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Research on the Transformation of College English Translation Teaching Driven by Artificial Intelligence

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Abstract

In response to the current predicaments faced by university English translation teaching in the era of artificial intelligence, such as narrowed goals, fixed content, monotonous models, lagging evaluation, and the absence of AI literacy among teachers and students, this study has constructed a transformation analysis framework covering five dimensions: goal positioning, content organization, teaching model, evaluation method, and teacher-student roles. Based on this framework, a four-stage process-oriented teaching model of "AI pre-translation - comparative diagnosis - post-translation editing - reflection and summary" for human-machine collaboration has been proposed. The study adopts a quasi-experimental design and implements a 12-week teaching intervention for 82 non-English major undergraduate students at a certain university. The experimental results show that the post-test translation scores and post-translation editing abilities of the experimental class are significantly better than those of the control class; at the same time, the experimental class also shows significant improvements in various dimensions of AI usage strategies, the accuracy of critical judgment, the level of intrinsic motivation, and the perception of task value. The analysis based on qualitative data further confirms the positive changes in students' awareness of strategies, repositioning of human-machine roles, and enhanced metacognitive monitoring. In summary, these findings indicate that structured human-machine collaborative training can simultaneously enhance translation quality, process strategy level, and learning motivation quality, providing an evidence-based basis and operational practical paths for the digital transformation of university English translation teaching.

Keywords

Artificial Intelligence, English Translation, Teaching Reform, Experimental Design

1. Introduction

With the maturity of neural machine translation technology and the emergence of large language models such as the GPT series, the automation level of language conversion has reached an unprecedented height. These technologies not only perform well in general fields but have also gradually permeated into the foreign language education scenario through post-editing tools, intelligent writing correction systems, etc., quietly changing the basic face of translation practice. At the same time, the national level has continuously promoted educational digitalization strategic actions and new liberal arts construction. The "University English Teaching Guidelines" have also set more explicit requirements for students' translation abilities, emphasizing accurate and appropriate information transformation in cross-cultural contexts. On the industry front, the working form of the translation profession is undergoing a fundamental transformation. The collaboration between translators and artificial intelligence has become the mainstream practice model, and the demand for post-editing ability in the market has significantly increased. These technologies and policy and industry changes converge to form a force, forcing university English translation teaching to re-examine its target positioning and ability cultivation path.

However, in contrast to these development trends, the practical difficulties of university English translation teaching remain prominent. Under the limited class hours and large-class teaching conditions, teachers find it difficult to provide students with sufficient and differentiated translation feedback. The teaching process has long emphasized the correctness evaluation of translation products but neglected the guidance on students' translation strategy application and decision-making process. This preference for results over process, combined with the scarcity of real translation practice opportunities outside of class, leads to students lacking systematic training in translation thinking, being unable to develop the ability to critically examine the quality of machine-translated texts, and being unable to calmly handle complex translation tasks involving human-machine collaboration. Facing the deep integration of the translation profession and technology, the traditional teaching model is no longer able to support students in building an ability structure that suits current needs. Exploring the transformation path of translation teaching driven by artificial intelligence thus becomes particularly urgent.

2. Issues in College English Translation Teaching Driven by Artificial Intelligence

The problems exposed by university English translation teaching in the current era of rapid development of artificial intelligence technology can be systematically summarized from five dimensions: target positioning, content organization, mode operation, evaluation mechanism, and subject literacy.

First, the tendency of narrow teaching objectives is particularly prominent. Most classes still regard translation as a means to consolidate vocabulary and grammar knowledge or a tool for passing the CET-4 and CET-6 exams. The more superior and higher-level literacy goals such as cross-cultural

understanding ability, information screening and integration ability, critical judgment ability of machine translation output, and awareness of human-machine collaboration are basically absent. What students acquire through learning is not a complete sense of translation ability, but rather an exam-oriented language code conversion skill detached from real communication scenarios.

Second, the fixed characteristics of teaching content are also worthy of attention. The translation exercises in textbooks are mostly single-sentence practice and short passage translation that are disconnected from the context. The form of exercises has long remained at the level of mechanical repetition in the form of after-class exercises, lacking task texts from real fields such as enterprise translation practice, academic exchanges, or new media dissemination, and rarely seeing the teaching design that incorporates the review and revision of machine translation drafts. This fragmented exercise system is difficult to help students form an overall cognition of translation tasks and cannot guide them to make strategic translation decisions in complex contexts.

