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Innovative Research on AI-Supported Practical Teaching Models for University English Translation Programs

Qingshan Yin[1,*], Shiqiang Jiang[1] and Lanjie Li[1]
[1] Basic Courses Department, Rocket Force University of Engineering, Xi'an, Shaanxi, 710025, China
Corresponding authors: (e-mail: yinqingshan99@163.com).

Abstract The gradual improvement and maturation of artificial intelligence technology has opened up new avenues for the application of corpora in translation teaching and learning in university English programs. This paper focuses on the intelligent detection of typical errors in student translations, leveraging the advantages of corpus-assisted translation instruction. For common omissions in actual English translation learning scenarios, we introduce information-based measures of sentence context variables and establish a set of synonyms for each sentence. Combining these with an XGBoost model, we construct an error detection model for omissions. Additionally, association rule mining is used to identify relationships between errors, generate an error node network, derive patterns among errors, and build an omission error detection model based on association rules. Using Chinese traditional culture as a case study, a Chinese-English bilingual corpus of Chinese traditional culture is established, and an AADAA teaching strategy based on the output-oriented approach is designed. Two classes of first-year English majors from K University were selected as control variables for the application experiment of the proposed model and teaching strategy. The post-test scores of the two classes in the translation course showed a significance level of less than 0.001, indicating a statistically significant difference, which validated the feasibility of the proposed model and teaching strategy in practical applications.

Index Terms omission error detection, association rules, AADAA teaching strategy, English translation

I. Introduction

In recent years, artificial intelligence (AI) technology has rapidly emerged, driving transformation across various industries. Breakthroughs in technologies such as big data, deep learning, and natural language processing have enabled AI to achieve significant results in fields such as image recognition and speech recognition [1], [2]. The education sector has also benefited from the development of AI technology, and language intelligence may inevitably empower the transformation of educational systems and mechanisms, optimizing educational structures and outcomes [3], [4].

English translation education, due to the uniqueness of its professional skills and limitations in faculty resources, urgently needs to adapt to new changes and integrate innovative teaching models to meet students' learning needs. However, university English translation teaching has long been plagued by the phenomenon of “high time investment and low returns,” primarily due to teachers lacking scientific and effective translation teaching methods, students having low self-learning efficiency and limited engagement, a monotonous translation learning environment, and traditional large-class teaching models and standardized teaching content failing to address individual differences and personalized needs [5]-[8]. Additionally, in actual teaching, many teachers have found that traditional translation teaching methods struggle to meet students' diverse learning needs. Most teachers still use manual grading to provide feedback to students or implement peer feedback, but such feedback mechanisms struggle to address student differences, lack timeliness, and have unstable accuracy, with severe shortages in the use of intelligent tools [9]-[12]. Furthermore, in current translation teaching, students have limited opportunities for real-world practical training, with extremely low coverage of practical training bases. Even when practical cases are present in the classroom, students lack sufficient practice time, and the scenarios are too narrow, failing to align with current industry demands [13]-[15].

With the continuous development of artificial intelligence, English translation teachers have recognized that applying artificial intelligence can effectively improve translation teaching methods, enhance teaching quality, and facilitate personalized learning for students [16], [17]. The integration of artificial intelligence into translation teaching offers new possibilities for optimizing teaching resources, improving learning environments, and implementing innovative teaching methods, thereby promoting comprehensive reform and innovation in English translation practical teaching [18], [19]. Therefore, exploring an artificial intelligence-driven practical teaching model for university English translation programs is particularly important.

