Implementing E-Learning in English Translation Teaching Using Deep Learning Models and Output-Oriented Methods

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Abstract. 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 paper researches English translation teaching based on the deep learning model to improve the EM algorithm and the guidance of the output-oriented method system. The experiment proves that the output-oriented method can effectively mobilize students' enthusiasm for translation learning, improve the efficiency of internalizing human knowledge into output ability, optimize teachers' teaching effect, and significantly improve students' English translation and output application abilities by more than 30%.

Keywords: output-oriented approach; driving; enabling; evaluation; translation teaching; E-Learning in English
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1 INTRODUCTION

It is an essential task of English teaching in the era to cultivate advanced and complex English translation talents with good comprehensive application ability[18]. In educational practice, the training methods are primarily focused on "teacher-centered" and "student-centered." The "teacher-centered" teaching mode often consists of the teacher explaining some translation skills, students practicing in class, and the teacher commenting [1]. To a certain extent, this lecture mode enables students to grasp the fundamental translation theories and skills effectively and, to a certain extent, stifles students' initiative and creativity in learning translation[3].

Translation activities require a complete understanding of the translation object, a thorough knowledge of the corpus, and the ability to reproduce the original text accurately in another language according to faithfulness, elegance, and quality[6]. The current translation teaching method cannot meet the requirement of improving students' translation skills. The main problems are as follows. The teaching of English translation needs to receive more attention. While the status of English subjects and teaching has been significantly improved, the reform of English translation teaching has yet to. It needs to catch up being in an embarrassing situation of being neglected for a long time.2. The teaching mode and teaching method of English translation teaching needs more innovation. The mode mainly centers on text, teacher, and classroom, ignoring students' central role, and English translation teaching is no exception[22]. The teaching of English translation is not an exception, and the teaching of English translation is mainly based on the transmission of knowledge but needs to pay attention to the education of process and method, ability, and value. 3. The teachers' strength in English translation teaching must be enriched. University English translation teachers must have a certain degree of translation theory and practice[16].

The core concept of the "output-oriented method" is "learning center," "learning-use integration," and "whole-person education"[7]. The "output-oriented method" is based on the core concepts of "learning center," "learning-use integration," and "whole-person education" 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[4]. In English translation teaching based on the "output-oriented method," teachers should actively build a suitable translation teaching mode and clarify the teaching objectives. In classroom teaching practice, they should guide students to learn and master translation knowledge and skills to improve their translation learning and training and communicate better[13]. To this end, teachers should have a particular understanding of the general requirements of translation. Based on this, teachers should effectively set translation teaching objectives. To ensure that the goals set are appropriate to translation needs so that students can gain specific practical experience in learning translation to strengthen their abilities and promote their good development[20]. On the other hand, teachers should also keep abreast of students' needs and weaknesses in translation learning and then set corresponding goals so that students can make up for their deficiencies in translation learning while achieving the goals.

2 RELATED WORK

Most English speakers in China have conducted numerous research studies on this theoretical system suitable for China's local context, among which academic system research has enriched the specific content of the output-oriented method. In contrast, practical research has explored a new path for foreign language teaching in China. [9] Adopted an experimental approach to conduct an in-depth study on the enabling aspects of the output-oriented method. Based on classroom practice, [11] explained the teaching design of a unit and focused on the teaching process of the facilitation session, dividing the facilitation into viewpoint facilitation, language facilitation, and chapter facilitation, which brought vitality to the classroom and significantly increased learners' motivation. [10] Three rounds of independent experimental studies were conducted over three years to explore the specific principles of the facilitation process.