Third, the single nature of the teaching mode has still not been effectively broken through. Classroom practice is still dominated by the linear process of teachers issuing translation tasks, students submitting finished translations, and teachers correcting them. The crucial aspects such as strategy selection, resource retrieval, difficulty diagnosis, and self-correction in the translation process have not entered the focus of teaching attention. Translation learning is largely simplified to a static result presentation rather than a dynamic ability construction process.

Fourth, the lag of the evaluation mechanism hinders the continuous improvement of learning effects. Current translation teaching evaluation still mainly takes the form of final exams or after-class homework grading, with the core standard being right or wrong judgment. Feedback is seriously delayed in time and highly homogeneous in content, making it difficult to provide personalized information with diagnostic value and improvement orientation for different students' error types and cognitive characteristics. The formative function of evaluation has not been fully exerted.

Fifth, the absence of AI literacy among teachers and students constitutes a structural shortcoming that restricts the effect of technology empowerment. From the teacher's perspective, some teachers have scattered and shallow use of artificial intelligence translation tools. The introduction of tools in the classroom often only stops at the level of immediate word lookup or simple acquisition of reference translations, and there are few systematic attempts to incorporate translation post-editing strategies, human-machine collaboration processes, tool efficacy evaluation, etc. into teaching design. From the student's perspective, a considerable proportion of learners lack the awareness of critical examination when facing machine translations and also lack strategic knowledge for effectively revising and optimizing the output results, easily forming blind reliance on technology or simple rejection.

3. The Logic and Framework Construction of AI-Driven Transformation in Translation Education

3.1 The Intrinsic Logic of AI-driven Educational Transformation

The intrinsic logic of how artificial intelligence technology drives the transformation of university English translation teaching can be explained from three dimensions: technology, profession, and learning. The core of the technological logic lies in the language generation, multi-round interaction, real-time feedback, and adaptive learning capabilities of generative large language models, which precisely form a structural match with the deep needs of translation teaching. The long-standing problem of the absence of personalized guidance in large-class teaching scenarios can be broken through with the help of AI's real-time feedback function. After students submit their translations, they can receive multi-dimensional reviews on grammar, word choice, and sentence structure, and pragmatics. The boundaries of time and energy for teachers' feedback can thus be expanded. The ability of AI to generate multiple reference translations also helps to break students' inertia towards a single standard answer, providing rich materials for comparison and selection. The interactivity enables students to continuously question translation strategies through continuous dialogues with AI, transforming translation training from a one-way output to a two-way exploration. From the perspective of professional logic, the translation workflow has been profoundly reshaped by AI tools, and the focus of the profession is shifting from independently completing bilingual conversions to judging, editing, and optimizing machine translations, namely post-editing skills, as well as the ability to allocate tasks and monitor quality under the framework of human-machine collaboration. This forces a redefinition of teaching goals, requiring students to learn to judge the quality of machine translations, identify error types, and effectively correct them, while also learning to reasonably divide tasks with AI and cooperate efficiently. From the learning logic perspective, AI makes contextualized, process-oriented, and personalized learning a reality. Teachers can use AI to generate real translation tasks for specific industries or styles to bridge the gap between textbooks and reality. Learners can use AI to track and make their thinking processes explicit, obtain process-based self-awareness by leaving traces of the initial draft, revision records, and reflection notes, and different levels of learners can obtain differentiated tasks and feedback based on their own progress, promoting teaching from a uniform transmission model to an adaptive learning path. The interweaving of these three logics collectively constitutes the internal driving mechanism of AI-driven translation teaching transformation.

