Research on the Construction of a Classical Chinese Medicine Health Management System from the Perspective of Big Data and AI Integration

Lian Jian, Haiyang Huang, Xiaohong Liu, Fengping Li, Wanmei Wu, Baoshan Qian
Dongguan Traditional Chinese Medicine (TCM) Hospital, Dongguan 523000, Guangdong, China
Corresponding author: Haiyang Huang (e-mail: seasunhuang@163.com)

ABSTRACT Existing Traditional Chinese Medicine (TCM) health management systems continue to face challenges including dispersed data, limited intelligent correlation of physiological signal acquisition, and insufficient objective quantification of health interventions. This paper proposes a TCM health management system centered on intelligent textile health monitoring based on the integration of Big Data and Artificial Intelligence (AI). As wearable electromagnetic sensing and wireless physiological monitoring technologies become increasingly important for precision healthcare, the proposed framework designs a textile sensing unit integrating temperature, pulse, and skin conductance sensors to enable continuous physiological data acquisition. Multi-source heterogeneous data fusion algorithms are employed to establish personalized health profiles, while Deep Neural Networks (DNNs) and TCM diagnostic knowledge graphs are combined to predict pathological trends. Reinforcement learning is further introduced to dynamically optimize health intervention strategies. The system is validated using 12,000 clinical samples, achieving a prediction accuracy of 93.1% and a personalized intervention satisfaction rate of 88.6%. The results demonstrate the effective integration of AI-driven intelligent textile perception with TCM health management, providing a feasible solution for wearable health monitoring, precise conditioning, and electromagnetic sensing-assisted intelligent healthcare applications.

INDEX TERMS smart textiles, artificial intelligence, traditional Chinese medicine health management, electromagnetic sensing, wearable health monitoring

I. INTRODUCTION

CHINESE health management systems have traditionally relied on Traditional Chinese Medicine (TCM), which is characterized by empirical diagnosis and subjective observation, lacking uninterrupted quantitative descriptions of individual health status. Significant differences exist in data collection methods and measurement dimensions across various medical institutions, making it difficult to standardize modeling for indicators such as constitution, pulse, and qi and blood [1,2]. Available data sources are scattered among electronic medical records, wearable devices, and experimental testing systems, which remain independent and semantically incompatible, thus preventing temporal analysis and trend forecasting of TCM health information. Health conditioning recommendations are often based on static data, and the impact of interventions is not evaluated or optimized dynamically, hindering the smart transformation of TCM within current health management systems [3,4].

Artificial intelligence (AI) models demonstrate high prediction and recognition accuracy in medical contexts; however, conventional models have primarily been constructed using standardized biomedical data, making it challenging to extract semantic features and diagnostic reasoning unique to TCM. Although textile health sensing systems can monitor temperature, pulse, and skin conductance in real time, signal noise and unstable sensor contact with the skin create difficulties in deriving quantifiable medical meaning from sensor data. The absence of semantic mapping and knowledge limitations between AI models and textile sensing data leads to inadequate handling of individual differences in health assessment outcomes [5,6]. This organizational barrier creates a gap between data gathering, model inference, and classical TCM diagnosis, curtailing the practical use of intelligent textiles for TCM diagnosis and treatment management. This paper aims to develop a smart textile-based TCM health management system that integrates Big Data and AI to achieve an ordered representation of perceived textile data and collaborative modeling of TCM diagnostic data. Classical diagnostic data and wearable physiological data are combined using a multi-source heterogeneous data fusion algorithm; a knowledge graph (KG) based on TCM theory and physiological indicators provides semantic constraints for the AI model; and a reinforcement learning (RL) model optimizes personal health intervention recommendations, enabling adaptive learning and dynamic adjustment capabilities. This study focuses on the intensive integration of textile sensing, data intelligence, and TCM expertise to enable digital health condition descriptions and customized treatment choices, providing an engineering solution that is verifiable within the domain of medical intelligent textiles and precision health management.

II. SYSTEM DESIGN AND OVERALL FRAMEWORK

The overall system design consists of an intelligent textile data acquisition layer, an AI analysis layer, and a health intervention layer. The smart clothing data acquisition layer continuously monitors physiological data such as temperature, pulse, and skin conductance using conductive fiber sensing units, converting analog electrical data to digital data via a micro-signal conversion module. Multi-source sensing data is encrypted and transmitted to the AI analysis layer, where a big data fusion algorithm performs feature analysis and semantic matching to create a unified health status vector. This layer constructs a health profile using TCM characteristics of constitution and a deep neural network (DNN) to predict trend evolution. The health intervention layer outputs individualized conditioning recommendations, leveraging semantic reasoning from a KG and strategy optimization via RL, thus creating a closed loop between data acquisition, analysis, decision-making, and intelligent feedback. This constitutes a complete TCM health management process, from perception to intervention.

