Translation Service Implementation in Cloud: Automation Trends in English Translation Industry

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Abstract

INTRODUCTION: The development of information technology has led to the renewal of teaching methods, and cloud translation combining offline and online learning has become a trend in higher education.

OBJECTIVES: It is becoming increasingly apparent that the "surface issues" of blended learning are being addressed, especially the lack of consistency in online task development, which leads to inefficiencies in deep understanding.

METHODS: Through literature research, the factors affecting task planning in cloud translation are analyzed, and a cloud computing task planning model is established based on task learning theory.

RESULTS: The results show that task-based cloud translation can increase students' learning engagement and that targeted group task design is critical in improving students' interest and translation skills.

CONCLUSION: Using complex task modeling can improve the academic level of translation students and increase their involvement in translation projects.

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1. Introduction

Cloud computing, a new learning model that combines e-learning with traditional learning, has become a focus of higher education reform and has significantly increased the acceptance of blended learning. Much research has been conducted on the use of cloud computing in foreign language teaching, but in general, although researchers have emphasized the use of cloud computing in English language teaching over the past two decades, little research has been conducted on learning strategies. In the early 2000s, the pedagogy of English language courses in higher education institutions explicitly recommended implementing targeted and diverse learning activities. The redesign of cloud translation tasks based on task-oriented learning theory proved its importance(Glasco et al.,

2021). This chapter examines the research background, questions, relevance, and methodology and details the framework of the work. With the rapid development of information technology and continuous innovation in teaching methods, cloud translation has gradually penetrated different education levels. 2020 has seen the Introduction of online textbook instruction, real-time learning, and online discussions on various e-learning platforms.

Researchers abroad have begun to conduct in-depth research on cloud computing in higher education English courses, but related research has yet to provide a framework or model for cloud-based translation tools. In cloud-based translation design, teachers usually cannot use curriculum theory to guide the design of individual learning levels(Xu & Lockwood, 2021). Therefore, more research is needed on the effectiveness of education. With the development of cloud translation, it has become a trend in cloud translation to develop cloud translation

technology based on cloud translation theory for specific courses.

This paper analyzes the types and characteristics of online and offline cloud translation tasks, organizes them according to the content of cloud translation theory, proposes a task-based cloud translation model, and refines the guiding principles of task learning. The cloud translation model provides additional insights and perspectives for developing cloud translation theories and learning strategies, as well as theoretical support and backing for improving the quality of English teaching. The task-based cloud translation model developed in this paper can provide empirical examples of cloud translation development, partially addressing the issues of offline task design and online activity integration in a hybrid environment and providing a reference for cloud translation practice. The study's results and reflections can help teachers address translation design in the cloud. Implementing this work has improved students' competence and interest in translating natural sciences to some extent.

This paper proposes a new data growth strategy to improve the quality of embedded data and the performance of the GEC model. The model uses an alternative approach to provide a more comprehensive semantic representation, optimizing the occurrence of syntactic errors in the data correction task and syntactic error correction in the GEC task(Hayes et al., 2020). Several researchers provided 3.3 million training data pairs for the CNN-based GEC model and proposed ways to increase the translation data. When trained using only the LANG-8 body, the F-value can rise to 0.49. By reusing, the model is more accurate than previous models, and the probability of detecting and correcting model errors increases with alternative learning(Ramsay, 2020). Second, the model makes better use of sentence context information for correction, and the model itself has powerful search capabilities that allow better tuning and control of sentence flow. As a result, the liquidity of the EU rate exceeds 8%.

2. Research Methodology and Theory

Different researchers have different ways of defining tasks. In task language learning, task definitions can be narrow and broad. The mission of an assignment is not to provide mechanical language training but to teach students the skills or strategies to complete the assignment. All activities, including language training, are generally referred to as tasks. The educational goal is the process by which the student strives to achieve a set goal. From a linguistic perspective, assignments are various learning activities in which students comprehend, process, publish, or communicate in the target language. Some researchers argue that students complete assignments and that the activity process emphasizes the importance of expression in solving practical problems in language teaching(Kabir et al., 2021). Assignments are language application activities whose primary purpose is to express meaning.

