Nova Science Press

Journal of Psychology & Education

Vol. 1, No. 3 (2026)

Artificial Intelligence Diagnostic Systems and the Cognitive Model of Traditional Chinese Medicine: Knowledge Transformation under Technological Mediation

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Journal of Psychology & Education • Vol. 1, No. 3 (2026)

DOI:https://doi.org/10.66581/h51akd76

Received 10 April 2026 • Accepted: 18 April 2026 • Published 30 April 2026

CITATION

Mahib, A. S. M. (2026). Artificial Intelligence Diagnostic Systems and the Cognitive Model of Traditional Chinese Medicine: Knowledge Transformation under Technological Mediation. Journal of Psychology & Education, 1(3), 23. https://doi.org/10.66581/h51akd76

Abstract

The application of artificial intelligence (AI) to Traditional Chinese Medicine (TCM) diagnosis has generated a profound epistemological debate concerning the nature of medical knowledge, the status of clinical experience, and the transformation of diagnostic cognition under technological mediation. Focusing on the four diagnostic methods of inspection, auscultation-olfaction, inquiry, and palpation, this paper examines how AI systems reshape the traditional cognitive model of TCM by transforming sensory, experiential, and holistic forms of judgment into standardized and computable data. Drawing on systems theory, fuzzy logic, tacit knowledge theory, and recent studies of machine learning in TCM diagnosis, the paper argues that AI can improve diagnostic consistency, data integration, and knowledge transmission, but it may also intensify tensions between standardization and individualization, reductionist feature extraction and holistic pattern differentiation, and algorithmic authority and the physician's clinical responsibility. To address these tensions, the paper proposes a human-AI collaborative diagnostic model in which AI serves as an augmentative instrument rather than a replacement for the TCM physician. The proposed model emphasizes TCM-informed algorithm design, multimodal data integration, transparent reasoning, longitudinal personalization, and ethical governance. The study contributes to debates on the modernization of TCM by showing that knowledge transformation should not be understood as the passive digitization of tradition, but as a reciprocal process in which classical diagnostic wisdom and contemporary computational technologies jointly reshape the future of medical cognition.

Keywords: artificial intelligence; Traditional Chinese Medicine diagnosis; inspection, auscultation-olfaction, inquiry, and palpation; cognitive model; human-AI collaboration; knowledge transformation

1. Introduction

The diagnostic core of Traditional Chinese Medicine (TCM) is conventionally summarized as the four diagnostic methods: inspection, auscultation-olfaction, inquiry, and palpation. Through observation of the complexion and bodily form, attention to voice and odor, systematic questioning about symptoms and life history, and palpation of the pulse and related bodily signs, the physician forms an integrated judgment about the patient's pattern of disharmony. This diagnostic practice is not merely a collection of techniques. It embodies a distinctive cognitive style that emphasizes relational thinking, dynamic balance, contextual interpretation, and individualized pattern differentiation.

In recent years, AI technologies have begun to enter the domain of TCM diagnosis. Machine learning methods are now used to analyze tongue images, pulse-wave signals, clinical notes, and multimodal diagnostic data. Recent reviews show that AI-enabled TCM diagnosis has rapidly expanded across the four diagnostic methods and that machine learning is increasingly used to reduce subjectivity, improve reproducibility, and support clinical decision-making (Tian et al., 2024). Similar developments are visible in AI-assisted tongue image analysis, electronic health record mining, and syndrome prediction (Liu et al., 2023; Wang et al., 2020; Zhang et al., 2020).

This technological transformation raises questions that are philosophical as well as clinical. Can an AI system genuinely participate in TCM pattern differentiation, or can it only approximate visible correlations among signs and syndromes? How should the ambiguity of TCM categories, such as 'slippery pulse,' 'greasy coating,' or 'deficiency heat,' be represented in computational models? What happens to the authority of tacit clinical experience when diagnostic suggestions are generated by statistical or neural-network systems? These questions point to the deeper issue of knowledge transformation: AI does not simply copy traditional practice, but reorganizes how diagnostic knowledge is collected, represented, validated, and transmitted.

