

# Exploring The Role Of Computational Linguistics In English Translation Pedagogy To Develop Effective Teaching Strategies

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Received: Jan. 01, 2026; Accepted: Mar. 27, 2026

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Computational Linguistics tools enhance translation teaching by improving accuracy, fluency, and vocabulary; surveys showed higher scores and fewer errors after use. TS measures translation quality; TE counts grammatical, lexical, structural errors. Results show CL-based teaching improves translation quality, increasing learning efficiency and effectiveness, and supports integrating technology-based techniques into translation pedagogy.

**Keywords:** Computational Linguistics, Translation Pedagogy, Machine Translation, Error Reduction, Lexical Richness

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[http://dx.doi.org/10.6180/jase.202609\\_32.022](http://dx.doi.org/10.6180/jase.202609_32.022)

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## 1. Introduction

CL tools are vital as technology transforms translation teaching practices [1]. Translation in language learning often faces accuracy and fluency challenges [2]. Development of CL tools: machine translation, error correction, lexical databases [3]. Proposes new approaches to tackle and solve these challenges [4]. Students practice translation with real-time feedback to improve skills [5, 6]. Digital resources offer broader learning opportunities than traditional methods [7, 8]. CL integration in translation pedagogy improves quality and learning efficiency [9, 10]. This framework highlights how CL tools support personalized instruction [11, 12], allow teachers to monitor student progress more effectively, and provide immediate feedback [13, 14], ultimately enhancing the translation learning experience [15, 16]. Traditional translation education relies on textbooks, paper tasks, and manual corrections [17] which may not meet the growing demand for efficient and flexible teaching practices [18].

Computational Linguistics (CL)-based instruction differs from general technology-assisted learning in its theoretical and methodological foundation. CL instruction uses corpus analysis, NLP, and error detection for feedback.

Grounded in translation competence theory, particularly the PACTE model, Translation ability includes bilingual competences; CL tools improve strategy, terminology, accuracy. Technology-supported translation pedagogy, computational linguistics tools constitute part of the instrumental dimension of translation competence. Corpora, concordances, and feedback enhance lexical choice, collocation, and translation revision. CL tools in translation pedagogy enhance accuracy, fluency, vocabulary, reduce errors; evaluate efficacy with surveys, statistics, correlations, and hypothesis testing.

- RQ1: Does the instructing type (CL-based instruction versus traditional instruction) have any effect on the performance of the students in a translation task?
  - RQ2: What is the extent to which CL-based pedagogical strategies minimize translation errors when used by students in translating?
  - RQ3: What is the relationship between attitudes to CL tools and performance in translations and lexical richness of translations among students?
- ✓ H1: Students taught using computational linguistics tools will score significantly higher on translation tasks

than those taught traditionally.

- ✓ H2: There will be a significant reduction in translation errors after using CL-based pedagogical strategies.
- ✓ H3: There will be a significant positive correlation between students' attitudes toward CL tools and their translation performance.
- ✓ H4: Computational linguistics-based instruction will significantly improve lexical richness in students' translations.

Computational linguistics-based instruction has increasingly been integrated into translation pedagogy; CL-supported instruction's impact on translation accuracy, errors, and lexical richness.

Ma et al. [19] while experience influences teacher well-being Nazari and Alizadeh Oghyanous [20] AI and machine translation enhance translation and language learning Wang [21] explored AI integration in translator training, showing its potential to develop digital-era translation competencies. Kelly and Hou [22] found that multilingual learners widely use machine translation as a flexible learning support tool. Ma et al. [23] and Adel et al. [24] examined ChatGPT in education, highlighting its benefits for personalized learning while noting ethical concerns. Wedyan et al. [25] reported that augmented reality improves language proficiency and student engagement. Xiao and Zhi [26] showed that students critically evaluate ChatGPT outputs during language learning. Crompton et al. [27] and Liu et al. [28] analyzed translanguaging pedagogy in EAP classes. Li and Liu [29] further highlighted AI-Big Data instruction for personalized learning and real-time feedback. Study examines CL tools and MT impact on learners' perceptions and translation competence using surveys. Framework includes pre-test measuring accuracy, CL tool intervention with feedback, and post-test evaluating translation performance improvement. Participants complete pre- and post-surveys measuring translation performance, patterns, and error reduction. Pre/post translation tests-controlled variables; improvements attributed to CL instruction. Improvement scores were calculated as the numerical difference between post-test and pre-test translation scores for each participant. Pretest ensured equivalence; regression analyzed post-test translation accuracy, errors, lexical richness. Figure 1 shows research design.