With the development of deep learning, more and more researchers are defining higher-level tasks that often define educational activities. In foreign countries, deep learning tasks are classified as advanced, integrated, and reflective. Completing these tasks can be an important indicator of student engagement in learning. Training activities in education and training systems reflect a solid commitment to organizing teaching tasks and content in a dynamic and controlled manner, implementing training objectives, and determining assessment strategies. The training program consists of three phases in a cloud-based translation environment: pre-school, classroom, and classroom. When planning the learning, special attention was paid to the logical sequence of learning activities such as communication, problem-solving, assessment and reflection, and the evaluation of the learning process during the learning process. This study was divided into four phases: knowledge sharing, knowledge consultation, knowledge construction, and knowledge integration. Each step includes problem observation, questions and discussion, and demonstration.

English translation programs at universities significantly impact students' translation skills and are essential for developing translation skills. Translation training began in the early days. Since 1992, researchers have studied the teaching of translation. However, most previous studies have demonstrated the importance of studying translation teaching and teaching methods without empirical studies on the nature and characteristics of translation teaching(Beames et al., 2020). However, problems of consistency in teaching content, creativity in teaching methods, practicality and practice of translation skills, and understanding of context and cultural background often arise in translation teaching, resulting in students' insufficient knowledge of the original text. In the translation process, it is impossible to understand the original text's meaning accurately and to change the code between the two languages correctly. Students can better adapt to the translation process through proper practice, and teaching translation courses should give students the time and opportunity to stay on level.

3. Case and study design
3.1 Case Introduction

The English translation is a comprehensive academic English course between the comprehensive university and specialized English courses. Due to its interdisciplinary and holistic nature, the English translation has become a representative translation course. To test the effectiveness of the task-based cloud translation model and promote its application in teaching translation courses, this paper takes business language translation courses in foreign universities as an example. It uses the cloud translation model to study and review two English courses in the first year. One is experimental. This paper tracks and collects

process data based on nine English translation topics in three steps.

The study involved 49 business English students who completed their business English translation in the second half of the academic year 2020-2021. The two classes were divided into experimental and control types, with 26 students, 22 girls and four boys. There are 19 girls and four boys in this school. Students in both classes attended translation courses during their first two years and had a specific foundation in learning translation. The traditional business English translation course has been popular with students for many years. Over the past two years, students have begun to improve instruction, including a desire for teachers to use more e-learning materials and to increase the share of hands-on learning activities. For these reasons, this study focuses on a business English course to develop a translation-guided cloud computing application and apply critical learning to a pilot course to test its educational effectiveness.

The task-based cloud translation model was used for the test group, and the traditional cloud translation model was used for the control group. To ensure accuracy and professionalism, the independent parameters for this test were as follows:

(1) Teacher: The two courses were taught by a teacher with many years of experience teaching business English translation. (2) Teaching content: In this study, the teaching content of both courses was the same, with the main teaching content being the nine topics of the Business English Translation course. The teaching resources involved in this study include SPOC platform videos, tests, documents, and PPT courseware. (3) Teaching time: The experimental class and the control class in this study conducted a total of 36 hours of study for 18 weeks, and the 18 weeks of study were divided into three stages, in which the first three topics were taught as the first stage, 3-6 topics were taught as the second stage, and 7-9 topics were taught as the third stage; (4) Students' learning styles: survey and interview the learning styles of students in both classes to understand the learning styles of students in both classes and to ensure that the learning styles of students in both classes did not affect the experiment; (5) others: the whole experimental process included a pretest and a post-test with two phases of testing.

3.2 Experimental design

The researchers are conducting a comparative experimental study based on the above example. The following are the methods used to plan, collect data, and evaluate the implementation of the survey (Aitzhanova et al., 2022). The study is divided into six phases, including pre-experimental grouping, pre-experimental testing, study implementation, post-experimental testing, questionnaires and interviews, data processing, and analysis of results.