The purpose of this paper is to analyze the impact of AI diagnostic systems on the cognitive model of TCM and to propose a framework for human-AI collaborative diagnosis. The paper proceeds in eight parts. Section 2 clarifies the major cognitive characteristics of TCM diagnosis. Section 3 examines the mechanisms through which AI intervenes in diagnostic practice. Section 4 analyzes the tensions and possible integrations between TCM cognition and computational reasoning. Section 5 proposes a human-AI collaborative model. Section 6 discusses future technological pathways. Section 7 provides illustrative case analyses. The conclusion argues that the modernization of TCM should be understood as an interactive process in which AI augments, but does not replace, the interpretive and ethical work of the physician.

2. Cognitive Characteristics of TCM Diagnosis

2.1 Holism and Systemic Reasoning

The first cognitive feature of TCM diagnosis is holism. Classical TCM theory assumes that the human body is an integrated system in which local signs reflect systemic conditions. The traditional maxim that internal disorder manifests externally expresses this assumption: visible changes in the face, tongue, posture, voice, or pulse are not treated as isolated symptoms but as clues to an underlying pattern. This holistic orientation has affinities with modern systems theory, which argues that the properties of a system cannot be fully reduced to the sum of its parts (Bertalanffy, 1968).

Inspection, especially the assessment of vitality or spirit, illustrates this holistic logic. When physicians evaluate whether a patient has 'spirit' or has lost vitality, they are not simply recording an objective feature in the manner of a laboratory value. They are integrating multiple cues, including facial expression, eye brightness, voice, responsiveness, complexion, and bodily movement. Such judgments are difficult to quantify, yet they often guide clinical expectations about disease severity and prognosis.

The six-channel differentiation system associated with the Shanghan tradition also demonstrates dynamic systemic thinking. The six channels are not discrete compartments but patterns of transformation through which disease may progress, reverse, or change direction. Diagnostic reasoning therefore requires attention to temporal evolution, not merely static classification. This is a crucial challenge for AI systems: a TCM-informed model must represent dynamic relations among signs, patterns, constitutions, seasons, and treatment responses rather than only map symptoms to labels.

2.2 Ambiguity, Fuzzy Categories, and Tacit Judgment

A second feature of TCM diagnosis is its productive use of ambiguity. Many diagnostic descriptors, including 'yellow and greasy coating,' 'slippery pulse,' 'wiry pulse,' 'cold-dampness,' or 'blood stasis,' are not rigid categories with sharply defined boundaries. Their meanings are graded, contextual, and relational. Ambiguity in this sense is not a failure of scientific precision; it is a flexible cognitive strategy that allows physicians to reason under conditions of complexity and individual variation.

Zadeh's (1965) theory of fuzzy sets offers a useful conceptual bridge. In fuzzy logic, an object may belong to a category by degree rather than simply being inside or outside it. This logic resonates with the TCM understanding of yin-yang transformation, where pathological states are often transitional, mixed, or coexisting rather than binary. A patient may show signs of both deficiency and excess, or cold in one domain and heat in another. Computational models that force these patterns into hard labels risk losing clinically meaningful intermediate states.

TCM diagnosis also relies heavily on tacit knowledge. Polanyi (1966) famously argued that human beings know more than they can explicitly state. This insight is highly relevant to the diagnostic expertise of experienced TCM physicians. Experts often recognize a pattern quickly, not because they follow a fully verbalized checklist, but because years of practice have trained their perceptual and interpretive capacities. The challenge for AI is therefore not only to extract explicit rules, but also to approximate forms of pattern recognition that have historically been transmitted through apprenticeship, observation, and repeated clinical practice.

2.3 Individualization and Pattern-Based Treatment

A third feature is individualization. TCM is often summarized by the principle that the same biomedical disease may require different treatments, while different biomedical diseases may be treated similarly if they share the same pattern. This principle reflects the centrality of pattern differentiation rather than disease naming alone. The diagnostic object is not simply the disease entity but the patient as a situated, temporally changing organism.

