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AI-Driven TCM Constitution Identification and Personalized Health Management Research Progress

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Abstract This review systematically summarizes the research progress in artificial intelligence (AI)-based constitution identification and personalized health management, encompassing mobile terminal image acquisition, tongue and facial feature recognition, multimodal fusion, and intelligent intervention strategies. Current systems have preliminarily achieved a "identification-intervention-feedback" closed loop; however, they still face challenges such as inconsistent data quality, poor model interpretability, and a lack of clinical validation. Future efforts should focus on constructing high-quality multimodal databases, enhancing algorithmic transparency, conducting randomized controlled trials, and integrating 5G and AR technologies to advance the precision and universality of TCM intelligent health management.

Key words Artificial intelligence (AI), Constitution identification, Personalization, Health management

1 Introduction

The theory of Traditional Chinese Medicine (TCM) constitution has a long history, with its conceptual roots traceable to the *Yellow Emperor's Inner Canon* (*Huangdi Neijing*). It emphasizes the relatively stable physical and mental characteristics of an individual formed through the combined influence of innate heredity and acquired environment. This constitution not only determines the physiological and psychological differences among individuals in a healthy state but also plays a pivotal role in the occurrence, development, progression, prevention, and treatment of diseases[1-2]. However, traditional TCM constitution identification relies on the clinician's experiential synthesis of the "four diagnostic methods combined" (inspection, auscultation/olfaction, inquiry, and palpation). Its diagnostic outcomes are highly dependent on the physician's personal experience and subjective judgment. This inherent characteristic makes it difficult to meet the urgent demands of modern health management systems for precision, standardization, and scalability, thereby limiting the application of TCM constitution theory in large-scale population screening, telemedicine, and modern health management[3-4]. In recent years, artificial intelligence (AI) technology, particularly represented by deep learning, has presented a historic opportunity to overcome these limitations. AI technologies, especially computer vision and natural language processing, can perform quantitative analysis and intelligent interpretation of digitized information[5], providing the technical foundation for constructing objective, precise, and highly accessible TCM constitution identification and health management systems. This study provides a systematic review of AI-driven TCM constitution identification technologies and their applications. Building upon this, it analyzes the current research landscape, summarizes methodologies, and offers novel insights to enhance its effectiveness in clinical service.

2 Mobile terminal imaging and AI image recognition

2.1 Mobile terminal acquisition technology The widespread adoption of smartphones has revolutionized the digital acquisition of TCM "inspection" information, particularly tongue and facial images. Its advantages lie in enabling users to perform data collection using their everyday phones without specialized equipment, breaking the spatiotemporal constraints of traditional diagnosis; significantly lowering the barrier and cost of data collection, making it suitable for large-scale epidemiological surveys and self-health monitoring; and laying the groundwork for remote TCM consultation and health management[6]. However, the user selfie mode presents significant challenges. The acquisition environment is uncontrolled, involving factors such as uneven lighting, arbitrary shooting angles, complex backgrounds, blurry focus, and interference from facial expressions and makeup[7]. These factors result in inconsistent quality of the acquired image data, directly impacting the training of subsequent AI models. To address this, researchers and developers typically employ interactive guidance interfaces, ambient light detection prompts, and standardized photo-taking procedures to enhance data standardization at the source. In the preprocessing stage, utilizing color correction algorithms based on standard color charts, deep learning-based precise tongue/facial region segmentation models, and image standardization techniques become crucial steps for extracting valid signals from noisy data[8].

2.2 Tongue image recognition technology Tongue diagnosis is a core component of TCM inspection, where the morphology, color, and texture of the tongue image contain rich health information. AI-based tongue image analysis typically involves the following steps:

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2.2.1 Tongue body segmentation. Accurately separating the tongue body from regions such as lips, teeth, and the background. Early methods predominantly used traditional image processing techniques like thresholding, edge detection, and active contour models. In recent years, convolutional neural networks (CNNs) based on architectures like U-Net and DeepLab have become the mainstream methods for tongue segmentation due to their powerful feature learning capabilities, significantly improving segmentation accuracy[9].

2.2.2 Feature extraction and classification. The features such as tongue body color, coating color, tongue shape, and coating texture are extracted from the segmented tongue image. Wu Yun *et al.* [10] developed a tongue image analysis system capable of automating this feature extraction. Classification models then utilize these features, or employ end-to-end deep learning models, to directly perform constitution classification or assist in disease diagnosis. The research results indicate stable associations between specific tongue features and constitution types; for instance, an enlarged tongue with tooth marks is often associated with qi deficiency or phlegm-dampness constitutions, while a red tongue with a yellow coating frequently suggests damp-heat or Yin deficiency with effulgent fire[11].

