

REVIEW ARTICLE

Multimodal data-driven intelligent diagnosis in traditional Chinese medicine: Current status and future perspectives

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Abstract

With advances in artificial intelligence, traditional Chinese medicine diagnosis is gradually becoming more intelligent. This review departs from the conventional framework that categorizes the four diagnostic methods in isolation. Instead, it starts from five heterogeneous data modalities, namely vision, audition, olfaction, textual, and tactile, and systematically reconstructs the digital mapping relationships of traditional Chinese medicine diagnostic information, thereby directly aligning traditional Chinese medicine diagnostic problems with the input paradigms of artificial intelligence. This study comprehensively examines the current state of research on multimodal acquisition technologies, fusion methods, and clinical applications, and analyzes the core challenges and future directions in this field. This study aims to provide a theoretical foundation for achieving truly intelligent integration of the four diagnostic methods.

Keywords: Multimodal data; Intelligent diagnosis in traditional Chinese medicine; Integrated four diagnostic methods; Data fusion; Artificial intelligence

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1. Introduction

As a cultural treasure of the Chinese nation, traditional Chinese medicine (TCM) embodies millennia of clinical wisdom¹, with its core strengths lying in the “holistic approach” and “differential diagnosis and treatment.” The four diagnostic methods—inspection, auscultation, inquiry, and palpation—serve as the primary means for physicians to gather clinical information and determine disease pathogenesis, while the “integration of the four diagnostic methods” is the key process for synthesizing and logically analyzing multidimensional information. However, under the traditional model, the acquisition of information from the four diagnostic methods relies heavily on the practitioner’s sensory perception and personal experience, resulting in diagnostic outcomes that are significantly subjective, ambiguous, and non-reproducible. This characteristic, which can be “understood intuitively but not fully articulated,” has become the primary bottleneck hindering the standardization, internationalization, and large-scale promotion of TCM.

The rapid advancement of artificial intelligence (AI) technology offers new opportunities to overcome these challenges. Many studies have simulated the diagnostic logic of the four diagnostic methods in TCM, driving the transformation of TCM diagnosis from an “experience-driven” to a “data-driven” approach.² In particular, the maturation of deep learning has made it possible to automatically extract features from heterogeneous data such as images, signals, and text³, the development of multimodal fusion technology has provided the algorithmic foundation for integrating information from the four diagnostic methods of observation, auscultation, inquiry, and palpation⁴, and the rise of large language models has ushered in a new paradigm of intelligent medical consultation and interpretable reasoning.⁵ Against this backdrop, TCM intelligent diagnosis, driven by multimodal data, has rapidly emerged as a frontier in interdisciplinary research in recent years. By integrating information from the four diagnostic methods, the objectification, standardization, and intelligentization of TCM diagnoses can be achieved.

In recent years, the field of intelligent diagnosis in TCM has seen a surge in research, prompting numerous reviews. Some reviews focus on the current state of development of a single diagnostic method—for example, Bhatnagar *et al.*⁶ provided a comprehensive review of automated tongue diagnosis, summarizing research on tongue image acquisition, color correction, segmentation, feature extraction, and classification methods. Guo *et al.*⁷ reviewed and evaluated studies on pulse signal acquisition, preprocessing, and recognition. Other reviews have focused on the current status of the application of devices and technologies for the four examinations in TCM. Sui *et*

*al.*⁸ reviewed the development of digital signal acquisition devices and algorithms for the four examinations of TCM. Tian *et al.*⁹ summarized the current status of machine learning applications in TCM diagnosis, including data collection, data preprocessing, machine learning models, and evaluation metrics. Zhang *et al.*¹⁰ examined the AI technologies used in modern TCM diagnosis, as well as the application of AI in clinical documentation, pharmacological modeling, and knowledge discovery on intelligent platforms. Another study reviewed the current status and trends in the intelligent development of TCM diagnosis based on scientometric methods.² Table 1 summarizes the relevant reviews on the application of AI in TCM diagnosis. However, focusing on a single diagnostic method or listing the technological advancements of the four examinations separately fails to demonstrate the holistic view of TCM’s “integrated application of the four examinations” and the intrinsic synergistic relationships among different modalities of data. Therefore, this study integrates five categories of heterogeneous modal data—visual, auditory, olfactory, textual, and tactile—to reconstruct the digital mapping relationships among the four examinations. It examines the current status and bottlenecks in multimodal data acquisition and fusion technologies, to provide theoretical guidance and practical pathways for achieving a truly intelligent “integrated application of the four examinations.”

2. Multimodal mapping of the four diagnostic methods

Multimodal data refer to heterogeneous data that represent information about the same object from different sources and in various forms. Its core lies in integrating

Table 1. Summary of the application of artificial intelligence in traditional Chinese medicine diagnosis

Areas of TCM	Details	Published year	Reference
Tongue diagnosis	image acquisition, color correction, segmentation, feature extraction, and classification	2022	6
Pulse diagnosis	Pulse signal acquisition, signal preprocessing, feature extraction, and signal recognition	2022	7
Diagnostic of TCM	Datasets, digital signal acquisition devices, and algorithms	2022	8
Diagnostic of TCM	Current research status of machine learning in TCM diagnosis	2024	9
Multiple TCM aspects	Applications of AI in the four diagnostic methods of TCM, knowledge discovery, and intelligent platforms	2023	10
Diagnostic of TCM	Scientometric statistics on the current status of AI research in the four diagnostic methods of TCM	2023	2

Abbreviations: AI: Artificial intelligence; TCM: Traditional Chinese medicine.

information from multiple sensory channels to achieve a more comprehensive and accurate characterization of the research subject.¹¹ In the field of TCM diagnosis and treatment, the concept of multimodality aligns closely with the holistic philosophy of the “four diagnostic methods combined” in TCM. TCM diagnosis emphasizes the concurrent use of the “four diagnostic methods” (inspection, auscultation, inquiry, and palpation) to gather health information from patients across different dimensions and make a comprehensive judgment regarding the pathogenesis and clinical manifestations. Modern multimodal fusion technology represents the digital reconstruction of these traditional diagnostic methods.

Figure 1 illustrates the framework of the five major modalities—visual, auditory, textual, tactile, and olfactory—included in TCM multimodal data for the four diagnostic methods of TCM. Specifically, visual modality data primarily correspond to inspection. Tongue and facial images captured by high-definition cameras or dedicated diagnostic devices enable the objective documentation of the patient’s complexion, vitality, and physical form. Auditory modal data correspond to the “listening” component of auscultation. Using high-fidelity microphones to capture the patient’s voice, coughing sounds, and respiratory sounds, it transforms TCM’s identification of the “five tones” into computable acoustic features. Olfactory modal data correspond to the “smelling” component of auscultation. Using gas-sensing devices such as electronic noses, it captures the patient’s exhaled breath and body odors, forming an objective odor

fingerprint spectrum. Textual modal data correspond to the “questioning” aspect of diagnosis. Using structured questionnaires or natural language processing techniques, the patient’s symptom descriptions and medical history are converted into analyzable textual data. Tactile modal data correspond to the “palpation” aspect of diagnosis. Using pressure sensor arrays in pulse-taking devices to simulate the “floating, medium, and deep” techniques of a doctor’s fingers, the position, frequency, shape, and momentum of the pulse are converted into pulse waveform signals. The mapping relationship between these five types of modal data and the four diagnostic methods enables TCM diagnosis to gradually shift from the traditional empirical medical model of “observing the exterior to infer the interior” to a quantifiable, computable, data-driven model, laying a solid foundation for subsequent multimodal fusion diagnosis.

3. Current status of data collection technologies for traditional Chinese medicine across various modalities

The collection and preprocessing of multimodal data are fundamental prerequisites for research on intelligent diagnosis in TCM, as they directly determine the accuracy and generalization ability of subsequent model development. In recent years, with advancements in sensor technology, computer vision, and natural language processing, methods for collecting multimodal TCM data have gradually become more standardized and intelligent. Table 2 lists the primary feature-extraction and modeling techniques for each modality. Figure 2 illustrates the

Table 2. Data types and core technologies for different perceptual modalities

Modality type	Technology	Clinical applications	Advantages	Limitation
Visual modality	U-Net ¹²	Tongue segmentation	Strong global feature extraction, accurate segmentation in complex environments, and high efficiency	Insufficient extraction of two-dimensional spatial positioning
	TransUNet ¹³	Tongue coating segmentation	Accurately segments complex tongue coating. Model accuracy: 96.36%	Small dataset, limited generalization, and insufficient mobile deployment
	DCNNs ¹⁴	Classify tongue lesion	Fuses multi-model voting and achieves high classification accuracy. Binary classification accuracy was 95.15%, five-class classification accuracy was 88.76%	Generalization requires improvement
	MSI ¹⁵	Predicting hypertension using facial characteristics	Non-contact and convenient for hypertension screening.	Many confounding factors limit the ability to generalize

(Cont’d...)