1. Grouping: The study was open to all Business English students in the second semester of the academic year 2020-2021. The second year is a pilot class of 26-year-old students.

2. Pretest: To understand students' initial learning level and learning style at two levels, a pretest was developed to test students' initial teaching level and learning approach at two levels. The pretest consisted of five Chinese sentences (5 points), five Chinese statements (15 points), one English text (20 points), and one error correction (10 points), for a total of 50 points.
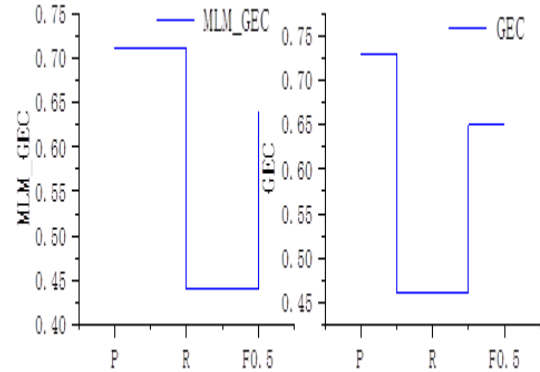

Figure 1 Comparison of experimental results in this paper

3. Teaching practice: The teaching experiment will be conducted in two classrooms from March to June 2021. The test group will use task-based cloud conversion, while the control group will use traditional cloud conversion. The table below shows the detailed training plan. The study has three phases(B. Li & He, 2021). Students at both levels must take an exam at the end of the first and second year. The authors attended an 18-week experimental course, taught a control course, and were observed in two sections by completing an observation registration form.

4. Post-test: At the end of the 18-week course, students will take a final exam in the evening. The following documents are of the same topic type and numbering as the above documents and include 5 Chinese sentence translation questions, 5 Chinese statement translation questions (, 1 English short text translation question, and one correction question for a total of 50 minutes. As with the entrance exam, the post-test also includes basic translation skills, information related to the course content, and advanced translation information. During the post-test, the following model is developed in this paper:

$$attention = output - Attention(Q, K, V)$$
(1)

The Introduction of three variables in equation (1) to better calculate the type of grammatical errors in translation;

$$Multihead(Q, K, V) = Concat(head_1......head_n)W^o$$ (2)

Equation (2) is added to the infinite loop to improve the accuracy of the calculation further;

$$head_i = Attention(QW_i^q, KW_i^k, VW_i^v) \tag{3}$$

Equation (3) adds the values and weights of the corresponding variables to the associated values, respectively, and calculates the value of each associated value;

$$Attention(Q, K, V) = soft \max(\frac{QK^T}{\sqrt{d_k}})V \tag{4}$$

(a) The maximum value of the maximum weighting is treated uniformly in equation (4) to calculate the type of grammatical errors better;

$$P_t(w) = (1 - \alpha_t^{copy}) * p_t^{gen}(w) + (\alpha_t^{copy}) * p_t^{copy}(w) \tag{5}$$

5. Surveys and interviews: At the end of the course, students were studied at two levels in terms of three dimensions: access to education, social presence, and cognitive presence. Teaching implies developing, facilitating, and adapting students' mental and social processes to achieve personal and educational values(Williams, 2020). Research on instructional goals, learning activities, and survey results can reflect student satisfaction with teacher support. Social presence emphasizes the level of knowledge of others in the learning process and the interaction between students and others in the online learning environment. Social learning surveys and interactions with other students can reflect student satisfaction with collaborative learning(Konttinen, 2021). Cognitive presence emphasizes the extent to which students build and define values through continuous reflection and dialogue in the community through critical research.

3.3 Data collection

This study aimed to compare and analyze the learning outcomes of the two classes and examine students' learning levels and engagement in learning from two perspectives. Regarding the level of student learning, the course evaluation was combined with process evaluation, teacher evaluation and peer evaluation in five components. Process evaluation refers to classroom performance (10%) and includes the presence and participation of classroom interactions. Online learning and conversations (10%), including videos and online discussions; electronic assessments, homework (20%), including exams, homework assignments, and online peer reviews; project tasks (30%), including group or individual project tasks; SPOC data on online learning behaviors explain behaviors in this study, cognitive contributions are measured in the SPOC discussion forum through constructed knowledge and self-assessment, and affective contributions were studied through student experience interviews(Díaz-Cintas & Zhang, 2022).

