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Knowledge Transfer in the Teaching of English Translation Based on Deep Learning

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This study was conducted to explore the utilization of deep learning concepts and techniques in the education domain as a means of improving the effectiveness of English translation teaching and the transfer and application of students' translation knowledge and skills. The model-building process consists of three stages: the pre-training stage, the fine-tuning stage and the translation stage. The pre-training stage involves deep learning on a large-scale teaching dialog or text corpus; the fine-tuning stage involves knowledge transfer on a relatively small-scale real-world corpus; and the translation stage involves the translation of new real-world texts. This study collected and analyzed data collected by means of an experiment designed and implemented A deep-learning-based English translation teaching experiment was designed and implemented to compare three teaching models (a traditional model, a guided classroom model, and a transfer learning model) in terms of students' translation competence, deep learning competence, and learning satisfaction. The results of the study suggest that the knowledge transfer model incorporating deep learning was the most effective, the guided classroom model was the second most effective, and the traditional model was the least effective.

Keywords: deep learning, English translation, pedagogical knowledge transfer

1. INTRODUCTION

As an important facilitator of cross-cultural communication, English translation plays a crucial role in human information exchange and knowledge sharing. Therefore, the teaching of English translation strategies, as an important part of English teaching, is also attracting an increasing amount of attention and concern from the education sector and society [1]. The purpose of English translation teaching is to cultivate students' translation literacy and competence, and to improve students' language use and cross-cultural communication skills. However, traditional English translation teaching practices tend to focus more on the rules and techniques of translation and neglect the essence and purpose of translation, making it difficult for students' translation knowledge and skills to be transferred and applied to different domains, situations and tasks, and affects the effectiveness and efficiency of translation teaching. This problem provided the motivation for this study, which explores ways to utilize the concept and technology of deep learning to improve the effectiveness of English translation teaching and to facilitate the transfer and application of students' translation knowledge and competence [2, 3].

The model of transfer teaching is shown in Figure 1. The concepts and techniques of deep learning are consistent with the purposes and requirements of English translation teaching, which require learners to be able to apply their knowledge and skills flexibly to solve practical problems and create new value. Therefore, this study believes that deep learning can provide a new perspective and method for English translation teaching, which can help to improve the quality and level of English translation teaching, cultivate the transfer and application of students' translation knowledge and abilities, and improve students' language use and cross-cultural communication skills [4-6].

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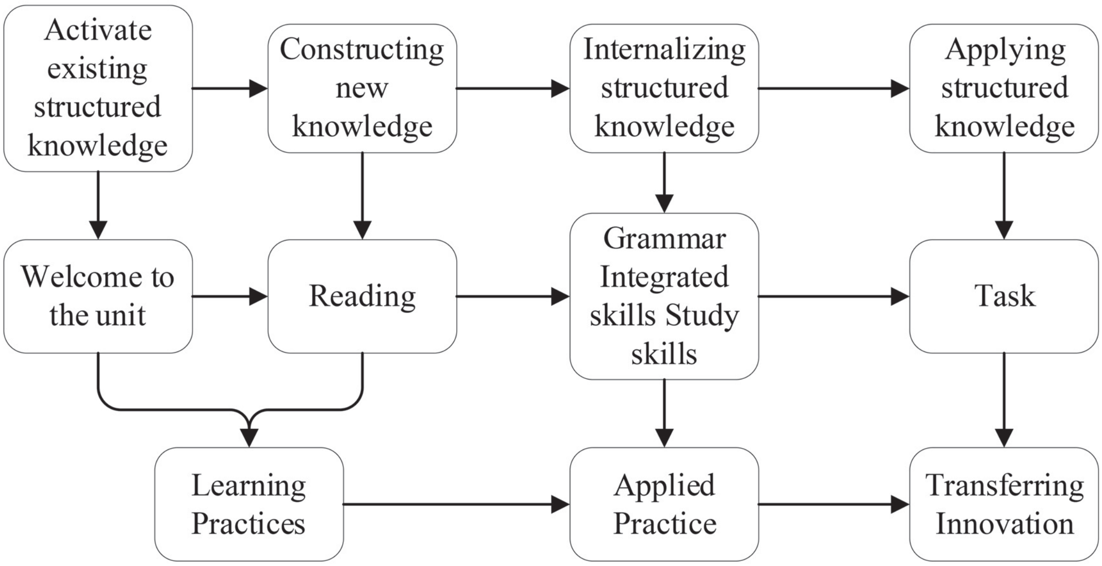

Figure 1 Instructional model of English knowledge transfer.

