

Research Article

Application of Production-Oriented Approach and Deep Learning Model in English Translation Teaching Model

Aman Qi 

School of Humanities and Education, Xijing University, Xi'an 710123, Shaanxi, China

Correspondence should be addressed to Aman Qi; 20070027@xijing.edu.cn

Received 17 May 2022; Revised 1 July 2022; Accepted 8 August 2022; Published 4 October 2022

Academic Editor: Abid Yahya

Copyright © 2022 Aman Qi. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Translation is an important index to assess students' English learning ability. In the current English translation teaching, there are still dilemmas such as poor professionalism of curriculum, insufficient knowledge reserve of students, and single teaching methods and approaches. Therefore, this study carries out research on English translation teaching based on the deep learning model to improve the EM algorithm and the guidance of Production-Oriented Approach (POA). The experiment proves that POA can effectively mobilize students' enthusiasm in translation learning, improve the efficiency of internalizing human knowledge into output ability, optimize teachers' teaching effect, and significantly improve students' English translation ability and output application ability by more than 30%.

1. Introduction

It is an important task of English teaching in the era to cultivate advanced and complex English translation talents with good comprehensive application ability [1]. In educational practice, the training methods are mostly focused on “teacher-centered” and “student-centered.” Among them, the “teacher-centered” mode of teaching often consists of the teacher explaining some translation skills, students practicing in class, and then the teacher making comments. To a certain extent, this lecture mode enables students to grasp the basic translation theories and skills effectively, and to a certain extent stifles students' initiative and creativity in learning translation [2].

Translation activities require a full understanding of the translation object, a thorough understanding of the corpus, and the ability to accurately reproduce the original text in another language according to the standards of faithfulness, elegance, and quality [3, 4]. The current translation teaching cannot really meet the requirement of improving students' translation ability. The main problems are as follows: 1. The teaching of the

English translation has not received enough attention. While the status of English subject and teaching has been significantly improved, the reform of English translation teaching is relatively lagging behind and has been in an embarrassing situation of being relatively neglected for a long time. 2. The teaching mode and teaching method of English translation teaching lack innovation. The mode is mostly focused on text, teacher, and classroom, ignoring the main role of students, and English translation teaching is no exception [5]. The teaching of English translation is mostly based on the transmission of knowledge but ignores the education of teaching process and method, ability, and value. 3. The teachers' strength in English translation teaching needs to be enriched. English translation teachers in colleges and universities must have certain translation theory and practical abilities. [6].

The core concept of Production-Oriented Approach (POA) is learning-centered, learning-using integration, and whole-person education [7], and is driven by reasonable output tasks, so that students can learn in a targeted manner under the guidance of goals and objectives, and input knowledge with the goals and objectives, and thus contribute

to the output of translation. In the English translation teaching based on POA, teachers should actively build a good translation teaching mode and clarify the translation teaching objectives. In classroom teaching practice, they should guide students to learn and master translation knowledge and skills, so as to improve their translation learning and practice, and then communicate better [8]. To this end, teachers should, on the one hand, have a certain understanding of the general requirements of translation. Based on this, teachers should effectively set translation teaching objectives to ensure that the objectives set are appropriate to the needs of translation, so that students can gain certain practical experience in the process of learning translation, so as to enhance their own abilities and promote their development. On the other hand, teachers should also keep abreast of students' own needs and weaknesses in translation learning, and then set corresponding goals so that students can make up for their own deficiencies in translation learning in the process of achieving the goals.

With the help of Production-Oriented Approach theory, this study integrates three main elements of English translation teaching: driving, facilitating, and evaluating, and verifies the feasibility of POA for non-English major university English translation classrooms. Therefore, in teaching practice, the effective implementation of POA can greatly improve students' English translation ability. Applying the theoretical system of POA to the teaching of the English translation is not only feasible but also has a more far-reaching significance.

2. Related Work

The majority of English speakers in China have conducted numerous researches on this theoretical system suitable for China's actual conditions, among which the study of the theoretical system has enriched the specific content of the POA, while practical research has explored a new path for foreign language teaching in China. [9] adopted an experimental approach to conducting an in-depth study on the enabling aspects of POA. Based on classroom practice, [10] explained the teaching design of a unit and focused on the teaching process of the enabling session, dividing the enabling into viewpoint enabling, language enabling and chapter enabling, which brought vitality to the classroom and significantly increased learners' motivation. [11] Three rounds of independent experimental studies were conducted over 3 years to explore the specific principles of the enabling process.

The literature [12] provides guidance for the refinement of POA. [13] affirms that POA has a strong theoretical foundation and interesting teaching materials and output-driven tasks are essential for translation teaching. The experiment shows that POA is a typical application based on design research, and that it can be extended to other educational contexts and to beginners by expanding its scope, geographical area, and target audience. [14] reflects on the motivating, enabling, and evaluating aspects of POA. In contrast, [15] argues that the design of

the three components of POA promotes students' curiosity and weakens teachers' role of "scaffolding," which has a positive effect on students' independent learning. Study [16] affirms the innovative and localized effectiveness of POA, another study [17] argues that POA overturns the traditional input-to-output teaching model, and that its motivating-enabling-evaluating teaching model enhances students' curiosity, enables them to become language users, and does not limit teachers' choice of teaching materials, which has a positive effect on effective language output. In a study [18], the pedagogical principles of POA are discussed, and the question of how to design activities to transform textual knowledge into students' speaking and writing skills is raised.