Traditional translation pedagogy is instructor-centered, limiting feedback and engagement [21, 23]. Integrating CL tools enhances accuracy, motivation, lexical richness, and learning efficiency [26, 27]. Translation competence is

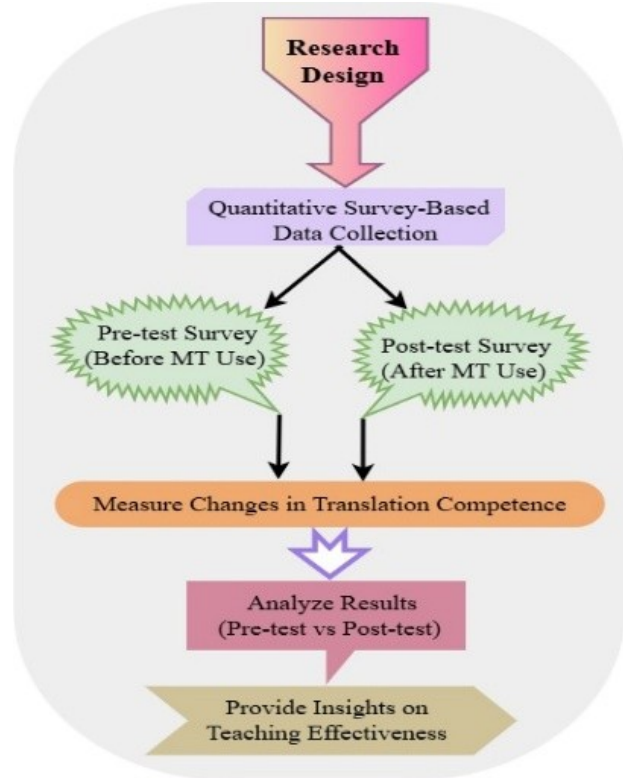


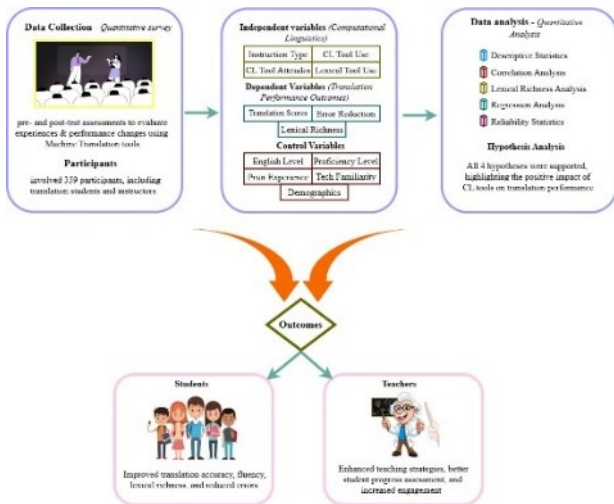
Fig. 1. Research Design

widely understood as a multidimensional construct comprising several interrelated sub-competences. PACTE Group defines translation competence: bilingual, instrumental, and strategic. CL tools enhance both.

## 2. Materials and methods

This study surveys 359 students and instructors on CL tools' impact. Participants were recruited from undergraduate and graduate translation courses at two universities. Computational linguistics tools were used in translation instruction; experimental and control groups were formed. Survey collected pre- and post-test data assessing translation performance, errors, lexical richness. Students' engagement with computational linguistics (CL) tools was measured using a structured questionnaire, the instrument, adapted from established tools, showed high reliability (Cronbach's  $\alpha = 0.877$ ). Hierarchical regression analysis was conducted to Regression modeling and bootstrap mediation analyzed instructional, attitudinal, proficiency, and experience variables' predictive contributions. SPSS analyzed data, Python generated coefficients; CL-based teaching improved translation.