The literature [17] guides the refinement of the output-oriented approach. [12] affirmed that the output-oriented approach has a solid theoretical foundation and exciting teaching materials and that the activities in the driving session were designed. He points out that the output-oriented approach is a typical application based on design research. It can be extended to additional educational contexts and beginners in English by expanding the output-oriented approach's scope, geographical area, and target audience. [8] reflects on the driving, enabling, and evaluating aspects of the output-oriented approach. In contrast, [15] argues that the design of the three components of the output-based approach promotes students' curiosity and makes the teacher's role as a "scaffold" slowly diminish, which has a positive effect on students' independent learning. [14] affirmed the innovative and localized effectiveness of the output-oriented approach. [19] argues that the output-oriented approach overturns the traditional input-to-output teaching model and that its output-input-output 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 [21], the pedagogical principles of the output-oriented approach 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. [15] firstly, deep learning is based on understanding, where learners can critically accept new ideas and facts and construct them with their original cognition. [14] believes that focusing on critical understanding, emphasizing information integration and applying by transfer, pointing to the development of learners' higher-order abilities and cultivating students' ability to solve complex problems, which have become an essential grip for implementing students' core literacy and innovative ability development in China. [19] believes that deep learning is to link the knowledge points in traditional teaching and to learn to build 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] scientific monitoring, regulation, and evaluation of one's English translation learning plan through theoretical guidance also enable students to perform more confidently in the English classroom. Deep learning also gives teachers some ideas for teaching English vocabulary, allowing them to focus on developing students' awareness of vocabulary learning and their learning strategies.

3 ARCHITECTURE

The Production-oriented Approach 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; secondly, the "output-driven-input-enabled" hypothesis proposed by Wen Qiufang (2014) in 2014. "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 :

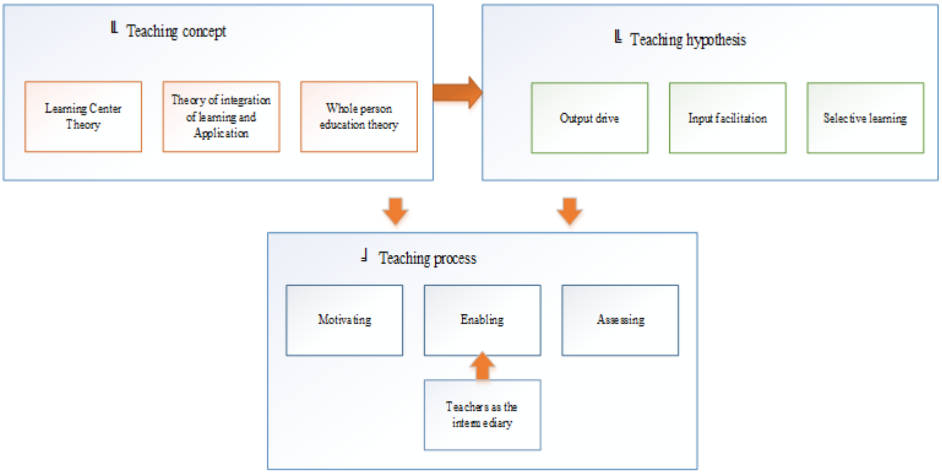

Figure 1: POA theory system.

The output-oriented method puts the "drive" at the very beginning of teaching, and its teaching steps and requirements are shown in Table 1 :

	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 cognitively challenging.
2	Students try to finish the task.	Let 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

Table 1: "Drive" teaching steps and requirements.

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

	Teaching steps	Teaching requirements
1	The teacher explains the assigned tasks and describes 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 practice the output task, and teachers check the output results and give guidance.	Enable students to apply the results of selective learning to output tasks immediately.

Table 2: "Enabling" teaching steps and requirements.

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

	Teaching steps	Teaching requirements
1	Teachers and students work together to develop and learn evaluation criteria.	The standard is straightforward, easy to understand, and easy to check
2	In-class evaluation of teachers and students	Clear submission deadline and clear submission form
3	In-class assessment of teachers and students	Teachers should use the limited classroom time effectively, put forward precise student requirements, and create targeted evaluations.
4	After-class evaluation of teachers' and students'	results submitted in succession serve as the basis for formative evaluation

Table 3: Steps and requirements for delayed evaluation outputs.

As shown in Figure 2, the output-oriented method divides the classroom into three main parts by combining the three "drive, facilitate, evaluate" teaching processes.