The introduction of artificial intelligence has transformed traditional teaching and learning methods in education, opening up new possibilities for English translation practice-based instruction. Literature [20] explores the application of human translation technology and natural language processing (NLP) technology in the design of meaning-oriented professional translation training course learning activities, not only addressing the challenges of meaning-oriented translation but also verifying the accuracy of translation operations. Literature [21] combines NLP and communication technology to assist foundational English translation tasks through effective reading comprehension under deep learning models of semantic rounding and semantic fusion, and establishes a new university English translation classroom model within a wireless classroom interaction system. Literature [22] and Literature [23] utilize deep learning to respectively construct a feedback mechanism for English translation instruction and an automatic error detection system for engineering English translation. By automatically detecting grammatical errors and spelling mistakes, these systems assess translations. With the assistance of the feedback mechanism, they enhance students' translation skills while optimizing the learning experience. Literature [24] constructs a grammar correction algorithm for English translation based on a deep learning-based encoder-decoder machine translation structure, and optimizes the algorithm under an attention mechanism, achieving good correction performance. Literature [25] introduces interactive artificial intelligence—ChatGPT—which can provide real-time feedback for English translation teaching, construct authentic interactive scenarios, enrich teaching content, and promote the improvement of students' translation skills and cultural awareness. However, this tool requires students to pay more attention to professional ethics and technical ethics when translating. Literature [26] shares an AI-driven university English translation teaching software that integrates modules such as voice input, speech recognition, text translation, and speech translation. Under an adaptive learning recommendation system and student learning monitoring system, it provides personalized learning for students, which is beneficial for improving learning efficiency and translation quality. Literature [27] verifies that AI-based neural machine translation and language learning models, as well as the combination of the two models, can help improve students' translation abilities, with the best results achieved when combined.

This paper first summarizes the advantages of corpus-assisted teaching in university English translation courses, laying the practical foundation for the development of translation teaching assistance models and strategies. It then provides a detailed explanation of the identification principles and implementation methods for omissions in student assignments, constructing an omission error model based on information volume and synonym sets. Additionally, it explains the process of using association rules to identify relationships between errors, establishing an omission error detection model based on association rules. Using Chinese traditional culture as an example, the paper demonstrates the steps for establishing a Chinese-English bilingual corpus and designs an AADAA teaching strategy based on the output-oriented approach. Combining the proposed model and teaching strategy, the paper forms a corpus-based translation teaching assistance model and teaching strategy. Finally, the structure of the proposed omission error detection model is optimized through the form of controlling variables, and the performance of the optimized model is evaluated. A control group and an experimental group are set up, and the actual application effects of the proposed model and teaching strategy are evaluated by comparing the post-test scores of the experimental group.

II. Corpus-based translation teaching assistance models and strategies

II. A. Translation Teaching Assisted by Corpora

Traditional translation instruction is teacher-centered, with students' translation skills often relying on dictionaries and formulaic examples. Translation content tends to be monotonous, lacking variety and diversity, especially when dealing with Chinese-to-English translation, where there is often no unified standard, leaving it entirely up to the teacher's subjective judgment. Bilingual corpora, due to their inherent characteristics, are highly suitable for translation instruction. On one hand, they can provide translation examples to enhance translation efficiency. On the other hand, they can objectively assess the quality of students' translations, helping them improve their translation skills. In translation teaching practice, the Tmxmall corpus platform can be selected. The platform's advantages include not only providing bilingual parallel search functionality but also offering text alignment features, enabling translation content to be promptly converted into parallel corpora for storage, effectively functioning as a translation memory database.

II. B. Translation omission error detection model based on association rules

II. B. 1) Detection of omissions based on information content and synonym sets

Omission errors are also common mistakes in student assignments. Unlike grammatical errors such as article errors, omission errors are typical translation errors that cannot be identified by common grammar checks. An omission error refers to the absence of certain information from the original text in the translated sentence. Omissions can result in incomplete sentences, and if relevant words or phrases are omitted in critical positions, the final meaning may be completely different.

Currently, there is limited research on identifying omissions, and most studies analyze them from the perspective of the generative principles of neural network-based machine translation. There is no existing research specifically targeting omissions in student translation review scenarios. The omissions discussed here are not errors in machine-translated texts but rather errors made by students during the translation review process. Due to differences in the order of machine translation and the actual sentence order, as well as significant discrepancies with students' own sentence translation order, students may still omit information even when revising based on machine translation. In this new scenario, the system not only collects students' proofreading texts but also includes the corresponding original assignment texts and machine translation texts. This provides additional auxiliary information for identifying omissions.