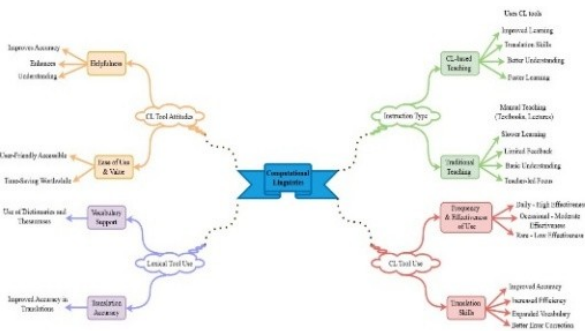
Computational linguistics tools were integrated into classroom practice through Students reviewed and revised



**Fig. 2.** Methodology for Assessing the Impact of Computational Linguistics Tools in Translation Pedagogy

translations, justifying changes for academic accountability.

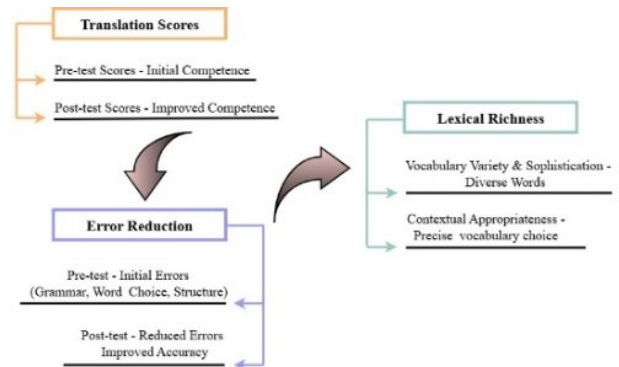
Moderation analysis was conducted using hierarchical regression procedures in which interaction terms represented the interaction effects included in regression; multicollinearity diagnostics ensured stability. The CL-based instructional model was designed to operationalize distinct components of translation competence through technological tools improved translation accuracy, grammar, vocabulary, and consistency. Figure 3 shows CL integration in translation education.



**Fig. 3.** Computational Linguistics Integration in Translation Education

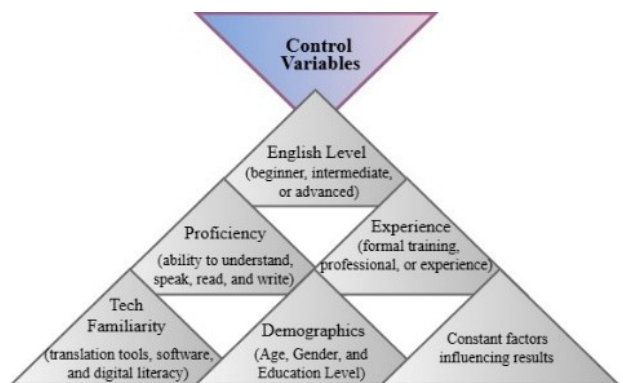
- CL-based Teaching is the application of CL tools (Google Translate, DeepL, SDL Trados Studio) to facilitate individualization in learning. Instruction across the experimental and control conditions was structured around an identical syllabus, Uniform objectives, tasks, difficulty, assessment, and duration with consistent classroom time and CL tool integration. The eight-week duration provided sufficient time for students

to engage in repeated translation practice, Translation competence develops through sustained feedback and reflection over eight weeks, aligning with semester durations. The translation tasks consisted of general academic and expository texts appropriate for undergraduate learners. Materials included consistent, university-themed texts matching pre- and post-test tasks. Researchers controlled CL tool use, improving translation accuracy, vocabulary, and error reduction.



**Fig. 4.** Translation Performance Outcomes

Post-tests show improved accuracy, fluency, vocabulary richness, fewer errors. Vocabulary diversity measured using TTR, text length, MTLT, Python tokenization. Measures how language skill, experience, and tech familiarity affect translation. Background questionnaire measured experience, proficiency, technology; regression found no interactions. Figure 5 shows control variables in translation study.



**Fig. 5.** Control Variables in Translation Study

CL tools improve students' translation accuracy; teachers enhance strategies and engagement is shown in Figure 6.

