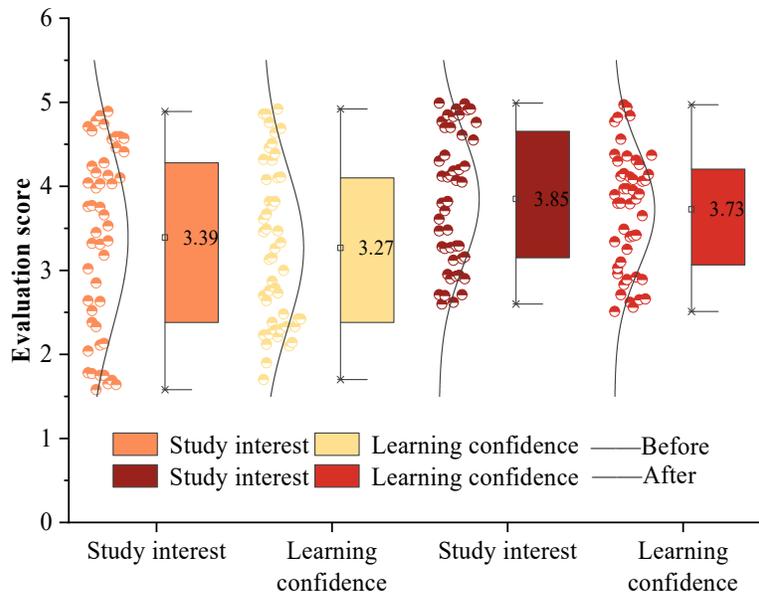


Figure 2: The evaluation results of learning emotional experience

IV. A. 2) Stimulating the cognitive level of student learning

The second dimension evaluates the impact of the production-oriented approach on students' perceived motivation to learn. Motivation is categorized into two types: integrative motivation, which refers to the interest in the language being learned itself and a strong willingness to learn, and instrumental motivation, which refers to learning in order to pass an exam or get a job. The results of the evaluation of the cognitive level of learning are shown in Figure 3. The evaluation scores of post-experimental fusion-type motivation and instrumental motivation are 3.80 and 3.90, and in comparison, students have stronger instrumental motivation for literacy learning. While the evaluation scores of fusion-based motivation and instrumental motivation before the experiment were 3.19 and 3.28. Literacy teaching based on AI technology support and production-oriented method can motivate students' cognitive level of learning.

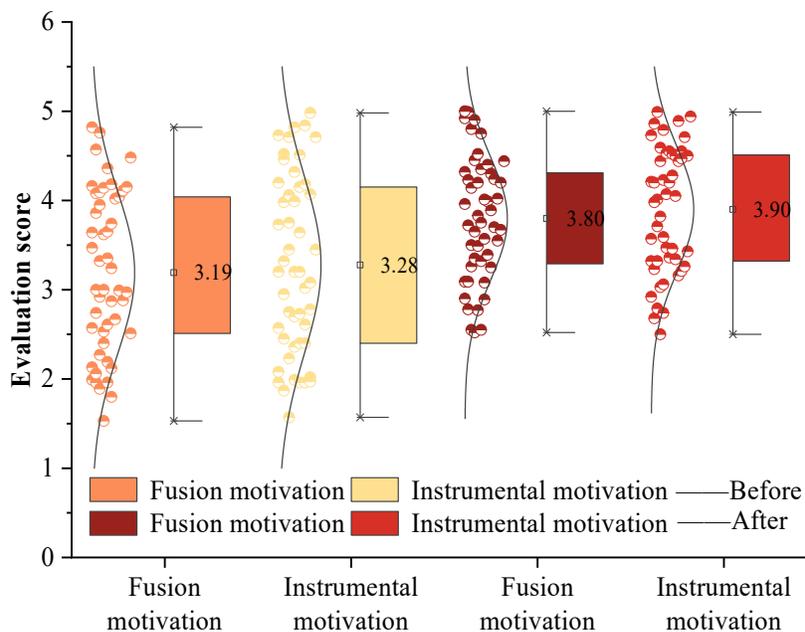


Figure 3: Evaluation results of cognitive level learning

IV. A. 3) Stimulating students' learning behavioral tendencies

The evaluation results of learning behavioral tendencies are shown in Figure 4. After using AI technology support and production-oriented method for literacy teaching, students' scores on learning initiative performance, learning planning performance and learning cooperative performance increased from 3.28, 3.12 and 3.23 to 3.66, 3.77 and 3.78, which indicates the stimulating effect of AI technology support and production-oriented method on students' behavioral tendencies in literacy learning.

The production-oriented method of instruction helps students develop a sense of cooperative learning and increase participation in cooperative classroom activities. The teaching philosophy of the production-oriented approach focuses particularly on collaborative teacher-student assessment, in which students will be asked to work together in the classroom to provide comments on their peers' writing and make suggestions for revisions. As a result, there was a significant increase in the number of students who indicated a willingness to engage in collaborative assessment in the posttest, indicating that students were very productive in this type of assessment.