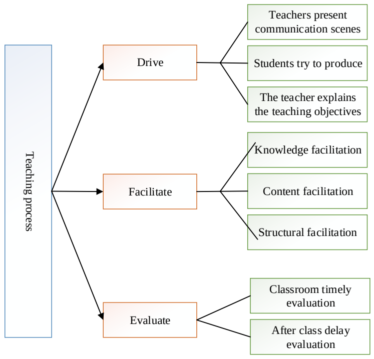

Figure 2: Flow chart of classroom vocabulary teaching.

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

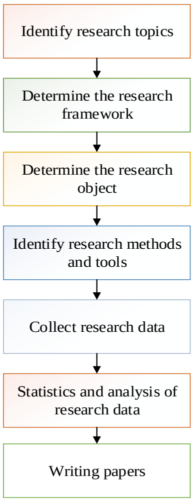

Figure 3: Flow chart of the research process.

Firstly, the research topic was determined by combining the researcher's research interests with the careful guidance of the supervisor 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. Secondly, the stage of determining the research framework is where the researcher defines the research framework and ideas according to the research topic and theories. Thirdly, the stage of determining the research object, in which the researcher chooses a suitable research object according to the situation of the internship site, sets the foundation for smooth development. Fourth, in the stage of determining method and tools, the researcher chose the test method to investigate the translation ability of the research subjects before and after the experiment and used the questionnaire method to investigate the emotional experience of learning of research subjects before and after the research. The qualitative reasons for the questionnaire data were explored using semi-structured interviews. Fifth, in the data collection stage, the main content of the data collection includes, first, the collection of test papers and questionnaires; the researcher chose a suitable time for the research subjects to complete the test and questionnaires. The second is the interview, mainly preliminary questionnaires from the high, middle, and low groups of two students, each randomly selected, a total of six students, and interview them and the interview process with their permission to use the device to record the interview content to facilitate later analysis. Sixth, in the statistical analysis of the research data stage, the researcher organized counted interviews collected by the semi-structured interview method. Seventh is the thesis writing stage after the data results are obtained and the thesis 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.

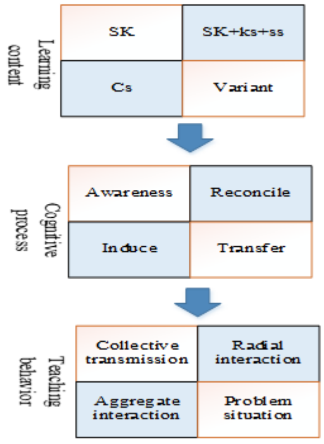

Figure 4: Deep learning model.

The deep learning mechanism model is further constructed with the above description, as shown in Figure 5. Figure 5 combines the horizontal and vertical sections to show it more intuitively for easy understanding. The flat section consists of culture, technology, and learners.

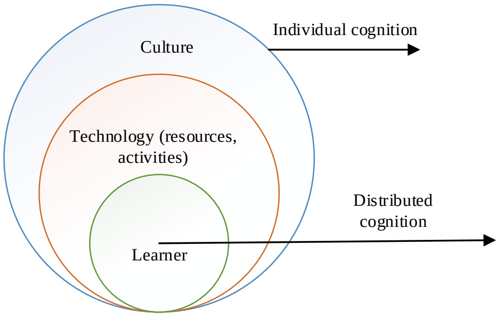

Figure 5: Deep learning mechanism modeling.

4 IMPROVED EM ALGORITHM

The experiment was three phases: "pretest, intervention, posttest," and the experimental procedure was designed according to the study phases, as shown in Figure 6 below：