Survey data analyzed with SPSS/Python on CL tools' translation impact. Researchers used SPSS for tests,

**Table 1.** Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Pre_TranslationScore	359	20.00	55.42	23.1777	5.06200
Post_TranslationScore	359	20.00	78.21	36.9117	12.53517
Pre_ErrorCount	359	13	30	21.24	3.065
Post_ErrorCount	359	0	29	11.23	8.681
Pre_LexicalRichness	359	0.1500	0.6415	0.402391	0.0884928
Post_LexicalRichness	359	0.2034	0.9500	0.571928	0.1796351
Valid N (listwise)	359	-	-	-	-

**Table 2.** Paired Samples Statistics

Model	Variables	Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Pre_TranslationScore	23.1777	359	5.06200	0.26716
	Post_TranslationScore	36.9117	359	12.53517	0.66158
Pair 2	Pre_ErrorCount	21.24	359	3.065	0.162
	Post_ErrorCount	11.23	359	8.681	0.458

**Table 3.** Paired Samples Correlations

Model	Variables	N	Correlation	Sig.
Pair 1	Pre_TranslationScore & Post_TranslationScore	359	0.465	0.000
Pair 2	Pre_ErrorCount & Post_ErrorCount	359	0.358	0.000

**Table 4.** Paired Samples Test

Model	Variables	Paired Differences					t	df	Sig. (2taile d)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Pre TranslationScore – Post TranslationScore	-13.73398	11.12627	0.58722	-14.88882	-12.57915	-23.388	358	0.000
Pair 2	ErrorCount – Post ErrorCount	10.008	8.105	0.428	9.167	10.850	23.397	358	0.000

**Table 5.** Paired Samples Effect Sizes

		Standardizer	Point Estimate	95% Confidence Interval	
				Lower	Upper
Pair 1	Pre TranslationScore – Post TranslationScore	Cohen's d	11.12627	-1.234	-1.371
		Hedges' correction	11.13794	-1.233	-1.370
Pair 2	Pre ErrorCount – Post ErrorCount	Cohen's d	8.105	1.235	1.097
		Hedges' correction	8.113	1.234	1.096

Python for regression and visualization. Statistical analysis: pre/post tests, t-tests, correlation, regression, reliability, lexical richness. SPSS handled statistics; Python performed regression, text processing, and lexical analysis.

Higher Translation Scores reflect stronger overall performance in terms of accuracy, Fewer errors and richer vocabulary indicate improved translation quality and better lexical appropriateness after instruction. Table 1 shows descriptive statistics show improved scores, reduced errors,

richer lexicon.

Figure 7 presents pre and post test scores of translations between two groups traditional instructions and CL-based instructions.

Figure 8 is a comparison of pre and post-test errors in the Traditional (Control) and CL-Based (Experimental) groups.

**Table 6.** Correlation Analysis

	Pre AttitudeScore	Post AttitudeScore	Post TranslationScore	Score Improvement	Post ToolHelpful	Post Confidence	Post Recommend
Pre AttitudeScore	1	0.009	0.030	0.029	0.019	-0.044	0.038
Post AttitudeScore	-	0.871	0.574	0.584	0.726	0.403	0.472
	359	359	359	359	359	359	359
Post TranslationScore	0.009	1	0.747	0.822	0.653	0.833	0.856
Post TranslationScore	0.871	-	0.000	0.000	0.000	0.000	0.000
	359	359	359	359	359	359	359
Post TranslationScore	0.030	0.747	1	0.915	0.721	0.673	0.680
Score Improvement	0.574	0.000	-	0.000	0.000	0.000	0.000
	359	359	359	359	359	359	359
Score Improvement	0.029	0.822	0.915	1	0.760	0.737	0.743
Post ToolHelpful	0.584	0.000	0.000	-	0.000	0.000	0.000
	359	359	359	359	359	359	359
Post ToolHelpful	0.019	0.653	0.721	0.760	1	0.573	0.597
Post Confidence	0.726	0.000	0.000	0.000	-	0.000	0.000
	359	359	359	359	359	359	359
Post Confidence	-0.044	0.833	0.673	0.737	0.573	1	0.610
Post Recommend	0.403	0.000	0.000	0.000	0.000	-	0.000
	359	359	359	359	359	359	359
Post Recommend	0.038	0.856	0.680	0.743	0.597	0.610	1
	0.472	0.000	0.000	0.000	0.000	0.000	-
	359	359	359	359	359	359	359