Deep learning originated from machine learning and was slowly introduced into the field of education. It first pointed out that deep learning is a kind of learning based on understanding, where learners can critically accept new ideas and facts, construct their own knowledge with their original cognition. Studies [19, 20] believe that focusing on critical understanding, emphasizing information integration and applying by transfer, aiming at the development of learners' higher-level abilities and cultivating students' ability to solve complex problems, has become an important grip for implementing students' core literacy and innovative ability development in China. Studies also holds that deep learning is to connect the traditional teaching with the knowledge points in learning, and to construct the knowledge layer of deep learning and the application layer of deep learning; finally, it points to the thinking layer of deep learning, to cultivate talents with growth-oriented thinking, big data thinking, problem-solving and innovative thinking, etc. to reserve talents for realizing the Chinese dream. [21] believes that scientific monitoring, regulation and evaluation of one's English translation learning plan through the theoretical guidance, can also enable students to perform more confidently in the English classroom. Deep learning also provides teachers with some ideas for teaching English vocabulary, allowing them to focus on developing students' awareness of vocabulary learning and their learning strategies.

3. Architecture

POA has undergone three rounds of exploration and modification, and is still being improved. The prototype of this approach is the "output-driven hypothesis" proposed by Wen Qiufang (2008) in 2007. The second is the "output-driven-input-enabled" hypothesis proposed by Professor Wen Qiufang (2014); finally, the approach was officially named POA (Production-Oriented Approach) at the 7th International Symposium. The relationship between these three parts is Figure 1:

The "teaching philosophy" is the basis of "teaching assumptions" and "process" leads the development of the latter two; "teaching assumptions" provides theoretical support for "teaching process"; "teaching process" is the

concrete form and realization of the former two, and teachers play a leading role in all aspects of this process.

POA puts the “motivating” at the very beginning of teaching, and its teaching steps and requirements are shown in Table 1:

The enabling session consists of three steps as shown in Table 2:

The steps and requirements of the delayed evaluation of output tasks are shown in Table 3:

The classroom is divided into three main parts by combining the three teaching processes of “motivating-enabling-evaluating” of POA, as shown in Figure 2.

This study went through seven stages, as shown in Figure 3.

First, the research topic was determined by combining the researcher’s personal research interests, and by carefully studying the literature and books on the current research status of English translation teaching, translation competence, and translation learning emotional experience in libraries, reference rooms, and relevant databases. Second, the stage of determining the research framework, in which the researcher determines the research framework and ideas according to the research topic and research theories. Thirdly, the stage of determining the research object, in which the researcher chose a suitable research object according to the situation of the internship site, and set the foundation for smooth development. Fourth, during the stage of determining method and tools, the researcher chose test to investigate research subjects’ translation ability’s difference before and after the experiment, and used the questionnaire to investigate research subjects’ emotional experience of learning’s difference before and after the research. The qualitative reasons for the questionnaire data were explored using semi-structured interviews. Fifth, the data collection stage and the main content of the data collection includes: first, to collect test papers and questionnaires, the researcher chose a suitable time for the research subjects to complete the test and questionnaires; second, the interview, mainly preliminary questionnaires from two students each randomly selected from the top students, the average students and poor students, that is to say, a total of six students are interviewed, and they are allowed to use some devices to record the interview process, to facilitate later analysis. Sixth, statistical and analysis of the research data stage, the researcher organized, and analyzed interviews collected by the semi-structured interview method. Seventh, the paper writing stage, after the data results are obtained, the paper is written.

Deep learning is mainly composed of “learning content,” “teaching behavior” and “learning resources,” and the deep learning design model is constructed by statistically integrating these three aspects and their related relationships. The learning content is mainly composed of four dimensions (referred to as “4C”), as shown in Figure 4.

From model in Figure 4, we can see that: 1. the cognitive process consists of four stages as shown in Figure 1, each stage corresponds to different learning contents, learning methods and resources, and has different learning aspects. 2. The awareness stage is the introductory learning stage, i.e., the spontaneous learning that human beings experience through participating in activities and practices, and this module emphasizes active learning. 3. The reconcile stage is a process in which learners continuously acquire new knowledge through their own learning, and new knowledge is continuously integrated with old knowledge. 4. The induce stage refers to the process of grouping the same knowledge points together after the learners have built their own knowledge network in the previous stage. 5. The transfer stage is mainly the formation of stereotypical thinking, in the encounter of a certain situation will be transferred to the context of thinking to solve the problem. In these four stages of learning content, the learners can adjust their own learning condition at any time, and return to it if there is something wrong, which reflects the plurality of deep learning. Combined with the above description, the deep learning mechanism model is further constructed, as shown in Figure 5. In order to show it more intuitively for easy understanding, Figure 5 combines the horizontal and vertical sections together. The horizontal section consists of culture, technology, and learners.

4. Improved EM Algorithm

The experiment has gone three phases: “pre-test, intervention, post-test,” and the experimental procedure was designed according to the study phases, as shown in Figure 6 below:

In the process of conducting the experiment, the researcher set class 2 as the experimental group and class 1 as control group, and experimental model is shown in Figure 7 below:

A basic formula to deal with during training is $p(C = c, A = a, E = e)$. C is the random variable representing Chinese word string, e is the random variable representing word string, and a is the random variable representing the relationship between the two. The probability of sentence pair $P_r(c|e)$ can be expressed by $P_r(c, a|e)$:

$$P_r(c|e) = \sum_a P_r(c, a|e). \quad (1)$$

In this alignment model, a Chinese word can only have one English word or the corresponding empty word. If the English word string $e = e_1^I = e_1 e_2 \cdots e_I$ has I words and the Chinese word string $C = C_1^I = C_1 C_2 \cdots C_I$ has J words, a can be expressed as $a = a_1^I = a_1 a_2 \cdots a_I$ with J values, each value between $[0, I]$.