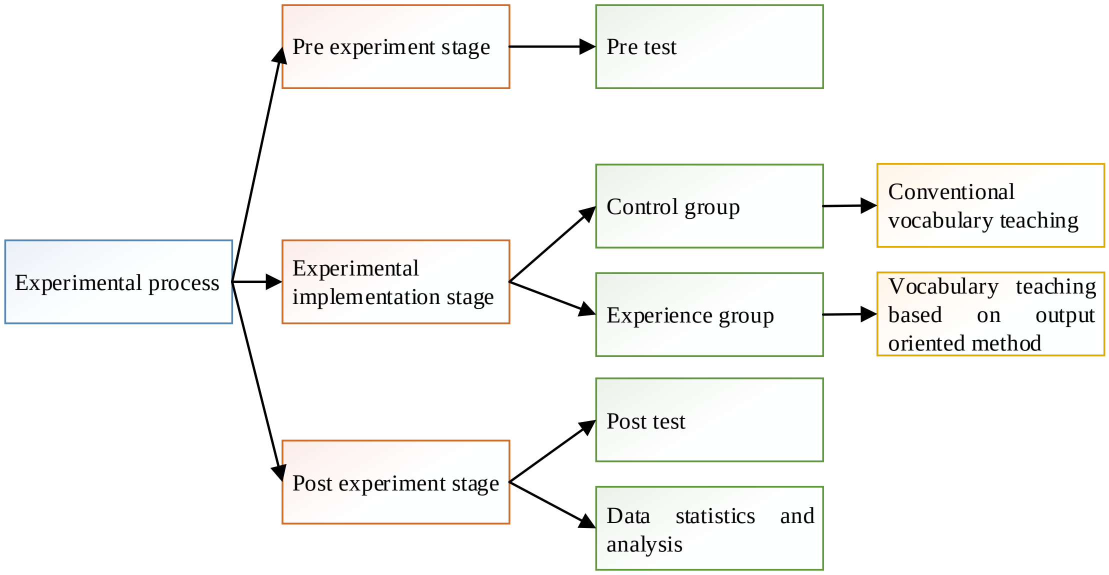

Figure 6: Experimental procedure.

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

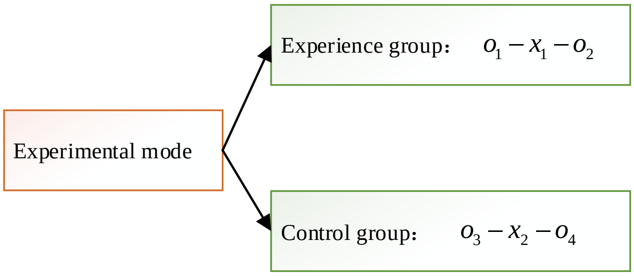

Figure 7: Experimental model diagram.

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

$$P_r(c \mid e) = \sum_a P_r(c, a \mid e) \tag{1}$$

In this alignment model, a Chinese word only has 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 / words and the Chinese word string $C = C_1^I =$

$C_1C_2\cdots C_J$has J words, a can be expressed as$a = a_1^J = a_1a_2\cdots a_J$ with J values, each value between [0, I].

Model 1

$$Pr(c \mid e) = \frac{\varepsilon}{(I+1)}\sum_{a_1=0}^{I}\cdots\sum_{a_J=0}^{I}\prod_{j=1}^{J} t\left(c_j \mid e_{a_j}\right) \tag{2}$$

$\left(C_j \mid e_{a_j}\right)$ denotes the translation rate of the word pair $\left(c_j, e_{a_j}\right)$. Given the constraint: For each word, e

$$\sum_c t\,(c \mid e) = 1 \tag{3}$$

Set the coefficientλ_e and get an auxiliary function

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

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 $t(c \mid e)$ can be

$$Pr(c \mid e) = \varepsilon\sum_{a_1=0}^{I}\cdots\sum_{a_J=0}^{I}\prod_{j=1}^{J} t\left(c_j \mid e_{a_j}\right)\cdot a(i \mid j,J,I) \tag{5}$$

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

$$\sum_{i=0}^{I} a\,(i \mid j,J,I) = 1 \tag{6}$$

Similarly, the auxiliary function can be obtained :

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

$$Pr(c \mid e) = \sum_{a_1=0}^{I}\cdots\sum_{a_J=0}^{I\sum cae} Pr\sum_{a_1=0}^{I}\cdots\sum_{a_J=0}^{I}\binom{m-\phi_0}{\phi_0} p_0^{m-2\phi_0} p_1^{\phi_0}\prod_{i=1}^{I}\phi_i\, n(\phi_i \mid e_i)\times\prod_{j=1}^{J} t\left(c_j \mid e_{a_i}\right)\cdot d\left(j \mid a_j,J,I\right) \tag{8}$$

$D\left(j \mid a_j,J,I\right)$ is the distortion rate. Given the constraints :

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

Auxiliary Functions :

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

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 fruitful. The first Chinese word generated by an English word is called head; the non-first Chinese word generated by a very productive English word is called non-head.

