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CONSTRUCTION AND PRELIMINARY APPLICATION EFFECTIVENESS OF AN INFORMATICS-INTEGRATED TRADITIONAL CHINESE MEDICINE PREVENTIVE TREATMENT SERVICE MODEL

Lei Zhang, SiSi Li, ZiYang Wang, WenHui Lu*
Shanghai Municipal Hospital of Traditional Chinese Medicine, Shanghai University of Traditional Chinese Medicine, Shanghai 200090, China.
Corresponsing Author: WenHui Lu, Email: 49949745@qq.com

Abstract: **Objective:** To construct an informatics-integrated Traditional Chinese Medicine (TCM) preventive treatment service model and evaluate its effectiveness in improving service efficiency, patient compliance, satisfaction, and health outcomes. **Methods:** Based on the TCM preventive treatment concept, a digital service model was designed, incorporating intelligent constitution identification, personalized intervention, remote follow-up, and real-time monitoring, implemented using a B/S architecture and cloud deployment. A randomized controlled study was conducted at our hospital's preventive treatment clinic from June 2024 to February 2025, involving 216 sub-health patients (aged 18–65 years) randomly assigned to an informatics service group (n=108) or a traditional service group (n=108). Evaluation metrics included service efficiency, follow-up completion rate, compliance, satisfaction, and sub-health improvement rate, analyzed using t-tests and χ^2 tests. **Results:** The informatics group outperformed the traditional group in constitution identification accuracy (90.4% vs. 82.1%, $P<0.05$), follow-up completion rate (92.5% vs. 69.3%, $P<0.001$), compliance (89.7% vs. 74.2%, $P=0.003$), satisfaction (95.4% vs. 78.7%, $P<0.001$), and sub-health improvement rate (86.1% vs. 72.3%, $P=0.009$), with a 40.1% increase in service efficiency ($P<0.001$). **Conclusion:** This informatics-integrated service model significantly enhances service efficiency and patient health management, providing practical evidence for the modernization of TCM preventive treatment.

Keywords: TCM preventive treatment; Informatics technology; Personalized intervention; Service efficiency; Health management

1 INTRODUCTION

As one of the core concepts in Traditional Chinese Medicine (TCM), "preventive treatment of disease" emphasizes three key principles: preventing disease before it occurs, preventing the progression of existing diseases, and preventing recurrence after recovery. With the growing emphasis on chronic disease prevention and health management in modern medicine, this concept has shown great potential for wider application. In recent years, along with the national strategy to promote TCM development, the "preventive treatment" system has gradually transitioned from theoretical exploration to clinical practice. However, current implementation still faces numerous challenges, such as fragmented service processes, inconsistent documentation, irregular follow-up management, and poor patient compliance, all of which significantly hinder improvements in service efficiency and quality [1].

With the rapid advancement of information technology, healthcare service models are evolving toward digitalization, intelligence, and interconnectivity [2]. In this context, integrating digital solutions into the full service process of TCM preventive treatment can facilitate the consolidation and sharing of diagnostic and treatment information, enhance service continuity and accessibility, and leverage data-driven approaches to optimize intervention strategies. This integration also holds promise for improving the personalization and precision of health management [3]. Nevertheless, systematic research on the construction and evaluation of such integrated models—combining TCM preventive care with digital technology—remains limited. There is an urgent need for empirical studies in real-world clinical settings to explore the mechanisms and effectiveness of such models.

This study, grounded in the concept of "Digital Qihuang, Smart Health", integrates modern information technology with TCM preventive treatment theory to develop a comprehensive service model encompassing assessment, intervention, and follow-up. We applied this model in real clinical scenarios to evaluate its impact on service efficiency, patient compliance, and satisfaction. The goal is to provide both theoretical support and practical guidance for the modernization and standardization of preventive TCM services.

2 METHODS

2.1 Overall Design of the Service Model

Based on the core concept of preventive treatment in Traditional Chinese Medicine (TCM), this study utilized big data, artificial intelligence (AI), and mobile internet technologies to develop a digital full-process service model encompassing intelligent assessment, personalized intervention, dynamic follow-up, and outcome feedback. The model comprises four functional modules:① Intelligent Constitution Identification and Risk Assessment;② Automated Generation of Personalized Intervention Plans;③ Remote Dynamic Follow-Up;④ Real-Time Data Monitoring and Quality Feedback. The overall architecture adopts a B/S (Browser/Server) structure, with server-side deployment supported by cloud computing technologies. The client-side supports both web and mobile platforms. Data exchange between front-end and back-end systems is conducted using the standardized JSON format.