Table 2. (Continued)

Modality type	Technology	Clinical applications	Advantages	Limitation
Auditory modality	QCP+ZFF ¹⁶	Detection of voice pathology	Provide strong discrimination and complement traditional features.	It involves complex computation, depends on fundamental frequency, and shows limited robustness
	Hybrid DL ¹⁷	Pulmonary disease detection	Dual time-frequency transformation provides rich features, accuracy: 94.16%	Complex model and unbalanced dataset
	NLP ¹⁸	Predicting dementia	Strong semantic features, no manual design required.	Small dataset, high cost, poor interpretability
Olfactory modality	MCC/IMS ¹⁹	Non-invasive urine VOC detection for bladder cancer	Non-invasive, high sensitivity, and specificity	Small sample, manual analysis, not clinically validated
	SIFT-MS ²⁰	Non-invasive breath VOC detection for HNSCC	Non-invasive, rapid, real-time quantification	Small sample, easily interfered with by smoking
	MHMF ²¹	Non-invasive disease diagnosis via urinary volatiles.	Non-invasive, portable, fast response, accuracy: 91.7%	Requires ML assistance; material preparation is complex
	Optical spectroscopy ²²	Non-invasive disease diagnosis via exhaled volatiles	Non-invasive, rapid implementation	Severe environmental interference, limited specificity
Textual modality	VisualBERT ²³	Intelligent VQA	Multimodal fusion, IoT adaptation, and high accuracy	Data-dependent, limited professional understanding
	LLM ²⁴	Medical consultation and health advice	Leading performance, open-source	Limited professional understanding
Tactile modality	CNN ²⁵	Radial artery localization for TCM pulse diagnosis	3D CNN, high accuracy, temporal features	Relies on NIR images, high hardware demands
	SEA ²⁶	Digital TCM pulse information collection	4-DOF, high positioning accuracy, stable force control	Complex structure, poor portability
	RN-LSTM ²⁷	Intelligent TCM pulse recognition	High accuracy, automatic feature extraction	Small dataset, manual positioning required

Abbreviations: CNN: Convolutional neural network; DCNN: Deep convolutional neural network; DL: Deep learning; DOF: Degree of freedom; HNSCC: Head and neck squamous cell carcinoma; IMS: Ion mobility spectrometry; IoT: Internet of things; LLM: Large language model; MCC: Matthews correlation coefficient; MHMF: Microchamber-hosted MF; ML: Machine learning; MSI: Multispectral imaging; NIR: Near-infrared; NLP: Natural language processing; QCP: Quasi-closed-phase; RN-LSTM: Recurrent neural network–long short-term memory; SEA: Series elastic actuator; SIFT-MS: Selected ion flow tube mass spectrometry; TCM: Traditional Chinese medicine; TransUNet: Transformer-based U-Net; U-Net: U-shaped convolutional network; VOC: Volatile organic compound; VQA: Visual question answering; ZFF: Zero-frequency filtering.

application workflow of standardized collection and AI processing of multimodal TCM data, supported by modern technology, in scenarios such as clinical disease prediction, constitution identification, chronic disease management, and psychological screening.

3.1. Visual modality data

In terms of visual modality data acquisition, early approaches primarily relied on digital cameras to capture images of the face, tongue and eyes. By incorporating traditional machine learning methods, such as linear discriminant analysis and support vector machines, researchers have extracted basic features, including color and texture. They also explored techniques such as color

space conversion²⁸, color chart calibration^{29,30}, and natural light simulation³¹ to obtain highly accurate images.

With the rise of machine vision, deep learning, and new optical imaging technologies, visual modality data are no longer limited to static image capture and superficial analysis but now incorporate dynamic feature monitoring and deep feature mining. For example, Huang *et al.*¹² used deep learning methods to develop a tongue surface segmentation model, ensuring accurate acquisition of tongue surface images in open and complex scenarios. Yan *et al.*³² proposed a segmentation-based deep learning network for extracting and identifying tongue fissures, addressing the challenge of color similarity between fissures and the tongue coating. Zhang *et al.*³³ enhanced

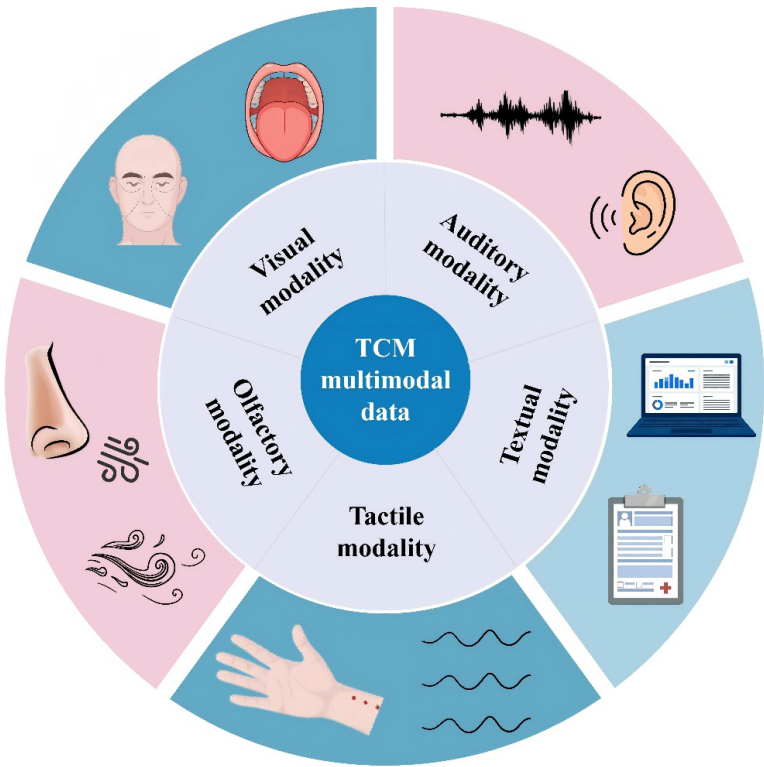


Figure 1. Modal framework of traditional Chinese medicine (TCM) multimodal data. This figure illustrates the mapping model between the TCM four examinations and the five modal data. The visual modality corresponds to facial and tongue diagnosis data in inspection; the auditory modality to sound data in auscultation; the olfactory modality to odor data in smelling; the textual modality to textual data in inquiry; and the tactile modality to pulse signal data in palpation. The figure was created with WPS Presentation (Kingsoft Office Software Corporation, China).

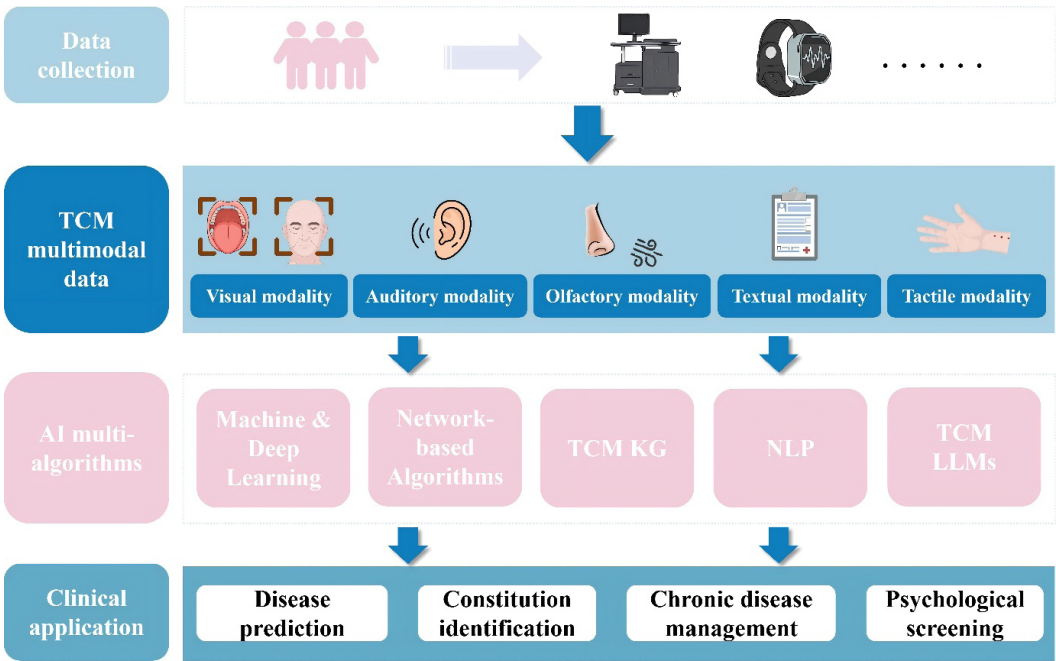


Figure 2. Framework of traditional Chinese medicine (TCM) multimodal data collection and intelligent application. The figure was created with WPS Presentation (Kingsoft Office Software Corporation, China).
Abbreviations: AI: Artificial intelligence; KG: Knowledge graph; LLM: Large language model; NLP: Natural language processing.

the existing U-Net deep learning method for tongue fissure extraction by incorporating a hybrid parallel attention mechanism. Additionally, some studies have analyzed consecutive frames to capture the movement trajectories and morphological changes of the tongue³⁴, which holds promise for an in-depth analysis of tongue thickness and the depth of tooth marks. In facial information acquisition, spectral reflectance analysis across different wavelength bands is used to assess blood flow distribution, tissue oxygenation, and metabolic byproducts, thereby extending the depth of “color observation” from the epidermis to the microcirculatory level.³⁵ The application of structured light and stereo vision technologies has enabled three-dimensional quantitative reconstruction of facial contours.^{36,37} The introduction of techniques such as laser speckle contrast imaging allows researchers to observe differences in blood perfusion across different facial regions in real time, providing quantitative evidence for assessing the severity of facial paralysis and stratified diagnosis of inflammatory diseases.^{38,39}

Simultaneously, the widespread adoption of mobile devices such as smartphones has driven a shift in tongue and facial diagnosis data collection toward lighter, more convenient methods. Relevant AI assistants for tongue diagnosis can rapidly capture and perform preliminary analysis of tongue images via smartphone photography⁴⁰, enabling tongue recognition, segmentation, and classification of tongue features.⁴¹ Facial examination data collection has also gradually expanded to remote settings. Some physicians use cloud platforms to view facial images taken by patients themselves, enabling remote preliminary screening.⁴² This has further broadened the application scope of visual modality data collection in TCM and laid a more convenient foundation for collecting the data required for multimodal data fusion.

3.2. Auditory modality data

Early research on voice data largely relied on general-purpose recording devices or digital phonographs, which merely recorded cough sounds.⁴³⁻⁴⁵ Although these methods enable the digital storage and analysis of voice signals, the equipment lacks standardization and offers limited sampling parameters. In recent years, specialized data acquisition systems for TCM clinical settings have gradually matured. Researchers now employ high-sensitivity microphone arrays and electronic stethoscopes, which can precisely locate the patient's sound source and automatically filter out ambient noise, simultaneously recording various sounds and their subtle spectral details.