In model 4, $D\left(j \mid a_j,J,I\right)$ 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 volume A of receptive translation ability tests to test sensory translation ability. After that, the researchers sorted and analyzed the collected data.

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

Table 4: Statistics of receptive vocabulary ability pretest.

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

		Levene test				T-test			95% confidence	
		F	Sig	t	df	Sig (bilateral)	Mean difference	Standard error value	Lower limit	Upper limit
Total score	Assuming equal variance	2.30	0.13	-0.78	88	-0.44	-0.52	-0.67	-1.86	-0.82
	Assume unequal variance			-0.77	75.84	0.44	-0.52	-0.68	-1.88	-0.83

Table 5: T-Test of receptive vocabulary ability before the test.

The independent sample t-test requires that the population variance be equal. Therefore, the chi-square test needs to be considered first. As shown in Table 5 above, indicating that the pretest is similar, it is necessary to look at the data in the assumed equal variance row. The average value of the receptive translation ability of the experiment and the control is -0.52, which is insignificant. 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. Ninety 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.

Total score	Class	N	Mean value	Standard deviation	Standard error of the mean
	Experimental	46	26.70	7.86	0.27
	Control	44	25.14	4.57	0.69

Table 6: Descriptive statistics of receptive vocabulary ability of the experimental and control classes in the posttest.

As can be seen from Table 6, the average score of volume B on the translation ability test is 26.70, and the average score of volume B on the translation ability test 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. The standard deviation of the average value of volume B in the practical translation ability test is 1.86, while the standard deviation of the average value of volume B in the translation ability test is 4.57. The dispersion of the average value of translation ability is still higher than that of the experiment, indicating that the experimental group's polarization degree of translation ability is still low after the experiment.

		Levene test of variance equation				*T-test of the mean equation*			*95% confidence interval of difference*	
		F	*Sig*	*t*	*df*	*Sig (bilateral)*	*Mean difference*	*Standard error value*	*Lower limit*	*Upper limit*
Total score	*Assuming equal variance*	*30.45*	*0*	*2.14*	*88*	*0.35*	*1.56*	*0.73*	*0.11*	*3.01*
	Assume unequal variance			*2.10*	*56.37*	*0.40*	*1.56*	*0.74*	*0.75*	*3.04*

Table 7: Independent sample t-test of receptive vocabulary skills.

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 must 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 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 a substantial difference. Therefore, the above analysis shows that the receptive translation ability of students in the experimental and control classes 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 must 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 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 a substantial difference. Therefore, the above analysis shows that the receptive translation ability of students in the experimental and control classes is different after the experiment.

To determine the impact of output-oriented 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.

Right 1	*Class*	*N*	*Mean value*	*Standard deviation*	*Standard error of the mean*
	experimental	*46*	*24.02*	*2.57*	*0.38*

	Control	*46*	*26.70*	*1.86*	*0.27*

Table 8: Descriptive statistics of pre and post-tests of receptive vocabulary ability.

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

		Pairwise difference							
		Mean value	*Standard deviation*	*Standard error of the mean*	*95% confidence interval of difference*		*t*	*df*	*Sig (bilateral)*
					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 9: Paired sample t-test for pre and post-test of receptive vocabulary skills in the experimental class.

The researchers studied the results to understand students' translation ability changes under traditional teaching. The results are shown in table 10.

	Class	*N*	*Mean value*	*Standard deviation*	*Standard error of the mean*
	Experimental	*44*	*24.52*	*3.78*	*0.57*
Right 2	*Control*	*44*	*25.14*	*4.57*	*0.69*

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

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

To determine whether there are changes in the pretest and posttest of control translation ability, the researchers analyzed the pretest and posttest of control translation ability using a paired sample t-test. They obtained the following results in Table 11.