Omission of translation generally leads to changes in the amount of information in a sentence, so we introduce a measure of information to quantify the changes before and after the sentence. For a given sentence, there are N words in the sentence, with a total of T different words. For a given word w_i, its probability of occurrence in the sentence and its information content are given by equations (1)-(2):

$$p_{w_i} = \frac{n_i}{N} \tag{1}$$

$$S = \sum_{i=1}^{T} \log_2 \frac{1}{p_{w_i}} \tag{2}$$

Given the differences in linguistic expression between Chinese and English, translation may result in situations where the same meaning is expressed in different ways. In such cases, comparing the changes in entropy before and after translation from a single perspective may not be entirely accurate. Therefore, we first directly calculate the entropy of the three sets of data: the original text, machine translation, and student assignments. Then, based on the preprocessing described earlier, we perform additional processing on the three sets of data before calculating the entropy, including standardizing symbol formats, removing stop words (including punctuation), tokenization, word form normalization, and spelling error correction. The six sets of data are saved for subsequent model processing.

Similarly, considering the issue of different expressions with the same meaning, a certain method is needed to construct a set of synonyms s for sentences:

(1) After word segmentation of the original text, translate each word to obtain the set $a1$ and add it to s.
(2) After word segmentation of the machine translation, obtain the set $t1$ and add it to s.
(3) Obtain the synonyms of set $a1$ and add them to s.
(4) Obtain the synonyms of set $t1$ and add them to s.

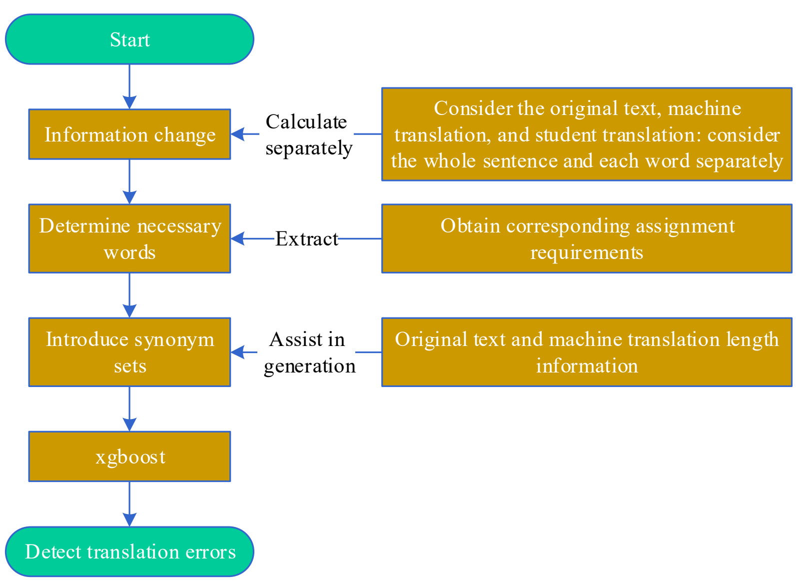

Figure 1: Construction process of the missed translation error detection model

Some assignments in the original data set also contain “required words,” which are words that teachers require students to use when reviewing translations. Therefore, the presence or absence of these words also affects the determination of omissions. Compare the student assignments with the synonym sets and calculate the occurrence of words. Additionally, include the sentence length of the original assignment and the corresponding machine translation sentence length as auxiliary information to measure the occurrence of words.

After processing the above features, use the xgboost model for the final determination to construct the omission error detection model. The overall model construction process is shown in Figure 1.

II. B. 2) Error correlation rules

Errors may be related to each other, i.e., errors are not entirely independent, and some errors may occur in pairs. For example, for a given dataset, analysis of the data reveals that whenever error A occurs, error B is also likely to occur at the same time, so we can derive the rule $A \Rightarrow B$. Therefore, association rules can be used to discover the relationships between errors.