Modern medical analysis of acoustic signals has focused primarily on coughing, breathing, and heartbeat. Many

scholars have begun to investigate the principles of sound production, analytical techniques, and clinical implications. Some researchers have proposed a set of basic standard acoustic parameters for automatic voice analysis, while emphasizing the need to account for confounding factors such as gender, age, and history of smoking and alcohol consumption when collecting voice data, thereby providing a reference framework for future research.⁴⁶ Kadir *et al.*¹⁶ extracted glottal source features using methods such as quasi-closed-phase inverse filtering and zero-frequency filtering. They found that these features can effectively distinguish between normal and pathological speech and are complementary to traditional acoustic features; when used in combination, they can improve the accuracy of speech pathology detection. Song *et al.*⁴⁷ integrated voice features with TCM syndromes to investigate differences in vocal resonance peak frequencies among patients with lung nodules classified under deficiency, excess, and mixed deficiency-excess syndromes. Khan *et al.*¹⁷ combined deep learning with signal processing techniques to enhance the analysis and classification capabilities of lung auscultation using parallel transformation methods. Given the advantages of natural language processing for speech data processing, recognition, and modeling, it has been applied to the assessment of neurological disorders.⁴⁸ Leveraging the classification and regression capabilities of machine learning methods, algorithms were developed to classify normal individuals, Alzheimer's disease patients, and Parkinson's disease patients by extracting time-series features such as pitch, tremor, and respiratory cycle.⁴⁹

With the improvement of smartphone performance and embedded algorithms, significant progress has been made in mobile device-based auxiliary diagnostic technologies for respiratory diseases.⁵⁰ Researchers have developed an Android cough monitoring system based on an ensemble convolutional neural network, enabling 72-h continuous monitoring of patients with pneumonia with a specificity of 99%.⁵¹ One study utilized smartphone microphones and the ResAppDx algorithm to diagnose respiratory diseases in children.⁵² Building on this, researchers developed an intelligent auscultation application using the MATLAB deep learning framework, combining GoogleNet transfer learning to achieve remote visual auscultation of heart and lung sounds.⁵³ These studies indicate that mobile terminal-based speech analysis technology has clinical potential for disease assessment.

3.3. Olfactory modality data

The olfactory modality is a distinctive yet highly challenging aspect of TCM diagnosis. Early studies on olfactory modality data primarily relied on chemical analysis methods, utilizing sophisticated instruments such

as gas chromatography–mass spectrometry to conduct precise chemical analyses of volatile components in patients' exhaled breath, body odors, or excretions^{54–56}, to identify signature compounds associated with specific diseases or TCM syndromes.

With breakthroughs in micro- and nano-sensing technology and bionics, electronic nose devices have been developed.^{57–59} These devices mimic the human olfactory system and utilize arrays of various sensors, such as metal-oxide-semiconductor, conductive polymers, or quartz microbalances, to generate cross-sensitive responses to volatile organic compounds in odors, converting complex odor chemical signals into quantifiable digital fingerprint profiles.⁶⁰ Previous studies have shown that volatile components in biological samples, such as breath⁶¹, sweat⁶², urine^{19,21}, and blood⁶³ serve as non-invasive biomarkers for early disease diagnosis^{64–67}. They demonstrate particular promise in the early detection of tumors and the monitoring of metabolic disease.^{68–70} Li *et al.*⁷¹ found that characteristic volatile compounds in exhaled breath can not only effectively distinguish between lung cancer patients and healthy controls, but also further differentiate between the histological subtypes of lung adenocarcinoma and lung squamous cell carcinoma. In a meta-analysis of urinary volatile organic compounds, van Liere *et al.*⁷² demonstrated that these compounds exhibit extremely high sensitivity and specificity in colorectal cancer screening and can serve as a powerful supplement to traditional fecal occult blood tests. Additionally, researchers have used non-invasive monitoring of blood glucose levels via exhaled acetone concentrations and found that odor fingerprinting technology exhibits unique clinical value.^{22,73} Meanwhile, regarding neurodegenerative diseases such as Parkinson's disease, researchers have pioneered new avenues for non-invasive early screening of neurological disorders by analyzing changes in specific volatile compounds in patients' skin sebum and exhaled breath.⁷⁴ This aligns with the principles of TCM, in which specific odors such as “corpse-like odor” or “rotten apple odor” are used to diagnose critical conditions.

3.4. Textual modality data

Textual data serve as a vital repository of information in TCM diagnosis and treatment, encompassing diverse formats, including electronic TCM medical records, classical texts, consultation records, and prescription information. It systematically captures in-depth semantic information, including syndrome descriptions, diagnostic reasoning, clinical experience, and patterns of medication use. In TCM clinical diagnosis, consultations generate vast amounts of textual data; traditional data collection

methods primarily rely on practitioners taking notes by hand or on patients completing paper questionnaires.

Modern technology has evolved this into an interactive, AI-powered medical consultation system based on large language models.²³ Through multi-turn dialog, the system actively guides patients to describe their symptoms and maps their colloquial descriptions into standard TCM terminology.²⁴ The Zhongjing model⁷⁵, based on the large language model meta-AI architecture, has established a comprehensive training workflow that encompasses pre-training, supervised fine-tuning, and reinforcement learning with human feedback. Additionally, a large-scale Chinese medical multi-turn question-answering dataset, CMtMedQA, was constructed, and more standardized annotation rules and evaluation criteria were defined.⁷⁵

In terms of analytical techniques, the focus has been on the development of large language models and knowledge graphs for specialized domains.⁷⁶ For example, the Qibo model, which leverages high-quality TCM training corpora and a two-stage training strategy, has not only mastered foundational TCM knowledge but also demonstrated strong diagnostic reasoning and auxiliary diagnostic capabilities, providing a viable path for building large models in the TCM field.⁷⁷ As a large-scale language model specifically designed for TCM, the BianCang model effectively addresses modeling challenges in TCM diagnosis and syndrome differentiation through a two-stage training method, outperforming existing open-source medical LLMs across multiple TCM tasks.⁷⁸ The Tianyi model integrates 3.4 billion words of the TCM corpus, encompassing multi-source texts such as classical texts, renowned medical case records, clinical guidelines, and TCM formulas.⁷⁹ Through continuous training and optimization, it has achieved high accuracy on simulated TCM practitioner qualification examinations and prescription-generation tasks, thereby preliminarily validating its potential for real-world clinical applications.

3.5. Tactile modality data

Pulse diagnosis in TCM (the tactile modality) is the most technically challenging and subjective component of the “four diagnostic methods.” Its core lies in using the tactile sensation of the fingers to perceive the location, rate, shape, and force of the pulse, thereby inferring the state of vitality or depletion of “qi” and blood in the internal organs. Early pulse diagnostic devices often required physicians to assist with probe positioning, and most were single-probe devices that collected data from a single point at the “Guan” position. Consequently, the amount of data was limited, and their clinical reference value was insufficient.

In recent years, equipment and data acquisition technologies have focused on bionic robotic fingers and intelligent positioning, deploying multiple sensor units simultaneously at the “cun,” “guan,” and “chi” points to simulate the tactile sensation of a physician using three fingers. For example, Kong *et al.*⁸⁰ developed a robotic palpation hand system featuring a three-finger independent-driven mechanism and a flexible capacitive sensor array, enabling the first engineering-level replication of the TCM lifting, pressing, and searching techniques. Zhu *et al.*²⁶ developed a digital pulse diagnosis platform that, based on an image localization model and a three-dimensional reconstruction algorithm, achieved precise “three-finger parallel” pressing in a bionic system for the first time.

With advances in machine vision and AI, intelligent localization technology has made significant progress. Chen *et al.*²⁵ developed a near-infrared video analysis model based on a three-dimensional convolutional neural network, which achieved 87% localization accuracy by capturing the spatiotemporal characteristics of radial artery pulsations. Zhu *et al.*²⁶ achieved 93% accuracy using a fusion-based visual localization method. In the field of pulse diagnosis information processing, Quanyu⁸¹ combined time-frequency domain feature extraction of pulse signals with convolutional neural networks, achieving the classification of 10 pulse patterns with an average accuracy of 94.12%. Cui²⁷ used a residual network with identity mapping and a long short-term memory network capable of time-series extraction to identify pulse wave signals based on different physical characteristics. This approach comprehensively covered 29 pulse patterns with an identification accuracy rate exceeding 89%.

Advances in wearable technology have transformed pulse diagnosis from a static outpatient procedure to dynamic home monitoring. Flexible electronic skin and smartwatches enable long-term, continuous tracking of pulse patterns^{82–84}, offering new approaches to chronic disease management and the monitoring and prevention of cardiovascular diseases.

4. Current status of multimodal fusion technology

The core of multimodal data fusion lies in extracting and integrating complementary information and contextual cues across modalities to improve decision quality. This characteristic is particularly important in the medical field. By integrating the distinct characteristics of multimodal data, their complementary informational advantages can be fully leveraged⁸⁵, providing a more comprehensive

basis for disease assessment. Compared with single-modality approaches, the application of multimodal fusion technology in medical practice has demonstrated significant advantages, particularly in disease diagnosis and prediction.^{86,87} For example, in the classification of Alzheimer’s disease, the use of multimodal data yields higher classification accuracy.⁸⁸ A multi-kernel support vector machine that fused diffusion tensor imaging and functional magnetic resonance imaging features achieved 98.4% accuracy in classifying Alzheimer’s disease from healthy controls, whereas the highest accuracy for either modality alone was only 90.9%.⁸⁸ Additionally, researchers have found that multimodal data fusion, based on tongue surface images, pulse waves, and health information, effectively compensates for information loss in single-modality data, yielding classification results significantly superior to those of single-modality approaches.⁸⁹ In the objective diagnosis of sub-health conditions characterized by liver “qi” stagnation and spleen deficiency, discriminant analysis was performed on single-modality data, including tongue diagnosis, pulse diagnosis, and medical history. The results showed that the highest accuracy for a single modality was 81%, whereas the accuracy of a multimodal model integrating tongue diagnosis, pulse diagnosis, and medical history increased to 84%, significantly outperforming both single-modality approaches and other multimodal combinations.⁹⁰ A study that fused multimodal features combining tongue diagnosis images and textual descriptions achieved an accuracy rate 23.81% higher than the best single-modal approach, significantly improving the effectiveness of TCM constitution identification.⁹¹ Another study, using ablation experiments, confirmed that a multimodal model integrating tongue images and textual descriptions significantly outperformed monomodal models using only images or only text in terms of accuracy, precision, recall, and F1 score for the diagnosis of TCM organ pathology.⁹² Table 3 provides a detailed comparison of monomodal and multimodal performance.