	Pairwise difference							
	Mean value	*Standard deviation*	*Standard error of the mean*	*95% confidence interval of difference*		*t*	*df*	*Sig (bilateral)*
				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 11: Paired sample t-test for pre and post-test of receptive vocabulary skills in the control.

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 performance improvement is insignificant.

The researchers used the translation part of the first unified test paper in the region to test the subjects' output translation ability. Ninety-one 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 of the collected data and obtained the following results, as shown in Table 12.

	Class	*N*	*Mean value*	*Standard deviation*	*Standard error of the mean*
Total score	*Experimental*	*44*	*6.10*	*1.96*	*0.30*
	Control	*47*	*5.72*	*1.33*	*0.19*

Table 12: Descriptive statistics of productive vocabulary ability.

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

		Levene test of variance equation		*T-test of the mean equation*					*95% confidence interval of difference*	
		F	*Sig*	*t*	*df*	*Sig (bilateral)*	*Mean difference*	*Standard error value*	*Lower limit*	*Upper limit*
Total score	*Assuming equal variance*	*6.6*	*0.01*	*1.05*	*89*	*0.30*	*0.37*	*0.35*	*-0.33*	*1.06*
	Assume unequal variance			*1.04*	*74.98*	*0.30*	*0.37*	*0.35*	*-3.34*	*1.07*

Table 13: Independent sample t-test of output vocabulary ability.

As shown in the above table, the significance probability of the 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, more significant than 0.05, showing no difference. The difference is 0.37, which is a slight difference. The 95% confidence interval (- 0.34,1.07) of the difference score includes 0, indicating that the difference is insignificant. Therefore, there is no difference, and it can be used as the research object of this study.

To investigate the impact of translation teaching under the guidance of the output-oriented method 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 in subjects' output-oriented translation ability. Ninety-one 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 of the collected data and obtained the results in Table 14.

Total score	*Class*	*N*	*Mean value*	*Standard deviation*	*Standard error of the mean*
	Experimental	*44*	*6.71*	*1.68*	*0.25*
	Control	*47*	*7.38*	*1.05*	*0.15*

Table 14: Descriptive statistics of the output vocabulary ability.

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 power, with little difference. The standard deviations are 1.05 and 1.68, respectively, indicating that the concentration of the output translation ability score is still lower than that in the experiment and the degree of polarization of the output translation ability score is slightly lower.

The results are shown in Table 15 to help us understand the differences more clearly.

		Levene test of variance equation		*T-test of the mean equation*					*95% confidence interval of difference*	
		F	*Sig*	*t*	*df*	*Sig (bilateral)*	*Mean difference*	*Standard error value*	*Lower limit*	*Upper limit*
Total score	*Assuming equal variance*	*10.14*	*0.002*	*-2.33*	*89*	*0.002*	*-0.68*	*.29*	*-1.26*	*-0.9*
	Assume unequal variance			*-2.29*	*71.50*	*0.03*	*-0.68*	*0.30*	*-1.27*	*-0.89*

Table 15: T-test of output vocabulary ability.

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, there are differences between the two, meaning that translation teaching under the guidance of the output-oriented method can improve students' output-based translation ability.

To better understand the impact of an output-oriented approach on students' productive translation ability, the researchers analyzed the data before and after the test and obtained the following results. The researchers analyzed the pretest and post-test scores of the experiment using paired sample t-tests and got the following results in Table 16.

Right 1		N	Mean value	Standard deviation	Standard error of the mean
	Productive vocabulary proficiency pretest	47	5.72	1.33	0.19
	Post-test of productive vocabulary ability	47	7.83	1.05	0.15

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

It can be seen from the above table that the average scores of the pretest 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 pretest, with little difference. The pretest and post-test standard deviations 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.