Constitution theory further illustrates this individualized orientation. Wang's (2009) model of nine constitutional types provides a structured way to think about relatively stable bodily tendencies, but clinical reality often involves mixed constitutions, life-stage changes, environmental influences, and lifestyle factors. A clinically useful AI system must therefore move beyond population-level classification toward models capable of learning patient-specific baselines and trajectories.

Time is also integral to TCM cognition. Seasonal rhythms, circadian variation, disease progression, and treatment timing all influence interpretation. The maxim of nourishing yang in spring and summer and nourishing yin in autumn and winter reflects a broader diagnostic temporality. AI has potential value here because longitudinal data, wearable signals, and repeated clinical observations can help model temporal patterns that are difficult for physicians to track manually. However, such models must remain interpretable within TCM conceptual categories rather than functioning as opaque correlations detached from clinical meaning.

3. AI Intervention in Diagnostic Practice

3.1 Data Collection and Standardization

The first mode of AI intervention is datafication: the conversion of sensory and experiential diagnostic information into digital data. Tongue diagnosis systems use cameras and image-processing algorithms to identify tongue body color, coating thickness, coating texture, fissures, tooth marks, and sublingual veins. Pulse diagnosis devices use pressure sensors and signal-processing methods to capture pulse rate, amplitude, rhythm, waveform, and spatial differences across cun, guan, and chi positions. Inquiry data may be extracted from electronic health records through natural language processing or collected through structured questionnaires.

Datafication enables standardization. When lighting conditions, image calibration, signal acquisition, and annotation procedures are carefully controlled, AI systems can reduce inter-practitioner variability. Studies of tongue image analysis, for instance, have shown that deep learning can classify specific visual features such as tooth-marked tongue with high accuracy under defined experimental conditions (Wang et al., 2020). Broader surveys also indicate that tongue image analysis has become one of the most active areas in AI-TCM research (Liu et al., 2023).

At the same time, standardization may narrow the diagnostic field. A tongue image captured under standardized lighting may improve color consistency, but it may not capture the physician's broader impression of vitality, moisture, odor, patient behavior, or clinical context. Similarly, a pulse waveform can quantify pressure and rhythm, but it may not fully reproduce the tactile experience of palpation. Thus, datafication should be treated as a partial translation of TCM diagnosis, not as its complete replacement.

3.2 Pattern Recognition and Knowledge Extraction

The second mode of intervention is pattern recognition. Deep learning systems can identify statistical associations among diagnostic signs, disease categories, and TCM syndromes. Convolutional neural networks are particularly suited to tongue and facial image analysis, whereas recurrent architectures and temporal models can be applied to pulse-wave data. Natural language processing can extract symptoms, treatment histories, and syndrome-related entities from unstructured clinical notes.

An illustrative example is the AI-based TCM assistive diagnostic system validated by Zhang et al. (2020). The system used natural language processing to extract clinical information from electronic health record notes and then predicted both biomedical disease categories and TCM syndromes. The study reported that the system could predict 187 TCM-related disease types from clinical notes, with top-one, top-three, and top-five accuracy levels of 80.5%, 91.6%, and 94.2%, respectively (Zhang et al., 2020). These findings suggest that AI can help organize large-scale clinical data and extend the knowledge base available to physicians.

However, pattern recognition also introduces the problem of opacity. Many high-performing models are difficult to interpret. A neural network may classify a tongue image as suggestive of damp-heat or spleen deficiency, but the physician may not know which features drove the output or whether the model relied on clinically meaningful cues. This black-box problem conflicts with the TCM tradition in which diagnosis is expected to be explainable in relation to pattern, pathogenesis, and therapeutic principle. Explainability is therefore not an optional technical feature; it is a condition for integrating AI into TCM reasoning.

3.3 Decision Support and Human-Computer Interaction

Current AI systems in TCM are best understood as decision-support tools. They can provide preliminary screening, retrieve similar cases, suggest possible syndromes, identify inconsistencies in medical records, and remind physicians of overlooked signs. They should not be treated as autonomous diagnosticians because TCM diagnosis involves interpretive, ethical, and communicative dimensions that exceed data classification.