Pearson Correlation  
Sig. (2-tailed)  
N

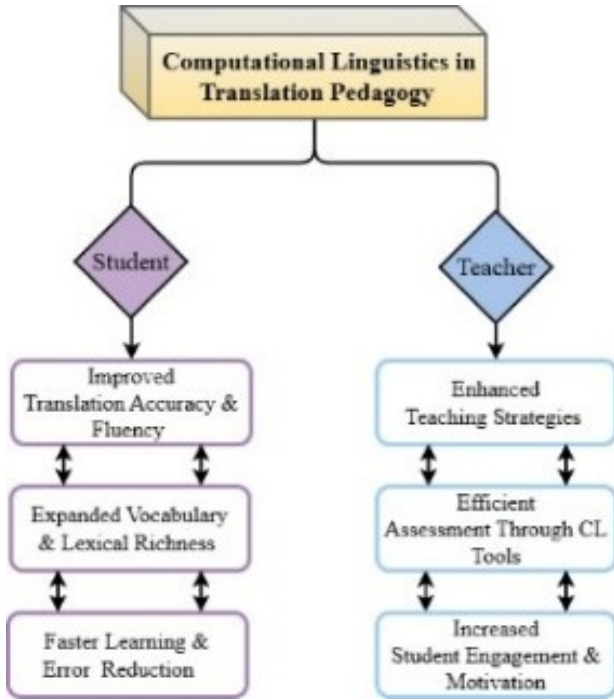


Fig. 6. Impact of Computational Linguistics on Students and Teachers in Translation Pedagogy

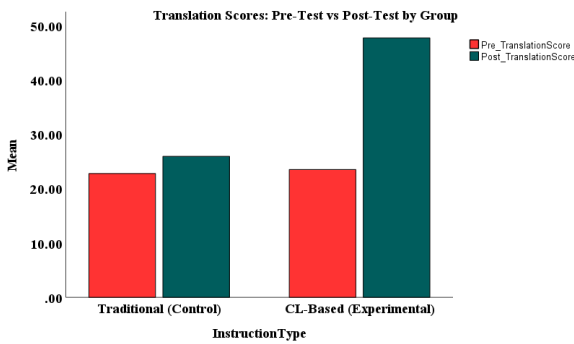


Fig. 7. Pre-Test vs Post Test Comparison of Translation Scores

Table 2 shows the average, Translation scores increased from 23.18 to 36.91, while errors reduced from 21.24 to 11.23 after using CL tools.

Table 3 shows scores ( $r = 0.465$ ) and Errors ( $r = 0.358$ ), both significant.

Table 4 presents the paired-samples  $t$ -test results comparing pre-test and post-test Translation Scores and Error Counts. Translation scores increased; errors decreased significantly, showing large effects overall. The magnitude of the reported effect sizes indicates substantial improvement in classroom translation performance. Effect sizes above 1.0 show significant improvements in translation competence.

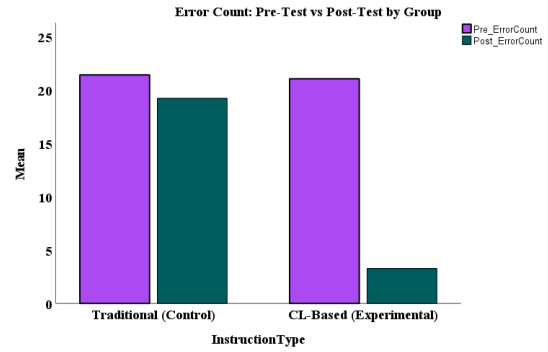


Fig. 8. Pre-Test vs Post Test Comparison of Error Reduction

Table 5 Use Cohen's  $d$  and Hedges' correction for paired effect sizes. CL-based teaching improves translation accuracy and fluency over traditional methods. CL-based instruction greatly improved translation performance with large, precise effects.