2.2 Key Technologies and Module Implementation

2.2.1 Intelligent constitution identification and risk assessment module

Patient self-reported symptoms and constitution scale data were collected via a custom-developed mobile application, alongside TCM four-diagnostic information (inspection, auscultation/olfaction, inquiry, and palpation) to generate a basic health profile. A deep learning model based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks was constructed in Python to achieve automated constitution classification. Additionally, a health risk prediction model was built using patients' historical data and real-time inputs, with risk stratification and early warnings implemented via the random forest algorithm.

2.2.2 Automated generation of personalized intervention plans module

A TCM knowledge graph was constructed using a Neo4j graph database, incorporating classical literature and expert consensus guidelines. Based on patients' constitution types and risk levels, an inference engine matched personalized intervention strategies. A hybrid rule-based and machine learning algorithm was developed to automatically generate tailored recommendations for diet, exercise, and TCM-specific therapies (e.g., the "Three-Step Therapy for Fatty Liver").

2.2.3 Remote dynamic follow-up module

Real-time follow-up data transmission was implemented using the WebSocket communication protocol. Natural Language Processing (NLP) techniques were employed to automatically parse and structure patients' chief complaints. A built-in alert mechanism, based on predefined threshold indicators, was designed to automatically notify healthcare professionals of abnormal conditions requiring timely intervention.

2.2.4 Real-time data monitoring and quality feedback module

Real-time visualization of service indicators—such as follow-up response rate, patient compliance, and satisfaction—was achieved using ECharts technology. A multidimensional data analysis framework was used to construct a quality scoring system and generate regular service quality reports. Integration of Tableau and Python enabled interactive dashboards for continuous quality monitoring(Figure 1).

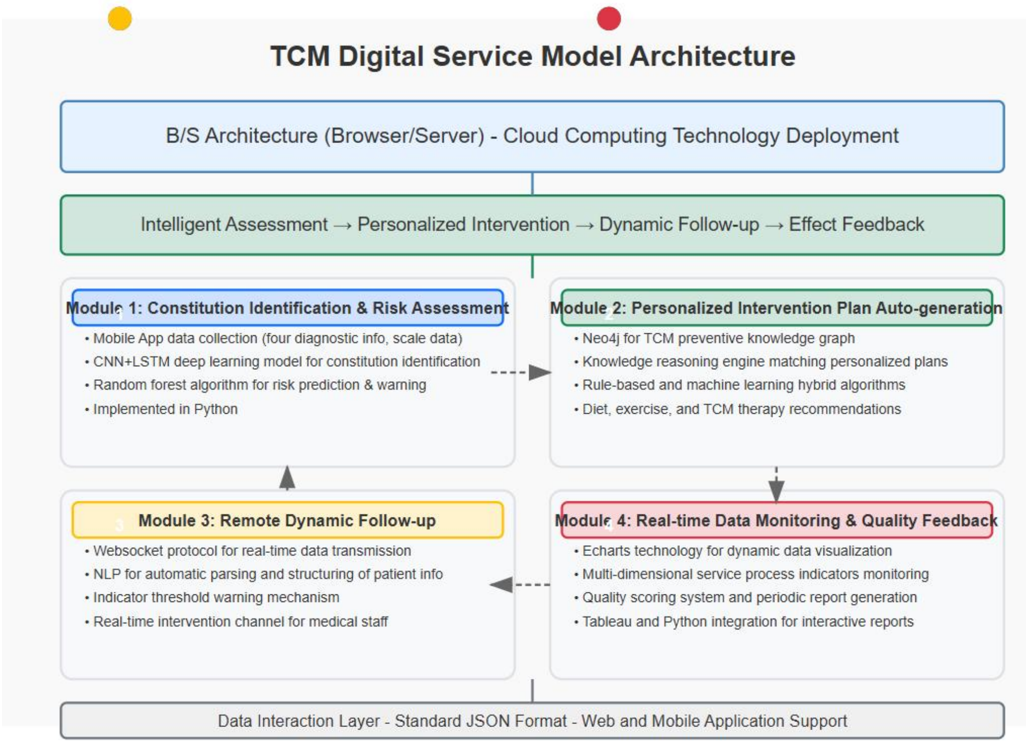

Figure 1 Architecture of the Digital Service Model Based on the TCM Concept of Preventive Treatment

2.3 Application and Implementation Scenario

The digital service model was deployed in the Preventive Treatment Outpatient Clinic of our hospital and applied to patients between June 2024 and February 2025. The sample size was calculated based on the primary outcome indicator—patient compliance rate. According to preliminary study data, the expected compliance rate in the digital service group was 90%, compared with 75% in the traditional service group, yielding an effect size of 15%. A two-sided test with a statistical power of 80% and a significance level of $\alpha = 0.05$ indicated that each group would require at least 102 participants. Considering a 10% dropout rate, 108 patients were included in each group, for a total of 216 participants.