Association rules: Suppose there is a set of items $I = \{i_1, i_2, \ldots, i_m\}$ and a set of transactions D. A transaction contains many items $i_1, i_2, \ldots, i_k$. An association rule is an expression of the form $X \Rightarrow Y$, where $X, Y \subset I$ and $X \cap Y = \varnothing$. X is called the antecedent of the association rule, and Y is called the consequent of the association rule. The support of a rule $X \Rightarrow Y$ is defined as the ratio of the number of transactions where X and Y appear together to the total number of transactions, as shown in equation (3):

$$\sup port(X \Rightarrow Y) = \sup port(X \cup Y) \tag{3}$$

The confidence of the rule $X \Rightarrow Y$ refers to the ratio of the number of transactions in which both X and Y appear to the number of transactions in which only X appears, as shown in Equation (4):

$$confidence(X \Rightarrow Y) = \frac{\sup port(X \Rightarrow Y)}{\sup port(X)} \tag{4}$$

The generation of association rules involves selecting rules where both the support and confidence scores exceed the minimum threshold. In the context of this system, an “item” refers to a specific error. A transaction represents a single error sentence, which may contain multiple errors. Association rules identify which errors can be inferred from other errors.

The main association rule mining algorithms are the FP-Growth algorithm and the Apriori algorithm. The Apriori algorithm scans the transaction set multiple times, with each frequent item set generated from candidate frequent item sets. However, the FP-Growth algorithm uses a tree-like structure that can directly generate frequent item sets without first generating candidate frequent item sets, thereby improving the overall efficiency of the algorithm and greatly reducing the number of scans of the transaction set. Therefore, in this system's research, association rules are generated based on the FP-Growth algorithm.

For each error, an association analysis is performed. First, the FP-Growth algorithm is applied to calculate frequent item sets, and then association rules are further calculated based on them.

In terms of rule filtering, although support and confidence were introduced as two filtering metrics earlier, they are still insufficient in practical applications. Support represents the frequency of occurrence of a certain item set, reflecting the proportion of that item set in the overall set. Confidence is calculated based on support (i.e., the ratio of the support values of two different item sets). Through the calculation process, it is not difficult to see that confidence is highly influenced by the number of item sets. If the transaction counts for two item sets are too high, it is easy to generate association rules between them, but they may not actually have a real association relationship, merely a coincidence under high transaction counts. At the same time, if the transaction count is too low, the association rule may be directly filtered out by confidence and support, even if a genuine association exists. Therefore, lift is used to measure the validity of the rule.

The degree of enhancement is $(lift)$, defined by equation (5):

$$lift(X \Rightarrow Y) = \frac{confidence(X \Rightarrow Y)}{\sup port(Y)} \tag{5}$$

Given the large number of errors, it is necessary to set appropriate thresholds to effectively identify hidden error associations in subsequent analyses. Based on the results of multiple experiments, the minimum support was ultimately set to 0.003 and the minimum confidence to 0.2. Under these conditions, a sufficient number of rules can be filtered out while relatively ensuring the validity of the derived results. Further filtering is performed on the screening results based on lift values. Generally, a lift value greater than 1 indicates a positive correlation, and the higher the lift value, the stronger the correlation. A lift less than 1 indicates a negative correlation, i.e., mutual exclusion. A lift equal to 1 indicates no correlation, meaning no relationship exists. Therefore, selecting a larger lift can filter out weakly correlated rules. After multiple experiments, the lift threshold was finally set to 3, and rules with a lift greater than 3 were further filtered from the previously screened results.

The final association rules include both those where a single antecedent leads to a single consequent and those where multiple antecedents lead to multiple consequents. Some rules overlap to a certain extent, and some rules have overly complex antecedents and consequents, requiring further filtering.

II. C.AADAA teaching strategy based on the output-oriented approach

This paper establishes a bilingual Chinese-English corpus of traditional Chinese culture, primarily collecting commonly used materials related to traditional Chinese culture in the field of English translation. It also provides online access to multiple museums of traditional Chinese culture and related online libraries. The compiled corpus includes: commonly used materials related to traditional culture, official promotional materials from traditional culture websites, English editions of news publications and cultural heritage materials, as well as bilingual Chinese-English promotional materials for cultural tourism. The content covers introductions to traditional culture, the history of traditional culture, prefaces and postfaces of traditional culture exhibition halls, traditional culture attractions, videos introducing traditional culture, and important classical texts related to traditional culture. The Chinese-English bilingual corpus of traditional Chinese culture is organized at the corpus unit level, including vocabulary, sentences, paragraphs, and chapters.