1. Model 1

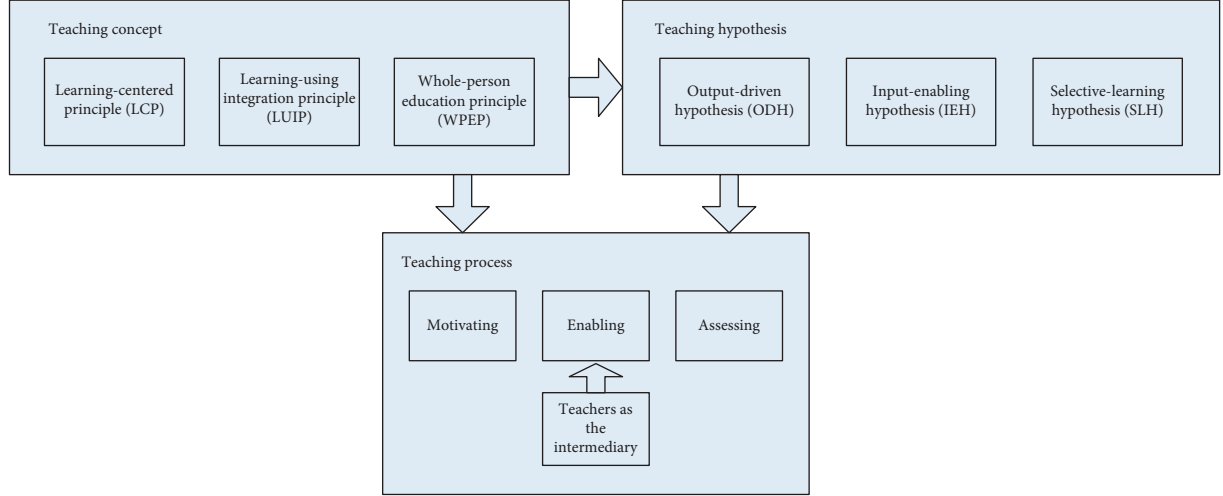


FIGURE 1: POA theory system.

TABLE 1: “Motivating” teaching steps and requirements.

Teaching steps	Teaching requirements
1 The teacher shows the students a communicative scene or a conversational scene	The scene is communicative and the topic is cognitive challenging
2 Students try to complete the task	Make students realize their lack of language knowledge and ability and generate motivation for learning
3 Teachers explain classroom teaching objectives and output tasks	Make students clearly understand the communicative and language objectives of this class. Make students understand the type and content of output tasks

$$\Pr(c|e) = \frac{\varepsilon}{(I+1)} \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \prod_{j=1}^J t(c_j|e_{a_j}). \quad (2)$$

$(c_j|e_{a_j})$ denotes the translation rate of word pair (c_j, e_{a_j}) . Given the constraint: For each word e

$$\sum_c t(c|e) = 1. \quad (3)$$

Set the coefficient λ_e , and get an auxiliary function

$$(t, \lambda) \equiv \frac{\varepsilon}{(I+1)} \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \prod_{j=1}^J t(c_j|e_{a_j} - \sum_e \lambda_e \left(\sum_c t(c|e) - 1 \right)). \quad (4)$$

In order to find the extreme value, the partial derivative of the function $h(t, \lambda)$, the partial derivative of λ means that it is equal to the restriction condition, so the partial derivative of $t(c|e)$ can be

$$\Pr(c|e) = \varepsilon \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \prod_{j=1}^J t(c_j|e_{a_j}) \cdot a(i|j, J, I). \quad (5)$$

$a(i|j, J, I)$ is the distortion rate. Adding constraints:

$$\sum_{i=0}^I a(i|j, J, I) = 1. \quad (6)$$

Similarly, the auxiliary function can be obtained

$$\begin{aligned} h(t, a, \lambda, \mu) \equiv & \varepsilon \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \prod_{j=1}^J t(c_j|e_{a_j}) \cdot a(i|j, J, I), \\ & - \sum_e \lambda_e \left(\sum_c t(c|e) - 1 \right) \\ & - \sum_j \mu_{jml} \left(\sum_i a(i|j, J, I) - 1 \right). \end{aligned} \quad (7)$$

Model 1 can be considered as a special case of model 2, when $a(i|j, J, I)$ is fixed to $(I+1)^{-1}$. So the set of parameters of model 1 can be considered as the set of parameters of model 2, which can be used as the initial value of parameters of model 2.

Model 3 introduces the reproduction rate $n(\phi|e_i) \equiv P_r(\phi|\phi_1^{i-1}, e)$

$$\begin{aligned} \Pr(c|e) = & \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \Pr(c, a|e) =, \\ & \sum_{a_1=0}^I \cdots \sum_{a_j=0}^I \binom{m-\phi_0}{\phi_0} P_0^{m-2\phi_0} P_1^{\phi_0} \prod_{i=1}^I \phi_i n(\phi_i|e_i) \\ & \times \prod_{j=1}^J t(c_j|e_{a_j}) \cdot d(j|a_j, J, I), \end{aligned} \quad (8)$$

$d(j|a_j, J, I)$ is the distortion rate. Given the constraints:

TABLE 2: “Enabling” teaching steps and requirements.

	Teaching steps	Teaching requirements
1	The teacher explains the assigned tasks and explains the specific requirements	Completion of output tasks
2	Students learn by themselves, and teachers give appropriate guidance and inspection	Provide students with the required materials to choose from
3	Students completes the output task, and teachers check the output and give guidance	Enable students to immediately apply the selective learning to output tasks

TABLE 3: Steps and requirements of delayed evaluation of output tasks.

