Construction of a Dual-Driven AI Literacy Framework for Traditional Chinese Medicine Translation Based on the Transformer Architecture from a Human–Machine Symbiosis Perspective

Huangyi Zhang[a*], Huairong Li[b]

Hubei University of Chinese Medicine, Wuhan, Hubei, 430000, China

*a3308252489@qq.com
b3438154522@qq.com

Abstract. The deep integration of generative artificial intelligence is reshaping knowledge production in Traditional Chinese Medicine (TCM) translation education. At present, learners encounter issues such as semantic dilution, fragmented AI literacy, and weakened cultural subjectivity in the process of technological application. The underlying cause lies in the structural tension between the statistically driven operational logic of large language models and the flexible, holistic, and context-sensitive nature of TCM thinking. From a human-machine symbiosis perspective, this study constructs a dual-driven framework of "AI literacy-cross-cultural translation competence". AI literacy is further decomposed into three sub-dimensions: prompt structuring competence, generation process regulation competence, and critical post-editing competence. By introducing the Transformer architecture and pre-trained models, the study develops a quantitative evaluation model for translation quality based on cosine similarity in vector space. In addition, an evaluation formula coupling language fluency metrics with the degree of cultural connotation alignment is proposed, enabling learners to intuitively identify regions of semantic loss and to achieve a bidirectional integration of technical rationality and cultural rationality. Furthermore, implementation pathways are proposed across three levels—competence compensation, collaborative integration, and paradigm reconstruction—facilitating the transformation of learners from passive tool users into active leaders in human-machine collaborative translation, and providing a theoretical reference for the paradigm shift in TCM translation education.

Keywords: Human-machine symbiosis; TCM translation; AI literacy; Cross-cultural communication; Transformer architecture; Translation pedagogy

1 Introduction

The ongoing new wave of global technological revolution and industrial transformation is advancing rapidly, with artificial intelligence emerging as a key variable in reshaping educational paradigms. In April 2026, China's Ministry of Education, together with

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four other ministries, jointly issued the *"AI Empowering Education" Action Plan*, explicitly proposing a people-centered, literacy-first, application-oriented, and ethically aligned approach to building a comprehensive AI general education system across all educational stages, and promoting systemic transformations in teaching models, governance structures, and talent cultivation systems[1]. Traditional Chinese Medicine (TCM), embodying thousands of years of life wisdom and philosophical reflection of the Chinese nation, requires more than mere linguistic conversion in its translation and international dissemination; it entails a dialogue between heterogeneous cultural cognitive paradigms and value systems. In the context of breakthrough developments in generative artificial intelligence (GenAI), the practice and pedagogical models of TCM translation are undergoing a subtle yet profound structural transformation. Large language models, represented by systems such as ChatGPT and DeepSeek, are evolving from conventional "auxiliary tools" into "collaborative partners" with cognitive participation. This shift in role implies that the objectives of TCM translation education can no longer be confined to training students in the use of translation software; rather, learners must be guided toward a new stage of deep co-construction and mutual empowerment with intelligent systems—namely, human-machine symbiosis. Against this backdrop, AI literacy is not merely a set of technical skills but a redesign of cognitive and value systems[2]. It no longer exists as an independent instructional module separate from cross-cultural translation competence; instead, the two function as dual driving forces that continuously interact and co-shape each other within human-machine symbiotic practices.

This study aims to construct a dual-driven framework integrating AI literacy and cross-cultural translation competence for TCM translation learners from a human-machine symbiosis perspective. It should be noted that this framework is not a singular pedagogical operation model, but rather a generative mechanism model of translation competence oriented toward human-machine collaborative contexts. Its core objective is to reveal how technical rationality and cultural rationality operate synergistically within the cognitive process of translation. The study first diagnoses the practical challenges currently faced by TCM translation education, then conducts a causal analysis based on the structural differences between algorithmic logic and TCM thinking. Building on this, it systematically elaborates the components, implementation strategies, and operational mechanisms of the dual-driven framework, and finally envisions a developmental pathway toward a "smart + humanities" symbiotic ecosystem in TCM translation education.

2 Inserting Content Elements

GenAI refers to technologies that generate content—such as text, images, audio, video, and code—based on algorithms, models, and rules. In essence, it constitutes an unsupervised or partially supervised machine learning framework that produces artificial artifacts through statistical and probabilistic methods[3]. With its deep integration into translation practice, structural problems in TCM translation education have gradually surfaced. These issues are no longer confined to a lack of competence; rather, they are increasingly manifested as imbalances in competence structures and shifts in cognitive mechanisms following technological intervention. Overall, these challenges can be summarized into three aspects: semantic weakening induced by technological dependence, uneven development of AI literacy, and the relative attenuation of cultural subjectivity.