Human-computer interaction design is therefore crucial. A useful system should support, rather than interrupt, the physician's diagnostic reasoning. It should allow physicians to enter qualitative observations, revise labels, document disagreement with AI outputs, and view the evidence behind each recommendation. In addition, it should support uncertainty rather than force premature closure. A ranked list of possible patterns, with interpretable evidence and confidence intervals, is often more clinically appropriate than a single categorical answer.

This design orientation is consistent with recent discussions of AI in TCM, which emphasize that AI can enhance diagnostic capacity but cannot replace the humanistic, relational, and contextual role of the practitioner (Li et al., 2024; Lu et al., 2024). The practical question is not whether AI or the physician should have sole authority, but how responsibilities should be distributed across a collaborative diagnostic system.

4. Tensions and Integrative Possibilities in Cognitive Transformation

4.1 Reductionism and Holism

A central tension lies between computational reductionism and TCM holism. AI systems often decompose diagnosis into measurable features: tongue color values, pulse amplitudes, symptom keywords, and probability scores. This decomposition is necessary for computation, but it may obscure the relational logic that gives TCM signs their meaning. A yellow greasy tongue coating, for example, is not merely a color-texture combination; its significance depends on appetite, stool, thirst, pulse, constitution, duration, season, and treatment history.

Systems theory offers a conceptual remedy. If the body is understood as a complex adaptive system, then AI should not only classify isolated features but also model interactions among signs and contexts. Graph neural networks, knowledge graphs, causal models, and multimodal transformers are promising because they can represent relationships among symptoms, organs, patterns, formulas, and outcomes. The aim should be to translate TCM holism into relational computational structures rather than reduce it to a checklist of signs.

This point has practical consequences. A model that achieves high accuracy on a narrow image-classification task may still be insufficient for clinical TCM diagnosis if it cannot integrate inquiry, pulse, constitution, and temporal change. Conversely, an integrated multimodal system may be clinically more meaningful even if its performance on a single task appears less impressive. Evaluation metrics should therefore be aligned with the cognitive goals of TCM diagnosis.

4.2 Determinacy and Uncertainty

A second tension concerns uncertainty. AI systems often produce determinate outputs: a predicted label, a probability, or a ranked list. TCM diagnosis, however, frequently works through provisional judgment. Physicians may begin with a tentative pattern, observe treatment response, and revise the diagnosis as the patient's condition changes. Uncertainty is not merely a technical limitation; it is part of clinical reasoning.

Fuzzy logic and probabilistic reasoning provide potential solutions. Fuzzy membership functions can represent degrees of cold, heat, deficiency, excess, dampness, or stasis. Bayesian networks can update diagnostic probability as new information becomes available. Causal reasoning can help distinguish correlation from pathogenesis, a distinction especially important in TCM's principle of examining manifestations to infer causes. Pearl's (2009) causal framework is useful here because it directs attention from prediction alone to mechanisms and counterfactual reasoning.

AI outputs should therefore make uncertainty visible. Instead of presenting a diagnosis as a fixed truth, systems should display competing pattern hypotheses, supporting and contradictory evidence, and possible next questions for clinical clarification. Such a design would better reflect TCM's diagnostic process, in which uncertainty is progressively reduced through observation, questioning, palpation, and therapeutic feedback.

4.3 Clinical Inheritance and Algorithmic Learning

A third tension concerns knowledge transmission. TCM has historically relied on classical texts, case records, apprenticeship, and embodied clinical training. AI introduces a new mode of learning based on large-scale data aggregation and algorithmic optimization. This can support the preservation and dissemination of expert knowledge, especially in contexts where apprenticeship resources are limited. Knowledge graphs and ontologies can formalize relations among symptoms, syndromes, formulas, herbs, and outcomes (Long et al., 2019).

Nevertheless, algorithmic learning cannot fully replace clinical inheritance. A dataset contains selected traces of practice, not practice itself. It may overrepresent certain hospitals, regions, diagnostic schools, or documentation habits. If the training data are biased, the model may reproduce or amplify those biases. In addition, some expert judgments are embodied and situational, emerging only in interaction with the patient. The challenge is therefore to build systems that learn from clinical tradition without flattening it into a rigid database.