To reduce selection bias, a quasi-randomized controlled design was adopted, using a sealed envelope method for group allocation. Patients were assigned in a 1:1 ratio to the digital service group and the traditional service group according to enrollment sequence. Due to the significant differences in intervention delivery methods (digital platform vs. manual operations), this study was conducted as an open-label trial. To minimize observation bias, data collection and outcome evaluation (e.g., compliance and satisfaction surveys) were conducted by third-party evaluators independent of the intervention process. These evaluators received standardized training before assessments. The study protocol was approved by the institutional ethics committee, and written informed consent was obtained from all participants.

The digital service model was implemented via a mobile application and web platform to enable intelligent constitution identification, automated generation of personalized intervention plans, remote dynamic follow-up, and real-time data monitoring. In contrast, the traditional manual service model relied entirely on human operation: constitution identification was performed by TCM physicians using paper-based questionnaires and face-to-face consultations, taking approximately 15–20 minutes; intervention plans were manually formulated by TCM physicians based on experience and clinical guidelines, requiring around 10 minutes; follow-up was conducted via telephone or in-person clinic visits, with records maintained in paper files, lacking real-time data transmission and early warning mechanisms; service quality feedback was manually collected through patient satisfaction questionnaires without dynamic visualization. Both groups received the same TCM-based preventive interventions (diet, exercise, and TCM-specific therapies), but the digital group benefited from process automation and data integration via the digital platform, whereas the traditional group depended entirely on manual processes and paper-based documentation.

2.4 Evaluation Indicators and Data Analysis

Evaluation indicators included: Functional realization rate of the model; Service process indicators (e.g., service efficiency, follow-up completion rate, personalized plan matching rate); Patient satisfaction; Improvement magnitude of intervention outcomes. Statistical analysis was performed using SPSS version 26.0. Continuous variables were expressed as mean ± standard deviation, and intergroup comparisons were conducted using independent sample t-tests. Categorical variables were presented as percentages and compared using chi-square tests. A P-value < 0.05 was considered statistically significant.

3 RESULTS

3.1 Baseline Characteristics of the Study Population

A total of 216 patients were enrolled in this study, with 108 in the digital service group and 108 in the traditional service group. Baseline characteristics for both groups are presented in Table 1. There were no statistically significant differences between the two groups in terms of age, gender, sub-health scores, or distribution of primary TCM constitution types (P > 0.05), indicating good comparability between the groups.

Table 1 Comparison of Baseline Characteristics Between the Two Groups

Characteristic	Digital Service Group (n = 108)	Traditional Service Group (n = 108)	Test Statistic	*P-value*
Age (years, mean ± SD)	42.3 ± 12.5	43.1 ± 11.8	t=0.47	0.639
Gender (male/female, n)	52/56	50/58	χ^2=0.07	0.791
Sub-health score (mean ± SD)	65.4 ± 10.2	66.1 ± 9.8	t=0.52	0.604
Primary TCM Constitution Types (n, %)			χ^2=0.92	0.821
Balanced Constitution	30 (27.8%)	28 (25.9%)		
Qi-Deficiency Constitution	25 (23.1%)	27 (25.0%)		
Damp-Heat Constitution	20 (18.5%)	22 (20.4%)		
Others (Yin-deficiency, Phlegm-dampness, Blood stasis, Qi stagnation, Special diathesis)	33 (30.6%)	31 (28.7%)		

Note: The sub-health score was assessed using the standardized Sub-health Status Scale (range: 0–100, with higher scores indicating more severe sub-health conditions). Constitution types were determined using the standardized TCM Constitution Identification Scale.

3.2 Outcomes of the Digital TCM Preventive Service Model Construction

This study successfully developed an integrated digital service model for TCM-based preventive care, comprising four core components: intelligent constitution identification and risk assessment, automated generation of personalized intervention plans, remote dynamic follow-up, and real-time data monitoring with quality feedback.