2.1 Technological Dependence and the Phenomenon of "Semantic Dilution"

With the widespread adoption of neural machine translation and large language models, TCM translation learners have become increasingly reliant on intelligent tools. While such dependence improves the efficiency of linguistic expression, it also, to some extent, weakens learners' ability to actively construct the semantic structure of the source language. As a treasure of Chinese civilization, TCM culture encapsulates centuries of health preservation practices and clinical experience, enriched with profound philosophical insights[4]. On the surface, AI-generated translations have reached a high level of fluency and grammatical correctness. However, closer examination reveals a concerning phenomenon of "semantic dilution"—that is, the rich connotations of core TCM concepts are simplified, narrowed, or even reinterpreted within a Western biomedical framework in AI-generated texts. For instance, the core TCM concept qi is often directly translated by AI as "energy" or rendered as the pinyin "qi." The former reduces a multi-layered concept encompassing cosmological origins, vital force, organ function, and pathological changes into the Western notion of "energy", while the latter provides no cultural adaptation, leaving target-language readers unable to grasp its essential meaning. As a result, the translation process has gradually shifted from a cognition-centered activity based on "understanding–transformation" to a technology-driven mode characterized by "invocation–revision."

In this process, the meaning-making mechanism of TCM texts—highly dependent on context and theoretical systems—fails to be fully represented. Translation activities thus exhibit a shift from "deep semantic construction" to "surface-level expression matching." This transformation weakens the structural integrity of TCM knowledge in cross-linguistic transfer and lays the groundwork for the accumulation of subsequent cognitive biases. The consequences of such semantic dilution are twofold: at the textual level, the fidelity of TCM knowledge dissemination declines; at the cognitive level, prolonged exposure to simplified AI-generated translations may lead learners to develop superficial and Westernized understandings of TCM concepts, thereby creating a negative feedback loop between cognitive competence and technological convenience.

2.2 Fragmentation of AI Literacy

The emergence of AI literacy originates from the evolution of the concept of literacy and the catalytic role of artificial intelligence. It is not merely an understanding and application of AI technologies, but a comprehensive and evolving system of skills and knowledge that enables individuals to select appropriate AI tools and use them effectively[5]. In current TCM translation pedagogy, however, the integration of AI is largely confined to the level of tool application, lacking a systematic design of competence structures. As a result, AI literacy exhibits a pronounced tendency toward fragmentation. In most instructional practices, AI is positioned as a "high-level dictionary" or a "rapid translator." Although learners may possess basic operational skills, they demonstrate notable deficiencies in higher-order cognitive regulation and logical evaluation.

Specifically, this imbalance is manifested in a greater reliance on technological outputs than on an understanding of their generative mechanisms, a higher degree of acceptance of results than control over processes, and a stronger emphasis on efficiency gains than on the assessment of quality risks. Learners often describe translation tasks in unstructured natural language, without mastering the construction of structured prompts. Consequently, they are unable to guide AI toward high-quality outputs through precise role specification, terminological constraints, and contextual embedding. At the post-editing stage, they also lack a critical methodological framework. When evaluating AI-generated translations, students tend to focus on surface-level criteria such as grammatical fluency and terminological consistency, while lacking the tools and validation pathways to identify deeper risks, including errors in medical logic, conceptual confusion, and cultural misinterpretation. Typical "hallucinations" of large language models in TCM translation—such as fabricating classical citations, conflating the viewpoints of different physicians, or misrepresenting the hierarchical relationships among medicinal components—further illustrate this issue. For example, in the translation of formulas, an AI system may incorrectly identify Renshen (the principal herb) in Sijunzi Decoction as a subordinate ingredient, while elevating Rhizoma Atractylodis Macrocephalae or Radix et Rhizoma Glycyrrhizae to primary status. Such misclassification distorts the original hierarchical structure of the formula and leads to a functional deviation from its core therapeutic principle of tonifying qi and strengthening the spleen. Although these issues have not yet been fully incorporated into teaching content, they hinder learners from establishing an appropriate calibration of trust in their use of AI systems.

2.3 Weakening of Cultural Subjectivity

Under the continuous intervention of technological logic in translation activities, learners' sense of subjectivity in cross-cultural expression shows a tendency toward attenuation. Cultural subjectivity—also referred to as translator subjectivity—denotes the translator's agency in translation activities, shaped by external contexts, marginal positions, and their own interpretive horizon, and manifested in their ability to meet the needs of the target culture through active and conscious mediation[6]. In cross-cultural communication, it involves maintaining an awareness of and commitment to the core values, cognitive paradigms, and discursive systems of one's own culture. In the context of TCM translation, this subjectivity is primarily reflected in the capacity to creatively re-present indigenous modes of thinking—such as holism, syndrome differentiation and treatment, and analogical reasoning—within the target language.