The advantages of multimodal fusion depend on the specific fusion method used, and different strategies vary in terms of the level at which information is integrated. Currently, data fusion strategies are primarily divided into three categories: data-level, feature-level, and decision-level fusion.

4.1. Data-level fusion

Data-level fusion is one of the earliest strategies, in which raw data from different sensors or modalities is directly combined through simple preprocessing to achieve physical or mathematical integration. By performing minimal or no feature extraction, this approach aims to

Table 3. Comparative performance of single-modal and multimodal artificial intelligence in clinical applications

Clinical applications	Specific modalities/features	Best single-modal performance (accuracy)	Multimodal performance (accuracy)	Reference
Alzheimer's disease classification	DTI, fMRI	90.9%	98.4%	88
TCM constitution classification	Tongue images, face images, pulse waves	73.81%	75.31%	89
Liver depression and spleen deficiency syndrome diagnosis	Tongue diagnosis, pulse diagnosis, inquiry	81%	84%	90
TCM constitution identification	Tongue images, tongue description texts	59.52%	84.52%	91
TCM visceral pathological organ diagnosis	Tongue images, tongue description texts	56.58%	62.90%	92

Abbreviations: DTI: Diffusion tensor imaging; fMRI: Functional magnetic resonance imaging; TCM: Traditional Chinese medicine.

preserve as much of the original information as possible, allowing subsequent single models to learn cross-modal correlations from the ground up.

Data-level fusion has widespread applications in specific scenarios within the medical field. For example, multimodal, multi-view ultrasound images have been used for breast cancer detection.⁹³ Studies have explored the correlation between gene expression and histological changes by integrating histological and genomic features or radiological images for cancer classification⁹⁴ and survival prediction⁹⁵; they have also combined pathological features with genomic or radiological images to predict treatment response in cancer.^{96,97} Other studies have fused imaging data with electronic medical records for the classification of skin lesions.⁹⁸ One research team combined knowledge graphs with multimodal large language models to achieve one-stop fusion imaging and intelligent interpretation of the four diagnostic methods of TCM.⁹⁹

However, this fusion strategy imposes extremely high demands on the synchronization and parameter consistency of acquisition devices, requiring strict temporal and spatial alignment of data from different modalities. Consequently, it faces significant challenges in real-world medical applications. When dealing with highly heterogeneous data such as clinical images, signals, and text, direct concatenation can easily lead to a “curse of dimensionality.” Moreover, the data-level fusion model lacks explicit cross-modal interaction mechanisms, which leads to poor interpretability.

4.2. Feature-level fusion

Feature-level fusion is suitable for combinations of modalities that are structurally heterogeneous yet semantically aligned. Its core strategy involves extracting deep semantic features from each modality and then performing vector-space concatenation or interaction.

Figure 3 illustrates feature extraction pathways based on convolutional neural networks and transformers. Currently, feature-level fusion has become the mainstream approach.

Clinical examples include combining imaging features with clinical pathological features to predict the risk of cancer recurrence.¹⁰⁰ Visual features extracted from tongue images have been jointly encoded with blood tumor marker features for cancer detection.¹⁰¹ Some studies have mapped tongue images to a common representational space together with tongue diagnosis texts or consultation texts, thereby enabling multi-label classification in TCM tongue diagnosis¹⁰² and better simulating the diagnostic process of the four examinations in TCM.¹⁰³ Other studies have combined tongue image data with pulse signals for disease differentiation.^{104,105} To achieve an objective, quantitative assessment of constitutional types, a mapping relationship has been established between multimodal data (including tongue images, acoustic signals, and pulse biometric signals) and constitutional scores.¹⁰⁶ By employing knowledge-enhanced feature-level fusion, TCM multimodal information, such as symptoms, tongue images, and pulse signals, is fused with text features through knowledge injection to enable the intelligent generation of TCM prescriptions.¹⁰⁷

However, existing algorithms still face challenges in precisely aligning heterogeneous data across spatiotemporal dimensions and lack adaptation to the logic of TCM syndrome differentiation. Consequently, the fusion results often devolve into technical “data overlay” rather than “semantic fusion” grounded in medical theory.

4.3. Decision-Level fusion

Decision-level fusion is suitable for scenarios involving asynchronous data collection or heterogeneous models. At this level, raw data or intermediate features are not

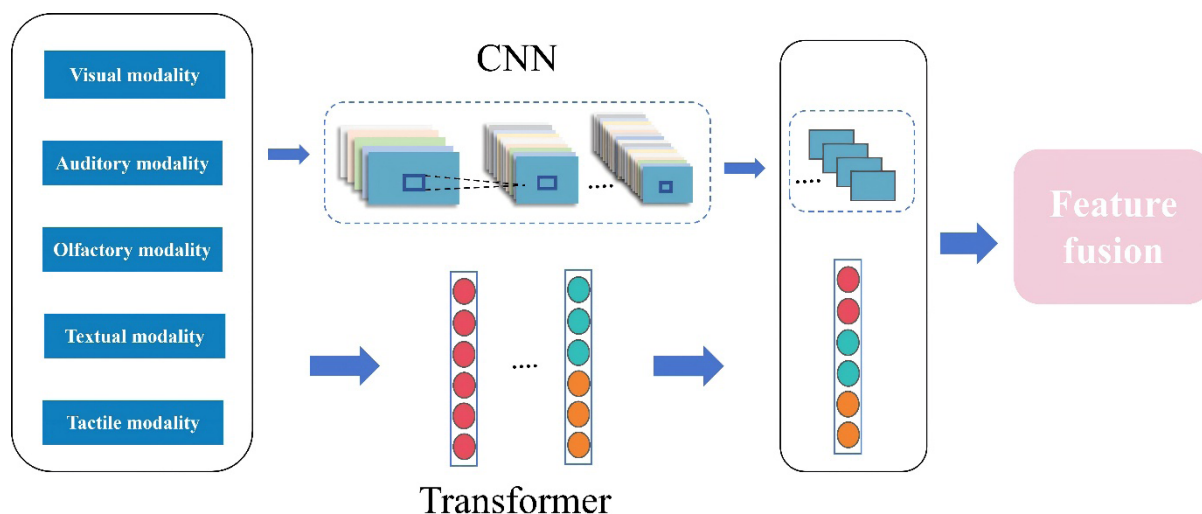


Figure 3. Traditional Chinese medicine multimodal feature-level fusion framework. This figure shows the potential feature-extraction pathways for five modal data in feature-level fusion. The figure was created with WPS Presentation (Kingsoft Office Software Corporation, China). Abbreviation: CNN: Convolutional neural network.

fused directly; instead, each multimodal submodel first generates its own diagnostic output, and these outputs are then integrated to produce a comprehensive decision.

Clinical examples include the integration of genomic and histological features to predict survival.¹⁰⁸ Imaging data has been combined with non-imaging inputs for cancer diagnosis.¹⁰⁹ Researchers have analyzed changes in patients' symptoms, complexion indices, pulse parameters, and tongue appearance before and after "Reducing the South and Reinforcing the North" treatment. By employing social network analysis to explore the relationships among these four diagnostic modalities, they synthesized multidimensional evidence and concluded that "Reducing the South and Reinforcing the North" exerts a regulatory effect on postmenopausal atherosclerosis.¹¹⁰

Decision-level fusion fails to preserve fine-grained correlations in the raw data due to the independent processing of each modality, making it difficult to capture complex, nonlinear, complementary features across modalities. Furthermore, the interpretability of its final decisions relies heavily on predefined rules or the inference logic of large models, posing a risk of a "black box" problem.

5. Challenges

The application of multimodal data fusion in the medical field has achieved breakthrough progress, and its practical exploration in intelligent diagnosis of TCM has provided strong impetus for the modernization of TCM and the development of precision medicine.¹¹¹⁻¹¹⁴ However, key

challenges remain in terms of data, algorithms, and clinical translation during the process of technological implementation.¹¹⁵⁻¹¹⁸

5.1. Data level

In research on intelligent diagnosis in TCM and multimodal data fusion, the core challenges at the data level center on two aspects: insufficient dataset scale and completeness, and the lack of standardization and sharing mechanisms.

On the one hand, existing datasets are limited in scale and suffer from severe modality gaps; currently available multimodal TCM datasets suffer from insufficient sample size, geographic coverage, and modality completeness. Take ShizhenGPT¹¹⁹, currently the largest TCM dataset, as an example. It contains over 100 GB of text data and over 200 GB of multimodal data (specifically including 1.2 million images, 200 h of audio, and physiological signals), marking a milestone in the field of TCM. However, compared to general-purpose large models, this dataset remains relatively small, making it difficult to support the generalization capabilities required for fine-grained visual diagnosis and multimodal joint reasoning. Consequently, the diagnostic reliability and robustness of the model cannot be effectively guaranteed in complex and diverse TCM clinical scenarios. Furthermore, most existing TCM fusion models integrate only two or three of these modalities, and research that comprehensively covers all five modalities remains rare. Therefore, there is an urgent need to continuously expand the dataset and the range of modalities, and to perform detailed data annotation.

On the other hand, the lack of standardization and data barriers severely hinders the integration of multi-source data. Data remains siloed and unshared among medical institutions, research organizations, and equipment manufacturers, creating information silos¹²⁰, making cross-platform, cross-institutional, and cross-regional data flow difficult to achieve.¹²¹ Furthermore, information from the four diagnostic methods of TCM lacks unified collection protocols, annotation systems, and data format standards; multimodal data obtained by different devices and practitioners exhibit significant differences in feature definitions, quality control, and storage structures.¹²² Terminology related to TCM syndromes and pathogenesis is abstract and context-dependent, making it difficult to quantify and map.¹²³ Only by simultaneously establishing data security and sharing mechanisms and a standardized framework can these barriers be broken down, laying the foundation for large-scale development of intelligent TCM diagnosis.