2.2.3 Clinical application and validation. Li Candong *et al.* [12] employed deep learning to classify tongue images, demonstrating promising results in constitution screening for patients with chronic diseases like diabetes and hypertension. Chen Qianyu *et al.* developed a lightweight tongue image constitution identification model based on MobileNetV2, which is more suitable for deployment on mobile terminals[8].

2.3 Facial image recognition technology Facial diagnosis involves inferring the abundance or deficiency of visceral qi and blood by observing changes in facial complexion, luster, and morphology. Compared to tongue diagnosis, AI facial diagnosis research faces greater challenges, primarily due to strong interference from factors like ambient lighting, individual skin tone variations, cosmetic use, facial expressions, and shooting angles. First, precise localization of the face and key facial regions is required. Common methods include Haar features combined with AdaBoost classifiers and deep learning-based face detection algorithms. Song Haibei *et al.* [13], in their system, used hierarchical clustering algorithms to cluster pixel color information, extracted color features, and then employed a BP neural network for facial complexion recognition; more advanced methods directly utilize CNNs for end-to-end facial complexion classification. Zhang Ying *et al.* [14] analyzed facial texture, color, and other features using CNNs, finding correlations with constitution types such as qi deficiency and blood stasis.

Currently, the accuracy and robustness of facial diagnosis AI generally remain lower than those of tongue diagnosis. Beyond technical challenges, the inherent complexity of TCM facial diagnosis theory itself poses difficulties for quantitative modeling. Consequently, current facial diagnosis AI is primarily used as an auxiliary and supplementary information source alongside tongue diagnosis and inquiry.

3 Single-modal and multi-modal fusion analysis

3.1 Single-modal analysis Early research predominantly focused on single-modal analysis of either tongue or facial images. Although some progress was made, its fundamental flaw lies in the single dimension of information, which significantly deviates from TCM's holistic perspective of "combining the four diagnostic methods". Solely relying on visual information fails to capture key symptoms such as feelings of cold/heat, sweating patterns, urination/defecation, sleep, and emotional state, making misjudgments highly likely. For example, a "red tongue" alone might suggest a heat syndrome, but when combined with inquiry information like "aversion to cold, cold limbs, clear and abundant urine", it may indicate true cold with false heat. This limitation of "seeing only the part, not the whole" has spurred an urgent need for multimodal fusion technology[15].

3.2 Multi-modal fusion TCM emphasizes a holistic concept, and the fusion of multi-source information from the combined four diagnostic methods is a crucial means to improve the accuracy of constitution identification. Multimodal machine learning is a hotspot in AI research, aiming to comprehensively utilize diverse modal information such as images, text, audio, and sensor data to achieve decision-making capabilities superior to any single modality[16]. The "image + text + speech + data" combination currently represents a new trend in research. Liu Baoyan *et al.* [17] proposed building an auxiliary diagnosis and treatment system for TCM integrating the four diagnostic methods; Huang Wei *et al.* [18] proposed using deep learning models with multimodal data fusion for constitution identification, preliminarily validating the effectiveness of this approach. However, most of these studies remain at the stage of theoretical exploration or laboratory prototypes and have not yet materialized into complete, easy-to-use products for the general public.

3.3 Overall system architecture A complete mobile terminal and AI-based TCM constitution health management platform typically adopts a layered architecture, including a client application, cloud server, and server/management backend[19-20]. Within this architecture, the knowledge graph plays the role of the "intelligent brain". It materializes TCM concepts and constructs a rich semantic relationship network among them, such as "phlegm-dampness constitution should consume Coix Seed" and "Zusanli (ST36) belongs to the Stomach Meridian". Once the constitution identification model outputs a result, the intervention generation engine performs multi-hop reasoning within the knowledge graph, dynamically generating personalized health regimens covering dimensions like dietary therapy, exercise, acupoint health care, and emotional regulation, tailored to the user's real-time context[21]. This integration of data-driven perception and symbolic knowledge reasoning enables the system not only to compute accurately but also to elucidate the underlying TCM logic, thereby enhancing explainability and user trust.