	Teaching steps	Teaching requirements
1	Teachers and students work together to develop and learn evaluation criteria	The standard is clear, easy to understand and easy to check
2	Teacher-students’ in-class evaluation	Clear submission deadline and clear submission form Teachers should make effective use of the limited classroom time, put forward clear requirements for students, and make targeted evaluation
3	After class evaluation of teachers and students	Results submitted in succession serve as the basis for formative evaluation

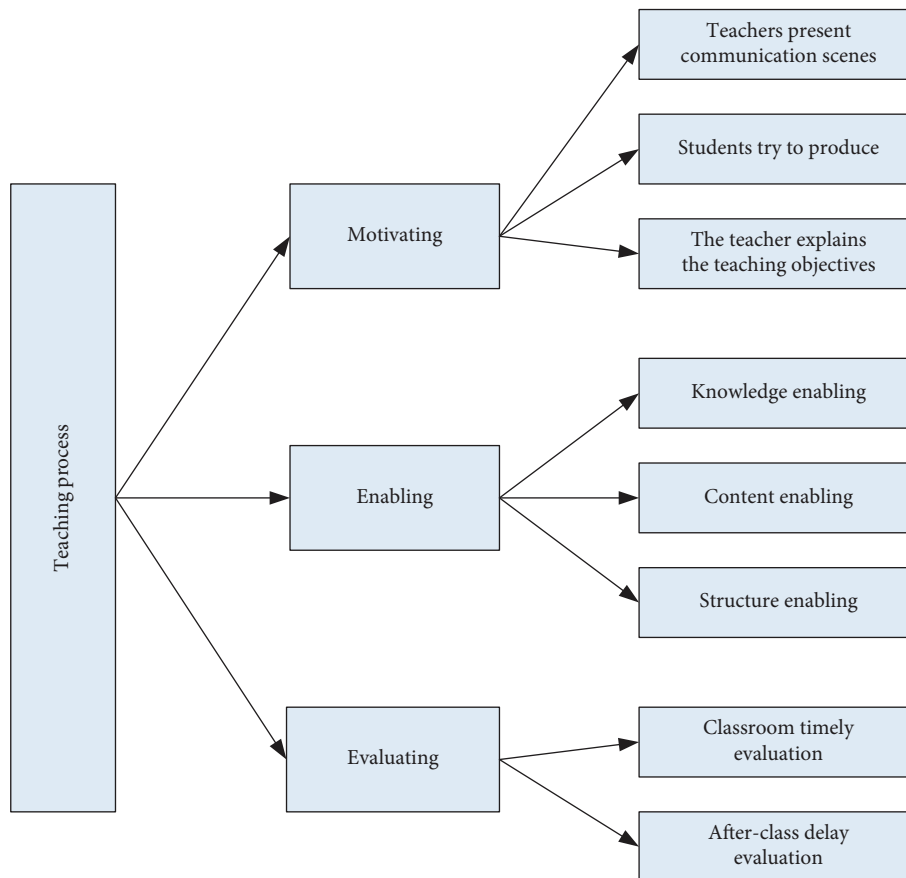


FIGURE 2: Flow chart of classroom translation teaching.

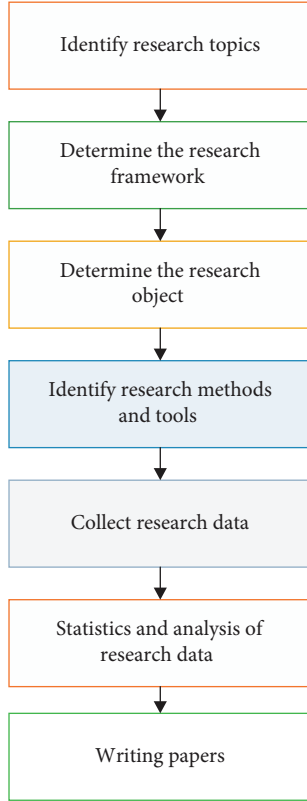


FIGURE 3: Flow chart of the research process.

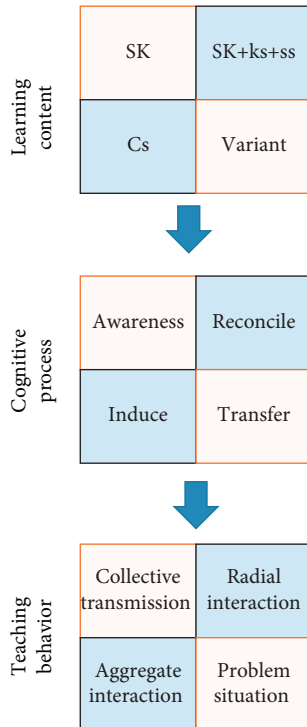


FIGURE 4: Deep learning model.

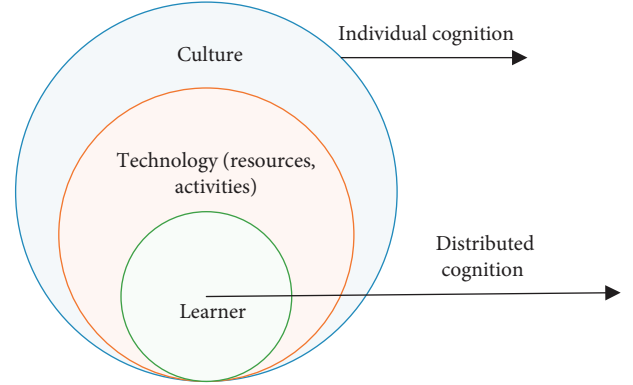


FIGURE 5: Deep learning mechanism modeling.

$$\begin{aligned}
 \sum_c t(c|e) &= 1, \\
 \sum_{i=0}^l d(i|j, J, I) &= 1, \\
 \sum_{\phi} n(\phi|e) &= 1, \\
 p_0 + p_1 &= 1.
 \end{aligned} \tag{9}$$

Auxiliary Functions:

$$\begin{aligned}
 h(t, d, n, \lambda, \mu, v, \xi) &\equiv \Pr(c|e) - \sum_e \lambda_e \left(\sum_c t(c|e) - 1 \right) - \\
 &\sum_j \mu_{jml} \left(\sum_i d(i|j, J, I) - 1 \right) \\
 &- \sum_e v_e \left(\sum_{\phi} n(\phi|e) - 1 \right) \\
 &- \xi(p_0 + p_1 - 1),
 \end{aligned} \tag{10}$$

p_1 means the probability of the occurrence of the empty word, p_0 means the probability of the absence of the empty word. To find the extreme value, the partial derivative of the auxiliary function can be found.