However, AI models, at the level of underlying logic, pursue statistical regularity and output determinacy, and are inherently inclined to establish "greatest common denominator" correspondences between source and target languages. This tendency potentially conflicts with the TCM cognitive characteristics of flexibility, contextual adaptation, and meaning construction based on discourse. As learners become accustomed to the efficient workflow of “inputting the source text—obtaining AI output—making minor revisions”, their intrinsic motivation to deeply engage with the conceptual structure of the source text and to explore creative expression strategies within the target culture may gradually diminish. Some learners even regard AI-generated translations as “authoritative references”, substituting algorithmic statistical judgments for their own value judgments grounded in TCM theoretical foundations and cultural knowledge. In doing so, they relinquish their subjectivity at critical points of cross-cultural decision-making. This shift weakens the translator’s leading role in meaning negotiation and reduces their capacity to consciously preserve the internal logic and cultural value of TCM knowledge systems. In cross-cultural communication, tasks that should be undertaken by the translator—such as cultural interpretation and meaning reconstruction—are partially displaced by technological generation mechanisms, resulting in translations that favor formal equivalence over semantic re-presentation. Over time, this may exert a structural impact on the cross-cultural articulation of the TCM discourse system.

3 Causal Analysis of the Challenges in TCM Translation Education

The aforementioned challenges are not incidental; their deeper roots lie in the structural tension between algorithmic operational logic and the representational mode of TCM knowledge. From the perspective of technological mediation, artificial intelligence, as a cognitive intermediary, is not a neutral tool. Rather, in participating in translation practice, it actively reshapes both the pathways of meaning generation and the structure of cognition.

3.1 Limitations of Algorithmic Logic

Large language models, in essence, belong to the category of deep neural networks. They primarily extract linguistic features through self-supervised learning on large-scale text corpora and generate new texts that conform to linguistic conventions[7]. From the perspective of the distinction between technical rationality and value rationality, such models tend to optimize outputs along the dimensions of efficiency and computability, while struggling to respond to the value orientations and meaning-generation logic embedded in the TCM knowledge system.

These two cognitive logics differ at the ontological level: the former relies on data-driven pattern induction, whereas the latter depends on system construction grounded in experiential integration. This disparity makes it difficult for AI to fully reproduce the intrinsic mechanisms of meaning generation when processing TCM texts, thereby leading to deviations between semantic expression and theoretical reference. Consequently, while technological outputs may exhibit linguistic plausibility, inconsistencies may arise at the level of knowledge structure.

3.2 Imbalance in Competence Dimensions

From an educational perspective, the imbalance in competence dimensions stems from the lag in curricular systems responding to technological transformation. Traditional translation pedagogy centers on linguistic competence and domain knowledge. In TCM translation education, curricula are typically structured around three dimensions: foundational language skills, TCM knowledge acquisition, and translation skills training (As shown in Figure 1). The integration of AI technologies remains marginal and supplementary. Core components of AI literacy—such as prompt engineering, algorithmic evaluation, and human–machine collaboration strategies—have not yet been systematically incorporated, resulting in a lack of effective synergy between technical competence and cultural competence. In this context, learners' competence development exhibits a "dual disconnection." On the one hand, technological application lacks deep understanding, making it difficult to form stable regulatory capabilities. On the other hand, cultural understanding is not effectively translated into the technological context, limiting learners' ability to critically calibrate and correct AI-generated outputs. This structural disconnection directly leads to imbalances in the development of translation competence across different dimensions, thereby weakening the overall coherence and coordination of the competence system.