A productive approach is to treat AI as a new medium of inheritance. Expert physicians can participate in annotation, rule design, case interpretation, and model evaluation. Younger physicians can use AI systems as learning tools that expose them to similar cases, alternative interpretations, and evidence behind diagnostic suggestions. In this way, AI can extend rather than interrupt the lineage of clinical learning.

Table 1 summarizes the main epistemic tensions and the corresponding design requirements for a human-AI collaborative TCM diagnostic system.

Epistemic tension	**Risk in AI-mediated diagnosis**	**Collaborative design requirement**
Holism vs. reductionism	Fragmenting pattern differentiation into isolated features.	Use multimodal and relational models that integrate tongue, pulse, inquiry, constitution, and temporal change.
Ambiguity vs. hard classification	Forcing fuzzy signs into rigid labels.	Represent graded membership, competing hypotheses, and diagnostic uncertainty.
Tacit expertise vs. explicit rules	Marginalizing experiential judgment and apprenticeship knowledge.	Include expert annotation, case-based explanation, and physician feedback loops.
Standardization vs. individualization	Overgeneralizing from population-level patterns.	Support patient-specific baselines, longitudinal learning, and individualized interpretation.
Algorithmic authority vs. clinical responsibility	Encouraging uncritical reliance on AI suggestions.	Maintain physician-led decision-making, transparent reasoning, and documented accountability.

5. A Human-AI Collaborative Model of TCM Diagnosis

5.1 Division of Labor

An appropriate collaborative model should assign tasks according to the strengths and limitations of each actor. AI is strong in large-scale data processing, consistent measurement, pattern retrieval, and the identification of statistical regularities. Human physicians are strong in contextual interpretation, ethical judgment, flexible reasoning, patient communication, and the handling of atypical cases. Collaboration should therefore be designed around complementarity rather than substitution.

In practical terms, AI can assist with preliminary data acquisition, standardization, case retrieval, and risk alerts. For example, an AI system may identify subtle changes in tongue coating over repeated visits or detect inconsistencies between symptom reports and pulse-wave features. The physician then evaluates whether these findings fit the patient's overall presentation, life context, constitution, and treatment goals. Final diagnostic and therapeutic responsibility remains with the physician.

Feedback loops are essential. When a physician accepts, modifies, or rejects an AI suggestion, this decision should be recorded together with the clinical rationale and subsequent treatment outcome. Over time, such feedback can improve model calibration and help identify cases in which the system performs poorly. Human-AI collaboration should therefore be dynamic and learning-oriented rather than a one-way delivery of algorithmic recommendations.

5.2 Knowledge Augmentation and Capacity Expansion

AI can augment physicians' cognitive capacity by expanding the range of cases, literature, and historical records available during diagnosis. An expert system linked to a curated knowledge base could retrieve classical passages, modern clinical trials, similar cases, common formula modifications, and contraindications. This is especially valuable for younger physicians who are still developing clinical experience.

Visualization can also serve as a cognitive tool. Network diagrams that display relationships among symptoms, patterns, organs, formulas, and herbs may help physicians recognize hidden structures in complex cases. Longitudinal visualizations may show how a patient's tongue, pulse, sleep, appetite, pain, and emotional state change across treatment. Such tools support TCM's dynamic view of illness and make the diagnostic process more transparent to both clinicians and patients.

Predictive modeling can further extend the TCM principle of preventive treatment. By learning from historical trajectories, AI may help identify patients at risk of pattern transformation, relapse, or adverse response. However, predictive suggestions should be framed as clinical prompts, not deterministic forecasts. The goal is to enhance the physician's anticipatory reasoning while preserving clinical judgment.

5.3 Ethics, Transparency, and Responsibility

Human-AI collaboration also requires ethical governance. The World Health Organization (2021) stresses that AI for health should protect autonomy, promote human well-being and safety, ensure transparency, foster responsibility, promote inclusiveness and equity, and remain responsive and sustainable. These principles are directly applicable to AI-TCM systems, particularly because TCM diagnosis often involves subjective signs, culturally specific concepts, and individualized treatment decisions.