The textile sensing unit involves creating an interwoven network of sensing fibers and a stretchable substrate, enabling real-time acquisition of gradients of temperature, pulse waves, and changes in skin conductivity while the garment is worn. The acquisition module employs an adaptive filtering algorithm to minimize signal distortion due to motion interference and changes in contact impedance. After edge processing node compression, the sensing data enters a big data fusion channel. This channel utilizes a feature mapping matrix to achieve multimodal fusion of perceived signals, associating the four diagnostic modalities of TCM (inspection, auscultation, inquiry, and palpation) with physiological parameters and TCM semantic indicators to develop a multidimensional health dataset.

The AI analysis layer uses a DNN architecture to learn and predict regressions from fused data, enabling pathological trend prediction and health risk classification through high-level feature extraction. Concurrently, the KG represents the relationship between the TCM causal chain, structured according to expert knowledge systems, and contemporary physiological parameters, providing interpretable logical constraints for the AI model. The system's decision output is fed into the RL module, which continuously updates the decision strategy based on historical intervention effects, lifestyle feedback, and user bodily response data, thereby self-learning to optimize intervention plans. Inspired by TCM conditioning theory [7,8], the health intervention layer also delivers real-time health management recommendations to users by displaying digital and wearable indicators, establishing a constantly updating intelligent conditioning feedback platform.

III. INTELLIGENT TEXTILE SENSING AND DATA FUSION METHODS

A. DESIGN OF THE SENSING TEXTILE SYSTEM

The smart textile system employs silver-coated, highly conductive, flexible polyurethane fibers and thermally responsive polymer materials. The interwoven composite design integrates sensing regions with standard fibers to ensure both wearing comfort and signal stability. Fiber electrodes are arranged as microelectrode arrays on the chest, wrists, and back to record changes in body surface temperature, pulse waves, and skin conductivity. The signal acquisition circuit includes a high-sensitivity differential amplifier to capture amplitude variations of weak physiological electrical signals. The system features a miniature analog-to-digital converter to quantify voltage signals in real time, enabling stable acquisition of dynamic health data streams at a sampling frequency of 2–10 Hz.

A multi-layered approach is adopted for noise control: at the physical layer, electromagnetic interference is minimized by shielding fabric layers; at the algorithmic layer, adaptive Kalman filtering combined with wavelet threshold denoising eliminates motion artifacts. To compensate for the effects of textile bending and stretching on signal amplitude-frequency response, deformation compensation wires are integrated into the material structure, ensuring signal reconstruction errors under dynamic motion conditions remain within 3%. This design balances fit, signal fidelity, and mechanical stability in the textile sensor network, providing a reliable multi-dimensional physiological interface for TCM health data acquisition.

B. DATA FUSION METHODS

The multimodal signal fusion procedure focuses on structural mapping between human physiological signals and the information obtained from the four diagnostic methods of TCM. To achieve signal alignment, temporal normalization is applied to sensor outputs with disparate sampling rates, and the intervals of correlation between physiological and semantic features are estimated using the principle of maximizing mutual information. For denoising, a principal component analysis (PCA-D) model is added to the feature space to enhance stability and discriminability. The feature-level fusion algorithm utilizes a weighted multi-source complementary model (WMSCM), which dynamically adjusts the weights of various signals by adapting to the varying confidence levels of each modality. After fusion, an individual health profile matrix is generated, and a constitution classification model is created using K-means clustering and fuzzy membership functions. The model infers sub-health trends based on constitution attributes and produces a composite index vector comprising pulse type, metabolic characteristics, and emotional state—a highly dimensional health data input for the AI analysis layer.

IV. AI HEALTH MODELING AND INTELLIGENT DECISION-MAKING MECHANISM

A. DEEP LEARNING STRATEGIES

The DNN model employs a multi-layer nonlinear mapping structure, consisting of an input layer, four hidden layers, and an output layer. The input layer receives a health profile matrix from the data fusion module, with an input dimension of 256×1. Batch normalization and a residual mapping structure enhance the model's feature representation capabilities. Leaky ReLU is selected as the activation function to improve gradient convergence. The hidden layers utilize dropout to prevent overfitting, while the output layer applies the softmax function for health status classification. Samples are divided into 80% training and 20% validation sets. The Adam optimizer adaptively adjusts the learning rate, and the iteration count is set to 120 epochs, with convergence loss below 0.01 as the termination condition.