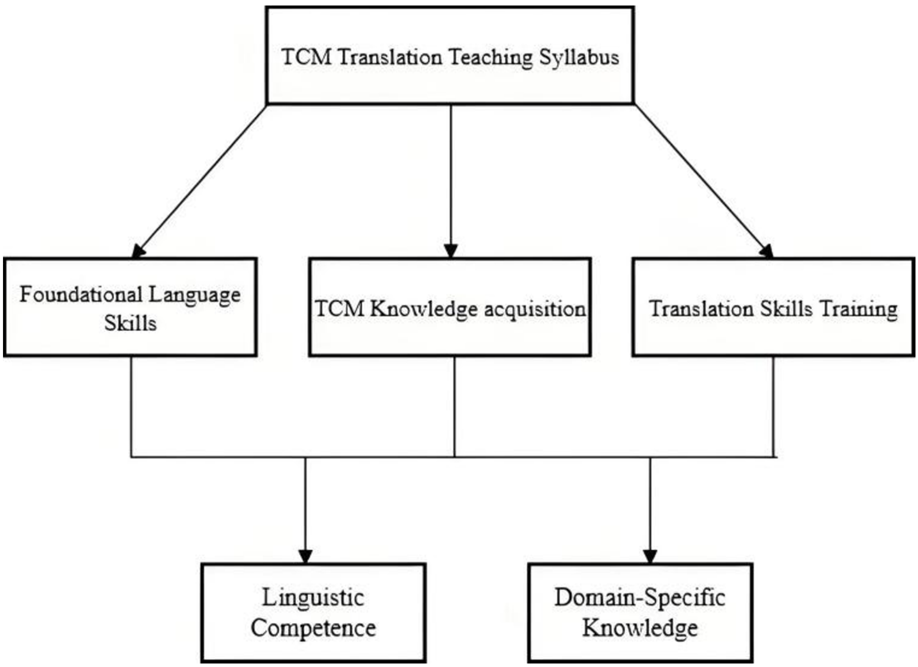

Fig. 1. Three-Dimensional Structural Diagram of the TCM Translation Teaching Syllabus.

3.3 Imbalance in the Human-Machine Symbiotic Relationship

With the deepening integration of intelligent technologies into human production and everyday life, the relationship between humans and machines is gradually evolving from “human–machine collaboration” toward “human–machine symbiosis.” Coordinated development and co-creation between humans and machines are becoming a dominant trend in future societal development[8]. However, from the perspective of interaction patterns in human–machine collaboration, learners in current translation practices generally remain in a state of passive following rather than active leadership. Ideally, human–machine collaboration should manifest as a dynamic equilibrium, in which different cognitive tasks are rationally distributed between humans and technology. Yet under conditions of strong AI intervention, this distribution mechanism becomes imbalanced, leading to a weakening of learners’ cognitive agency. An ideal symbiotic relationship should follow the principle of “human-led, machine-assisted”: translators, drawing on their professional judgment, define translation objectives, establish terminological strategies, and make decisions regarding cultural adaptation, while AI serves as an efficient executor and information provider that responds to and supports these decisions. In practice, however, due to the aforementioned fragmentation of AI literacy and the weakening of cultural subjectivity, the collaborative relationship often degenerates into a pattern of “machine-led, human-following”. Learners unconsciously adopt AI-generated initial outputs as the basis for decision-making, relegating themselves to the role of post-editing proofreaders, while their proactive strategic thinking and creative cross-cultural design are significantly constrained.

From the perspective of distributed cognition theory, while the interaction among multiple agents is emphasized, the central role of the individual in cognitive processes is also affirmed[9]. When technological systems dominate in information processing and expression generation, human cognitive activity tends to contract toward lower-level monitoring functions, while higher-order decision-making and meaning construction remain underdeveloped. This condition shifts the human–machine relationship from complementary collaboration to structural imbalance, thereby affecting the overall quality and stability of the translation process.

4 Construction and Implementation Pathways of the Dual-Driven Framework

In response to the three interrelated issues identified—namely, the limitations of algorithmic logic, the imbalance in competence dimensions, and the dysfunction of the human–machine relationship—this study constructs a dual-driven framework of “AI literacy–cross-cultural translation competence” from the perspective of human–machine symbiosis. Furthermore, it proposes systematic implementation pathways across three levels—competence compensation, collaborative integration (As shown in Figure 2), and paradigm reconstruction—in order to achieve the holistic optimization of the competence system of TCM translation learners.

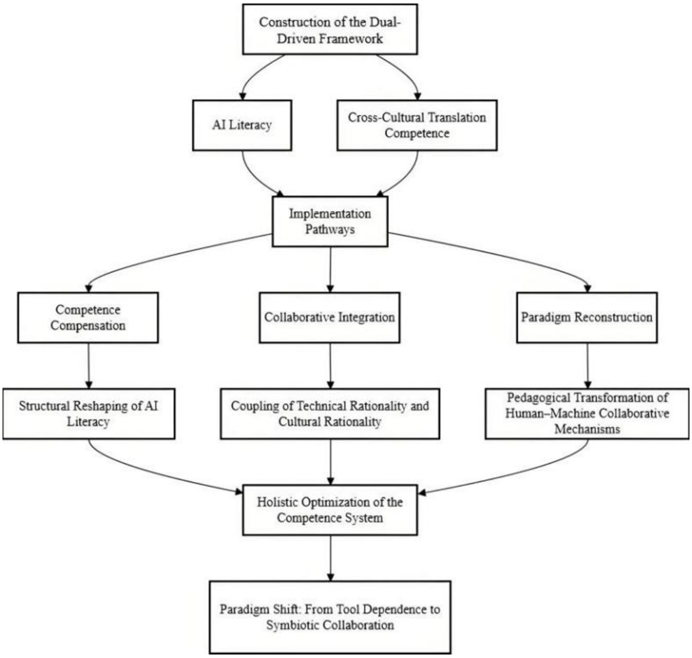

Fig. 2. A Dual-Driven Framework of "AI Literacy–Cross-Cultural Translation Competence" Constructed from a Human–Machine Symbiosis Perspective.