If the reproduction rate of an English word is greater than 0, we call it fertile; if it is greater than 1, we call it very fertile. the first Chinese word generated by an English word is called head; the non-first Chinese word generated by a very fertile English word is called non-head.

In model 4, $d(j|a_j, J, I)$ is divided into two sets of parameters: one for the heads and one for the non-heads, as described in the previous section.

5. Results

Before the experiment, the researcher distributed the volume of the receptive translation ability test to test receptive translation ability. After that, the researchers sorted and analyzed the collected data.

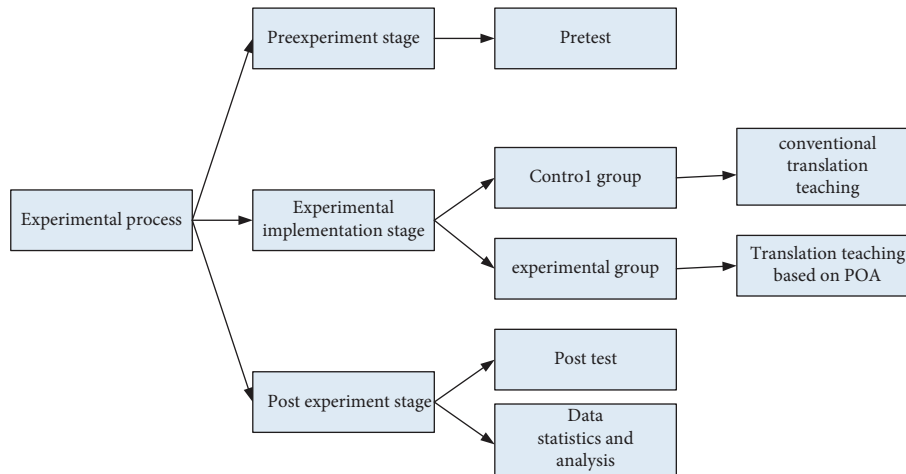


FIGURE 6: Experimental procedure.

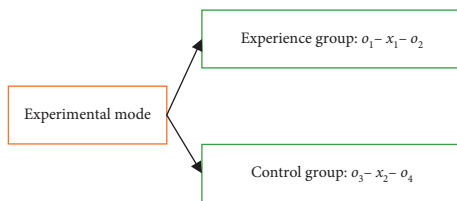


FIGURE 7: Experimental model diagram.

As can be seen from Table 4, the average score of volume a in the translation ability test of the experimental group is 24.022, and the average score of volume a in the translation ability test of the control group is 24.55. The results show that the concentration of translation ability score of the experiment is high, while the polarization of receptive translation ability score of the control is low.

In order to determine whether there are differences, the researchers analyzed the collected data using an independent sample *t*-test, resulting in Table 5.

The independent sample *t*-test requires that the population variance must be equal. Therefore, chi-square test needs to be considered first. As shown in Table 5, indicating that the pre-test is equal, it is necessary to look at the data in the assumed equal variance row. The average value of receptive translation ability of the experiment and the control is -0.52 , which is not significant. The 95% confidence interval $(-1.86, 0.82)$ for the difference between the experiment and the control was 0. Therefore, they can be used as the research object of this study.

After the experiment, the researchers conducted a translation ability test volume B to check the level of translation ability. A total of 90 questionnaires were distributed and 90 valid questionnaires were recovered, with an effective rate of 100%. After that, the researchers analyzed the collected data and obtained the results in Table 6.

Table 6 shows that the average score for volume B of the translating ability exam is 26.70 and the average score for volume B is 25.14. This shows that after three months of translation education experiment, the average value of

experimental translation ability is 1.56 points higher, with little difference. In the experimental translation ability test, volume B's average value has a standard deviation of 1.86, but volume B's average value in the translation ability test has a standard deviation of 4.57. The dispersion of the average value of translation ability is still higher than that of the experiment, indicating that the polarization degree of translation ability of the experimental group is still low after the experiment.

As shown in Table 7, the significance probability of the Levene test is 0.000, which is far less than 0.05, indicating that the variance is not equal. The *t*-test result data needs to be obtained from the data in the row assuming unequal variance. Signal. The (bilateral) obtained from the above table is 0.040, less than 0.05, indicating that there are differences in the scores of receptive translation ability. The difference was not significant, with an average of 56.1 points. The 95% confidence interval $(0.075, 3.04)$ was not 0, indicating that the difference was significant. Therefore, the above analysis shows that the receptive translation ability of students in the experimental class and the control class is different after the experiment. As shown in Table 7, the significance probability of the Levene test is 0.000, which is far less than 0.05, indicating that the variance is not equal. The *t*-test result data needs to be obtained from the data in the row assuming unequal variance. Signal. The (bilateral) obtained from the above table is 0.040, less than 0.05, indicating that there are differences in the scores of receptive translation ability. The difference was not significant, with an average of 56.1 points. The 95% confidence interval $(0.075, 3.04)$ was not 0, indicating that the difference was significant. Therefore, the above analysis shows that the receptive translation ability of students in the experimental class and the control class is different after the experiment.