The technologies of deep learning include deep neural networks, natural language processing, machine translation, etc., which can provide powerful support and assistance for English translation teaching. These technologies can provide rich data and resources for English translation teaching, improve the quality and efficiency of translation, increase the diversity and flexibility of translation, stimulate students' learning interest and motivation, and encourage students to engage in active and independent learning [7].

2. LITERATURE REVIEW

Firstly, the study examines the relationship between knowledge migration and knowledge innovation, and argues that knowledge migration is an important prerequisite and condition for knowledge innovation, as well as being an important means of knowledge discovery. The article points out that knowledge migration leads to the updating, expanding and deepening of knowledge, so as to stimulate the power and potential of knowledge innovation [8]. Secondly, the article discusses the objectives and principles of English translation teaching, and describes the English translation teaching mode based on deep learning, i.e. The article proposes a teaching model of "translation analysis - translation training - translation evaluation - translation innovation". The article proposes an English translation teaching model based on deep learning, with this model as the main link, and introduces relevant teaching methods and evaluation methods. The article suggests that this teaching mode can improve students' translation ability and literacy, and the efficiency and quality of their translations, and encourage students to develop and implement innovations in the translation domain [9]. Furthermore, the article explores the relationship between translation and knowledge production, management and transformation, and puts forward the concept of knowledge translation studies, which considers translation as a process of knowledge transfer, discourse reconstruction and value creation, and an important way for local knowledge to go to the world. The article analyzes the theories and methods of knowledge management, as well as the significance and strategies of knowledge translation, pointing out that translation plays a key role in the production, management and transformation of knowledge [10]. Finally, the article summarizes the characteristics, modes and mechanisms of knowledge migration and knowledge innovation, as well as the implementation strategies and methods of knowledge migration and knowledge innovation. The article suggests that knowledge migration and knowledge innovation are mutually reinforcing and interdependent, and need to be achieved by adopting a variety of ways and means. The article also suggests several future research directions [11].

The core of the knowledge transfer concept is the transferability of knowledge, manifested in the ability to transform and apply knowledge in different contexts or domains, and is specifically associated with the versatility, structure, abstraction and innovation of knowledge. In order to achieve this goal, we have constructed an English translation teaching mode based on the concept of in-depth learning, which consists of four closely-connected teaching links: "Translation Analysis - Translation Training - Translation Evaluation - Translation Innovation". This model promotes the comprehensive knowledge transfer process of students in by providing a series of scientific and targeted teaching tools and assessment mechanisms. Firstly, in the "translation analysis" stage, students are guided to make an in-depth analysis of the textual content, linguistic features, cultural connotations and stylistic characteristics of various kinds of translated materials, so as to strengthen their awareness of the purpose of translation, clarify the needs of the translation target, overcome the difficulties of translating and form an effective personalized translation strategy, laying a solid foundation for subsequent translation practice.

Secondly, in the "translation training" stage, through repeated practice on a wide range of translation materials of different types, difficulty levels and specialties, students gradually acquire and become proficient in the basic skills and methodology of translation, so as to improve their overall ability and quality as translators, and at the same time provide evidence for the objective and fair evaluation of translation results.

The next part of the course is “Evaluation of Translation” [12, 13]. In this stage, a diversified and three-dimensional evaluation system is adopted which involves self-evaluation, peer evaluation and teacher’s professional comments, etc., so that students can closely examine their own translations, discover their strengths and weaknesses, and adjust and optimize their translation strategies, thus significantly improving their translation competencies and self-confidence. This process also creates favorable conditions for encouraging translation innovation. Finally, in the “Translation Innovation” stage, students are encouraged to actively engage in comparative research, in-depth analysis and improvement of translation works, to face new translation problems and challenges, to exercise their independent problem-solving ability, and to explore new translation perspectives and methods, so that they become excellent translators with an innovative spirit and a distinctive personal style, ensuring the vitality of the translation discipline and contributing to its development [14, 15].