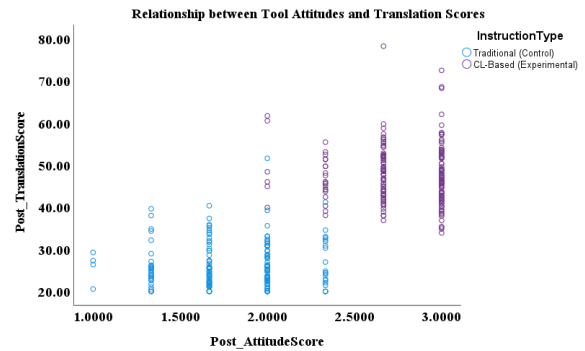


Fig. 9. Scatter Plot of Tool Attitudes vs Translation Scores

The values of pearson correlation and Sig. (2-tailed) between different variables are presented in Table 6, Positive post-test correlations: CL tool attitudes improve translation performance and scores.

Figure 9 shows a positive correlation between post-attitude and post-translation scores, especially in CL-Based instruction.

Figure 10 The data shows a positive correlation between positive attitudes toward CL tools and higher lexical richness in the CL-Based group.

The mean, standard deviation and the standard error mean of pre and post-test lexical richness are presented in Table 7.

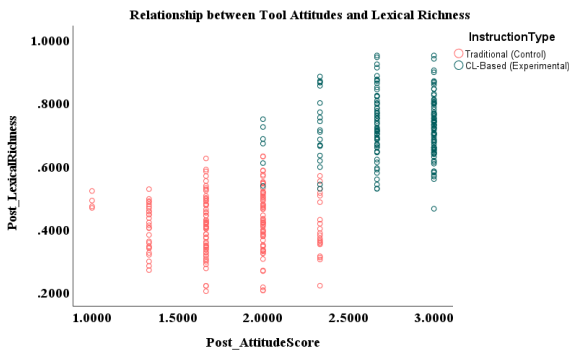
Table 8 pearson correlation analysis shows a moderate positive correlation ( $0.502$ ) between pre and post-test lexical richness, statistically significant ( $p = 0.000$ ), linked to CL tools.

**Table 7.** Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Pre_LexicalRichness	0.402391	359	0.0884928	0.0046705
	Post_LexicalRichness	0.571928	359	0.1796351	0.0094808

**Table 8.** Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Pre_LexicalRichness & Post_LexicalRichness	359	0.502	0.000



**Fig. 10.** Scatter Plot of Tool Attitudes vs Lexical Richness

Table 9 presents the paired-samples *t*-test results comparing pre-test and post-test Lexical Richness. Analysis showed a significant increase in lexical richness (M = 0.402 to M = 0.572,  $p < .001$ ), with a large effect size (Cohen’s  $d = 1.09$ ).

Table 10 shows large negative effect; CL tools increase lexical richness; regression tests relationships.

The summaries of the models for the 4 regression analyses are presented in Table 11 and R values show strong correlations; models explain 72.6-85.3% variance.

Table 12 presents the ANOVA results of the four regression models, all of which were statistically significant. Instruction Type predicted scores, errors, attitudes, lexical richness; explaining 73 – 85% variance.

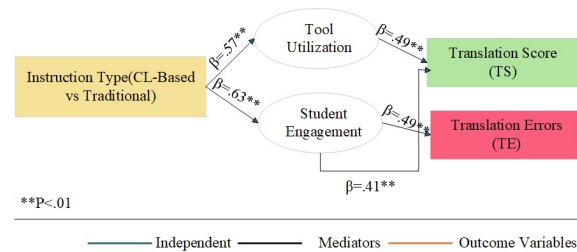
Table 13 InstructionType significantly predicts outcomes across models ( $\beta = 0.747 - 0.920$ ,  $p < 0.001$ ), showing strong effects. Examination of the regression diagnostics indicated that the underlying assumptions of linear modelling were adequately met. Residuals were approximately normal, variance was constant across predictions, and VIF values indicated no significant multicollinearity among predictors.

Reliability Statistics: Cronbach’s Alpha and inter-item correlations assess survey item reliability.