Table 1 illustrates the hierarchical design and parameter configuration of the DNN. The three output types correspond to three TCM health states: balance, deficiency, and excess. The input indicators use multidimensional feature encoding, mapping pulse variability index, skin conductance velocity, body surface temperature difference, and emotional stability coefficient into a continuous variable matrix. The loss function applies weighted cross-entropy, with weights dynamically adjusted according to the sample category distribution ratio to reduce prediction errors for imbalanced samples.

B. KG IMPLEMENTATION

The TCM KG is composed of symptom nodes, syndrome type nodes, mechanism nodes, and intervention nodes [9,10]. Its construction is based on expert experience and publicly available medical record databases. Causal relationship triples are generated through named entity recognition and relation extraction algorithms, with examples including <wiry pulse → liver qi stagnation> and <dark complexion → blood stasis constitution>. Graph relation edges include weighted confidence scores to quantify the probability of syndrome differentiation. The semantic mapping algorithm uses TransE embedding to map graph nodes into a 128-dimensional space, enabling the AI model to represent TCM relationships computationally. This graph provides constraints for AI decision-making. After the DNN makes an initial prediction, the system adjusts output weights according to the consistency of relationships and semantic distance within the KG, achieving interpretable corrections to the prediction results. The model can present the reasoning path to the user; for example, it can explain the path from body surface temperature difference and dull complexion to blood stasis constitution, then to circulation disorder and fatigue, thereby ensuring the medical logical traceability of the outputs. Interpretability analysis results are iteratively updated with expert feedback to improve graph confidence, allowing the system to continuously align with actual medical reasoning patterns.

C. RL OPTIMIZATION

The RL module utilizes intervention effects as feedback signals, which are dynamically used to update health management strategies. The state space consists of health profile vectors, while the action space includes modifiable treatment plans such as dietary adjustments, circadian rhythm regulation, emotional interventions, and TCM parameters. The reward function is determined by the rate of physiological indicator improvement and post-intervention subjective satisfaction. The agent employs a two-layer Q-learning framework, with a discount rate set at 0.87 to regulate the cumulative trend of returns, and achieves the optimal solution for treatment paths through ongoing interactive learning. Table 2 defines the state-action-reward structure:

The RL model uses multidimensional physiological signals as state input and calculates reward values by comparing changes in indicators before and after interventions. This optimization mechanism enables the health management system to autonomously correct decision-making strategies under continuous monitoring [11,12], resulting in individualized, iterative TCM conditioning recommendations.

V. EXPERIMENT AND RESULTS ANALYSIS

A. EXPLANATION OF EXPERIMENTAL DATA

This study utilized 12,000 clinical sample data points from Zhejiang Provincial Hospital of Traditional Chinese Medicine and a joint health monitoring platform. These included continuous physiological data for pulse, body temperature, skin conductance, heart rate variability, as well as complexion, mood, sleep, and diet information. The samples consisted of participants aged 22–75 years, with a gender ratio of approximately 1:1. All data were anonymized and recorded using specially designed smart textiles and apparel equipped with 1,080 sensor nodes distributed across the chest, wrist, neck, and back. The system transmitted data to a cloud storage module in real time via Bluetooth Low Energy, with an adjustable sampling rate of 8–12 Hz to ensure temporal integrity. Data cleaning involved sliding filtering and multidimensional anomaly detection to filter out low-confidence samples, which accounted for about 4.7%. A high-dimensional structured matrix was extracted after fusion algorithm processing, containing body type, health index, and symptom labels as input for training the DNN model and optimizing the RL strategy. This study was approved by the Ethics Committee of Dongguan Traditional

TABLE 1. DNN Hierarchical Design and Parameter Configuration

Model Hierarchy	Number of Parameters	Activation Function	Output Dimension
Input layer	256	-	256×1
Hidden layer 1	512	Leaky ReLU	512×1
Hidden layer 2	256	Leaky ReLU	256×1
Hidden layer 3	128	Tanh	128×1
Output layer	3	Softmax	Health classification results

TABLE 2. Definition of State-Action-Reward Structure

State Definition	Action Type	Reward Function Metrics	Update Method
Physical Health Vector	Dietary structure adjustment	Δ Body temperature stability	Off-policy Q update
Emotional state characteristics	Sleep rhythm regulation	Δ Heart Rate Variability Index	Double DQN
Qi–Blood Circulation Parameters	Breathing rhythm training	Δ Blood oxygen saturation	Experience replay
Physiological fatigue signals	Light physical exercise program	Δ Pulse wave smoothness	Dynamic learning rate adjustment
Overall status	TCM pharmacological intervention	Overall health benefits	Target network

Chinese Medicine Hospital and conducted in accordance with the principles of the Declaration of Helsinki. All eligible participants signed informed consent forms.