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

Pairwise difference									
		Mean value	Standard deviation	Standard error of the mean	95% confidence interval of difference		t	df	Sig (bilateral)
					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 17: Paired-sample t-test for the experimental's pre and post-tests of output vocabulary skills.

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 the 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 insignificant, translation teaching guided by the output-oriented method is efficacious in improving students' output-oriented translation ability[21,22].

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.

		N	Mean value	Standard deviation	Standard error of the mean
Right 2	Productive vocabulary proficiency pretest	44	6.09	1.96	0.30
	Post-test of productive vocabulary ability	44	6.71	1.68	0.25

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

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 pretest and posttest 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 pretest and posttest standard deviations are 1.96 and 1.68, respectively, indicating that after the traditional teaching of translation, the dispersion of the output translation ability score is reduced, and the bifurcation phenomenon is reduced.

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

Pairwise difference									
		Mean value	*Standard deviation*	*Standard error of the mean*	*95% confidence interval of the difference*		*t*	*df*	*Sig (bilateral)*
					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*

Table 19: T-test for pre and post-test of output-based vocabulary skills in the control.

It can be seen from the above table that the difference is -0.61; that is, the average score of the pretest is 0.61 points lower than that of the post-test. Sig (two-sided) is 0.082, more significant than 0.05, indicating no difference, which suggests that the effect of conventional translation teaching in improving students' output translation ability is not substantial. Therefore, based on the above data analysis, translation leading under the output-oriented method can effectively enhance 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-based improved EM algorithm and output-oriented method in English translation teaching can significantly improve students' motivation by more than 30%. It is proved that the application of the deep learning model-based improved EM algorithm and output-oriented method 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. Integrating e-learning platforms facilitates collaborative learning environments, enabling peer interaction, feedback exchange, and practical project-based experiences. Personalized feedback from AI-driven systems refines students' translation abilities, promoting continuous improvement.

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REFERENCES

[1] Alom, M. Z.; Taha, T. M.; Yakopcic, C.; Westberg, S.; Sidike, P.; Nasrin, M. S.; Asari, V. K.: A state-of-the-Art Survey on Deep Learning Theory and Architectures, Electronics, 8(3), 2019, 292. https://doi.org/10.3390/electronics8030292

[2] Alonso, F.; López, G.; Manrique, D.; Viñes, J. M.: An Instructional Model for Web-Based E-Learning Education with a Blended Learning Process Approach, British Journal of Educational Technology, 36(2), 2005, 217-235. https://doi.org/10.1111/j.1467-8535.2005.00454.x

[3] Chao, Z.: Research on English Translation Long Text Filtering Based on LSTM Semantic Relevance, Microprocessors, and Microsystems, 80, 2021, 103574. https://doi.org/10.1016/j.micpro.2020.103574

[4] Choudhury, P.; Wang, D.; Carlson, N. A.; Khanna, T.: Machine Learning Approaches to Facial and Text Analysis: Discovering CEO Oral Communication Styles, Strategic Management Journal, 40(11), 2019, 1705-1732. https://doi.org/10.1002/smj.3067

[5] Deng, L.: Artificial Intelligence in the Rising Wave of Deep Learning: The Historical Path and Future Outlook [perspectives], IEEE Signal Processing Magazine, 35(1), 2018, 180-177. https://doi.org/10.1109/MSP.2017.2762725

[6] Feng, X.; Wei, Y.; Pan, X.; Qiu, L.; Ma, Y.: Academic Emotion Classification and Recognition Method for Large-Scale Online Learning Environment—Based on A-CNN and LSTM-ATT Deep Learning Pipeline Method, International Journal of Environmental Research and Public Health, 17(6), 2020, 1941. https://doi.org/10.3390/ijerph17061941

[7] Fritzson, P.; Pop, A.; Abdelhak, K.; Asghar, A.; Bachmann, B.; Braun, W.; Östlund, P.: The Open Modelica Integrated Environment for Modeling, Simulation, and Model-Based Development, Modeling, Identification, and Control, 41(4), 2020, 241-295. https://doi.org/10.4173/mic.2020.4.1