3.2 The Analysis Framework for Change

Based on the above transformation logic, it is necessary to construct an analytical framework that combines theoretical explanatory power and practical operability to diagnose the depth of the transformation and guide the design of teaching practices. By examining the AI-driven translation teaching transformation with the framework of activity theory, the reason lies in that this theory regards human practice as a systematic activity composed of elements such as the subject, the object, the tool, the rules, the community, and the division of labor, and the transformation of the tool is often a key variable triggering the structural reorganization of the activity system. When artificial intelligence enters the translation teaching activity system as a new intermediary tool, its influence does not remain

at the level of using a certain translation software, but triggers a chain reaction along the logical chain of tools, objects, goals, rules, and division of labor: the learning object expands from the fixed textbook text to a composite information set including machine translations, multiple versions of reference translations, and process data, the teaching goal extends from the accuracy of language conversion to critical evaluation, strategy selection, and human-machine collaboration and so on, and the interaction rules and task allocation methods in the classroom are also adjusted. By introducing the SAMR model as a hierarchical scale, it can effectively avoid the risk of mistakenly regarding the superficial technology as a teaching transformation. This model divides the degree of integrating technology into teaching into four progressive levels: substitution, enhancement, modification, and redefinition. In the context of translation teaching, only replacing the paper dictionary with AI belongs to the substitution level, using its immediate feedback to improve the grading efficiency belongs to the enhancement level, and embedding post-editing training and human-machine collaboration processes into teaching touches the modification and even redefinition levels. By integrating the above theoretical perspectives, this study constructs a five-dimensional transformation framework covering goals, content, mode, evaluation, and roles: the goal dimension focuses on the expansion from language skills to translation literacy, the content dimension focuses on the extension from textbook texts to real tasks, the mode dimension focuses on the transformation from teacher instruction to human-machine collaboration, the evaluation dimension focuses on the evolution from final scoring to process diagnosis, and the role dimension focuses on the transformation of teachers from knowledge imparters to learning designers and collaborative constructors. The five dimensions interlock and support each other, forming an analytical framework for comprehensively examining and systematically promoting the transformation of university English translation teaching.

4. Practical Approaches and Experimental Design for Transforming Translation Teaching through AI

4.1 The Practical Approaches for Transforming Translation Teaching through AI-driven Technology

In the face of the systematic changes brought about by artificial intelligence, the practical advancement of university English translation teaching requires concerted efforts from four aspects: curriculum, classroom, assessment, and teachers.

At the curriculum level, a course module that integrates translation ability and AI literacy should be constructed. Its internal structure can be divided into four progressive units: the basic translation module, the AI tool application module, the post-editing module, and the project practice module. The basic translation module consolidates the core abilities of language conversion and cross-cultural understanding, the AI tool application module enables students to proficiently operate mainstream translation platforms and understand their working mechanisms, the post-editing module systematically trains critical review and revision strategies for machine translations, and the project practice module integrates the aforementioned skills through real translation tasks. These modules can be embedded in

the existing university English curriculum system and achieved through a combination of independent setting and content infiltration to ensure connection. They can be implemented either in translation elective courses or by integrating module elements into relevant units of the university English reading, writing, and translation courses.

At the classroom level, teaching activities should be organized around a human-machine collaborative translation task chain. The task design must follow three principles: authenticity, gradation, and reflection. The task context should be close to real communication needs, with difficulty gradually increasing to match students' cognitive development levels, and reflection nodes should be embedded in each stage to promote metacognitive development. A typical task chain can be designed as a complete process of initial human translation, AI translation, comparative analysis, post-editing, and quality assessment for the same text, allowing students to experience a complete translation decision-making cycle throughout the continuous human-machine dialogue.

At the assessment level, a process-based translation ability archive should be established. Translation logs should record the thinking trajectories at each stage, version comparisons should present the revision process, reflection reports should extract strategic gains, and AI usage records should present the characteristics of human-machine interaction behaviors. At the same time, corresponding evaluation rubrics should be designed to convert these process-based evidence into observable and measurable development indicators.

At the teacher level, enhancing teachers' AI teaching literacy is the key guarantee for the implementation of the transformation. The teacher AI literacy framework should cover four dimensions: technical operation ability, teaching integration ability, critical reflection ability, and ethical norms awareness. Through the establishment of a teaching research community and a school-based training mechanism, continuous professional development support can be provided to teachers, enabling them to share practical experience and solve teaching problems collaboratively with their peers, and gradually achieving a role transition from technology adopters to teaching innovators.