The Business English course aims to provide students with a theoretical and practical understanding of business translation, to increase their interest in translation, to learn about translation-related experiences, and to become familiar with various popular business translation styles and methods. Experience and master the general principles of "integrated" translation and improve fundamental translation skills and abilities. This course enables students to understand that business translation is characterized by "professionalism, conciseness, and clarity" and that translation strategies are "accuracy, fluency, standardized terminology, and appropriate intonation." Functional equivalence between English and Chinese texts can be achieved by replicating the original's message content, voice, style, and professional features (C. Li et al., 2023). By comparing English and Chinese, practicing translation, and appreciating translation, students can experience and immerse themselves in the beauty of language, culture, and translation, increasing cultural awareness and confidence. On the one hand, students' information systems are enriched, and on the other hand, a broad view of economic and human well-being is developed, resulting in an organic combination of knowledge transfer, learning skills, and valuable advice.

Based on the FSLSM learning style data analysis, the table below shows the students' learning styles in the experimental and control classes. The results show no significant differences in data processing, observation, acquisition, and comprehension learning styles. Therefore, this comparative experience excludes the effect of learning styles on the experimental results.
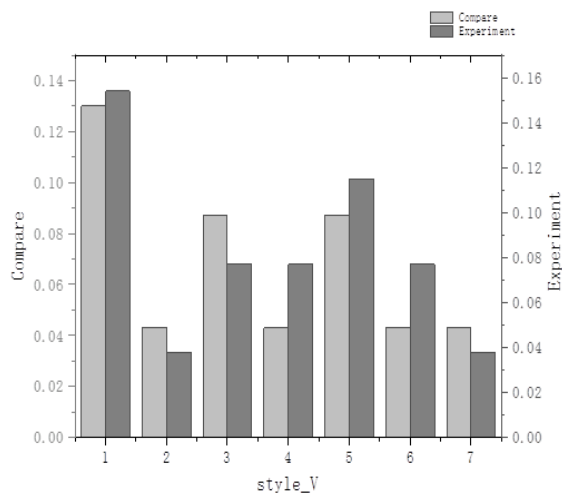

Figure 2 Comparison of control and experimental groups of style_V

The primary process of managing cloud translation in the classroom is that teachers submit teaching resources to the SPOC platform one week before the course starts, and students study relevant videos and practice and test on the SPOC platform before the class starts(Chang, 2021). During this period, instructors familiarize themselves with business card translation techniques and help students analyze the differences between English and English business cards through case studies and questions(Huimin, 2020). As part of the out-of-course activities, the instructor creates a discussion fund on the SPOC platform to encourage students to check and

summarize what they have learned. The experimental course was primarily based on task-based learning in a hybrid environment, and the design and implementation of the study followed the model of task-based education in a hybrid environment. For example, in learning to model the structure, exchange, and organization of tasks, students participate in a "business card course" based on task classification.

4. Empirical process
4.1 Translation Grammar Detection in Cloud Computing

Learn how to add data to the GEC model and train the library using a rule-based approach. The results are in the CONLL-2014 test series. As the size of the embedded data increases, the maximum values of F0.5-37.9% and F0.4-37.8% reach 23.7% and 15.7%, respectively. Only the training team trained at least 11.4% of the GEC. However, the accuracy of the GEC model is 18.4% lower than that of the GEC model introduced by the training team.

The rule-based data correction method improves the performance of the test set grammar error correction model as the amount of data increases(Tang et al., 2022). The results show that the data improvement significantly impacts the overall performance of the GEC model. When 200 m of synthetic data was used to train the GEC, it had a better memory than the GEC introduced using only physical training. When creating learning data, specific language, punctuation, and spelling errors are combined into different words. Error types are more general, accurate, and faster to recover than just replacing random words in the dictionary.