In order to determine the impact of POA translation teaching and traditional translation teaching on students' translation ability, the researchers conducted data analysis before and after the intra-group test. The results are shown in Table 8.

As can be seen from the above table, the average scores for pre-test and post-test of experimental translation ability are 24.02 and 26.70 respectively, and the average score of post-test is 2.67 points higher than that of pre-test, with little difference. The standard deviations of pre-test and post-test of translation ability are 2.57 and 1.86 respectively, indicating that the concentration of post-test translation ability is improved and the polarization phenomenon is reduced. In order to determine whether the pre-test and post-test of experimental translation ability have changed, the researchers analyzed the data obtained by paired sample *t*-test and obtained the following results in Table 9.

In order to understand the changes of students' translation ability under traditional translation teaching, the researchers studied the results. The results are shown in Table 10.

As shown in Table 10, the average scores of the pre-test and post-test of translation ability are 24.52 and 25.136 respectively. The post-test is 0.61 higher than the pre-test, and the difference is very small. The standard deviations of the pre-test and post-test are 3.78 and 4.57, respectively, indicating that after routine translation teaching, the control translation ability is low and the polarization is serious.

In order to determine whether there are changes in the pre-test and post-test of control translation ability, the researchers analyzed the pre-test and post-test of control translation ability using paired sample *t*-test, and obtained the following results in Table 11.

As shown in Table 11, the experimental control difference is -0.61 , indicating that the translation ability of the control is slightly improved after the experiment, and the standard deviation before and after the test is 5.50. The 95% confidence interval ($-2.29, 1.06$) for the difference is 0, indicating no difference. 0.05, indicating no difference, indicating that although traditional translation teaching methods can slightly improve students' translation ability performance, the improvement of performance is not very significant.

The researchers used the translation part of the first unified test paper in the region to test the subjects' output translation ability. 91 participants participated in the test and received 91 valid test papers, with a return rate of 100%. After that, the researchers made statistics and analyses on the collected data and obtained the following results, as shown in Table 12.

As can be seen from Table 12, the average scores of productive translation ability are 5.723 and 6.091, respectively. The difference is 0.368, which is not very big. The standard deviation of output translation ability is 1.330 and 1.963 respectively, indicating that the output translation ability of the experimental subjects is relatively concentrated.

The degree of polarization of productive translation ability in the experimental is slightly lower.

As shown in the above Table 13, the significance probability of Levene test is 0.01, less than 0.05, indicating that the variance is not equal and sig. The (double-sided) of the second line is 0.302, greater than 0.05, indicating no difference. The difference is 0.37, which is a small difference. The 95% confidence interval ($-0.34, 1.07$) of the difference

TABLE 4: Statistics of receptive translation ability pre-test.

Class	Total score	
	Experimental	Control
N	46	44
Mean value	24.02	24.55
Standard deviation	2.57	3.74
Standard error	0.38	0.56

score includes 0, indicating that the difference is not significant. Therefore, there is no difference and can be used as the research object of this study.

In order to investigate the impact of translation teaching under the guidance of a production-oriented approach on students' output-oriented translation ability, the researchers used the translation part of the final unified test paper in the region to investigate the changes of subjects' output-oriented translation ability. 91 people participated in the test and received 91 valid test papers, including 47 in the experiment and 44 in the control. The recovery rate of test papers was 100%. Subsequently, the researchers made statistics and analyses on the collected data and obtained the results shown in Table 14.

According to the above table, the average scores of the experimental control are 7.38 and 6.71 respectively, which shows that the average value of the experiment is 0.68 higher than that of the control, with little difference. The standard deviations are 1.05 and 1.68 respectively, indicating that the concentration of output translation ability score is still lower than that in the experiment, and the degree of polarization of output translation ability score in the experiment is slightly lower.

In order to understand more clearly the differences, the results are shown in Table 15.

As can be seen from the data in the table, SIG. In Levene's test, it is 0.002, far less than 0.05, so from the data in the second row, we can get sig. (bilateral) is 0.025, less than 0.05, indicating a difference. The average difference was 0.678, with little difference. The 95% confidence interval ($-1.269, -0.088$) of the difference score is not 0, which indicates that the difference is significant. Therefore, based on the above data analysis, it can be concluded that there are differences between the two, indicating that translation teaching under the guidance of POA can improve students' output-oriented translation ability.

In order to better understand the impact of POA on students' productive translation ability, the researchers analyzed the data before and after the test, and obtained the following results. The researchers analyzed the pre-test and post-test scores of the experiment using paired sample *t*-test, and obtained the following results in Table 16.

It can be seen from the above table that the average scores of the pre-test and post-test of the subjects' output translation ability are 5.72 and 7.38, respectively, and the average score of the post-test is 1.66 points higher than that of the pre-test, with little difference. The standard deviations of the pre-test and post-test are 1.33 and 1.05 respectively, indicating that after the experiment, the dispersion of the subjects' output translation ability score decreases, and the polarization phenomenon decreases.

TABLE 5: *T*-test of receptive translation ability before the test.

	Total score	Assuming equal variance	Assume unequal variance
Levene test	<i>F</i>	2.3	
	Sig	0.13	
	<i>t</i>	-0.78	-0.77
	df	88	75.84
<i>T</i> -test	Sig (bilateral)	-0.44	0.44
	Mean difference	-0.52	-0.52
	Standard error value	-0.67	-0.68
95% confidence	Lower limit	-1.86	-1.88
	Upper limit	-0.82	-0.83

TABLE 6: Descriptive statistics of receptive vocabulary ability of the experimental and control classes in the post-test.

	Total score	
Class	Experimental	Control
<i>N</i>	46	44
Mean value	26.7	25.14
Standard deviation	7.86	4.57
Standard error of mean	0.27	0.69

TABLE 7: Independent sample *t*-test of receptive translation skills.