Table 14 shows Cronbach’s alpha (0.877) shows high reliability. Regression analysis tested tool attitudes and instruction effects; beta and *p*-values ( $<0.05$ ) determined

hypothesis support.

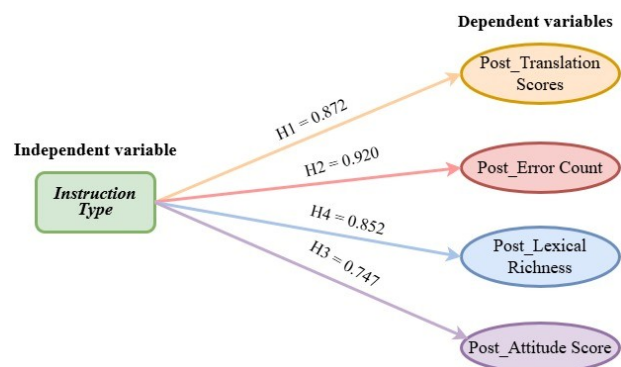
Table 15 CL instruction improved translation scores, reduced errors, attitudes, lexical richness. Participatory teaching and CL tools together improve students’ translation outcomes.



\*\* $p < .01$

**Fig. 11.** Standardized path model of instruction type, mediators, and translation outcomes

Figure 11 Instruction improves tool use and engagement, enhancing translation performance and reducing errors.



**Fig. 12.** Path Coefficients

Figure 12 Instruction Type strongly affects translation scores (0.872), error reduction (0.920), lexical richness (0.852), and students’ CL tool attitudes (0.747).

Inter-rater reliability was assessed using the Intraclass Correlation Coefficient (ICC) to ICCs (0.86-0.89 single; 0.92-0.94 average) show good-excellent inter-rater agreement across translation score, error count, and lexical richness.

**Table 9.** Paired Samples Test

Model	Variables	Paired Differences					t	df	Sig. (2taile d)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Pre_LexicalRichness – Post_LexicalRichness	-0.1695368	0.1553767	0.0082005	-0.1856639	-0.1534096	-20.674	358	0.000

**Table 10.** Paired Samples Effect Sizes

Pair 1	Pre_LexicalRichness – Post_LexicalRichness	Cohen's d Hedges' correction	Standardizer 0.1553767 0.1555397	Point Estimate -1.091 -1.090	95% Confidence Interval	
					Lower	Upper
					-1.220	-0.959

**Table 11.** Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Regression (H1)	0.872	0.760	0.759	6.15460
Regression (H2)	0.915	0.853	0.836	3.412
Regression (H3)	0.747	0.757	0.756	2.35223
Regression (H4)	0.852	0.727	0.726	0.726

**Table 12.** ANOVA

Model	Source	Sum of Squares	df	Mean Square	F	Sig.
Regression (H1)	Regression	42729.854	1	42729.854	1128.060	0.000
	Residual	13522.827	357	37.879	-	-
	Total	56252.681	358	-	-	-
Regression (H2)	Regression	22820.098	1	22820.098	1959.691	0.000
	Residual	4157.173	357	11.645	-	-
	Total	26977.270	358	-	-	-
Regression (H3)	Regression	31348.460	1	31348.460	449.378	0.000
	Residual	24904.221	357	69.760	-	-
	Total	56252.681	358	-	-	-
Regression (H4)	Regression	8.393	1	8.393	948.618	0.000
	Residual	3.159	357	0.009	-	-
	Total	11.552	358	-	-	-

**Table 13.** Coefficients

Model	Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
Regression (H1)	(Constant)	4.152	1.028	-	4.038	0.000
	InstructionType	21.820	0.650	0.872	33.587	0.000
Regression (H2)	(Constant)	35.169	0.570	-	61.699	0.000
	InstructionType	16.872	0.322	0.920	42.374	0.000
Regression (H3)	(Constant)	-0.744	1.830	-	-0.407	0.684
	InstructionType	16.473	0.777	0.747	21.199	0.000
Regression (H4)	(Constant)	0.113	0.016	-	7.178	0.000
	InstructionType	0.306	0.010	0.852	30.800	0.000