4.1 Competence Compensation for Algorithmic Limitations: Structural Reshaping of AI Literacy

Under the premise that generative artificial intelligence possesses inherent structural limitations, the improvement of TCM translation competence should not rely on the optimization of the technology itself, but rather shift toward the systematic reconstruction of learners' competence structure. Based on this, the dual-driven framework defines AI literacy as a key compensatory mechanism for addressing algorithmic uncertainty and semantic deviation. Whether viewed from a competency-based perspective or a comprehensive literacy-oriented perspective, AI literacy generally exhibits two salient characteristics: it encompasses elements such as AI knowledge, AI skills, and attitudes toward AI[10]. Its core lies in embedding TCM knowledge comprehension into the human–machine interaction process, thereby enabling constraint and calibration of the generative pathway. Accordingly, the structural reshaping of AI literacy can be further elaborated into three interrelated sub-dimensions: prompt structuring competence, generation process regulation competence, and critical post-editing competence.

Cognitive Modeling Mechanism of Prompt Structuring Competence.
A prompt refers to input information or instructions provided to a computer program or model to guide the direction of generated outputs[11]. In the context of generative

artificial intelligence participating in translation practice, prompts are not only a form of technical invocation input, but also an important carrier for cognitive modeling of translation tasks. Compared with unstructured natural language expressions, structured prompts can impose prior constraints on semantic scope, terminological systems, and translation strategies at the initial stage of a task, thereby providing a stable cognitive framework for subsequent generation processes.

From the perspective of competence composition, prompt structuring competence is reflected in the systematic integration of translation task elements, namely, making implicit cognitive processes explicit and operationalizable through clearly defining role positioning, delimiting contextual boundaries, and introducing terminological constraints. This process essentially embeds human understanding of the TCM knowledge system into the technical interface, so that AI outputs are guided and regulated by structured knowledge at the early stage of generation. Thus, prompts are no longer merely simple instructional expressions, but become a key mediating mechanism connecting human cognition and machine generation.

Dynamic Interaction Mechanism of Generation Process Regulation.

The process of interacting with AI is not merely an input–output exchange of information, but also a deeper cognitive process[11]. During the translation generation stage, AI outputs are characterized by probabilistic uncertainty, and a single generation cycle is often insufficient to fully meet the requirements of specialized discourse contexts. Therefore, learners must possess the ability to continuously regulate the generation process in order to shift from “passive acceptance” to “active intervention”.

The core of this competence lies in the dynamic management of the human–machine interaction process, namely providing directional guidance and strategic refinement of outputs through multi-turn interaction. Through iterative evaluation of generated content and continuous optimization of input conditions, translation activities gradually exhibit a cyclical feedback structure. In this process, learners are not only selectors of results but also designers of generation pathways, and their cognitive function expands from singular judgment to process regulation. Consequently, human–machine collaboration shifts from a linear workflow to a dynamic system, in which technological generation and human cognition are continuously aligned through interaction.

Taking the multi-round interaction around the term “脾虚” as an example: in the first round, the learner observed that the AI rendered it as “spleen weakness,” reflecting the bias of replacing the functional system of TCM with a Western anatomical organ. Based on this output, the learner then prompted: “Please distinguish the functional differences between the TCM spleen and the Western medical spleen, and retranslate the term,” thereby guiding the AI to revise it into “Spleen deficiency (TCM functional system, not the anatomical organ).” In the third round, the learner further specified: “Please clarify that ‘deficiency’ in the TCM context refers to functional insufficiency rather than structural damage,” ultimately obtaining a translation that preserves the ontological characteristics of TCM discourse. The three-round iteration demonstrates a regulatory closed loop of “output diagnosis–condition supplementation–path correction,” through which learners shift from passive recipients of single outputs to continuous designers of the generative process.

Multi-Dimensional Evaluation Mechanism of Critical Post-Editing.

In AI-assisted translation processes, although outputs may demonstrate linguistic plausibility at the surface level, their accuracy in terms of knowledge structure and cultural meaning still requires human post-editing for validation. Therefore, critical post-editing competence constitutes a key component of AI literacy, and its essence lies in the multi-dimensional systematic evaluation of technological outputs.