B. PERFORMANCE COMPARISON

System performance was evaluated across four dimensions: prediction accuracy, cross-validation error, intervention satisfaction, and response latency. Comparisons were made with a traditional TCM data management system (traditional AI models lacking KG constraints) and a standard wearable monitoring system. The experiment employed five-fold cross-validation, with a training to test set ratio of 4:1. All models were run on the same hardware environment, and GPU parallel training configuration parameters were kept consistent. Model stability was verified by averaging results from 10 repeated experiments to minimize the impact of sample batch fluctuations.

Table 3 displays the performance of different models on the same dataset. The fusion system constructed in this study improved prediction accuracy to 93.1%, increased intervention satisfaction to 88.6%, and reduced response latency by approximately two seconds compared to traditional methods. The average error rate was maintained at 3.2%, demonstrating the model's high clinical adaptability and dynamic response efficiency.

TABLE 3. System Performance Comparison Results

Model Type	Health Prediction Accuracy Rate (%)	Intervention Program Satisfaction Rate (%)	Intervention Response Delay (s)	Average Error Rate (%)
TCM Information System	82.4	75.8	6.7	7.8
AI Models without KG	87.5	81.2	5.9	5.6
Intelligent Textile Monitoring System	89.8	85.1	5.2	4.3
Big Data-AI Fusion System (This study)	93.1	88.6	4.7	3.2
Comparison Data Mean	88.2	82.7	5.6	5.2

VI. DISCUSSION

The increased accuracy shown in Table 3 is attributed to the effective combination of diagnostic data from the four diagnostic methods with continuous physiological curves, enabling the DNN to detect the nonlinear relationships between blood circulation and constitution differences within the feature space. The graphical representation of knowledge enhances the likelihood of correct classification in cases of semantic ambiguity, especially in distinguishing similar samples. The RL strategy adjustment mechanism also contributes to improved intervention satisfaction. As the system continuously receives user feedback on health status, the reward mechanism can optimize treatment plans in real time, ensuring individual differences are addressed rather than amplified by fixed instructions. Lower response latency is primarily due to the preprocessing of real-time signals by the edge computing module. Local discrimination and efficient caching ensure uninterrupted system output even during dense textile data streaming.

VII. CONCLUSION

This paper presents the development of a smart textile-based TCM health management system that integrates Big Data and AI. The system naturally connects TCM diagnostic reasoning with the latest textile sensing technologies, forming a continuous closed loop from physiological signal acquisition, data fusion, intelligent analysis, to health intervention. Sensing textiles obtain multi-dimensional, real-time measurements of body surface temperature, pulse, and skin conductance. A multi-source fusion algorithm performs feature reconstruction and standardization, providing high-confidence inputs for model learning. Health status recognition and trend prediction are conducted using DNN, TCM semantic association and interpretable reasoning are achieved with KG, and dynamic treatment plan adjustment is accomplished via a RL module based on user feedback, granting the management process self-learning and individual adaptability. Experimental results demonstrate the engineering viability and stability of the system in prediction accuracy, decision rationality, and interactive experience. As revealed by the study, intelligent textiles can serve as digital interfaces in TCM health management, digitizing and dynamizing traditional diagnostic concepts for sustainability. The system has broad potential applications in intelligent medical textiles, chronic disease treatment, and remote personalized health monitoring, offering a new technological direction for the modernization of TCM and the development of intelligent health equipment.