4.2 The experimental design and data analysis for AI-Driven translation teaching transformation

This study employed a quasi-experimental design to verify the effectiveness of the AI-driven translation teaching model. The subjects were 82 students from two parallel classes of non-English majors at a university. They were divided into the experimental class and the control class. The independent variable was the teaching model. The experimental class received human-machine collaborative process-oriented teaching, while the control class maintained traditional commentary-based teaching. The dependent variables included translation ability, post-editing ability, AI usage strategies, and learning motivation. The control variables included teachers, textbooks, class hours, and pre-test levels. The research tools included translation test papers, post-editing tasks, AI usage strategy questionnaires, learning motivation scales, and semi-structured interview outlines.

The teaching intervention lasted for 12 weeks. The teaching in the experimental class was centered around the four-stage model of AI pre-translation - comparative diagnosis - post-editing - reflection and

summary. The control class mainly relied on teacher explanations and model evaluation. Data collection was conducted in two rounds: pre-test and post-test. Simultaneous process data of students were collected. After the experiment, some students were selected for in-depth interviews.

This section conducts a systematic analysis of the quantitative and qualitative data collected from the experiment to verify the multi-dimensional effects of the AI-driven translation teaching model. The results are in the following:

(1) Translation performance and post-editing ability

The empirical results of translation scores and post-editing ability are presented in Table 1. In terms of translation scores, the pre-test average score of the experimental class was 74.52 (SD = 8.16), and it increased to 82.36 (SD = 7.52) after the test, with a significant difference within the group ($t = 5.73$, $p < 0.001$); the pre-test average score of the control class was 74.38 (SD = 7.93), and the post-test score was 76.14 (SD = 8.31), with no significant difference between the pre-test and post-test ($t = 1.42$, $p = 0.163$). The comparison of post-test scores between the two classes showed a significant difference ($t = 4.18$, $p < 0.001$), with an effect size of Cohen's d of 0.93, indicating that the teaching intervention has a substantial promoting effect on the improvement of translation ability.

Table 1. Empirical Results on Translation Scores and Post-Translation Editing Skills

Test Dimensions	Groups	Pre-Test Average (SD)	Post-Test Average (SD)	In-Group t-Value	Inter-Group Post-Test t-Value	Cohen's d
Translation Score	Experimental Class (N=41)	74.52 (8.16)	82.36 (7.52)	5.73***	4.18***	0.93
	Control class (N=41)	74.38 (7.93)	76.14 (8.31)	1.42	—	—
Post-Translation Editing Ability	Experimental Class (N=41)	68.21 (9.34)	81.45 (7.88)	8.19***	5.67***	1.26
	Control Class (N=41)	67.95 (9.12)	71.23 (8.56)	2.08*	—	—

*p<0.05,**p<0.01,***p<0.001.

The group difference in post-editing ability was more prominent. The pre-test average score of the experimental class was 68.21 (SD = 9.34), and it increased to 81.45 (SD = 7.88) after the test, with a significant difference within the group ($t = 8.19$, $p < 0.001$); the pre-test average score of the control class was 67.95 (SD = 9.12), and the post-test score was 71.23 (SD = 8.56), although it also reached a significant level ($t = 2.08$, $p = 0.044$), but the increase was significantly smaller than that of the experimental class. The comparison of post-test scores between the two classes showed a significant

result ($t = 5.67$, $p < 0.001$), with an effect size of Cohen's d of 1.26, belonging to a large effect level. The data indicate that the post-test average score of the experimental class was significantly higher than that of the control class, with an effect size reaching a large effect level, indicating that the teaching intervention has a substantial promoting effect on the improvement of translation ability; the group difference in post-editing ability was more significant. The post-test performance of the experimental class in the three dimensions of modification level, strategy application standardization, and error recognition rate was better than that of the control class, indicating that the process-oriented human-machine collaborative training effectively promoted students' critical review ability of machine translations.