This competence not only focuses on grammatical and stylistic correctness, but also emphasizes comprehensive judgment of medical logical consistency, conceptual referential accuracy, and cultural semantic integrity. By introducing multi-level evaluation criteria, learners are able to identify potential semantic deviations and cognitive errors, thereby revising and reconstructing translations when necessary. This process reflects the human role of final review and interpretive authority in translation activities, reintegrating machine-generated outputs into an evaluation system centered on human cognition. Thus, translation quality assurance no longer depends on a single generated result, but is instead established on a mechanism of continuous post-editing and dynamic correction.

Taking the AI-assisted review of the formula “Si Junzi Tang” as an example, learners can conduct the evaluation on three levels. The first is the linguistic level, which examines the pinyin transliteration and terminological consistency of “Sijunzi Decoction.” The second is the level of medical logic, which verifies whether the AI has correctly identified the hierarchical structure of sovereign, minister, assistant, and courier herbs. For instance, if the AI describes Baizhu (the minister herb) as “the main herb” while downgrading *Renshen* (the sovereign herb) to an auxiliary role, this constitutes a reversal of the medicinal hierarchy and requires immediate correction. The third is the level of cultural connotation, which assesses whether the rendering of “invigorating qi and strengthening the spleen” preserves the holistic functional theory of TCM, rather than reducing it to the Western medical notion of “digestive support.” Together, these three levels form a progressive review gradient from surface language to deeper conceptual meaning, enabling learners to systematically identify biases in AI-generated translations across multiple dimensions and reaffirming the translator’s cognitive authority as the final arbiter of meaning.

4.2 Collaborative Integration for Competence Imbalance: Bidirectional Coupling of Technical Rationality and Cultural Rationality

Within the bidirectional coupling of technical rationality and cultural rationality, machine learning can not only assist physicians in disease diagnosis and treatment planning, but also enhance the efficiency and accuracy of TCM research[12]. In this context, AI models should not be regarded merely as generative tools, but rather as “digital benchmarks” for evaluating and optimizing translation quality. To address the common issue of semantic loss in the translation of TCM discourse, learners can construct a quantitative evaluation model of translation quality, thereby transforming abstract cultural connotations into measurable data features.

Construction and Calculation Workflow of the Quantitative Evaluation Model for Translation Quality.

The quantitative evaluation model introduced in this framework is implemented via the following technical workflow: First, for encoder selection, BERT-base-Chinese (featuring 12 Transformer encoding layers, a 768-dimensional hidden layer, 12 attention heads, and a parameter scale of approximately 110M) serves as the backbone for encoding the Chinese source language, while the English target language is encoded using BERT-base-uncased, with both models loaded with pre-trained weights through the Hugging Face transformers framework. To account for the domain-specific nature of TCM classics, lightweight continual pre-training using specialized corpora—such as English-Chinese parallel corpora of the Huangdi Neijing and Shanghan Lun—can be further employed where conditions permit to enhance the representational capacity of terminology vectors. Second, for vectorization, the [CLS] position vector from the final encoder layer (or alternatively, mean pooling of all token vectors) is extracted as the sentence vectors v_S and v_T for the source sentence S and target sentence T, respectively, both of which undergo L2 norm normalization. Third, the semantic matching degree is determined using the cosine similarity formula:

$$Sim(S,T)=(v_S \cdot v_T)/(\|v_S\| \times \|v_T\|) \tag{1}$$

where the resulting values range from [-1, 1], with scores closer to 1 indicating higher semantic alignment. Fourth, regarding threshold setting, this framework suggests an initial threshold of $\theta = 0.75$ based on the actual tolerance in TCM translation pedagogy; scores falling below this threshold trigger a "semantic dilution" alert, prompting learners to conduct a focused review of that specific segment, with the threshold subject to dynamic optimization based on pedagogical feedback loops. Finally, for output visualization, the system generates sentence-by-sentence similarity scores presented as heatmaps, allowing semantic loss to be spatialized at the textual level and enabling learners to quickly pinpoint problematic sections.

Learners may employ pre-trained models based on the Transformer architecture (such as BERT or domain-specific TCM models) to calculate the cosine similarity in vector space between the source language (TCM classical texts) and AI-generated target language outputs. When the similarity falls below a predefined threshold, the model can visually indicate regions where “semantic dilution” occurs, compelling learners to reflect on the limitations of algorithms in processing high-density cultural terms from the perspective of TCM thinking modes (e.g., analogy through correspondence and categorization of phenomena). To achieve a more precise coupling of the dual competence dimensions, the following evaluation logic can be introduced:

$$Q_{Total}=w_1 \cdot Sim(S,T)+w_2 \cdot Cul(T) \tag{2}$$

In this formula, $Sim(S,T)$ represents linguistic fluency based on traditional machine learning evaluation metrics (such as BLEU or METEOR), while $Cul(T)$ denotes the degree of cultural connotation alignment. By adjusting the weighting coefficients w_1 and w_2, learners can clearly observe how the cultural integrity of core TCM concepts (such as Yin–Yang and Qi transformation) fluctuates when the model prioritizes "surface-level equivalence". In this mode, the role of learners undergoes a fundamental transformation—from traditional translators to data curators and model calibrators. By analyzing negative samples generated during model testing, learners can systematically identify structural biases in AI reasoning related to patterns such as zang–fu syndrome differentiation and the meridian attribution of medicinal properties. This data-driven falsification process, in turn, feeds back into the optimization of structured prompts (prompt engineering), enabling a dynamic shift from algorithmic stochastic generation toward human rational constraint.

Operational Definition and Calculation Basis of Cultural Connotation Fit $\boldsymbol{Cul(T)}$.
The metric $Cul(T)$ in the evaluation formula is designed to characterize the degree to which an AI-generated translation T preserves the cultural connotations of TCM inherent in the source text. Given the unique nature of the TCM knowledge system, this framework further decomposes $Cul(T)$ into three operational sub-indicators, synthesized through a weighted sum:

$$Cul(T) = \alpha \times TF + \beta \times CLC + \gamma \times CSI \tag{3}$$

In this formula, TF (Terminology Fidelity) utilizes the WHO International Standard Terminologies on Traditional Medicine and the International Standard Chinese-English Basic Nomenclature of Chinese Medicine (World Federation of Chinese Medicine Societies) as reference term databases; it employs terminology alignment tools to automatically compare the "hit rate" of standard translations for core terms within T, where a direct hit scores 1, an approximation scores 0.5, and a mistranslation scores 0, with the results normalized to the $[0,1]$ interval. CLC (Culture-Loaded Coverage) targets high-load TCM conceptual terms (such as Qi, Yin-Yang, Bian-Zheng (syndrome differentiation), and Qu-Xiang-Bi-Lei (reasoning by analogy)), calculating the proportion of instances where Pinyin is retained alongside supplemental cultural explanations to prevent these concepts from being oversimplified into Western medical equivalents. CSI (Conceptual Structure Integrity) assesses whether T maintains the relational structures of TCM (such as Jun-Chen-Zuo-Shi (Sovereign, Minister, Assistant, and Envoy), the generation and restriction of the Five Elements, and the Zang-Fu interior-exterior relationship) by performing matching detection via pre-constructed relational triples (Entity—Relation—Entity), thereby reflecting the "holistic connectivity" characteristic of TCM thought. The sum of the weights α, β, and γ equals 1, with a suggested initial configuration of $\alpha = 0.4$, $\beta = 0.3$, and $\gamma = 0.3$, which can be flexibly adjusted according to the text type (e.g., ancient classics, terminology standards, or clinical texts). Through this three-dimensional decomposition, $Cul(T)$ is transformed from an abstract concept of "cultural connotation" into a computable, comparable, and traceable composite indicator, providing a quantitative basis for the practical application of the evaluation formula.

4.3 Paradigm Reconstruction for Relational Imbalance: Human–Machine Collaborative Mechanisms and Pedagogical Transformation Pathways

In response to the phenomenon of learners' "passive dependency" in human–machine collaborative translation, the dual-driven framework further advances toward the paradigm reconstruction of human–machine relationships, promoting a shift from "technology-dominant" to "human–machine collaborative" modes, and achieving institutionalized integration and transformation at the pedagogical level. The core of this reconstruction lies in reaffirming the leading role of learners in the translation process, positioning artificial intelligence as a cognitive support system rather than a decision-making agent, thereby restoring the human authority of meaning judgment within the operational mechanism. On this basis, the translation process is reconfigured as a dynamic cyclical system composed of generation, evaluation, and regeneration, within which both humans and machines achieve functional differentiation and collaborative optimization through continuous interaction.

From the perspective of educational transformation, the stable operation of human–machine collaborative mechanisms must rely on institutionalized pedagogical structures; in other words, the aforementioned cognitive mechanisms must be systematically embedded into the curriculum system. The key to this paradigm shift lies in the structural adjustment of curriculum design. First, a human–machine collaboration-oriented learning environment should be established, situating translation training within dynamic interactive contexts to enhance learners' sense of agency, as an effective human–machine interaction mechanism is a necessary condition for achieving collaborative teaching outcomes[13]. On this basis, artificial intelligence ethics should be integrated into the teaching content system to strengthen learners' conscious awareness of the boundaries of technology use and ethical responsibility. At the same time, systematic reading and training of classical TCM cultural texts should be reinforced, thereby consolidating the knowledge foundation and clarifying the value orientation for cross-cultural translation. Through these pathways, the dual-driven framework is transformed from an abstract theoretical model into an operable pedagogical mechanism, thereby promoting a paradigm shift in TCM translation education in the intelligent era—from "tool dependence" to "symbiotic collaboration."