3. DEEP LEARNING-BASED KNOWLEDGE MIGRATION MODEL FOR TEACHING ENGLISH TRANSLATION

3.1 Modeling Framework

To achieve this goal, we have constructed an English translation teaching model based on the concept of deep learning, which consists of four closely linked teaching links: “Translation Analysis - Translation Training - Translation Evaluation - Translation Innovation”. This model promotes students’ knowledge transfer process in all aspects through a series of scientific and targeted teaching tools and evaluation mechanisms: First, in the “translation analysis” stage, students are guided to deeply analyze the content essence, language characteristics, cultural connotations and style characteristics of various translation materials to enhance their understanding of the purpose of translation, clarify the needs of the translation objects, master the difficulties of translation, and form effective personalized translation strategies, laying a solid foundation for subsequent translation practice. Second, in the “translation training” process, through repeated practice of a large number of translation materials of different types, difficulty levels and professions, students gradually master the basic skills and methods of translation, comprehensively improve their comprehensive ability and quality as translators, and also provide a basis for objectively and impartially evaluating translation results[16, 17].Next, in the “translation evaluation” section, a diversified and three-dimensional evaluation system is adopted, including self-evaluation, peer evaluation and professional comments from teachers, so that students can comprehensively examine their own translation works, discover their own strengths and weaknesses, adjust and optimize translation strategies, thereby significantly improving their translation level and self-confidence, and also creating favorable conditions for stimulating the motivation for translation innovation [18, 19]. Finally, in the “Translation Innovation” stage, students are encouraged to actively engage in comparative research, in-depth analysis and improvement of translated works, face new translation problems and challenges, exercise their ability to solve problems independently, and explore new translation perspectives and methods, so as to cultivate excellent translators with innovative spirit and distinctive personal style, and inject continuous vitality and contribution into the development of the translation discipline. The model structure is shown in Figure 2.

3.2 Model Flow

In the model, the feature space of the source domain is constructed by extracting the features of various types of source knowledge, such as English grammar, vocabulary, sentence patterns, etc., and then mapping the feature space of the source domain to that of the target domain by means of alignment and transformation, so as to achieve the transition from source knowledge to target knowledge. The target domain refers to the English translation knowledge that needs to be learned, such as English culture, context and style. Through knowledge transfer, students can obtain richer and more appropriate knowledge of English translation in the target domain, thus improving their skills and the impact of the English translation [20, 21].

The process we constructed from input to output is represented by this formula $o = i(f(s))$.

Where o is the output, s is the input, f is the translation function and i is the innovation function. This formula indicates that we first translate the input s to the output t using f and then innovate the output t to the output o using i. The f function and i function represent the processing [22, 23].

First, we adopt the LSTM (Long Short-Term Memory) encoder-decoder architecture to carry out the pre-training process on a large-scale teaching dialog or text corpus. The goal of this phase is to enable the model to master the linguistic patterns, syntactic structures, and potential semantic associations in the teaching corpus through extensive learning and iterative optimization, and to build a strong translation capability at the same time. After sufficient training, the model will obtain a set of encoder and decoder parameters suitable for language comprehension and generation tasks in teaching scenarios.

Subsequently, we applied the above pre-trained encoders and decoders to a relatively small, real-world corpus for fine-tuning operations. Due to the similarity and transferability between the teaching corpus and the real corpus, the model is able to further adapt to the complexity and diversity of the real context while maintaining the original knowledge structure. This phase aims to transfer and integrate the knowledge information from the teaching data to the real corpus environment, so as to obtain a set of encoder and decoder parameters optimized for the real scenario.