(2) AI usage strategies and critical judgment capabilities

The empirical results of AI usage strategies and critical judgment ability are presented in Table 2. In the pre-test of the AI usage strategies questionnaire, the average scores of each dimension in both classes were less than 2.5 (on a 5-point scale), indicating that students mainly relied on direct copying of translations or simple word lookup, with a single strategy and a lack of critical awareness. In the post-test, the diversity of strategies in the experimental class increased from 2.41 (SD=0.63) to 3.87 (SD=0.58) ($p<0.001$, $d=0.97$), the rationality of strategy selection increased from 2.28 (SD=0.57) to 3.74 (SD=0.61) ($p<0.001$, $d=0.92$), and the questioning awareness increased from 2.15 (SD=0.72) to 3.92 (SD=0.65) ($p<0.001$, $d=1.16$). The improvements in all three scores were at an extremely significant level within and between groups; the differences in each dimension between the pre-test and post-test of the control class were not significant ($p>0.05$). The critical judgment ability was measured by the accuracy rate of students in evaluating the types and severity of errors in machine translations. The accuracy rate of the experimental class increased from 54.32% (SD=11.47) to 76.85% (SD=9.23) ($p<0.001$, $d=1.30$), while that of the control class only increased from 54.18% (SD=10.95) to 59.41% (SD=10.68) ($p=0.019$, $d=0.48$). The post-test accuracy rate of the experimental class was significantly higher than that of the control class ($p<0.001$).

Table 2. Empirical Results on AI Usage Strategies and Critical Judgment Abilities

Test Dimensions	Groups	Pre-Test Average (SD)	Post-Test Average (SD)	In-Group t-Value	Inter-Group Post-Test t-Value	Cohen's d
Strategy Diversity	Experimental Class (N=41)	2.41 (0.63)	3.87 (0.58)	6.21***	4.35***	0.97
	Control Class (N=41)	2.39 (0.61)	2.52 (0.66)	1.08	—	—
Rationality of Strategy	Experimental Class (N=41)	2.28 (0.57)	3.74 (0.61)	5.89***	4.12***	0.92

Selection	Control Class (N=41)	2.31 (0.55)	2.43 (0.63)	1.15	—	—
Awareness of Questioning	Experimental Class (N=41)	2.15 (0.72)	3.92 (0.65)	7.34***	5.21***	1.16
	Control Class (N=41)	2.18 (0.69)	2.31 (0.71)	1.02	—	—
Accuracy Rate of Critical Judgment	Experimental Class (N=41)	54.32 (11.47)	76.85 (9.23)	8.67***	5.84***	1.30
	Control Class (N=41)	54.18 (10.95)	59.41 (10.68)	2.43*	—	0.48

*p<0.05,**p<0.01,***p<0.001.

(3) Learning motivation and learning experience

The empirical results of learning motivation and learning experience are presented in Table 3. Regarding learning motivation, the post-test average score of intrinsic motivation in the experimental class was 4.12 (SD = 0.61), while that in the control class was 3.52 (SD = 0.69), and the difference between the groups was significant (t = 3.58, p = 0.001, d = 0.79); the post-test average score of task value perception in the experimental class was 4.08 (SD = 0.64), and that in the control class was 3.41 (SD = 0.72), and the difference between the groups was extremely significant (t = 3.76, p < 0.001, d = 0.84). The pre- and post-test differences in extrinsic motivation and the group differences were not significant in both classes (p > 0.05), suggesting that the teaching intervention mainly stimulated learning motivation by enhancing the intrinsic attractiveness of the task rather than external stimuli. Regarding learning experience (only post-test), the post-test scores of task participation (4.25, SD = 0.56), human-computer interaction fluency (3.96, SD = 0.63), and self-efficacy (4.08, SD = 0.59) in the experimental class were significantly higher than those in the control class (t = 4.87, 3.92, 4.15; all p < 0.001; d = 1.08, 0.87, 0.92), and the three effect sizes all reached the large effect level. At the same time, some students reported that the cognitive load of AI tools was relatively high at the beginning, and this feedback provided a reference for optimizing the teaching rhythm. The post-test scores of the experimental class in the two subscales of the learning motivation scale (intrinsic motivation and task value perception) were significantly higher than those of the control class, while there was no significant difference in the extrinsic motivation dimension. This suggests that the teaching intervention mainly stimulated learning motivation by enhancing the intrinsic attractiveness of the task rather than external stimuli. The learning experience questionnaire further revealed that the positive experiences of students in the experimental class in terms of task participation, human-computer interaction fluency, and self-efficacy were significantly higher than those in the control class, but some students also reported that the cognitive load of AI tools was relatively high at the beginning, which provided a reference for optimizing the teaching rhythm.