4 Personalized health management

Systems based on AI and knowledge graphs can achieve dynamic and personalized generation of health management plans. Liu Xiaoyun *et al*.[19] noted that such intelligent health preservation systems are progressively extending from disease prevention towards holistic health promotion management. To bridge the gap between profound TCM theory and the understanding of ordinary users, thereby improving user comprehension and compliance, advanced platforms place special emphasis on interaction design. For instance, abstract concepts like yin-yang balance and qi-blood abundance/deficiency are translated into dynamic balance animations, thermometer-like cold/heat scales, and 3D models of human meridians and acupoints; by setting daily health preservation tasks and challenge levels, users earn points, virtual badges, or unlock new content upon completion, transforming health management into an engaging experience; establishing anonymous user communities based on constitution types can facilitate experience exchange and mutual encouragement, creating social support; it provides recipe guides, acupoint massage techniques, Baduanjin (a traditional Chinese exercise) tutorials, and other content with step-by-step graphics and short video demonstrations, effectively lowering the barrier to implementation.

Currently, most systems can achieve a basic "identification → intervention → feedback" closed loop, where users provide subjective feedback through methods like check-ins and ratings after executing the plan. However, a key bottleneck lies in the insufficient objectivity and continuity of the feedback loop. The lack of truly valuable quantitative feedback makes it difficult to perform precise, dynamic quantitative evaluation and optimization adjustments of the health regimens.

5 Conclusions

In summary, deep learning models struggle to provide diagnostic explanations that align with TCM logic; while the models can identify constitutions, they cannot articulate the reasoning chain like a physician, hindering clinicians' trust in and adoption of AI tools[22]. The vast majority of research remains at the stage of algorithm validation and system prototyping, lacking large-scale randomized controlled trials (RCTs) using clinical endpoints as evaluation metrics; thus, their effectiveness and safety have yet to be confirmed by high-level evidence-based medical evidence. Furthermore, how to convey and embody the cultural essence and experiential value of TCM through technical design presents a profound challenge in this field.

Addressing the aforementioned issues, future research could pursue optimization in the following directions: continuously expanding data volume and research algorithms like contrastive learning and self-supervised learning to enhance model generalization capabilities; introducing time-series methods to construct models of constitution changes over time, enabling dynamic identification and prediction; conducting large-scale RCTs within medical institutions to empirically test whether these systems can address specific clinical problems; integrating 5G and edge computing technologies, exploring fusion pathways with lightweight Augmented Reality (AR) technology to enhance interactive experiences and cultural perception while maintaining the advantage of low cost.

Through these efforts, it is anticipated that the precision, explainability, and universality of AI-driven TCM constitution identification systems can be further enhanced, promoting the deep integration and development of TCM modernization and intelligent health management services.

References

[1] WANG Q. Traditional Chinese medicine constitutionology[M]. Beijing: People's Medical Publishing House, 2008. (in Chinese).

[2] China Association of Chinese Medicine. Classification and determination of traditional Chinese medicine constitution: ZYYXH/T 157-2009[S]. 2009. (in Chinese).

[3] LI YS, WANG Q, DONG J, *et al*. Current status and thoughts on research of traditional Chinese medicine constitution identification[J]. Journal of Traditional Chinese Medicine, 2016, 57(20): 1730–1734. (in Chinese).

[4] LIU BY, HE LY, WEN TC. Big data and modernization of traditional Chinese medicine[J]. Journal of Traditional Chinese Medicine, 2015, 56(1): 1–5. (in Chinese).

[5] LI FF, WANG YQ, SUN Y. Research progress in informatization of traditional Chinese medicine inspection diagnosis[J]. Journal of Shanghai University of Traditional Chinese Medicine, 2018, 32(4): 1–5. (in Chinese).

[6] WU Y, ZHANG ZL, YU T, *et al*. Research on the construction of intelligent TCM constitution recommendation system based on multimodality[J]. China Digital Medicine, 2025, 20(6): 1–7. (in Chinese).

[7] ZHANG Y. Research on key technologies of traditional Chinese medicine facial diagnosis recognition based on deep learning[D]. Fuzhou: Fujian University of Traditional Chinese Medicine, 2021. (in Chinese).

[8] CHEN YY, ZHANG XD, LIU H, *et al*. Research on lightweight tongue image constitution identification model based on MobileNetV2[J]. World Science and Technology-Modernization of Traditional Chinese Medicine, 2022, 24(3): 345–351. (in Chinese).