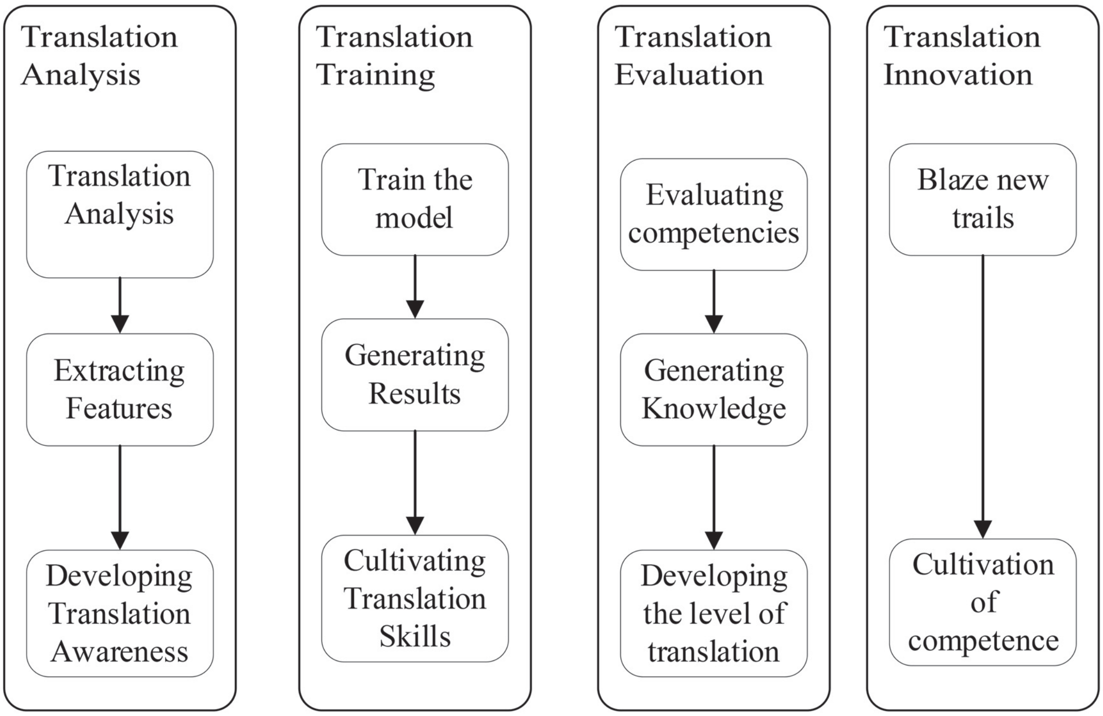

Figure 2 Model structure.

Finally, after completing the fine-tuning of the real corpus, we apply the adjusted encoder and decoder to handle the new real-world text translation task [24].

Pre-training phase: given the teaching corpus and Y^t, which denote the source and target language sentences respectively, the goal is to maximize the conditional probability $P(Y^{(t)}|X^{(t)})$, i.e.

$$\theta^{(t)} = \text{argmax}_\theta \sum_{(X^{(t)},Y^{(t)})} \log P(Y^{(t)}|X^{(t)};\theta)$$

Where θ denotes the parameters of the encoder and the decoder, and $P(Y^{(t)}|X^{(t)};\theta)$ can be computed using the LSTM encoder-decoder model, i.e.:.

$$P(Y^{(t)}|X^{(t)};\theta) = \prod_{j=1}^{|Y^{(t)}|} P(y_j^{(t)}|y_{<j}^{(t)}, X(t);\theta)$$

.

Where $y_j^{(t)}$ denotes the j-th word of the target language sentence, and $y < jt$ denotes the first $j-1$ words of the target language sentence, and $|Y(t)|$ denotes the length of the target language sentence.

Fine-tuning phase: given the real corpus X^r and Y^r, representing sentences in the source and target languages, respectively, the goal is to maximize the conditional probability $P(Y(r)|X(r))$, i.e:

$$\theta^{(r)} = \text{argmax}_\theta \sum_{(X^{(r)},Y^{(r)})} \log P(Y^{(r)}|X^{(r)};\theta)$$

.