5.2. Technical integration

At the level of technological integration, the alignment and fusion of heterogeneous cross-modal data present a fundamental challenge. Modal data (such as images, sounds, electrical signals, and natural language text) generated by the four diagnostic methods of observation, auscultation, inquiry, and palpation exhibit intrinsic differences in sampling frequency, data structure, and physiological significance. This makes achieving precise alignment and semantic correlation across temporal, spatial, and feature dimensions extremely technically challenging. A multimodal study integrating tongue diagnosis, olfactory diagnosis, pulse diagnosis, and inquiry revealed that the best single-modal accuracy was 81%.⁹⁰ The study found that the combination of tongue diagnosis, pulse diagnosis, and inquiry achieved the highest accuracy of 84.%, whereas the four-modal combination—which included olfactory diagnosis—actually saw its accuracy drop to 75.33%. This phenomenon of “multimodal performance inversion” stems from the difficulty of semantic alignment across modalities—the introduction of the auditory modality failed to achieve effective fusion, instead amplifying noise interference. The key to resolving this issue lies in developing a cross-modal alignment mechanism guided by TCM knowledge, rather than simply relying on generic fusion architectures.

Furthermore, most multimodal architectures require the simultaneous fitting of multiple feature extractors, resulting in a total number of parameters far exceeding that of monomodal models. However, due to a severe shortage of paired training samples, this approach is highly prone to overfitting (where the model learns the training data too

precisely, leading to reduced generalization ability in real-world settings), which may actually result in a decline in performance. Strategies such as parameter-efficient fine-tuning, model distillation, or knowledge-data dual-driven approaches can be employed to reduce reliance on large-scale paired samples while controlling parameter count or incorporating prior knowledge from TCM, thereby enhancing the model’s generalization ability.

5.3. Clinical applications

At the clinical application level, ensuring clinical utility and reliability is the final hurdle to successful implementation. The “black box” problem¹²⁴ prevalent in current AI models is particularly pronounced in the field of TCM. Regarding liability, the “black box” nature of AI creates legal dilemmas in assigning responsibility for medical decisions, and the division of liability in diagnostic assistance has yet to be clearly defined.¹²⁵ Insufficient algorithmic interpretability further exacerbates the clinical trust dilemma.¹²⁶ Coupled with the lack of full participation by clinicians and the absence of humanized explanations and empathetic communication, patients find it difficult to understand and accept these systems.¹²⁷ Collectively, these issues lead to a more severe reality: the clinical translation and implementation of TCM AI models are severely lacking. A large number of high-precision models remain confined to laboratory research, and cases in which they have truly entered real-world clinical settings and achieved large-scale application are extremely rare. Furthermore, clinical ethical constraints and privacy protection¹²⁸ for multimodal data are also key challenges that need to be addressed in future research.

6. Recommendations

In response to these challenges, we call for the following three specific measures:

- (i) Establish an international alliance for AI in TCM to develop an open benchmark dataset using standardized data collection protocols, while expanding the dataset to ensure modal completeness.
- (ii) Adopt a hierarchical multimodal fusion strategy. Centered on feature-level fusion, this approach first integrates visual features of the tongue and face, then temporal features of the pulse, and finally incorporates symptom text and constitutional information. A syndrome-guided attention mechanism is introduced to dynamically focus on key features of the tongue and pulse. Data-level fusion serves as a supplement, performing channel concatenation on raw signals from the tongue, face, and pulse to preserve fine-grained information. Decision-level fusion serves as a supplementary measure. To address issues such as

missing modalities and asynchronous data acquisition, weighted aggregation can be employed to enhance clinical generalization capabilities and stability.

- (iii) Establish a tiered clinical translation system covering multi-center prospective validation, real-world efficacy evaluation, and optimization for primary care settings. Clarify the accountability framework and privacy protection mechanisms for AI-assisted diagnosis to facilitate the transition of the model from high-precision laboratory research to highly reliable clinical implementation.

7. Conclusion

Multimodal data-driven intelligent diagnosis is an inevitable trend in the modernization of TCM.¹²⁹ To date, this field has achieved phased breakthroughs in single-modal quantitative analysis and partial modal combinations, thereby validating its technical feasibility. Moving beyond the traditional framework of the “four examinations” (inspection, auscultation, inquiry, and palpation), this review systematically reconstructs the digital mapping relationships of TCM diagnostic information based on five heterogeneous data modalities: visual, auditory, olfactory, textual, and tactile. It comprehensively reviews the current state of research on multimodal data acquisition technologies, fusion methods, and clinical applications, thereby promoting the return of digital TCM diagnosis to its theoretical roots and the realization of the “integration of the four examinations.” However, currently available complete, publicly accessible five-modal datasets are extremely limited. The majority of studies are based on combinations of only two or three modalities, which limits the depth of this review’s analysis of the underlying mechanisms of multimodal interaction. In the future, collaboration among multiple Grade A Level 3 TCM hospitals should be strengthened. By signing data-sharing agreements, complete five-modal clinical data that has undergone de-identification processing can be obtained. Simultaneously, university institutions and equipment manufacturers should be engaged to jointly build an open, shared five-modal data platform. This platform would aggregate more comprehensive samples encompassing the tongue, face, pulse, voice, and questionnaires, thereby addressing the current data shortage and providing a practical data foundation and methodological support for future research.

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Conflict of interest

The authors declare no conflict of interest.

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References

1. Tang JL, Liu BY, Ma KW. Traditional Chinese medicine. *Lancet*. 2008;372(9654):1938–1940.
doi: 10.1016/S0140-6736(08)61354-9
2. Tian Z, Wang D, Sun X, *et al*. Current status and trends of artificial intelligence research on the four traditional Chinese medicine diagnostic methods: a scientometric study. *Ann Transl Med*. 2023;11(3):145.
doi: 10.21037/atm-22-6431
3. Abdullahi M, Oyelade ON, Kana AFD, *et al*. A systematic literature review of visual feature learning: deep learning techniques, applications, challenges and future directions. *Multimed Tools Appl*. 2024;84(19):20439–20496.
doi: 10.1007/s11042-024-19823-3
4. Wang J, Liu YM, Li J, *et al*. Artificial Intelligence in Traditional Chinese Medicine: Multimodal Fusion and Machine Learning for Enhanced Diagnosis and Treatment Efficacy. *Curr Med Sci*. 2025;45(5):1013–1022.
doi: 10.1007/s11596-025-00103-6
5. Ren Y, Luo X, Wang Y, *et al*. Large Language Models in Traditional Chinese Medicine: A Scoping Review. *J Evid Based Med*. 2025;18(1):e12658.
doi: 10.1111/jebm.12658
6. Bhatnagar V, Bansod PP. Challenges and Solutions in Automated Tongue Diagnosis Techniques: A Review. *Crit Rev Biomed Eng*. 2022;50(1):47–63.
doi: 10.1615/CritRevBiomedEng.2022044392

7. Guo C, Jiang Z, He H, Liao Y, Zhang D. Wrist pulse signal acquisition and analysis for disease diagnosis: A review. *Comput Biol Med.* 2022;143:105312.
doi: 10.1016/j.combiomed.2022.105312
8. Sui Dong, Zhang L, Yang F. Data-driven based four examinations in TCM: a survey. *Digital Chinese Med.* 2022;5(4):377-385.
doi: 10.1016/j.dcmed.2022.12.004
9. Tian D, Chen W, Xu D, *et al.* A review of traditional Chinese medicine diagnosis using machine learning: Inspection, auscultation-olfaction, inquiry, and palpation. *Comput Biol Med.* 2024;170:108074.
doi: 10.1016/j.combiomed.2024.108074
10. Zhang S, Wang W, Pi X, He Z, Liu H. Advances in the Application of Traditional Chinese Medicine Using Artificial Intelligence: A Review. *Am J Chin Med.* 2023;51(5):1067-1083.
doi: 10.1142/S0192415X23500490
11. Baltrusaitis T, Ahuja C, Morency LP. Multimodal Machine Learning: A Survey and Taxonomy. *IEEE Trans Pattern Anal Mach Intell.* 2019;41(2):423-443.
doi: 10.1109/tpami.2018.2798607
12. Huang Z, Miao J, Song H, *et al.* A novel tongue segmentation method based on improved U-Net. *Neurocomputing.* 2022;500:73-89.
doi: 10.1016/j.neucom.2022.05.023
13. Wu J, Li Z, Cai Y, *et al.* A Novel Tongue Coating Segmentation Method Based on Improved TransUNet. *Sensors.* 2024;24(14):4455.
doi: 10.3390/s24144455
14. Tiryaki B, Torenek-Agirman K, Miloglu O, Korkmaz B, Ozbek İ Y, Oral EA. Artificial intelligence in tongue diagnosis: classification of tongue lesions and normal tongue images using deep convolutional neural network. *BMC Med Imaging.* 2024;24(1):59.
doi: 10.1186/s12880-024-01234-3
15. Ang L, Yim MH, Do JH, Lee S. A Novel Method in Predicting Hypertension Using Facial Images. *Appl Sci.* 2021;11(5):2414.
doi: 10.3390/app11052414
16. Kadiri SR, Alku P. Analysis and Detection of Pathological Voice Using Glottal Source Features. *IEEE J Sel Top Signal Processing.* 2020;14(2):367-379.
doi: 10.1109/JSTSP.2019.2957988
17. Khan R, Khan SU, Saeed U, Koo IS. Auscultation-Based Pulmonary Disease Detection through Parallel Transformation and Deep Learning. *Bioengineering.* 2024;11(6):586.
doi: 10.3390/bioengineering11060586
18. Agbavor F, Liang H. Predicting dementia from spontaneous speech using large language models. *PLoS Digit Health.* 2022;1(12):e0000168.
doi: 10.1371/journal.pdig.0000168
19. Heers H, Gut JM, Hofmann R, *et al.* Pilot study for bladder cancer detection with volatile organic compounds using ion mobility spectrometry: a novel urine-based approach. *World J Urol.* 2024;42(1):353.
doi: 10.1007/s00345-024-05047-5
20. Chandran D, Ooi EH, Watson DI, Kholmurodova F, Jaenisch S, Yazbeck R. The Use of Selected Ion Flow Tube-Mass Spectrometry Technology to Identify Breath Volatile Organic Compounds for the Detection of Head and Neck Squamous Cell Carcinoma: A Pilot Study. *Medicina.* 2019;55(6):306.
doi: 10.3390/medicina55060306
21. Ding X, Zhang Y, Zhang Y, *et al.* Modular Assembly of MXene Frameworks for Noninvasive Disease Diagnosis via Urinary Volatiles. *ACS Nano.* 2022;16(10):17376-17388.
doi: 10.1021/acsnano.2c08266
22. Kistenev YV, Borisov AV, Zasedatel VS, Spirina LV. Diabetes noninvasive diagnostics and monitoring through volatile biomarkers analysis in the exhaled breath using optical absorption spectroscopy. *J Biophotonics.* 2023;16(12):e202300198.
doi: 10.1002/jbio.202300198
23. Bi W, Xiong Q, Chen X, Du Q, Wu J, Zhuang Z. Intelligent visual question answering in TCM education: An innovative application of IoT and multimodal fusion. *Alex Eng J.* 2025;118(000):325-336.
doi: 10.1016/j.aej.2024.12.052
24. Zhang H, Chen J, Jiang F, *et al.* HuatuoGPT: Towards Taming Language Model to Be a Doctor. In: Proceedings of the Association for Computational Linguistics: EMNLP 2023. Singapore: Association for Computational Linguistics; 2023:10859-10885.
doi: 10.18653/v1/2023.findings-emnlp.725
25. Chen Q, Huang Y, Zhu X, *et al.* Palpation localization of radial artery based on 3-dimensional convolutional neural networks. *EURASIP J Image Video Processing.* 2022;2022(1):1-13.
doi: 10.1186/s13640-022-00587-5
26. Zhu X, Ji Z, Wang FY, Zhou P, Luo J. A Robotic Platform for Digitalized Pulse Information Collection. In: Proceedings of the 2022 12th International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER). Baishan, China; 2022:1055-1060.
doi: 10.1109/CYBER55403.2022.9907105