[9] WU Y, LI CD, YANG ZY, *et al*. A tongue image segmentation method combining attention mechanism[J]. Acta Automatica Sinica, 2022, 48(5): 1–10. (in Chinese).

[10] WU Y, LI CD, YANG ZY, *et al*. A review of tongue image recognition research based on deep learning[J]. Chinese Archives of Traditional Chinese Medicine, 2021, 39(5): 12–15. (in Chinese).

[11] PENG L, LYU CS, QIAN LC. Research of tongue features in Chinese medicine constitution classification and feasibility of differentiating tongue to test constitution[J]. Journal of Traditional Chinese Medicine, 2017, 58(12): 1002–1004. (in Chinese).

[12] LI C, WU Y, YANG Z, *et al*. Tongue image recognition for diabetes mellitus based on deep learning[J]. Evidence-Based Complementary and Alternative Medicine, 2021: 1–14.

[13] SONG HB, CHENG XE. Construction of AI-based traditional Chinese medicine tongue image and facial diagnosis system[J]. China Digital Medicine, 2020, 15(2): 82–85. (in Chinese).

[14] ZHANG Y, LI CD, WU Y, *et al*. Research on traditional Chinese medicine facial diagnosis recognition based on convolutional neural network[J]. China Digital Medicine, 2020, 15(10): 37–40. (in Chinese).

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(4): 865 – 873.
[65] SONG DF, LI HM, XU JY, *et al*. Development and quality analysis of mogroside zero sucrose yoghurt [J]. Journal of Liaoning Agricultural Technical College, 2025, 27(2): 11 – 14. (in Chinese).
[66] LI SB, LUO XQ, HUANG LX, *et al*. Application of *Siraitia grosvenorii* and *Siraitia grosvenorii* glycosides in Juanshan fermented milk instead of sucrose[J]. Food Safety Guide, 2024(19): 114 – 118, 122. (in Chinese).
[67] LI X. Study on the preparation and storage quality of *Siraitia grosvenorii* jujube jelly soft candy[D]. Xiangtan: Xiangtan University, 2024. (in Chinese).
[68] LONG ZX, WU WG, ZHANG Y, *et al*. Optimization of recipe and analysis of volatile flavor compounds of momordica grosvenorii flavor sunflower seed sweetener[J]. Journal of Beijing University of Agriculture, 2024, 39(2): 91 – 98. (in Chinese).
[69] PENG FY, XIONG L, LIU SC. Study on fermentation technology and quality analysis of low sugar mogroside goat milk[J]. China Food Additives, 2024, 35(5): 233 – 242. (in Chinese).
[70] ABDEL-HAMID M, ROMEIH E, HUANG D, *et al*. Bioactive properties of probiotic set-yogurt supplemented with *Siraitia grosvenorii* fruit extract[J]. Food Chemistry, 2019, 303: 125400.
[71] XU Y, XU GH. Development of Luohanguo Wumei Hawthorn instant tea [J]. Processing of Agricultural Products, 2024(22): 30 – 33. (in Chinese).
[72] SUN XG, ZHANG LH, WANG CH. Detection of sweeteners in food and its impact on human health[J]. Food Safety Guide, 2025(17): 185 – 189. (in Chinese).
[73] LEI WP, HUANG R, QU L, *et al*. Exogenous mogroside V drove microbial carbohydrate metabolism and consequently enhanced fruity aroma in greengage wine [J]. Journal of Agricultural and Food Chemistry, 2025, 73(19): 11248 – 11264.
[74] LI MY. Study on the preparation of fermented *Siraitia grosvenorii* drink and the flavor of *Siraitia grosvenorii* glycosides [D]. Wuxi: Jiangnan University, 2021. (in Chinese).
[75] YAN JW, JIANG XK. Optimization of extracting technology of mogroside and development of natural throat health candy[J]. Northeast Agricultural Sciences, 2019, 44(5): 116 – 122. (in Chinese).
[76] ZHOU JH, XIAO ZZ, TANG MJ, *et al*. Effect of fermentation time on the fermentation quality and microbial diversity of *Siraitia grosvenorii* pomace[J]. Feed Industry, 2024, 45(19): 106 – 112. (in Chinese).