Based on the output-oriented approach, develop specialized translation teaching designs for traditional Chinese culture. Combining the job requirements of talent cultivation programs, the standards for university English courses, and the analysis of pre-class big data survey results to understand student needs, we deeply explore multiple traditional Chinese cultural elements with regional characteristics, using the Chinese traditional culture bilingual corpus as a teaching aid. Relying on the Smart Vocational Education System platform, establish knowledge and skill objectives: students should be able to translate 150 to 200 words of traditional culture-related tourism introduction materials, internalize common translation methods and techniques, and flexibly master domestication and foreignization translation strategies. Establish objectives: high-quality translation and introduction of traditional culture, conscious inheritance of traditional culture, and dedicated, heartfelt, and earnest promotion of China's excellent traditional culture to the world. Establish a competency objective: cultivating good English self-learning habits. Carefully design the translation teaching process. To achieve the four-dimensional teaching objectives, the AADAA teaching strategy is adopted, which stands for Acquire (acquiring knowledge), Apply (applying knowledge), Display (displaying learning outcomes), Assess (evaluating learning outcomes), and Amend (improving and enhancing).

III. Optimization of Teaching Assistance Models and Application of Teaching Strategies

III. A. Optimization and Performance Evaluation of the Omission Error Detection Model

III. A. 1) Optimization of Model Structure

This section selects the CoNLL2015 and JFLEG test corpora and corresponding metrics as experimental conditions. In the CoNLL2015 corpus, all English writing errors are classified into 30 types, and the evaluation metrics are precision, recall, and F0.5. The JFLEG test corpus contains 1,532 sentences, with the evaluation metric being GLEU (weighted accuracy of n-grams). The GEC task is treated as a sequence generation task, without distinguishing specific error types.

Table 1: Experimental results based on the pre-trained language model method(%)

Method	CoNLL2015			JFLEG
	Precision	Recall	$F_{0.5}$	GLEU
CNN Seq2Seq	58.14	26.73	46.89	54.7
xgboost	57.46	27.79	47.19	55.18
xgboost+BERT-init	56.48	26.06	45.59	54.62
xgboost+BERT-fuse	63.59	35.85	54.98	59.77
xgboost+BERT-fiuse+4ens	64.32	40.68	57.57	60.69

First, the xgboost model is used as the baseline grammar detection and correction model, and it is compared with the CNN Seq2Seq model based on convolutional neural networks. Two methods—initialization parameters and vector fusion—are used to apply the XGBoost model to the detection and correction model. The initialization parameter method is denoted as (XGBoost+BERT-init), and the vector fusion method is denoted as (XGBoost+BERT-fuse). Then, we set different initialization factors to train four XGBoost models, perform model ensemble on the four models, and use the Beamsearch algorithm to select the sentence with the highest probability value from the results generated by the four models as the final result (XGBoost+BERT-fuse+4ens). The Beamsize setting used in the above experiments was 1, i.e., the greedy algorithm. The experimental results are shown in Table 1.

The xgboost model achieved an accuracy rate of 57.46%, a recall rate of 27.79%, and an F0.5 of 47.19% on CoNLL2015, and a GLEU value of 55.18% on JFLEG, outperforming CNN Seq2Seq in terms of recall rate, F0.5, GLEU metrics. The xgboost+BERT-init method did not yield improvements and saw slight decreases in all metrics. However, the xgboost+BERT-fuse method improved precision, recall, and F0.5 by 6.13%, 8.06%, and 7.79%, respectively, and increased the GLEU value by 4.59%. The above results demonstrate that the initialization method is not suitable for the GEC task. The reason is presumed to be the structural differences between the xgboost model and BERT, which disrupted the semantic representations obtained from BERT pre-training during fine-tuning. By incorporating model ensemble and masking language models, significant improvements were achieved, resulting in precision, recall, and F0.5 values of 64.32%, 40.68%, and 57.57%, respectively, on the CoNLL2015 corpus, and a GLEU value of 60.69% on the JFLEG corpus.