27. Cui YH. Ji yu shen du xue xi de zhong yi mai xiang shi bie fang fa yan jiu [Deep learning-based TCM pulse pattern recognition]. Master's thesis. Nanchang Hangkong University; 2023. [In Chinese]
doi: 10.27233/d.cnki.gnchc.2023.000912
28. Wang XZ, Zhang D. A New Tongue Colorchecker Design by Space Representation for Precise Correction. *IEEE J Biomed Health Inform.* 2013;17(2):381-391.
doi: 10.1109/titb.2012.2226736
29. Niu JL, Zhao CB, Li GZ. A comprehensive study on color correction for medical facial images. *Int J Mach Learn Cybern.* 2019;10(5):1-13.
doi: 10.1007/s13042-017-0773-6
30. Zhao C, Niu JL, Li GZ, Wang HH, He C. Facial Color Management for Mobile Health in the Wild. *IEEE Trans NanoBioscience.* 2016;15(4):316-327.
doi: 10.1109/TNB.2016.2553122
31. Huang HF, Tai SC. Robust Facial Expression Recognition Using Near Infrared Cameras. *J Adv Comput Intell Intell Inform.* 2012;11(1):41-54.
doi: 10.5565/rev/elcvia.451
32. Yan J, Cai J, Xu Z, et al. Tongue crack recognition using segmentation based deep learning. *Sci Rep.* 2023;13(1):511.
doi: 10.1038/s41598-022-27210-x
33. Zhang Z, Zheng J, Zhao R, Liu S, Liu Z, Wang J. Cracked Tongue Extraction Model Based on Improved U-Net Method. *IEEE Access.* 2023;11:126352-126364.
doi: 10.1109/access.2023.3329975
34. Mukai N, Mori K, Takei Y. Tongue model construction based on ultrasound images with image processing and deep learning method. *J Med Ultrason.* 2022;49(2):153-161.
doi: 10.1007/s10396-022-01193-8
35. Yizhuo Z, Yu R, Hongxing C, et al. A Novel Method for Rapid Measurement of Facial Blood Oxygen Saturation Using a Snapshot Multispectral Imager. *J Biophotonics.* 2025;18(6):e70001.
doi: 10.1002/jbio.70001
36. Hallgrímsson B, Aponte JD, Katz DC, et al. Automated syndrome diagnosis by three-dimensional facial imaging. *Genet Med.* 2020;22(10):1682-1693.
doi: 10.1038/s41436-020-0845-y
37. Meng T, Guo X, Lian W, et al. Identifying Facial Features and Predicting Patients of Acromegaly Using Three-Dimensional Imaging Techniques and Machine Learning. *Front Endocrinol.* 2020;11:492.
doi: 10.3389/fendo.2020.00492
38. Jiang C, Wu J, Zhong W, et al. Automatic Facial Paralysis Assessment via Computational Image Analysis. *J Healthc Eng.* 2020;2020:1-10.
doi: 10.1155/2020/2398542
39. Liao JF, Jiang XM, Xie Z, et al. Exploring the efficacy of laser speckle contrast imaging in the stratified diagnosis of rosacea: a quantitative analysis of facial blood flow dynamics across varied regions. *Front Immunol.* 2024;15:1419005.
doi: 10.3389/fimmu.2024.1419005
40. Lu E. Colorful Diagnosis: AI-powered tongue analysis borrows from traditional Chinese medicine. *Sci Am.* 2025;333(4):13.
doi: 10.1038/scientificamerican112025-5vE238wlBiRsMfL9Vmkm9k
41. Yang Z, Zhao Y, Yu J, Mao X, Xu H, Huang L. An Intelligent Tongue Diagnosis System via Deep Learning on the Android Platform. *Diagnostics.* 2022;12(10):2451.
doi: 10.3390/diagnostics12102451
42. Ridha AM, Shehieb W, Yacoub P, Al-Balawneh K, Arshad K. Smart Prediction System for Facial Paralysis. In: Proceedings of the 2020 7th International Conference on Electrical and Electronics Engineering (ICEEE). Antalya, Turkey: IEEE; 2020:321-327.
doi: 10.1109/ICEEE49618.2020.9102600
43. Hsu JY, Stone RA, Logan-Sinclair RB, Worsdell M, Busst CM, Chung KF. Coughing frequency in patients with persistent cough: assessment using a 24 hours ambulatory recorder. *Eur Respir J.* 1994;7(7):1246-1253.
doi: 10.1183/09031936.94.07071246
44. Drugman T, Urbain J, Bauwens N, et al. Objective study of sensor relevance for automatic cough detection. *IEEE J Biomed Health Inform.* 2013;17(3):699-707.
doi: 10.1109/jbhi.2013.2239303
45. Rece CA, Cherry AC, Jr., Reece AT, Hatcher TB, Diehl AM. Tape recorder for evaluation of coughs in children. *Am J Dis Child.* 1966;112(2):124-128.
doi: 10.1001/archpedi.1966.02090110068005
46. Eyben F, Scherer KR, Schuller BW, et al. The Geneva Minimalistic Acoustic Parameter Set (GeMAPS) for Voice Research and Affective Computing. *IEEE Trans Affect Comput.* 2016;7(2):190-202.
doi: 10.1109/taffc.2015.2457417
47. Song XY, Xu ZX, Wang SJ, Ding XD, Feng L, Wang YQ. 121 li fei jie huan zhe de yu yin gong zhen feng chu tan [A preliminary study of voice formants in 121 pulmonary nodule patients]. *World Sci Technol Mod Tradit Chin Med.* 2019;21(12):2904-2908. [In Chinese]
doi: 10.11842/wst.20180130001
48. de la Fuente Garcia S, Ritchie CW, Luz S. Artificial