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[25] AMSTERDAM JD, LORENZO-LUACES L, SOELLER I, *et al*. Short-term venlafaxine v. lithium monotherapy for bipolar type II major depressive episodes: Effectiveness and mood conversion rate [J]. The British Journal of Psychiatry, 2016, 208(4): 359 – 365.
[26] LORENZO-LUACES L, AMSTERDAM JD, SOELLER I, *et al*. Rapid versus non-rapid cycling bipolar II depression: Response to venlafaxine and lithium and hypomanic risk [J]. Acta Psychiatrica Scandinavica, 2016, 133(6): 459 – 469.
[27] AMSTERDAM JD, LORENZO-LUACES L, SOELLER I, *et al*. Safety and effectiveness of continuation antidepressant versus mood stabilizer monotherapy for relapse-prevention of bipolar II depression: A randomized, double-blind, parallel-group, prospective study [J]. Journal of Affective Disorders, 2015, 185: 31 – 37.
[28] NUÑEZ NA, COOMBES BJ, MELHUISH BEAUPRE L, *et al*. Antidepressant-associated treatment emergent mania: A meta-analysis to guide risk modeling pharmacogenomic targets of potential clinical value [J]. Journal of Clinical Psychopharmacology, 2023, 43(5): 428 – 433.
[29] KAHYACI KILIÇ E, GÖRGÜLÜ Y, KÖSE ÇINAR R, *et al*. Manic shift due to the use of bupropion in bipolar depression: Two case reports [J]. Turkish Journal of Psychiatry, 2019, 30(2): 145 – 148.
[30] DAI C, FU Y, LI X, *et al*. Clinical efficacy and safety of vortioxetine as an adjuvant drug for patients with bipolar depression[J]. Journal of Zhejiang University Science B, 2025, 26(1): 26 – 38.
[31] FORNARO M, MCCARTHY MJ, DE BERARDIS D, *et al*. Adjunctive agomelatine therapy in the treatment of acute bipolar II depression: A preliminary open label study[J]. Neuropsychiatric Disease and Treatment, 2013, 9: 243 – 251.
[32] ALEXANDER M, A VP, S NG, *et al*. Safety and efficacy of adjunctive second-generation antidepressant therapy with a mood stabiliser or an atypical antipsychotic in acute bipolar depression: Randomised systematic review and meta-analysis of placebo-controlled trials [J]. Focus, 2021, 19(1): 129 – 137.
[33] YATHAM LN, ARUMUGHAM SS, KESAVAN M, *et al*. Duration of adjunctive antidepressant maintenance in bipolar I depression[J]. The New England Journal of Medicine, 2023, 389(5): 430 – 440.

(From page 77)

[15] YANG FW, LI ZQ, ZHANG ZW, *et al*. A review and prospects of body constitution classification and identification techniques in traditional Chinese medicine[J]. Tianjin Journal of Traditional Chinese Medicine, 2024, 41(3): 398 – 402. (in Chinese).
[16] BALTRUSAITIS T, AHUJA C, MORENCY LP. Multimodal machine learning: A survey and taxonomy [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2019, 41(2): 423 – 443.
[17] LIU BY, GUO RJ, WANG YH, *et al*. Construction ideas of auxiliary diagnosis and treatment system integrating four diagnostic methods of traditional Chinese medicine[J]. Journal of Traditional Chinese Medicine, 2017, 58(13): 1089 – 1092. (in Chinese).
[18] HUANG W, WANG L, LIU JP, *et al*. Traditional Chinese medicine constitution identification model based on multimodal data fusion[J]. Application Research of Computers, 2022, 39(4): 1021 – 1025. (in Chinese).
[19] LIU XY, XIE YL. Current status and prospects of research combining artificial intelligence and traditional Chinese medicine constitution[J]. Lishizhen Medicine and Materia Medica Research, 2022, 33(10): 2467 – 2468. (in Chinese).
[20] SHENG QQ, XIE XY, WANG Z, *et al*. Development of traditional Chinese medicine intelligent health care platform based on mobile Internet[J]. Wireless Internet Technology, 2018, 15(1): 48 – 51. (in Chinese).
[21] ZHANG YF, ZHU ZH, ZHONG FR, *et al*. Design and application of TCM health-preserving intelligent system based on knowledge graph [J]. China Digital Medicine, 2023, 18(10): 77 – 82. (in Chinese).
[22] HU JL, DING YT, YAN HX. Tongue Body constitution classification based on machine learning[J]. Journal of Jiamusi University (Natural Science Edition), 2018, 36(5): 709 – 713. (in Chinese).