### 3. Result and discussion

The regression models account for a defined proportion of variance in translation performance, Instruction and attitudes contribute within many factors shaping translation competence. Computational linguistics-based instruction situates technological resource use Technology-supported

translation uses tools; strategic competence evaluates and refines solutions. The development of translation competence reflects not only immediate delayed post-tests show if learning gains and translation skills persist. CL tools and positive attitudes improve translation performance and learning. The effectiveness of computational linguistics

**Table 14.** Reliability and Correlation Analysis of Post-Test Tool Attitudes

Cronbach's Alpha	Cronbach's Alpha (Standardized)	N of Items	Item	Mean	Std. Deviation	N	Post_TestHelpful	Post_TestEase	Post_TestAccuracy	Post_ErrorCorrection	Post_Confidence	Post_Satisfaction	
0.877	0.882	6	Post_TestHelpful	2.176	0.742	359	1.000	0.565	0.570	0.543	0.573	0.594	
			Post_TestEase	2.196	0.992	359	0.565	1.000	0.570	0.545	0.528	0.570	0.570
			Post_TestAccuracy	2.150	0.730	359	0.570	0.570	1.000	0.547	0.553	0.545	0.545
			Post_ErrorCorrection	2.160	0.723	359	0.543	0.545	0.547	1.000	0.557	0.538	0.538
			Post_Confidence	2.210	0.696	359	0.573	0.528	0.553	0.557	1.000	0.529	0.529
			Post_Satisfaction	2.210	0.682	359	0.594	0.570	0.545	0.538	0.529	1.000	0.529

ticsbased instruction extends beyond the mere technology-supported translation helps students evaluate outputs, refine vocabulary, reduce errors. CL tools give instant feedback, detect errors, suggest translations and vocabulary, helping students correct mistakes immediately and improve translation performance. The instructional benefits observed in the present findings can also be interpreted through Computational tools guide learners to improve translation accuracy and lexical diversity. The article is more specific and thorough in its analysis of CL tools in translation pedagogy compared to the articles by [21] and [22].

#### 4. Conclusion

CL tools reduce errors, increase diversity, boost engagement and translation quality. The findings of this study suggest that computational linguistics tools can play a structured and MT analysis, error correction, lexical training improve translation accuracy, vocabulary. Study long-term CL tool effects, collaboration integration, automated personalized feedback.

#### Declaration

#### Data Availability

#### Google Form Link

<https://docs.google.com/forms/d/e/>

1FAIpQLSd73qR1J5rNSJHLiGuZvo-mJfdrkwPFHAcdsm77fjbfNO0uSQ/viewform

#### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

#### Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

#### Author Contribution

Ying Fan designed the research framework, collected the data, and performed the initial analysis.

Yujie Zang conducted statistical analysis, developed the computational linguistics teaching model, and prepared the final manuscript.

Both authors reviewed and approved the final version of the article.

#### Ethical Approval

This study adhered to institutional ethical guidelines. Ethical approval was obtained from the Research Ethics Committee of Shaoyang University.

**Table 15.** Hypothesis Testing Analysis

Hypothesis	Path	$\beta$ (Effect Size)	Result
H1	Instruction Type → Translation Scores	0.872	Supported
H2	Instruction Type → Error Reduction	0.920	Supported
H3	Attitudes Toward CL Tools → Translation Performance	0.747	Supported
H4	Instruction Type → Lexical Richness	0.852	Supported

**Table 16.** Inter-rater Reliability Estimates for Translation Performance Measures

Measure	ICC (Single)	ICC (Average)	95% CI (Single)	Interpretation
Translation Score	0.89	0.94	0.85–0.92	Excellent
Error Count	0.86	0.92	0.81–0.90	Good–Excellent
Lexical Richness	0.88	0.93	0.84–0.91	Excellent

### Consent to Participate

All participants were informed about the purpose of the study and voluntarily consented to participate.

### Consent for Publication

All authors consent to the publication of this manuscript and confirm that the content has not been previously published nor is under consideration elsewhere.

### Competing Interests

The authors declare no competing interests.

### Acknowledgment

The authors would like to thank the participating students and faculty members for their cooperation and support during the data collection process. Special appreciation is extended to the translation instructors who provided valuable insights into integrating computational linguistics tools into classroom instruction.

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