	Total score	Assuming equal variance	Assume unequal variance
Levene test	<i>F</i>	30.45	
	Sig	0	
	<i>t</i>	2.14	2.1
	df	88	56.37
<i>T</i> -test	Sig (bilateral)	0.35	0.4
	Mean difference	1.56	1.56
	Standard error value	0.73	0.74
95% confidence	Lower limit	0.11	0.75
	Upper limit	3.01	3.04

TABLE 8: Descriptive statistics of pre- and post-tests of receptive translation ability.

	Right 1	
Class	Experimental	Control
<i>N</i>	46	46
Mean value	24.02	26.7
Standard deviation	2.57	1.86
Standard error of mean	0.38	0.27

In order to determine the output translation ability of the class, the researchers obtained the results in Table 17 below through the paired sample *t*-test.

The difference is -1.67, which means that the prediction test is 1.67 points lower than the post-test, and the standard deviation of pre-test and post-test is 1.42. The 95% confidence interval (-2.08, -1.248) for the difference is not 0, which means there is a difference. This shows that although the difference is not significant, the translation teaching guided by the POA is effective in improving students' output-oriented translation ability.

In order to study the influence of traditional translation teaching methods on the output translation ability of the control group, the researchers analyzed the output translation ability data of the control group and obtained the following results.

As shown in Table 18, the average scores before and after the control test were 6.10 and 6.71, respectively. The standard deviations of the pre-test and post-test are 1.96 and 1.68 respectively, indicating that the dispersion of the control output translation ability score is reduced after conventional translation teaching. The standard deviations of the pre-test and post-test are 1.96 and 1.68, respectively, indicating that after the conventional translation teaching, the dispersion of the output translation ability score is reduced and the bifurcation phenomenon is reduced.

The above data cannot determine whether the pre-test and post-test of the control group's output translation ability have changed. Therefore, the researchers conducted paired sample *t*-test on the control group's output translation ability score, and the results are as follows Table 19.

TABLE 9: Paired sample *t*-test for pre- and post-test of receptive translation skills in the experimental class.

		Pairwise difference					<i>t</i>	df	Sig (bilateral)
	Mean value	Standard deviation	Standard error of mean	95% confidence interval of difference					
				Lower limit	Upper limit				
Right 1	Pre test post test	-0.67	2.75	0.41	-3.50	-1.86	-6.60	45	0

TABLE 10: Descriptive statistics of pre- and post-tests of receptive translation skills in the control.

Right 2		
Class	Experimental	Control
<i>N</i>	44	44
Mean value	24.52	25.14
Standard deviation	3.78	4.57
Standard error of mean	0.57	0.69

TABLE 11: Paired sample *t*-test for pre and post test of receptive translation skills in the control.

		Pairwise difference					<i>t</i>	df	Sig (bilateral)
	Mean value	Standard deviation	Standard error of mean	95% confidence interval of difference					
				Lower limit	Upper limit				
Right 2	Pre-test post-test	-0.63	4.50	0.83	-0.29	1.06	-0.74	43	0.46

TABLE 12: Descriptive statistics of productive translation ability.

Total score		
Class	Experimental	Control
<i>N</i>	44	47
Mean value	6.1	5.72
Standard deviation	1.96	1.33
Standard error of mean	0.3	0.19

TABLE 13: Independent sample *t*-test of output translation ability.

Total score	Assuming equal variance	Assume unequal variance
Levene test	<i>F</i>	6.6
	Sig	0.01
	<i>t</i>	1.05
	df	89
	Sig (bilateral)	0.3
<i>T</i> -test	Mean difference	0.37
	Standard error value	0.35
95% confidence	Lower limit	-0.33
	Upper limit	1.06
		1.04
		74.98
		0.3
		0.37
		0.35
		-3.34
		1.07

TABLE 14: Descriptive statistics of the output translation ability.

Total score		
Class	Experimental	Control
<i>N</i>	44	47
Mean value	6.71	7.38
Standard deviation	1.68	1.05
Standard error of mean	0.25	0.15

TABLE 15: T-test of output translation ability.

Total score		Assuming equal variance	Assume unequal variance
Levene test	<i>F</i>	10.14	
	Sig	0.002	
	<i>t</i>	-2.33	-2.29
	df	89	71.5
T-test	Sig (bilateral)	0.002	0.03
	Mean difference	-0.68	-0.68
	Standard error value	0.29	0.3
95% confidence	Lower limit	-1.26	-1.27
	Upper limit	-0.9	-0.89

TABLE 16: Descriptive statistics of pre- and post-tests of output translation ability in experimental classes.

Right 1	Productive vocabulary proficiency pre-test	Post-test of productive vocabulary ability
<i>N</i>	47	47
Mean value	5.72	7.83
Standard deviation	1.33	1.05
Standard error of mean	0.19	0.15

TABLE 17: Paired-sample *t*-test for pre and post-tests of output translation skills in the experimental.

		Pairwise difference			95% confidence interval of difference		<i>t</i>	df	Sig (bilateral)
	Mean value	Standard deviation	Standard error of mean	Lower limit	Upper limit				
Right 1	Pre test post test	-1.67	1.42	0.21	-2.08	-1.24	-8.02	46	0

TABLE 18: Descriptive statistics of pre- and post-tests of output translation ability in the control.

Right 1	Productive vocabulary proficiency pre-test	Post-test of productive vocabulary ability
<i>N</i>	44	44
Mean value	6.09	6.71
Standard deviation	1.96	1.68
Standard error of mean	0.3	0.25

TABLE 19: T-test for pre- and pos-test of output-based translation skills in the control.