4.4 Pedagogical Transformation Plan and Evaluation Indicators for the Dual-Dimension Driven Framework

To transform the dual-dimension driven framework from a theoretical model into an operational pedagogical scheme, this paper further designs a three-stage progressive curriculum structure that matches the aforementioned three implementation paths, covering a total of 32 credit hours over one semester (two hours per week for 16 weeks). The first stage, "Competency Compensation" (Weeks 1–5, 10 credit hours), corresponds to the structural reshaping of AI literacy. Teaching activities in this phase include an introduction to the basic principles of AI translation tools (2 credit hours), focusing on the Transformer attention mechanism and the cognitive boundaries of "statistical regularity"; a structured prompting workshop (4 credit hours) where learners practice drafting prompts for TCM classics based on the three-dimensional elements of “Role—Context—Terminology”; multi-round interaction and control training (2 credit hours) using terms such as “Spleen Deficiency” and “Liver Qi Stagnation” as vehicles to train iterative revision capabilities; and critical review training (2 credit hours) involving three-level review exercises based on cases of English translations for herbal formulas.

The second stage, “Synergistic Integration” (Weeks 6–11, 12 credit hours), corresponds to the bidirectional coupling of technical rationality and cultural rationality. Teaching activities include the hands-on implementation of the quantitative evaluation model (4 credit hours), guiding learners to deploy the BERT evaluation workflow using Python and the transformers library to calculate $Sim(S,T)$ and $Cul(T)$; reflection on thresholds and weight optimization (2 credit hours), understanding the tension between technical and cultural rationality by comparing evaluation results under different values of θ, α, β, and γ; an error diagnosis workshop (4 credit hours) for collective discussion on typical AI biases in tasks such as Zang-fu syndrome differentiation and medicinal properties or meridian tropism; and double-blind translation peer review (2 credit hours) where learners exchange translations for evaluation. The third stage, “Paradigm Reconstruction” (Weeks 12–16, 10 credit hours), corresponds to the paradigm shift in human-machine relationships. Teaching activities include a comprehensive translation project (6 credit hours), where each learner independently completes a human-AI collaborative translation of a TCM classic segment (approximately 500 words) and writes a process reflection log; a seminar on AI ethics (2 credit hours) debating topics such as AI translation authorship and risks of cultural appropriation; and a final presentation and summative evaluation (2 credit hours) involving tripartite assessment by teachers, domain experts, and AI systems.

The evaluation of the curriculum’s effectiveness employs an indicator system that combines formative and summative assessments. Formative indicators include the structural completeness of prompts (the mention rates of the three elements: role, context, and terminology), the median number of iterative control rounds and the rationality of the revision directions, and the level coverage of critical review reports. Summative indicators incorporate the composite scores of $Sim(S,T)$ and $Cul(T)$ for the final translation product, the frequency and depth of cultural subjectivity expressions in the translation reflection logs, and the variance in pre- and post-test AI literacy self-assessment scales. It should be noted that the aforementioned curriculum scheme and evaluation indicator system are design prototypes derived from the dual-dimension driven framework. Their complete empirical validation (such as control group experiments and longitudinal tracking across semesters) will be carried out as key focus areas for subsequent research to further confirm the framework’s effectiveness in real-world teaching scenarios.

5 Conclusions

The deep integration of generative artificial intelligence has confronted TCM translation education with challenges such as semantic dilution, fragmented literacy development, and the weakening of cultural subjectivity. The underlying cause lies in the structural tension between the statistical regularities of large language models and the flexible, context-sensitive nature of TCM thinking. From a human–machine symbiosis perspective, this study constructs a dual-driven framework of "AI literacy–cross-cultural translation competence," and further systematizes AI literacy into three dimensions: prompt structuring competence, generation process regulation competence, and critical post-editing competence. The cosine similarity-based evaluation model grounded in the Transformer architecture is introduced, and a weighted coupling formula is employed to achieve bidirectional calibration between technical rationality and cultural rationality. Through three pathways—competence compensation, collaborative integration, and paradigm reconstruction—the framework aims to transform learners from passive post-editing agents into active leaders in human–machine collaborative translation. Looking ahead, TCM translation education should reconstruct its order within a human–machine symbiotic paradigm, enabling learners to master intelligent tools while maintaining the integrity of original TCM thinking. This entails a shift from semantic fidelity to meaning regeneration, cultivating a new generation of translators who possess both technological literacy and cultural consciousness, thereby laying a cognitive foundation for the global sharing of Chinese civilizational wisdom.

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