The proposed model was compared with existing research methods: MIconv, SMT+NMT+4ens+LM, Transformer+Pre-training+LM, CNN+Dual learning+4ens+LM, and Transformer+Copying+DA+Multi-tasks. The experimental results are shown in Table 2.

Table 2: The comparison results on CoNLL2015 and JELEG(%)

Method	CoNLL2015			JFLEG
	Precision	Recall	$F_{0.5}$	GLEU
MIconv	66.41	34.37	56.02	58.7
SMT+NMT+4ens+LM	68	35.72	57.48	62.73
xgboost+Pre-training+LM	64.23	40.13	57.33	61.13
CNN+Dual learning+4ens+LM	75.35	37.53	62.57	62.64
xgboost+Copying+DA+Multi-tasks	72.8	39.88	62.38	62.23
xgboost	64.5	40.86	57.75	60.87

On the CoNLL2015 corpus, compared with the results obtained by the MIconv method, this paper achieved a 1.73% higher F0.5 score, but a 1.91% lower precision rate than the MIconv method. This is likely due to the fact that the MIconv method is based on a convolutional network, which has strong local modeling capabilities, and most grammatical errors are related to local information, resulting in a higher precision rate for the MIconv method. When compared to the results obtained using the MIconv method on the JFLEG corpus, this paper achieved a 2.17% higher GLEU value. Compared with the xgboost+Copying+DA+Multi-task method, the proposed method achieved 8.30%, 4.63%, and 1.36% lower precision, F0.5, and GLEU scores, respectively. This is likely due to the incorporation of a copying mechanism, which enables the model to be trained on pre-training tasks at the word and sentence levels and effectively retain the knowledge gained from pre-training during fine-tuning.

To gain a deeper understanding of the detection and correction effects of the present study's error detection model for various error types after incorporating the BERT structure, the tool ERRANT[2] was used on the CoNLL2015 dataset to analyze the recall rate of the present study's method for the syntactic errors categorized in CoNLL2015. To compare the experimental results, the MIconv method based on convolutional networks was selected as a comparison. The comparison results are shown in Table 3. The experimental results show that the proposed method has obvious advantages over the MIconv method. For example, in the categories of articles and determiners (ArtOrDet), noun possessives (Npos), and verb forms (Vform), the recall rates achieved by this paper are 14.75%, 4.89%, and 17.18% higher than those of the MIconv method, respectively, while the MIconv method only outperforms this paper's results by 3.14% and 6.51% in the two categories of grammatical errors: clause structure (Ssub) and word form (Wform).

Table 3: Correct the experimental results of multiple error types(%)

Type	Description	MIconv	Textual
Vt	Verb tense	11.56	14.85
Vm	Verb modal	6.72	10.45
V0	Missing verb	18.09	24.45
Vform	Verb formn	31.9	49.08
SVA	Subject-verb agreement	37.07	51.28
ArtOrDet	Article or deterniner	22.54	37.29

Nn	Noun number	38.26	56.89
Npos	Noun possessive	12.23	17.12
Pform	Pronoun form	14.27	16.58
Pref	Pronoum reference	2.58	12.35
Prep	Preposition	17.63	35.51
Wei	Wrong collocatian/idiom	4.91	6.72
Wa	Acronyms	0	0
Wform	Word form	37.82	31.31
Srum	Run-on sentences,comma splices	0.23	17.12
Smod	Dangling modifiers	0	0
Spar	Parallelism	12	28.57
Ssub	Subordinate clause	5.8	2.44
WOinc	Incorrect word order	2.9	4
WOadv	Inoorrect adjective/adverb order	14.71	27.27
Trans	Linking words/phrases	4.93	13.04
Mec	Spelling,punctuation,capitalization,etc	16.52	23.58
Rloc-	Redundancy	6.87	11.76
Others	Other crrors	1.22	3.12