- Intelligence, Speech, and Language Processing Approaches to Monitoring Alzheimer's Disease: A Systematic Review. *J Alzheimers Dis.* 2020;78(4):1547-1574.
doi: 10.3233/jad-200888
49. Sung SH, Hong S, Kim JM, Kang DY, Park H, Kim S. Cognitive Impairment Classification Prediction Model Using Voice Signal Analysis. *Electronics.* 2024;13(18):3644.
doi: 10.3390/electronics13183644
50. Tabatabaei SAH, Fischer P, Schneider H, Koehler U, Gross V, Sohrabi K. Methods for Adventitious Respiratory Sound Analyzing Applications Based on Smartphones: A Survey. *IEEE Rev Biomed Eng.* 2021;14:98-115.
doi: 10.1109/rbme.2020.3002970
51. Barata F, Cleres D, Tinschert P, *et al.* Nighttime Continuous Contactless Smartphone-Based Cough Monitoring for the Ward: Validation Study. *JMIR Form Res.* 2023;7:e38439.
doi: 10.2196/38439
52. Moschovis PP, Sampayo EM, Cook A, *et al.* The diagnosis of respiratory disease in children using a phone-based cough and symptom analysis algorithm: The smartphone recordings of cough sounds 2 (SMARTCOUGH-C 2) trial design. *Contemp Clin Trials.* 2021;101:106278.
doi: 10.1016/j.cct.2021.106278
53. Lu JW, Chen SY, Yuan LF, Chen FM, Xie CY, Li CT. Ji yu Matlab shen du xue xi de zhi neng ting zhen xi tong ying yong cheng xu kai fa [Development of intelligent stethoscope system based on Matlab deep learning]. *Chin J Med Phys.* 2023;40(5):602-608. [In Chinese]
doi: 10.3969/j.issn.1005-202X.2023.05.013
54. Zhang X, Frankevich V, Ding J, Ma Y, Chingin K, Chen H. Direct mass spectrometry analysis of exhaled human breath in real-time. *Mass Spectrom Rev.* 2025;44(1):43-61.
doi: 10.1002/mas.21855
55. Schmidt K, Podmore I. Current Challenges in Volatile Organic Compounds Analysis as Potential Biomarkers of Cancer. *J Biomark.* 2015;2015:1-16.
doi: 10.1155/2015/981458
56. Buszewski B, Grzywinski D, Ligor T, Stacewicz T, Bielecki Z, Wojtas J. Detection of volatile organic compounds as biomarkers in breath analysis by different analytical techniques. *Bioanalysis.* 2013;5(18):2287-306.
doi: 10.4155/bio.13.183
57. Chen H, Huo D, Zhang J. Gas Recognition in E-Nose System: A Review. *IEEE Trans Biomed Circuits Syst.* 2022;16(2):169-184.
doi: 10.1109/tbcas.2022.3166530
58. Turner AP, Magan N. Electronic noses and disease diagnostics. *Nat Rev Microbiol.* 2004;2(2):161-166.
doi: 10.1038/nrmicro823
59. Pajot E. Medical diagnosis by breath analysis: odor sensors. *médecine/sciences.* 2019;35(2):123-131.
doi: 10.1051/medsci/2019001
60. Vadala R, Pattnaik B, Bangaru S, *et al.* A review on electronic nose for diagnosis and monitoring treatment response in lung cancer. *J Breath Res.* 2023;17(2):024002.
doi: 10.1088/1752-7163/acb791
61. Su Y, Chen G, Chen C, *et al.* Self-Powered Respiration Monitoring Enabled By a Triboelectric Nanogenerator. *Adv Mater.* 2021;33(35):e2101262.
doi: 10.1002/adma.202101262
62. Sabilla IA, Purbawa DP, Sarno R, Fauzi AA, Gunawan R. Men and Women Classification at Night Through the Armpit Sweat Odor using Electronic Nose. In: Proceedings of the 2021 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob). Bandung, Indonesia: IEEE; 2021:121-127.
doi: 10.1109/APWiMob51111.2021.9435273
63. Hakim M, Broza YY, Barash O, *et al.* Volatile organic compounds of lung cancer and possible biochemical pathways. *Chem Rev.* 2012;112(11):5949-5966.
doi: 10.1021/cr300174a
64. Rieder F, Kurada S, Grove D, *et al.* A Distinct Colon-Derived Breath Metabolome is Associated with Inflammatory Bowel Disease, but not its Complications. *Clin Transl Gastroenterol.* 2016;7(11):e201.
doi: 10.1038/ctg.2016.57
65. Arasaradnam RP, McFarlane M, Daulton E, *et al.* Non-invasive exhaled volatile organic biomarker analysis to detect inflammatory bowel disease (IBD). *Dig Liver Dis.* 2016;48(2):148-153.
doi: 10.1016/j.dld.2015.10.013
66. Mani-Varnosfaderani A, Gao A, Poch KR, Caceres SM, Nick JA, Hill JE. Breath biomarkers associated with nontuberculosis mycobacterium disease status in persons with cystic fibrosis: a pilot study. *J Breath Res.* 2022;16(3):031001.
doi: 10.1088/1752-7163/ac6bb6
67. Ferrandino G, De Palo G, Murgia A, *et al.* Breath Biopsy(®) to Identify Exhaled Volatile Organic Compounds Biomarkers for Liver Cirrhosis Detection. *J Clin Transl Hepatol.* 2023;11(3):638-648.
doi: 10.14218/jcth.2022.00309
68. Jia Z, Jiang Y, Shang T, *et al.* Advanced strategy for cancer detection based on volatile organic compounds in breath. *J Nanobiotechnol.* 2025;23(1):468.
doi: 10.1186/s12951-025-03526-4
69. Zhou M, Wang Q, Lu X, *et al.* Exhaled breath and

- urinary volatile organic compounds (VOCs) for cancer diagnoses, and microbial-related VOC metabolic pathway analysis: a systematic review and meta-analysis. *Int J Surg*. 2024;110(3):1755-1769.
doi: 10.1097/js9.0000000000000999
70. Orduña-Medina FM, Díaz de León-Martínez L, Alarcón-Rivera GDD, Prieto-Gómez NA, Mizaikoff B, Alcántara-Quintana LE. Utility of Volatile Organic Compounds and Electronic Nose Technology for Breast Cancer Detection: A Systematic Review. *Breast Cancer*. 2025;17:805-817.
doi: 10.2147/bcct.S525265
71. Li X, Shi L, Long Y, *et al*. Volatile organic compounds in exhaled breath: a promising approach for accurate differentiation of lung adenocarcinoma and squamous cell carcinoma. *J Breath Res*. 2024;18(4):046007.
doi: 10.1088/1752-7163/ad6474
72. van Lier E, van Dijk LJ, Bosch S, *et al*. Urinary volatile organic compounds for colorectal cancer screening: A systematic review and meta-analysis. *Eur J Cancer*. 2023;186:69-82.
doi: 10.1016/j.ejca.2023.03.002
73. Rydosz A. Sensors for Enhanced Detection of Acetone as a Potential Tool for Noninvasive Diabetes Monitoring. *Sensors*. 2018;18(7):2298.
doi: 10.3390/s18072298
74. Belluomo I, Tarazi M, Lao-Kaim NP, Tai YF, Spänel P, Hanna GB. Detection of Volatile Organic Compounds as an emerging strategy for Parkinson's disease diagnosis and monitoring. *npj Parkinsons Dis*. 2025;11(1):161.
doi: 10.1038/s41531-025-00993-2
75. Yang S, Zhao H, Zhu S, *et al*. Zhongjing: Enhancing the Chinese Medical Capabilities of Large Language Model through Expert Feedback and Real-world Multi-turn Dialogue. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Washington, DC: AAAI Press; 2023;38(17):19368-19376.
doi: 10.1609/aaai.v38i17.29907
76. Soman K, Rose PW, Morris JH, *et al*. Biomedical knowledge graph-optimized prompt generation for large language models. *Bioinformatics*. 2024;40(9):btae560.
doi: 10.1093/bioinformatics/btae560
77. Jia Y, Ji X, Wang X, *et al*. Qibo: A Large Language Model for traditional Chinese medicine. *Expert Syst Appl*. 2025;284:127672.
doi: 10.1016/j.eswa.2025.127672
78. Wei S, Peng X, Wang Y, *et al*. BianCang: A Traditional Chinese Medicine Large Language Model. *IEEE J Biomed Health Inform*. 2025:1-12.
doi: 10.1109/jbhi.2025.3612415
79. Liu Z, Yang T, Wang J, *et al*. Tianyi: A traditional Chinese medicine all-rounder language model and its real-world clinical practice. *Inform Fusion*. 2026;126:103663.
doi: 10.1016/j.inffus.2025.103663
80. Kong KW, Lau WM, Wong KS, *et al*. A pulse-sensing robotic hand for tactile arterial palpation. In: *Proceedings of the 2016 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER)*. Chengdu, China; 2016:141-145.
doi: 10.1109/CYBER.2016.7574811
81. Quanyu E. Pulse Signal Analysis Based on Deep Learning Network. *Biomed Res Int*. 2022;2022:6256126.
doi: 10.1155/2022/6256126
82. Xu Z, Wang Z, Wang J, *et al*. A multi-indicator pulse monitoring system based on an ultra-sensitive and stable self-powered wearable triboelectric sensor with assistance of personalized deep learning. *Nano Energy*. 2025;140:111039.
doi: 10.1016/j.nanoen.2025.111039
83. Kang X, Zhang J, Shao Z, *et al*. A Wearable and Real-Time Pulse Wave Monitoring System Based on a Flexible Compound Sensor. *Biosensors*. 2022;12(2):133.
doi: 10.3390/bios12020133
84. Kang X, Huang L, Zhang Y, *et al*. Wearable Multi-Channel Pulse Signal Acquisition System Based on Flexible MEMS Sensor Arrays with TSV Structure. *Biomimetics*. 2023;8(2):207.
doi: 10.3390/biomimetics8020207
85. Zhang Y, Xia K, Jiang Y, *et al*. Multi-Modality Fusion & Inductive Knowledge Transfer Underlying Non-Sparse Multi-Kernel Learning and Distribution Adaption. *IEEE/ACM Trans Comput Biol Bioinform*. 2023;20(4):2387-2397.
doi: 10.1109/tcbb.2022.3142748
86. Teoh JR, Dong J, Zuo X, Lai KW, Hasikin K, Wu X. Advancing healthcare through multimodal data fusion: a comprehensive review of techniques and applications. *PeerJ Comput Sci*. 2024;10:e2298.
doi: 10.7717/peerj-cs.2298
87. Huang B, Yang F, Yin M, Mo X, Zhong C. A Review of Multimodal Medical Image Fusion Techniques. *Comput Math Methods Med*. 2020;2020:1-16.
doi: 10.1155/2020/8279342
88. Buvanewari P, Gayathri R. Detection and Classification of Alzheimer's disease from cognitive impairment with resting-state fMRI. *Neural Comput Appl*. 2023;35(31):22797-22812.
doi: 10.1007/s00521-021-06436-2
89. Gu TY, Yan ZZ, Jiang JH. Classifying Chinese Medicine