Where θ denotes the parameters of the encoder and decoder, and $P(Y^{(r)}|X^{(r)};\theta)$ can be computed using the LSTM encoder-decoder model, which is the same as the formula for the pre-training stage. The difference is that the parameter $\theta(r)$ in the fine-tuning stage is fine-tuned based on the parameter $\theta(t)$ in the pre-training stage, i.e.:$\theta^r = \theta^t + \Delta\theta$ where $\Delta\theta$ denotes the amount of fine-tuning of the parameter, which can be computed by gradient descent or other optimization algorithms.

Translation phase: given a new authentic corpus $X(n)$, representing sentences in the source language, the goal is to generate sentences $Y(n)$ in the target language such that the conditional probability $P(Y(n)|X(n))$ is maximized, i.e:

$$Y^{(n)} = \text{argmax } P(Y|X^{(n)};\theta^{(r)})$$

.

Where $\theta(r)$ denotes the parameters of the encoder and decoder after fine-tuning, and $P(Y|X(n);\theta(r))$ can be computed using the LSTM encoder-decoder model with the same formulas as those used in the pre-training and fine-tuning phases. The generation of sentences $Y(n)$ in the target language can be realized by the greedy method or other search algorithms.

4. EXPERIMENTAL PHASE

4.1 Data Sets

In order to determine the effect of the "deep learning-based knowledge transfer model for English translation teaching", we selected two datasets for the experiment, namely:

Source dataset: The English reading instruction dataset from [24] contains 20 English reading instruction units, each of which consists of an English reading text and several reading comprehension questions related to it. These texts

Table 1 Data sets.

Data set	Source data set	Target data set
Training set	16 units	16 units
Validation set	2 units	2 units
Test set	2 units	2 units

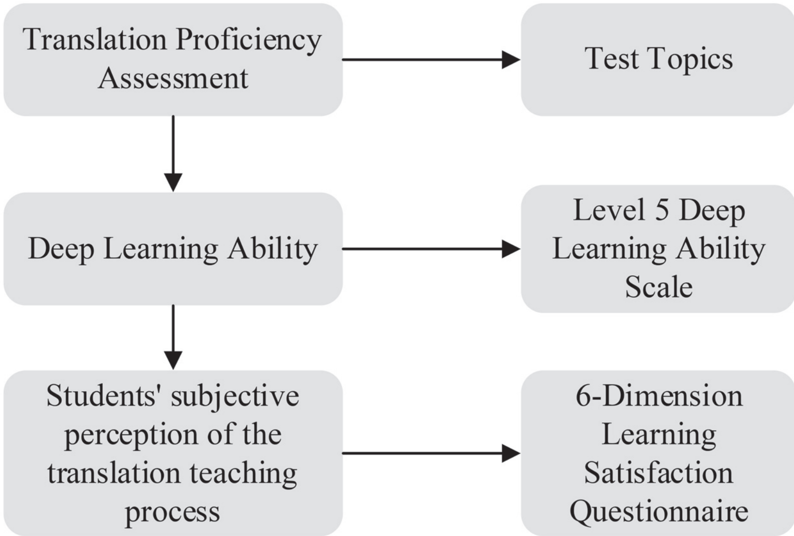

Figure 3 Evaluation process.

and questions cover a variety of topics, genres, levels of difficulty, and cultural backgrounds, and are designed to develop students' English reading skills and deep learning abilities.

Target dataset: the English translation teaching dataset from [25] contains 20 English translation teaching units, each of which includes an English translation text and several translation analysis questions, translation training questions, translation evaluation questions and translation innovation questions related to it.

We divided these two datasets into a training set, a validation set and a test set respectively with the ratio of 8:1:1. The amount of data in each set is given in Table 1 [26].

4.2 Experimental Design

We conducted the experiment to compare the effect of the "deep learning-based knowledge transfer model for teaching English translation" with two other common teaching models, namely, the traditional teaching model and the deep learning model, in teaching English translation [27].

Traditional Teaching Model: Based on the teaching model of teacher's lecture and student's practice, the teacher is mainly responsible for imparting to students the knowledge and skills required for translation. The students are responsible for completing the translation exercises and assignments set by the teacher, and the teacher corrects and assesses the students' translations [28].