		Pairwise difference			95% confidence interval of difference		<i>t</i>	df	Sig (bilateral)
	Mean value	Standard deviation	Standard error of mean	Lower limit	Upper limit				
Right 2	Pre test post test	-0.61	2.29	-0.34	-1.31	-0.8	-1.78	43	0.82

It can be seen from the above table that the difference is -0.61, that is, the average score of the pre-test is 0.61 points lower than that of the post-test. Sig (two-sided) is 0.082, greater than 0.05, indicating no difference, which indicates that the effect of conventional translation teaching in

improving students' output translation ability is not significant. Therefore, based on the above data analysis, it can be seen that translation teaching under POA can effectively improve students' output translation ability and promote the development of students' translation application ability.

6. Conclusions

After nearly three months of experimental research, as well as the study of the obtained receptive translation ability test papers and output translation ability test papers, it has been proved that the application of the deep learning model improved EM algorithm and POA in English translation teaching can significantly improve students' motivation by more than 30%. It is proved that the application of the deep learning model improved EM algorithm and POA in English translation teaching can significantly improve students' receptive translation ability and output translation ability by more than 30%, effectively enhance students' motivation to learn translation, reduce students' anxiety in learning translation, and increase students' self-confidence in learning translation to a certain extent.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that she has no conflicts of interest.

References

- [1] B. Ren, "The use of machine translation algorithm based on residual and LSTM neural network in translation teaching," *PLoS One*, vol. 15, no. 11, Article ID e0240663, 2020.
- [2] M. Z. Alom, T. M. Taha, C. Yakopcic et al., "A state-of-the-art survey on deep learning theory and architectures," *Electronics*, vol. 8, no. 3, p. 292, 2019.
- [3] Z. Chao, "Research on English translation long text filtering based on LSTM semantic relevance," *Microprocessors and Microsystems*, vol. 80, Article ID 103574, 2021.
- [4] W. Qiufang, "The production-oriented approach to teaching university students English in China [Electronic Version]," *Language Teaching*, vol. 51.4, pp. 526–540, 2018.
- [5] P. Choudhury, D. Wang, N. A. Carlson, and T. Khanna, "Machine learning approaches to facial and text analysis: discovering CEO oral communication styles," *Strategic Management Journal*, vol. 40, no. 11, pp. 1705–1732, 2019.
- [6] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, "A survey of deep neural network architectures and their applications," *Neurocomputing*, vol. 234, pp. 11–26, 2017.
- [7] L. Yiran, "Evaluation of students' IELTS writing ability based on machine learning and neural network algorithm," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 4, pp. 6743–6753, 2021.
- [8] A. K. Jaiswal, P. Tiwari, S. Garg, and M. S. Hossain, "Entity-aware capsule network for multi-class classification of big data: a deep learning approach," *Future Generation Computer Systems*, vol. 117, pp. 1–11, 2021.
- [9] H. Qun, L. Wenjing, and C. Zhangli, "B&Anet: combining bidirectional LSTM and self-attention for end-to-end learning of task-oriented dialogue system," *Speech Communication*, vol. 125, pp. 15–23, 2020.
- [10] M. B. Krockenberger, K. L. Bosward, and P. J. Canfield, "Integrated case-based applied pathology (ICAP): a diagnostic-approach model for the learning and teaching of veterinary pathology," *Journal of Veterinary Medical Education*, vol. 34, no. 4, pp. 396–408, 2007.
- [11] Y. Goldberg, "Neural network methods for natural language processing," *Synthesis lectures on human language technologies*, vol. 10, no. 1, pp. 1–309, 2017.
- [12] A. Ortigosa, J. M. Martín, and R. M. Carro, "Sentiment analysis in Facebook and its application to e-learning," *Computers in Human Behavior*, vol. 31, pp. 527–541, 2014.
- [13] B. McCann, N. S. Keskar, C. Xiong, and R. Socher, "The Natural Language Decathlon: Multitask Learning as Question Answering," 2018, <https://arxiv.org/abs/1806.08730>.
- [14] X. Xiang and S. Foo, "Recent advances in deep reinforcement learning applications for solving partially observable markov decision processes (POMDP) problems: Part 1—fundamentals and applications in games, robotics and natural language processing," *Machine Learning and Knowledge Extraction*, vol. 3, no. 3, pp. 554–581, 2021.
- [15] Y. Liu and G. Fu, "Emotion recognition by deeply learned multi-channel textual and EEG features," *Future Generation Computer Systems*, vol. 119, pp. 1–6, 2021.
- [16] S. Zhou, M. Ke, and P. Luo, "Multi-camera transfer GAN for person re-identification," *Journal of Visual Communication and Image Representation*, vol. 59, pp. 393–400, 2019.
- [17] H. Zhu, H. Wei, B. Li, X. Yuan, and N. Kehtarnavaz, "Real-time moving object detection in high-resolution video sensing," *Sensors*, vol. 20, no. 12, p. 3591, 2020.
- [18] J. Younes, H. Achour, E. Souissi, and A. Ferchichi, "A deep learning approach for the Romanized Tunisian dialect identification," *The International Arab Journal of Information Technology*, vol. 17, no. 6, pp. 935–946, 2020.
- [19] F. Alonso, G. López, D. Manrique, and J. M. Viñes, "An instructional model for web-based e-learning education with a blended learning process approach," *British Journal of Educational Technology*, vol. 36, no. 2, pp. 217–235, 2005.
- [20] L. Deng, "Artificial intelligence in the rising wave of deep learning: the historical path and future outlook [perspectives]," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 180–177, 2018.
- [21] F. Li, C. Wang, and X. Yue, "Impact of doctoral student training process fit on doctoral students' mental health," *International Journal of Mental Health Promotion*, vol. 24, no. 2, pp. 169–187, 2022.