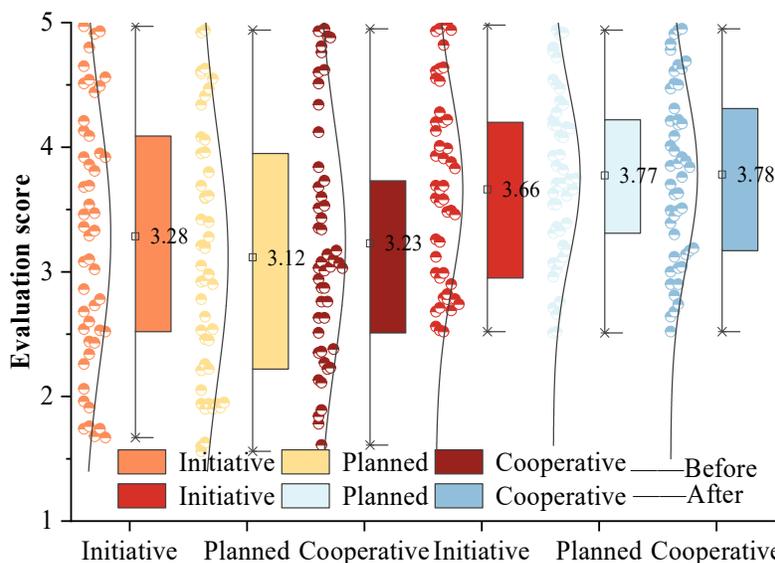


Figure 4: The evaluation results of the tendency of learning behavior

IV. B. Writing Test Results

IV. B. 1) Comparison of overall performance

The writing test was organized again after the teaching experiment for the students of the two classes with a time limit of forty minutes, and the descriptive statistics and sample t-test results of the post-test scores of the two classes are shown in Table 1. The lowest score of English 1 class is 10, the highest score is 25, the mean score is 18.45, and the standard deviation is 3.352. The lowest score of English 2 class is 5, the highest score is 24, the mean score is 14.24, and the standard deviation is 3.455. The data clearly show that the mean of English 1 class's continuation of the writing scores is significantly higher than that of English 2 class after the teaching experiment. From the results of the independent samples t-test, it can be seen that the Sig. (two-tailed) value is 0.024, which is less than the standardized value of 0.05, i.e., there exists a significantly significant post-test scores of English 1 and English 2 classes in writing. In other words, literacy teaching with the application of AI technology and production-oriented approach can significantly improve learners' literacy achievement.

Table 1: Experimental results of the two classes

Descriptive statistics							
	N	Min	Max	Mean	SD		
Class 1	48	10	25	18.45	3.352		
Class 2	47	5	24	14.24	3.455		
Independent sample t test							
	Levin variance equivalence test			Average equivalent t test			
	F	Sig.	t	Df	Sig. (Double tail)	MD	SE
Assumed equal variance	0.251	0.394	2.013	94	0.024	4.21	0.787
Unassuming equal variance			2.015	93.682	0.025	4.21	0.798

IV. B. 2) Different levels of analysis

The statistics of the pre and post-tests of the high, middle and low subgroups of English 1 class are shown in Table 2. The mean values of scores on the pre-test of the renewal test for the high, middle and low subgroups were 18.68, 14.79 and 8.86, and the reading and writing scores of both the middle and low subgroups were significantly low in the case of a full score of 25 points. After the teaching experiment was carried out, the mean score of the high subgroup's continuation test increased to 22.27 points, and the middle and low subgroups also increased to 18.17 and 12.68 points, respectively.

Table 2: Data statistics for front and rear testing

	N	Min	Max	Mean	SD
Pre-experiment					
High score group	12	17.43	22.74	18.68	1.642
Middle score group	25	11.92	18.35	14.79	3.715
Low score group	11	2.14	10.57	8.86	1.392
After experiment					
High score group	14	19.24	24.25	22.27	1.285
Middle score group	26	15.65	19.98	18.17	4.526
Low score group	8	6.36	12.51	12.68	1.271

V. Conclusion

The production-oriented approach supported by multimodal AI technology shows significant effects in enhancing students' motivation and writing ability. Through the experiments in this study, students showed positive changes in the three dimensions of learning motivation-emotional experience, cognitive level, and behavioral tendencies. Especially, in terms of affective experience, the experimental group students' interest in learning and confidence in learning increased by 13.57% and 14.07%. In terms of writing ability, the posttest scores of students in the experimental group were significantly higher than those of the control group, especially in the writing scores of students in the higher subgroups, which showed more significant progress.

The data analysis shows that AI technology provides strong support in the implementation of POA method, especially in the communication scene creation, learning motivation and personalized feedback. Through AI-generated multimodal content, students' learning experience became richer and more interactive, thus better promoting students' language production and competence. The teaching model combining AI and production-oriented method can effectively stimulate students' learning motivation and improve their writing level, which provides a new direction for the future development of education.

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