Transparency is fundamental. Patients should be informed when AI tools are used in diagnosis or treatment planning. Physicians should be able to inspect the evidence supporting AI suggestions. Developers should document model training data, intended use, limitations, update procedures, and known failure modes. Reporting standards such as CONSORT-AI also indicate the broader importance of transparent clinical evaluation for AI interventions (Liu et al., 2020).

Responsibility must be clearly defined. In the model proposed here, AI functions as a diagnostic assistant under physician supervision. The physician remains responsible for clinical judgment, while medical institutions and developers share responsibility for system validation, data security, usability, and post-deployment monitoring. This shared accountability is necessary to avoid both blind reliance on algorithms and unrealistic expectations that individual physicians can independently audit complex AI systems.

6. Future Pathways for Technological Development

6.1 TCM-Informed Algorithmic Architectures

Generic AI architectures may not fully fit the epistemology of TCM diagnosis. Future systems should be designed with TCM cognitive features in mind. Knowledge graphs can represent classical theory, syndrome relations, organ networks, formulas, and herbal properties. Deep learning can process high-dimensional clinical data. Hybrid systems that combine knowledge-driven and data-driven approaches may be especially appropriate because they can preserve theoretical structure while learning from clinical evidence.

Causal inference is another important direction. TCM diagnosis seeks to infer pathogenesis from manifestations, not merely to predict labels. Causal models can help distinguish symptoms that are central to a pattern from those that are incidental or confounded by other factors. Although causal inference in TCM will be methodologically challenging, it aligns better with the logic of pattern differentiation than purely correlational prediction.

Multimodal learning is also essential. Since the four diagnostic methods are complementary, AI systems should integrate visual, auditory, textual, tactile, and temporal data. A model that combines tongue images, voice features, pulse signals, inquiry responses, and treatment history would better approximate TCM clinical reasoning than a single-modality classifier. Yet multimodal integration requires careful attention to missing data, inconsistent measurement conditions, privacy, and interpretability.

6.2 Personalized and Longitudinal Models

The future of AI-TCM diagnosis should move from static classification to longitudinal personalization. Population-level models can provide useful baselines, but they often fail to capture individual constitution, environmental exposure, lifestyle, treatment history, and temporal change. Transfer learning and continual learning may allow general models to adapt to individual patients or specific clinical settings.

Longitudinal models are particularly important for chronic conditions. A patient's pattern may transform over weeks or months, and the meaning of a sign may depend on its direction of change. For example, a reduction in greasy coating after treatment may be more meaningful than a single cross-sectional measurement. Wearable devices, mobile health records, and repeated tongue or pulse measurements could provide data for modeling these trajectories, but clinical interpretation must remain grounded in TCM theory.

The concept of a digital twin is also relevant. A patient-specific digital model could simulate possible changes under different lifestyle or treatment scenarios. In TCM, such a model would need to incorporate not only biomedical variables but also constitution, pattern, emotional state, diet, sleep, seasonal exposure, and treatment response. While this remains an ambitious goal, it points toward a future in which AI supports individualized preventive care rather than merely classifying present symptoms.

6.3 Standardization, Interoperability, and Clinical Evidence

Standardization remains necessary for safe and reliable AI application. Data acquisition standards are needed for tongue images, pulse signals, voice recordings, inquiry forms, and syndrome labels. Without shared standards, models trained in one institution may fail in another because of differences in lighting, devices, annotation conventions, patient populations, or terminology.

Algorithmic evaluation should include metrics that reflect TCM diagnostic goals. Conventional accuracy, sensitivity, specificity, and area under the curve are useful but insufficient. Evaluation should also examine syndrome differentiation consistency, interpretability, agreement with expert panels, effect on physician learning, impact on treatment decision-making, patient outcomes, and safety across demographic groups. External validation and prospective clinical studies are essential before broad deployment.

Interoperability is equally important. AI-TCM systems should be able to communicate with electronic health records, hospital information systems, and research databases while protecting privacy. Data governance should define who may access diagnostic data, how patient consent is obtained, how de-identified datasets are used, and how model updates are monitored. These governance issues are not secondary to technology; they shape the trustworthiness of the entire diagnostic ecosystem.