AUTHOR CONTRIBUTIONS

Conceptualization –Lian Jian, Haiyang Huang, Xiaohong Liu, Fengping Li, Wanmei Wu and Baoshan Qian; methodology – Lian Jian, Haiyang Huang, Fengping Li, Wanmei Wu and Baoshan Qian; investigation – Lian Jian, Haiyang Huang, Xiaohong Liu, Fengping Li, Wanmei Wu and Baoshan Qian; writing-original draft preparation – Lian Jian, Haiyang Huang, Xiaohong Liu, Fengping Li, Wanmei Wu and Baoshan Qian. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Dongguan Traditional Chinese Medicine Hospital and was conducted in accordance with the principles of the Declaration of Helsinki. All eligible participants signed informed consent forms.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] Y. Yin and S. J. Ma, “Construction of TCM preventive medicine and TCM health management system,” Journal of TCM Management, vol. 29, no. 20, pp. 211-213, 2021, doi: 10.16690/j.cnki.1007-9203.2021.20.103.
[2] X. Y. Wang, C. X. Pan, and J. Y. Zhang, “Design of an age-appropriate health management system based on traditional Chinese medicine health preservation atlas,” Packaging Engineering, vol. 46, no. 12, pp. 112-122, 2025, doi: 10.19554/j.cnki.1001-3563.2025.12.010.
[3] Z. J. Tang, X. Y. Zhang, and Y. Y. Deng, “Research on the practicality of traditional Chinese medicine and the innovative development of its management system under the background of the big health industry,” Journal of Traditional Chinese Medicine Management, vol. 33, no. 11, pp. 68-70, 2025, doi: 10.16690/j.cnki.1007-9203.2025.11.101.
[4] C. Y. Wu and Y. R. Chen, “Construction and application of pediatric TCM nursing health management system,” Journal of Traditional Chinese Medicine Management, vol. 33, no. 5, pp. 190-192, 2025, doi: 10.3969/j.issn.1007-9203.2025.5.zyyglzz202505075.
[5] X. C. Xiao, Z. A. Cheng, and Hu Gub, “The influence of a community health management system with traditional Chinese medicine characteristics on the health awareness of elderly patients with osteoarthritis,” Guangdong Medical Journal, vol. 41, no. 13, pp. 1348-1351, 2020, doi: 10.13820/j.cnki.gdyx.20193949.
[6] L. S. Xie, S. H. Li, W. S. Hu, Z. Yang, Y. L. Yang, W. Y. Peng, et al., “Construction of a health management system for the elderly in remote areas based on the TCM concept of "prevention of disease" under the background of Healthy China—Taking Xiushan Tujia and Miao Autonomous County, Chongqing as an example,” Sichuan Journal of Anatomy, vol. 30, no. 2, pp. 143-145, 2022, doi: 10.3969/j.issn.1005-1457.2022.02.048.
[7] L. Luo, J. Jiang, C. Wang, M. Fitzgerald, W. Hu, Y. Zhou, et al., “Analysis on herbal medicines utilized for treatment of COVID-19,” Acta Pharmaceutica Sinica B, vol. 10, no. 7, pp. 1192-1204, 2020, doi: 10.1016/j.apsb.2020.05.007.
[8] X. Zhang, H. Qiu, C. Li, P. Cai, and F. Qi, “The positive role of traditional Chinese medicine as an adjunctive therapy for cancer,” Bioscience trends, vol. 15, no. 5, pp. 283-298, 2021, doi: 10.5582/bst.2021.01318.
[9] H. Z. DU, X. Y. Hou, Y. H. Miao, B. S. Huang, and D. H. Liu, “Traditional Chinese Medicine: an effective treatment for 2019 novel coronavirus pneumonia (NCP),” Chinese journal of natural medicines, vol. 18, no. 3, pp. 206-210, 2020, doi: 10.1016/S1875-5364(20)30022-4.
[10] D. Zhang, K. Wu, X. Zhang, S. Q. Deng, and B. Peng, “In silico screening of Chinese herbal medicines with the potential to directly inhibit 2019 novel coronavirus,” Journal of integrative medicine, vol. 18, no. 2, pp. 152-158, 2020, doi: 10.1016/j.joim.2020.02.005.
[11] L. Ni, L. Chen, X. Huang, C. Han, J. Xu, H. Zhang, et al., “Combating COVID-19 with integrated traditional Chinese and Western medicine in China,” Acta Pharmaceutica Sinica B, vol. 10, no. 7, pp. 1149-1162, 2020, doi: 10.1016/j.apsb.2020.06.009.
[12] S. Wang, S. Long, Z. Deng, and W. Y. Wu, “Positive role of Chinese herbal medicine in cancer immune regulation,” The American journal of Chinese medicine, vol. 48, no. 07, pp. 1577-1592, 2020, doi: 10.1142/S0192415X20500780.