Guided classroom: This is a teaching model based on teacher-guidance and student-inquiry, where teachers are responsible for providing students with translation problems, tasks and projects, students are responsible for in-depth learning through translation analysis, training, evaluation and innovation, and teachers provide results, feedback, and support for students' learning process [29].

At the end of the teaching cycle, in order to assess and acquire an in-depth understanding of the students' learning outcomes and feedback on the teaching activities, we presented each of the three participating classes with a detailed and multidimensional assessment task. Our assessment process is Figure 3.

First of all, to assess the students' translation skills, a set of test questions from the target data set was carefully selected for the final exam, in order to check the actual translation skills level of the students. Students were asked to complete a specific translation task within a limited time and their translation was assessed according to a set of rigorous grading criteria. This set of criteria comprised a number of core dimensions, such as the accuracy of the translated content, the fluency of language expression, and the appropriate and accurate delivery of information about the cultural context of the original text, etc., striving to measure the students' professional translation skills comprehensively [30].

Secondly, for the assessment of deep learning ability, we adopted the internationally recognized 5-level deep learning ability scale and, via a questionnaire, students gave a self-assessment of the various abilities they have demonstrated during their translation learning.

Finally, in order to understand students' subjective feelings about the whole translation teaching process, we designed a learning satisfaction questionnaire containing six dimensions. The questionnaire examines in detail the students' satisfaction with the teaching content (e.g. The practicality and cutting-

Table 2 Results of the Translation Competency Assessment.

Teaching model	Content accuracy	Fluency	Cultural adaptability	Average score
Traditional model	78.3	76.5	74.2	76.3
Guided Class-room Model	82.7	81.4	79.6	71.2
Knowledge transfer learning model	86.4	85.2	83.9	85.2

Table 3 Results of deep learning ability assessment.

Teaching model	Intellectual understanding	Application of knowledge	Migration of knowledge	Knowledge creation	Average score
Traditional model	3.21	3.15	2.98	2.87	3.05
Guided Classroom Model	3.67	3.54	3.41	3.29	3.48
Knowledge transfer learning model	3.82	3.76	3.68	3.59	3.71

edge of the course knowledge), the teaching method (e.g. The teacher's way of teaching, the effectiveness of interactive teaching), and the teaching effect (e.g. The degree of improvement of personal translation skills, deepening of the understanding of the field of translation, etc.). Through the collection and analysis of these feedback data, we aim to continuously optimize our teaching strategies to ensure that the quality of teaching is continuously improved and that the individual learning needs of students are effectively met [31].

4.3 Experimental Results

We statistically analyzed the scores of the students in the three classes in terms of translation ability, deep learning ability and learning satisfaction. The results are shown in Table 2 and Table 3 and in Figure 4.

As can be seen in Tables 2, Table 3 and Figure 4, the class that was exposed to the knowledge transfer learning model achieved the highest scores in translation ability, deep learning ability and learning satisfaction, which indicates that the transfer learning model can effectively improve the effectiveness of students' English translation teaching. In order to verify this conclusion, we used ANOVA to analyze the assessment results for the three classes. These results are shown in Table 4.

As can be seen in Table 4, the effect of instructional models on assessment results is significant, with an F-value of 18.23, a p-value of less than 0.001, much less than the significance level of 0.05, and a rejection of the null hypothesis that there is a significant difference between different instructional models on assessment results. In order to further explore which instructional models differ from each other, we conducted post hoc multiple comparisons. The results are shown in Table 5.

As can be seen in Table 5, the difference in the mean values of the three instructional models is significant, with p-values less than 0.05 indicating that there is a significant difference in the assessment results of the three instructional models. The assessment results of the transfer learning model are the highest, the guided classroom model is the second highest, and the traditional model is the lowest. This indicates that the transfer learning model can better improve students' translation skills, deep learning ability and learning satisfaction, and that this is more suitable for the purpose of English translation teaching than the traditional model and the guided classroom model.