7. Illustrative Cases and Empirical Implications

7.1 AI-Enabled Tongue Diagnosis

Tongue diagnosis has become a prominent testing ground for AI-TCM because tongue images are relatively easy to digitize. Studies have applied deep learning to tongue segmentation, color correction, coating classification, tooth-mark recognition, and disease or syndrome differentiation. Wang et al. (2020), for instance, used convolutional neural networks to recognize tooth-marked tongue and reported overall model accuracy above 90% under experimental conditions. Reviews further show that tongue image analysis now includes a broad range of tasks, from feature extraction to disease screening and syndrome differentiation (Liu et al., 2023).

The empirical implication is twofold. On one hand, AI can provide objective reference points for features that are vulnerable to subjective variation, such as coating thickness or tooth marks. On the other hand, tongue diagnosis in clinical practice is not merely image classification. The significance of tongue features depends on inquiry, pulse, complexion, constitution, and therapeutic response. Tongue AI should therefore be integrated into a broader diagnostic system rather than used as a standalone substitute for clinical judgment.

7.2 Pulse Diagnosis and Instrumentation

Pulse diagnosis presents a more difficult challenge because it involves tactile perception, pressure modulation, spatial discrimination, and temporal rhythm. Instrumented pulse diagnosis can record waveform features, pulse intensity, rhythm, and pressure responses at different positions. Machine learning may then classify pulse patterns or associate signal features with syndromes. Recent reviews indicate that palpation-related AI research has grown, especially around pulse signal acquisition and analysis (Tian et al., 2024).

Yet pulse diagnosis also shows the limits of datafication. The tactile phrase often translated as 'clear in the mind but difficult to express under the fingers' captures a form of embodied knowledge that sensors only partially reproduce. AI models may classify waveforms, but the physician must still interpret whether the pulse fits the patient's overall condition. Future pulse systems should therefore combine high-quality sensors with physician feedback, training modules, and interpretable representations of pulse features.

7.3 Integrated Multimodal Diagnostic Platforms

The most promising direction is integrated multimodal diagnosis. Since each of the four diagnostic methods has limitations, TCM relies on their synthesis. An integrated AI platform should combine image, sound, text, pulse, and longitudinal data to generate evidence-weighted diagnostic hypotheses. It should also explain how each modality contributed to the output and where evidence is insufficient.

Such platforms can be especially useful in primary care, education, and quality control. They may help junior physicians learn from expert cases, reduce missing information in medical records, and support more consistent documentation of pattern differentiation. However, their clinical legitimacy depends on external validation, transparent model governance, and careful preservation of physician authority. AI should strengthen the physician's capacity to see the whole patient, not replace holistic care with fragmented automation.

8. Conclusion

AI diagnostic systems represent an important encounter between traditional medical wisdom and contemporary computational technology. In TCM diagnosis, this encounter is especially significant because the four diagnostic methods are deeply tied to holistic observation, fuzzy categorization, tacit experience, and individualized pattern differentiation. AI can enhance diagnostic consistency, retrieve large-scale knowledge, support education, and improve the objectification of certain diagnostic signs. Yet it can also marginalize experiential judgment, oversimplify holistic reasoning, and create new forms of algorithmic authority.

This paper has argued that the most appropriate path is human-AI collaboration. AI should function as an augmentative instrument that supports data acquisition, pattern retrieval, uncertainty management, and knowledge transmission. Physicians should remain responsible for contextual interpretation, ethical communication, individualized decision-making, and final clinical judgment. The future of AI-TCM should therefore be guided by TCM-informed algorithms, multimodal integration, longitudinal personalization, transparent explanation, and rigorous ethical governance.

The broader significance of this analysis lies in its understanding of knowledge transformation. Modernization should not mean the simple replacement of traditional categories by technological measures, nor should tradition be protected by rejecting all computational tools. Instead, the development of AI-TCM diagnosis should be a reciprocal process: AI can make certain aspects of TCM more explicit, standardized, and evidence-responsive, while TCM's holistic and relational cognition can guide the design of more context-sensitive and human-centered AI systems. In this mutual shaping, the future of TCM diagnosis may become both technologically advanced and faithful to its classical cognitive spirit.

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