- Constitution Using Multimodal Deep-Learning Model. *Chin J Integr Med*. 2024;30(2):163-170.
doi: 10.1007/s11655-022-3541-8
90. Ding Y, Li Y, Wang Y, *et al*. Ji yu ke guan hua duo mo tai shu ju rong he de ya jian kang gan yu pi xu zheng zhen duan mo xing gou jian [Construction of a diagnostic model for sub-health liver-stagnation and spleen-deficiency pattern based on objective multimodal data fusion]. *China J Tradit Chin Med Pharm*. 2025;40(1):71-76. [In Chinese]
doi: 10.14148/j.issn.1672-0482.2026.0627
91. Yang L, Wang TS, Yang T, Hu KF. Ji yu zhong yi she tu de duo ceng ci te zheng rong he zhong yi ti zhi bian shi yan jiu [Multilevel feature fusion for TCM constitution identification based on tongue images]. *J Nanjing Univ Tradit Chin Med*. 2026;(4):627-636. [In Chinese]
doi: 10.14148/j.issn.1672-0482.2026.0627
92. Gan Q, Wang C, Zhong Z, *et al*. Cross-modal attention model integrating tongue images and descriptions: a novel intelligent TCM approach for pathological organ diagnosis. *Front Physiol*. 2025;16:1580985.
doi: 10.3389/fphys.2025.1580985
93. Qian X, Pei J, Zheng H, *et al*. Prospective assessment of breast cancer risk from multimodal multiview ultrasound images via clinically applicable deep learning. *Nat Biomed Eng*. 2021;5(6):522-532.
doi: 10.1038/s41551-021-00711-2
94. Khosravi P, Lysandrou M, Eljalby M, *et al*. A Deep Learning Approach to Diagnostic Classification of Prostate Cancer Using Pathology-Radiology Fusion. *J Magn Reson Imaging*. 2021;54(2):462-471.
doi: 10.1002/jmri.27599
95. Chen RJ, Lu MY, Wang J, *et al*. Pathomic Fusion: An Integrated Framework for Fusing Histopathology and Genomic Features for Cancer Diagnosis and Prognosis. *IEEE Trans Med Imaging*. 2022;41(4):757-770.
doi: 10.1109/tmi.2020.3021387
96. Sammut SJ, Crispin-Ortuzar M, Chin SF, *et al*. Multi-omic machine learning predictor of breast cancer therapy response. *Nature*. 2022;601(7894):623-629.
doi: 10.1038/s41586-021-04278-5
97. Feng L, Liu Z, Li C, *et al*. Development and validation of a radiopathomics model to predict pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer: a multicentre observational study. *Lancet Digit Health*. 2022;4(1):e8-e17.
doi: 10.1016/s2589-7500(21)00215-6
98. Yap J, Yolland W, Tschandl P. Multimodal skin lesion classification using deep learning. *Exp Dermatol*. 2018;27(11):1261-1267.
doi: 10.1111/exd.13777
99. Li C, Wang P, Zheng M, Li W, Zhou J, Fu L. One-stop multi-sensor fusion and multimodal precise quantified traditional Chinese medicine imaging health examination technology. *J Radiat Res Appl Sci*. 2024;17(4):101038.
doi: 10.1016/j.jrras.2024.101038
100. Zhang R, Wang K, Wang S, *et al*. Multimodal deep learning model for prediction of breast cancer recurrence risk and correlation with oncotype DX. *Breast Cancer Res*. 2025;27(1):178.
doi: 10.1186/s13058-025-02129-z
101. Yuan L, Yang L, Zhang S, *et al*. Development of a tongue image-based machine learning tool for the diagnosis of gastric cancer: a prospective multicentre clinical cohort study. *eClinicalMedicine*. 2023;57:101834.
doi: 10.1016/j.eclinm.2023.101834
102. Yang L, Dong Q, Lin D, Lü X. TongueNet: a multi-modal fusion and multi-label classification model for traditional Chinese Medicine tongue diagnosis. *Front Physiol*. 2025;16:1527751.
doi: 10.3389/fphys.2025.1527751
103. Dai Y, Wang G, Dai J, Geman O. A multimodal deep architecture for traditional Chinese medicine diagnosis. *Concurr Comput Pract Exp*. 2020;32(19):e5781.
doi: 10.1002/cpe.5781
104. Shi Y, Yao X, Xu J, *et al*. A New Approach of Fatigue Classification Based on Data of Tongue and Pulse With Machine Learning. *Front Physiol*. 2022;12:708742.
doi: 10.3389/fphys.2021.708742
105. Shi YL, Jiang T, Hu XJ, *et al*. A Study of Logistic Regression for Fatigue Classification Based on Data of Tongue and Pulse. *Evid Based Complement Alternat Med*. 2022;2022:1-11.
doi: 10.1155/2022/2454678
106. Huang CJ, Lin HJ, Liao WL, Ceurvels W, Su SY. Diagnosis of traditional Chinese medicine constitution by integrating indices of the tongue, the acoustic sound, and the pulse. *Eur J Integr Med*. 2019;27:114-120.
doi: 10.1016/j.eujim.2019.04.001
107. Zhuang Y, Yu L, Jiang N, Ge Y. TCM-KLLaMA: Intelligent generation model for Traditional Chinese Medicine Prescriptions based on knowledge graph and large language model. *Comput Biol Med*. 2025;189:109887.
doi: 10.1016/j.combiomed.2025.109887
108. Chen RJ, Lu MY, Williamson DFK, *et al*. Pan-cancer integrative histology-genomic analysis via multimodal deep learning. *Cancer Cell*. 2022;40(8):865-878.e6.
doi: 10.1016/j.ccell.2022.07.004
109. Reda I, Khalil A, Elmogy M, *et al*. Deep Learning Role in

- Early Diagnosis of Prostate Cancer. *Technol Cancer Res Treat*. 2018;17:1533034618775530.
doi: 10.1177/1533034618775530
110. Wu H, Dai W, Li S, Tu L, Xu J, Zhang Z. Evaluation of reducing the south and reinforcing the north method on postmenopausal atherosclerosis disease based on 4 diagnostic objectifications: A prospective observational study. *Medicine*. 2024;103(14):e37615.
doi: 10.1097/md.00000000000037615
111. Marra A, Morganti S, Pareja F, *et al*. Artificial intelligence entering the pathology arena in oncology: current applications and future perspectives. *Ann Oncol*. 2025;36(7):712-725.
doi: 10.1016/j.annonc.2025.03.006
112. Zhang P, Zhang D, Zhou W, *et al*. Network pharmacology: towards the artificial intelligence-based precision traditional Chinese medicine. *Brief Bioinform*. 2023;25(1):bbad518.
doi: 10.1093/bib/bbad518
113. Bonkhoff AK, Grefkes C. Precision medicine in stroke: towards personalized outcome predictions using artificial intelligence. *Brain*. 2022;145(2):457-475.
doi: 10.1093/brain/awab439
114. Song Z, Chen G, Chen CY. AI empowering traditional Chinese medicine? *Chem Sci*. 2024;15(41):16844-16886.
doi: 10.1039/d4sc04107k
115. Aravazhi PS, Gunasekaran P, Benjamin NZY, *et al*. The integration of artificial intelligence into clinical medicine: Trends, challenges, and future directions. *Dis Mon*. 2025;71(6):101882.
doi: 10.1016/j.disamonth.2025.101882
116. Marques M, Almeida A, Pereira H. The Medicine Revolution Through Artificial Intelligence: Ethical Challenges of Machine Learning Algorithms in Decision-Making. *Cureus*. 2024;16(9):e69405.
doi: 10.7759/cureus.69405
117. Carini C, Seyhan AA. Tribulations and future opportunities for artificial intelligence in precision medicine. *J Transl Med*. 2024;22(1):411.
doi: 10.1186/s12967-024-05067-0
118. Lu L, Lu T, Tian C, Zhang X. AI: Bridging Ancient Wisdom and Modern Innovation in Traditional Chinese Medicine. *JMIR Med Inform*. 2024;12:e58491.
doi: 10.2196/58491
119. Chen J, Cai Z, Liu Z, *et al*. ShizhenGPT: towards multimodal LLMs for traditional Chinese medicine. *arXiv*. 2025.
doi: 10.48550/arXiv.2508.14706
120. Zhu Y, Yao KY, Peng SY, Yang XL. Traditional Chinese Medicine (TCM) Domain Ontology: Current Status and Rethinking for the Future Development. *Chin Med Sci J*. 2022;37(3):228-233.
doi: 10.24920/004151
121. Liang W, Tadesse GA, Ho D, *et al*. Author Correction: Advances, challenges and opportunities in creating data for trustworthy AI. *Nat Mach Intell*. 2022;4(10):904.
doi: 10.1038/s42256-022-00548-7
122. Tang Z, Tang Z, Wu J. Anomaly detection in medical via multimodal foundation models. *Front Bioeng Biotechnol*. 2025;13:1644697.
doi: 10.3389/fbioe.2025.1644697
123. Long H, Zhu Y, Jia L, *et al*. An ontological framework for the formalization, organization and usage of TCM-Knowledge. *BMC Med Inform Decis Mak*. 2019;19(Suppl 2):53.
doi: 10.1186/s12911-019-0760-9
124. Klauschen F, Dippel J, Keyl P, *et al*. Toward Explainable Artificial Intelligence for Precision Pathology. *Annu Rev Pathol*. 2024;19(1):541-570.
doi: 10.1146/annurev-pathmechdis-051222-113147
125. Terranova C, Cestonaro C, Fava L, Cinquetti A. AI and professional liability assessment in healthcare. A revolution in legal medicine? *Front Med*. 2024;10:1337335.
doi: 10.3389/fmed.2023.1337335
126. Hallowell N, Badger S, Sauerbrei A, Nellåker C, Kerasidou A. "I don't think people are ready to trust these algorithms at face value": trust and the use of machine learning algorithms in the diagnosis of rare disease. *BMC Med Ethics*. 2022;23(1):112.
doi: 10.1186/s12910-022-00842-4
127. Li W, Ge X, Liu S, Xu L, Zhai X, Yu L. Opportunities and challenges of traditional Chinese medicine doctors in the era of artificial intelligence. *Front Med*. 2024;10:1336175.
doi: 10.3389/fmed.2023.1336175
128. Ouyang T, Yang J, Gu Z, *et al*. Research on privacy protection in the context of healthcare data based on knowledge map. *Medicine*. 2024;103(33):e39370.
doi: 10.1097/md.00000000000039370
129. Alum EU, Ugwu PC. Artificial intelligence in personalized medicine: transforming diagnosis and treatment. *Discov Appl Sci*. 2025;7(3):1-5.
doi: 10.1007/s42452-025-06625-x