To summarize, by assessing the translation skills, deep learning ability and learning satisfaction of students in three classes, this study found that different teaching models have significant effects on the assessment results. It was demonstrated that the transfer learning model is the most effective, the deep learning model is the second most effective, and the traditional model is the worst in terms of performance. This indicates that the transfer learning model can effectively improve the effectiveness of English translation teaching. Hence, it is recommended that the proposed transfer learning model in English translation teaching be adopted to improve students' learning outcomes and satisfaction.

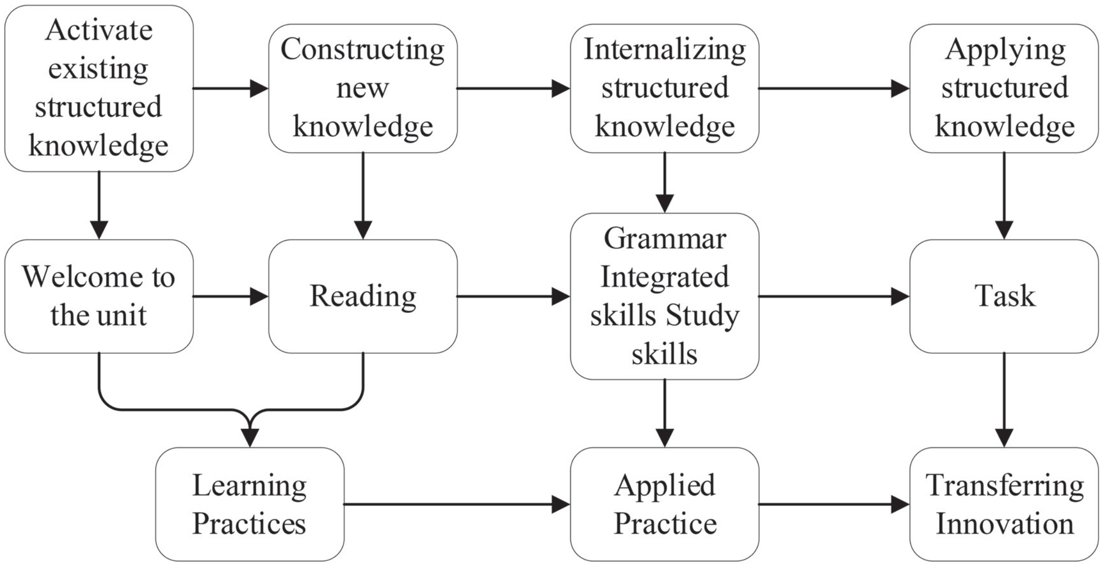

Figure 4 Results of Learning Satisfaction Assessment.

Table 4 ANOVA results.

Source of information etc.	Square sum (e.g. equation of squares)	Number of degrees of freedom (physics)	Mean square	F-value	P-value
Teaching model	123.45	2	61.73	18.23	<0.001
Inaccuracies	203.67	57	3.57		
Total	327.12	59			

Table 5 Post hoc multiple comparison results.

Teaching model	Relief (i.e. Height of land in geography)	Standard error	P-value
Traditional Model - Guided Classroom Model	−0.43	0.15	0.021
Traditional Model - Knowledge Transfer Learning Model	−0.89	0.15	<0.001
Guided Classroom Model - Knowledge Transfer Learning Model	−0.46	0.15	0.014

5. CONCLUSION

This paper discusses how to utilize the concepts and techniques of deep learning to improve the effectiveness of English translation teaching and to promote the transfer and application of students' translation knowledge and skills. The model building process consisted of three phases: the pre-training phase, the fine-tuning phase and the translation phase.

The main contributions and innovations of this paper are: (1) the design and implementation of an English translation teaching experiment based on deep learning, the collection and analysis of experimental data, and conducting a comparison of the three teaching models in terms of students' translation ability, deep learning ability and learning satisfaction. (2) Through empirical analysis, we found that our knowledge transfer model was the most effective, the guided learning model was the second most effective, and the traditional model had the worst performance, indicating that the proposed knowledge transfer model can significantly improve students' English translation skills, providing a theoretical basis and practical guidance for the adoption of the transfer learning model in the domain of English translation teaching.

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