III. A. 2) Simulation Experiment

To validate the effectiveness of the optimized translation error detection model in eliminating translation errors during Chinese-to-English conversion, a simulation experiment was conducted in this section. The experiment was designed using Matlab, with the association rule set for English language conversion represented in OAEI language. The simple semantic unit set consists of 3,000 units, the sample training set contains 100 instances, the iteration count is 200, the semantic attribute set comprises 90 attributes, the number of instances for similarity semantic feature distribution is 150, the number of deep learning iterations is 200, and the convergence step size is 50. Based on the aforementioned simulation environment and parameter settings, translation errors in English conversion were eliminated. The test semantic feature distribution is shown in Figure 2. It can be observed that the optimized omission error detection model is concentrated in the [-1.0, 0.8] interval in the semantic feature distribution.

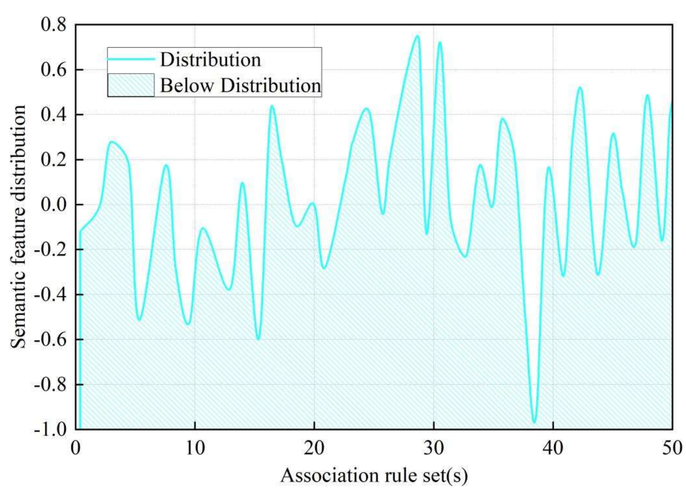

Figure 2: Simulation results of semantic feature distribution

Based on the test results of the semantic feature distribution shown in Figure 2, the optimization control for eliminating translation errors in English language conversion is shown in Figure 3, where the calibration feature distribution is also between [-1.0, 0.8].

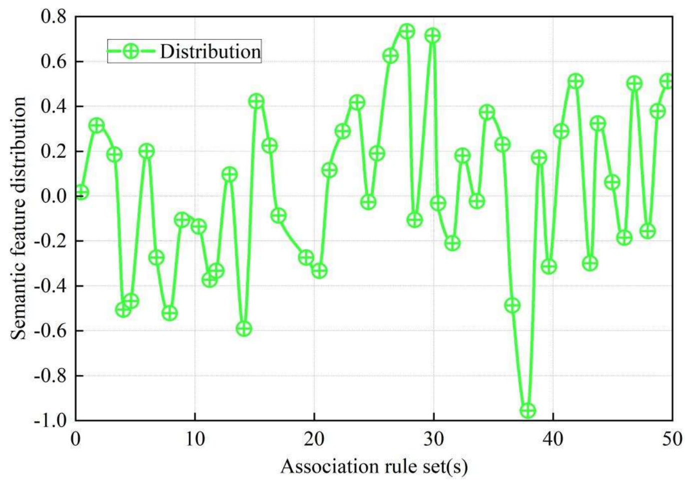

Figure 3: The feature distribution of English language conversion calibration

As can be seen from Figures 2 and 3, the accuracy and correction capabilities of the method described in this paper are effective in eliminating errors in English conversion translation. The accuracy of error elimination in English language conversion translation is high, and the correlation of translation calibration is strong.

III. A. 3) Effect of parameters on detection performance

Using R-precision (R-prec) and P@10 as evaluation metrics, we conducted experiments under five parameter threshold conditions of 0.1, 0.3, 0.5, 0.7, and 0.9. The Rigid dataset consists of word omissions, while the Relax dataset includes both omissions and grammatical errors. The average metric values of the proposed model algorithm on the two datasets are shown in Figure 4. As mc gradually increases, the P@10 value shows a slow decline and the R_prec value begins to gradually increase. When mc reaches 0.9, the detection results for omissions in students' translation assignments are optimal.