Regarding the model recognition accuracy, the model recognition results improve with the growth of complex learning data, but there are gaps in the model recognition accuracy, and it is trained only in the training group(Randles et al., 2022). A data validation method based on the same size data is proposed that differs from the GEC model based on complex data in terms of error type and number compared to the learning library. However, a large amount of data can fill this gap, so it is crucial to improve the data quality.
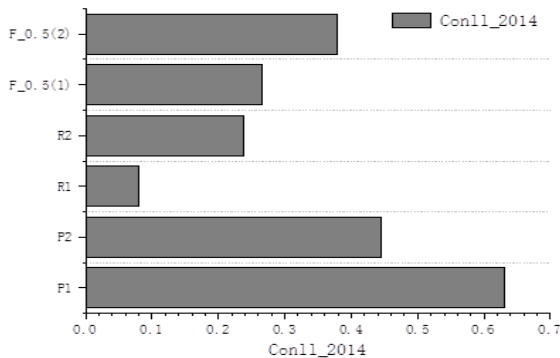

Figure 3 Efficiency considerations of the GEC model

The GEC model consists of complex data generated by different GEG models of various sizes. The best GEC F0.5 model derived from GEG1 is 0.286. Based on 200M learning data synthesized by GEG2, GEC outperforms GEG1 with a 5.2% improvement in P, R, and F0.5 and F0.9% improvement in F0.5, respectively. The increase was 4.9%.

In this paper, the Author uses rule-based data and learning corpora for error modeling and compares them with the GEC model. The results show that the GEC model has better learning results than previous error models, demonstrating the effectiveness of different approaches in improving knowledge. The GEG1 model is used to learn the English error correction model (GEG1) → GEC for complex data learning, and the improved model performance results from continuous data scaling. Among them, the performance improvement of 20M-80M is better than 80M-140M and 140M-200M models, and the reasons are analyzed. The performance of models that detect error types may reach relative saturation, and the addition of learning data has little effect on improving model performance. There are some limitations in error detection. The results show that optimizing the GEG and GEC models is essential to improve model performance.

GEC uses the same learning material as the GEG1 grammar error correction model, and the complex data generated by GEG2 is used for learning, call rate improvement, and the F0.5 error correction model. Also, the rule-based synthetic data improvement method increases the detection and correction of specific errors in the model. Improving the learning material's quality enhances the model's effectiveness for error correction.
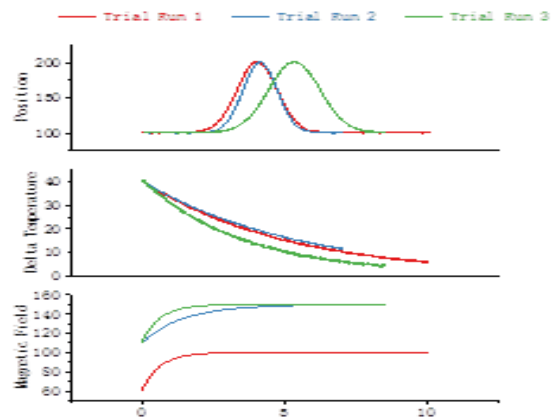

Figure 4 Comparison of GEC training results

This paper established a comprehensive error model of English through a comparative analysis of the learning process and experimental results. The parameters of the experimental data were determined through index evaluation, experimental process design, and experimental results analysis(Powers et al., 2021). Unlike previous work, the GEC model was formed using monolingual markers and data. The experimental results showed that the method improved the performance of the GEC model and the experiment's efficiency.

4.2 Automated syntax error correction

Spelling errors are usually corrected using different components, such as spell check and manually defined rule templates(Liu, 2021). The spell check only compares words in the text with many known words. The term is considered invalid and corrected if no comment exists. Structure errors can only be fixed by adding, deleting, or moving one or more words. Structure errors can be corrected by replacing an existing word with another (Heesbeen & Prieto, 2020). A language error is a text value error. This error is neither a component error nor a spelling error. Identifying language errors requires much knowledge and is difficult to correct.