Table 3. Empirical Results on Learning Motivation and Learning Experience

Test Dimensions	Groups	Pre-Test Average (SD)	Post-Test Average (SD)	In-Group t-Value	Inter-Group Post-Test t-Value	Cohen's d
Intrinsic Motivation	Experimental class (N=41)	3.36 (0.74)	4.12 (0.61)	5.47***	3.58**	0.79
	Control class (N=41)	3.41 (0.72)	3.52 (0.69)	0.86	—	—
Perception of Task Value	Experimental class (N=41)	3.24 (0.78)	4.08 (0.64)	5.83***	3.76***	0.84
	Control class (N=41)	3.27 (0.75)	3.41 (0.72)	1.05	—	—
Extrinsic Motivation	Experimental class (N=41)	3.62 (0.81)	3.71 (0.77)	0.64	0.43	—
	Control class (N=41)	3.58 (0.79)	3.63 (0.82)	0.37	—	—
Task Engagement	Experimental class (N=41)	—	4.25 (0.56)	—	4.87***	1.08
	Control class (N=41)	—	3.38 (0.74)	—	—	
Fluency of Human-Computer Interaction	Experimental class (N=41)	—	3.96 (0.63)	—	3.92***	0.87
	Control class (N=41)	—	3.21 (0.82)	—	—	
Self-Efficacy	Experimental class (N=41)	—	4.08 (0.59)	—	4.15***	0.92
	Control class (N=41)	—	3.35 (0.76)	—	—	

*p<0.05,**p<0.01,***p<0.001.

(4) Qualitative data analysis

The qualitative data analysis conducted on students' translation reflection logs and semi-structured interview transcripts involved thematic coding, resulting in the identification of three core themes. First, the awakening of strategic awareness, where students shifted from unconsciously relying on machine translations to strategically allocating AI resources. The reflection texts frequently contained discourse markers indicating critical evaluation followed by re-utilization of AI translations. Second, the

repositioning of human-machine roles, as students gradually defined AI as a questionable collaborative tool rather than an authoritative source of translations through continuous comparison and editing practices. This transformation was evidenced in their changes in emotional attitudes towards AI translations. Third, enhanced metacognitive monitoring, as students demonstrated a clearer self-awareness of their translation decision-making process in their reflection reports. They were able to clearly describe the reasons for revisions, the basis for strategy choices, and the remaining confusions. The triangulation of quantitative and qualitative results provides sufficient empirical support for the multi-dimensional effectiveness of teaching interventions.

5. Conclusion

In the era of artificial intelligence, university English translation teaching has exposed several prominent problems, including overly narrow teaching objectives, increasingly rigid teaching content, relatively monotonous teaching models, significantly lagging evaluation methods, and the general absence of AI literacy among both teachers and students. To address these challenges, this study, based on the activity theory as the basic framework and the SAMR model as the hierarchical reference, constructed a transformation analysis framework from five dimensions: target positioning, content organization, teaching model, evaluation method, and teacher-student roles. Subsequently, it proposed a four-stage human-machine collaborative process-oriented teaching model of "AI pre-translation - comparative diagnosis - post-translation editing - reflection and summary", and conducted a twelve-week quasi-experimental study with 82 non-English major undergraduate students from a certain university. The experimental results showed that structured human-machine collaborative training could simultaneously enhance students' translation quality, process strategy level, and learning motivation quality. This finding provides relatively systematic empirical support for related teaching practices. At the same time, these conclusions also to some extent address the concerns of the academic community regarding the potential weakening of students' independent thinking ability by AI tools, suggesting that if a critical review framework can be consciously embedded in teaching design, AI can instead become an effective support for cultivating students' high-level critical thinking abilities. Overall, the teaching intervention achieved observable positive effects in three aspects: cognitive output, strategic behavior, and learning motivation, providing evidence-based support for the practical application of AI-driven translation teaching models.

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