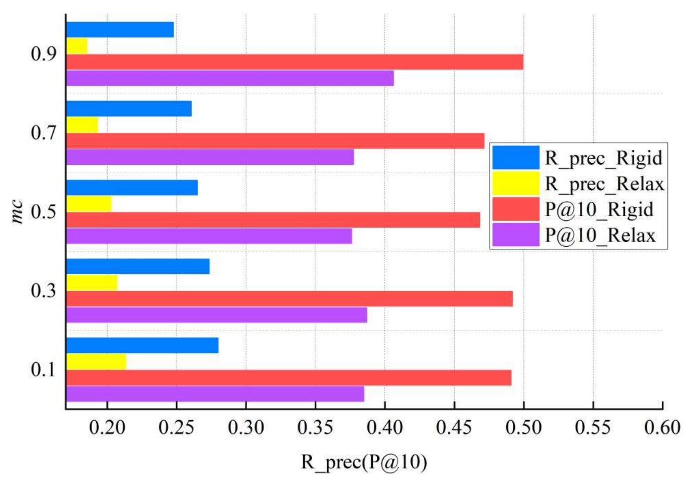

Figure 4: Search results with different confidence thresholds

III. B. Application of Teaching Assistance Models and Teaching Strategies

Two first-year English major classes from K University were randomly selected for the application experiment of the model proposed in this paper, with each class consisting of 25 students. One class used the model and teaching strategies proposed in this paper to study translation courses and was designated as the experimental class (C1), while the other class continued to use traditional methods to study translation courses and was designated as the control class (C2). After one semester of study, the final exam scores of the two classes were compared in this section to assess the reliability of the model and teaching strategies proposed in this paper in actual application.

III. B. 1) Comparison of Translation Results

A t-test was conducted on individual samples to compare the post-test scores of the two classes. The results are shown in Table 4. The significance level was less than 0.001, indicating that the data differences were statistically significant. This suggests that the teaching model based on the model and teaching strategies proposed in this paper is effective in improving students' English translation abilities.

Table 4: A comparison of the post-test scores of two classes majoring in translation

	Inter-group	Intra-group	Total
Quadratic sum	2537.19	175.99	2713.18
Degree of freedom	1	48	49
Mean square	2537.19	2.672	
F	984.29		
Significance	<0.001		

III. B. 2) Comparison of traditional cultural terminology scores

A paired samples t-test was conducted on the pre- and post-test scores for traditional cultural terminology in the experimental class, as shown in Table 5. The results revealed that the post-test scores for traditional cultural terminology were significantly higher than the pre-test scores, with a value of -45.031. Both the one-tailed and two-tailed significance levels were less than 0.001, indicating a statistically significant difference in means. This validated the high effectiveness of the teaching model combining the model and teaching strategies proposed in this paper in improving students' performance in translating traditional cultural terminology.

Table 5: Comparison of pre - and post-test terminology scores

Pairing difference	Mean value		-12.47
	Standard deviation		2.85205
	Average standard error		1.52614
	The difference is 95% confidence interval	Lower limit	-1430566.77
		Upper limit	-11.86432
t			-45.031
Degree of freedom			24
Significance	Unilateral P		<0.001
	Bilateral P		<0.001

IV. Conclusion

This paper proposes an association rule-based omission error detection model by combining an omission error detection model based on information quantity and synonym sets with error association rules. After incorporating the BERT structure, the proposed omission error detection model can accurately detect typical errors in student translation assignments. In terms of recall rate for grammatical errors as defined by CoNLL2015, it outperforms similar models by up to 17.18%, with only slight underperformance in two categories of grammatical errors.

By combining the error patterns identified by artificial intelligence with the guidance of the AADAA teaching strategy, university English teachers can achieve teaching outcomes in translation modules that are significantly superior to traditional teaching methods. In practical applications, the post-test scores of the experimental class and the control class showed a significance level of less than 0.001, and the pre- and post-test scores of the experimental class on traditional cultural terminology also showed a significance level of less than 0.001.

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