In the GEC system, learning speed is 0.02, weight loss is 0.5, training stop is 0, and patience is 0.99. Wait! Wait! CONLL-2014 and M2 test sets were applied as estimated values. In addition, the JFLEG test series and GLEU values were used to analyze the flow of GEC calibration results. In this paper, the GEC model was used to correct the source phrases of the student library. The calibration results of the learning library were combined with the standard reference set of the parallel library, added to the GEC learning materials, and retrained by the GEG. The model completed intensive training before meeting the system requirements.
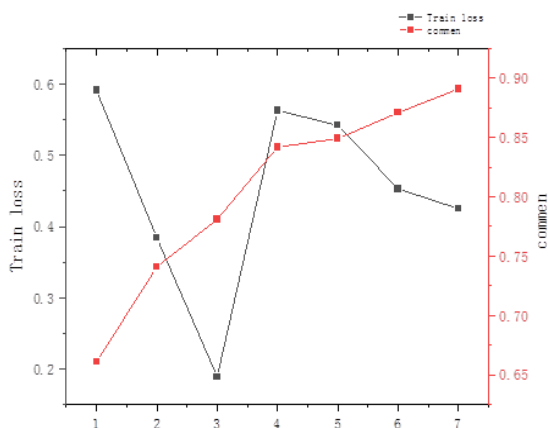

Figure 5 Train loss training results of EPOCH

In this paper, the Author uses data synthesis to pre-train the GEG model and then learn how to configure the GEG model. Just as monolingual libraries know anti-translation models, the monolingual archives used in this study are authentic because they are from native speakers.

To improve grammar error correction, the GEC model is used to correct the learning material in the learning corpus, and the default learning links are used as high-level data in the GEG model to create parallelism. Step 1: In the GEC translation model, there are no component errors in the target group of the reward model, and low-performance model errors are unrealistic. Since the performance of the GEC model is relatively low, synthetic data was used for training to avoid partial correction of non-spandex words due to the poor performance of the GEC model. Therefore, the most efficient GEC model

presented in Section 3.2.2 was chosen to handle the original containers in the three learning groups(Alsharari, 2022). After that, the initial references of the model applicants are combined with the standard reference references of the learning library, and the learning data are mixed with the rule-based data inputs to learn how to create spurious models. The GEG3 error generation model is implemented by comparing the three learning corpora. Step 2 (GEG3) → GEC: The GEG3 model processes the monologues and reconstructs the synthetic data of different sizes of 20m, 80m, 140m, and 200m to form a separate GEC model. Step 3: To improve the GEC model's performance, the Author aims to expand the data range based on the existing complete data before training.

By correcting the first sentence, the Author concludes that the template better corrects errors at the beginning of the article and thus makes it easier to add article errors to candidate sentences in the language section. All errors in Amendment #2 have been corrected. Compared to the first sentence, sentence one does not contain punctuation errors, which indicates that the GEC model can identify and correct punctuation errors. However, no other changes were made in Option 2, meaning that the GEC model still has some deficiencies in correcting some parts of the defect in some cases. The use of alternative training partially fills this gap. Based on the rule-based data validation method created in this paper, the synthetic learning data included fixed word combinations, preposition distributions, and spelling errors.

5. Conclusion

English language learners often make grammatical, syntactic, and semantic errors under the influence of their native language. While English teachers can help ESL students correct errors by providing continuous feedback, manual grammar error correction can be complex and daunting. Therefore, developing an automated grammar error correction system can alleviate this phenomenon. GEC students and teachers worldwide benefit from the practical application because it can provide continuous and timely error correction feedback. Functional GEC system for text input, automatic analysis, and error detection Correct a grammatical error, keeping the original meaning of the sentence intact. Practical training of GEC systems often faces problems due to a lack of training knowledge. It is essential to study how much multilingual data can be used to obtain high-quality learning data, optimize GEC models, and produce correct results.

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