[8] Goldberg, Y.: Neural Network Methods for Natural Language Processing, Synthesis Lectures on Human Language Technologies, 10(1), 2017, 1-309. https://doi.org/10.2200/S00762ED1V01Y201703HLT037

[9] Jaiswal, A. K.; Tiwari, P.; Garg, S.; Hossain, M. S.: Entity-Aware Capsule Network for Multi-Class Classification of Big Data: A Deep Learning Approach, Future Generation Computer Systems, 117, 2021, 1-11. https://doi.org/10.1016/j.future.2020.11.012

[10] Jingchun, Z.; Dehuan, Z.; Weishi, Z.: Cross-View Enhancement Network for Underwater Images, Engineering Applications of Artificial Intelligence, 121, 2023, 105952. https://doi.org/10.1016/j.engappai.2023.105952

[11] Jingchun, Z.; Lei, P.; Weishi, Z.: Underwater Image Enhancement Method by Multi-Interval Histogram Equalization, IEEE Journal of Oceanic Engineering, 48(2),2023, 474-488. https://doi.org/10.1109/JOE.2022.3223733

[12] Krockenberger, M. B.; Bosward, K. L.; Canfield, P. J.: Integrated Case-Based Applied Pathology (ICAP): A Diagnostic-Approach Model for the Learning and Teaching of Veterinary Pathology, Journal of Veterinary Medical Education, 34(4), 2007, 396-408. https://doi.org/10.3138/jvme.34.4.396

[13] Liu, W.; Wang, Z.; Liu, X.; Zeng, N.; Liu, Y.; Alsaadi, F. E.: A Survey of Deep Neural Network Architectures and their Applications, Neuro Computing, 234, 2017, 11-26. https://doi.org/10.1016/j.neucom.2016.12.038

[14] McCann, B.; Keskar, N. S.; Xiong, C.; Socher, R.: The Natural Language Decathlon: Multitask Learning as Question Answering, arXiv Preprint arXiv:1806.08730, 2018.

[15] Ortigosa, A.; Martín, J. M.; Carro, R. M.: Sentiment Analysis in Facebook and its Application to E-Learning, Computers in Human Behavior, 31, 2014, 527-541. https://doi.org/10.1016/j.chb.2013.05.024

[16] Pouyanfar, S.; Sadiq, S.; Yan, Y.; Tian, H.; Tao, Y.; Reyes, M. P.; Iyengar, S. S.: A Survey on Deep Learning: Algorithms, Techniques, and Applications, ACM Computing Surveys

(CSUR), 51(5), 2018, 1-36. https://doi.org/10.1145/3234150
[17] Qun, H.; Wenjing, L.; Zhangli, C.: B&Anet: Combining Bidirectional LSTM and Self-Attention for End-to-End Learning of Task-Oriented Dialogue System, Speech Communication, 125, 2020, 15-23. https://doi.org/10.1016/j.specom.2020.09.005
[18] Ren, B.: The Use of Machine Translation Algorithm Based on Residual and LSTM Neural Network in Translation Teaching, Plos One, 15(11), 2020, e0240663. https://doi.org/10.1371/journal.pone.0240663
[19] Xiang, X.; Foo, S.: 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, 3(3), 2021, 554-581. https://doi.org/10.3390/make3030029
[20] Yiran, L.: Evaluation of Students' IELTS Writing Ability Based on Machine Learning and Neural Network Algorithm, Journal of Intelligent & Fuzzy Systems, 40(4), 2021, 6743-6753. https://doi.org/10.3233/JIFS-189508
[21] Younes, J.; Achour, H.; Souissi, E.; Ferchichi, A.: A Deep Learning Approach for the Romanized Tunisian Dialect Identification, Int. Arab J. Inf. Technol., 17(6), 2020, 935-946. https://doi.org/10.34028/iajit/17/6/12
[22] Young, T.; Hazarika, D.; Poria, S.; Cambria, E.: Recent Trends in Deep Learning Based Natural Language Processing, IEEE Computational Intelligence Magazine, 13(3), 2018, 55-75. https://doi.org/10.1109/MCI.2018.2840738.