3.2.1 Intelligent constitution identification module

Using a deep learning model based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), the system achieved an accuracy rate of 90.4% in identifying TCM constitution types. This was significantly higher than that of traditional manual methods (82.1%), with the difference being statistically significant ($P < 0.05$). Additionally, the health risk prediction model demonstrated an accuracy rate of 88.6%.

3.2.2 Automated personalized intervention plan module

The module generated personalized intervention plans in an average time of 1.5 ± 0.3 minutes, which was significantly shorter than the time required for traditional manual planning (10 ± 2.6 minutes, $t = 28.45$, $P < 0.001$). The satisfaction rate with the individualized plans reached 92.6%(Figure 2).

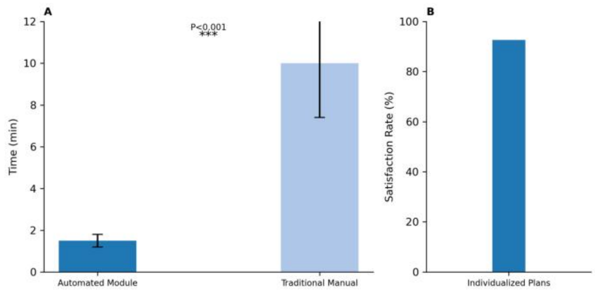

Figure 2 Comparison of Average Time for Personalized Intervention Plan Generation Between Modules

3.2.3 Remote dynamic follow-up module

By leveraging WebSocket communication and Natural Language Processing (NLP) technologies, the follow-up module enabled real-time acquisition of patient follow-up data and automatic alerts for abnormal findings. The follow-up completion rate increased by 23.2% compared to the traditional service model (92.5% vs. 69.3%, $\chi^2 = 17.84$, $P < 0.001$). Moreover, the rate of timely intervention for patient health management reached 87.9%(Figure 3).

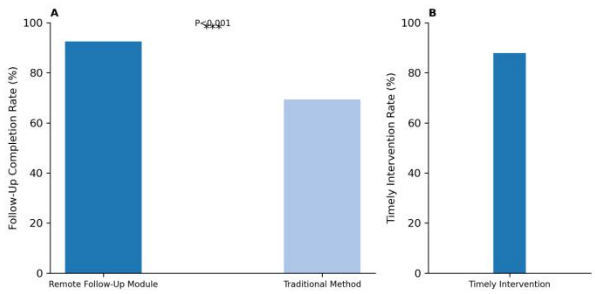

Figure 3 Comparison of Follow-Up Completion Rates Between Modules

3.2.4 Real-time data monitoring and quality feedback module

Powered by ECharts and Tableau, the real-time data monitoring and feedback module enabled dynamic visualization and interactive display of key service process indicators. Service quality evaluation showed that overall satisfaction with service quality reached 93.8% in the digital model group, significantly higher than 80.6% in the traditional service group ($\chi^2 = 8.12$, $P = 0.004$)(Figure 4).

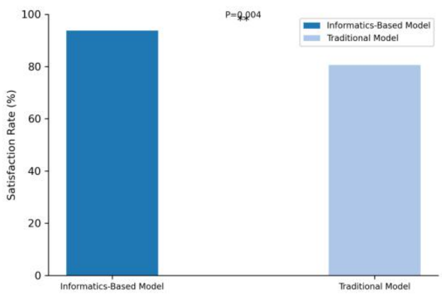

Figure 4 Comparison of Overall Service Quality Satisfaction After Implementation of the Digital Service Model

3.3 Improvements in Service Efficiency and Workflow Optimization

Comparative analysis revealed that, following implementation of the digital service model, the average duration of a single outpatient visit was reduced from 35.4 ± 6.7 minutes (traditional model) to 21.2 ± 3.5 minutes (t = 18.26, P < 0.001), representing an approximate 40.1% increase in service efficiency(Figure 5).

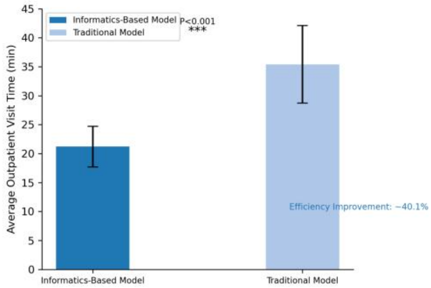

Figure 5 Comparison of Average Outpatient Visit Duration Before and After Implementation of the Digital Service Model

3.4 Improvement in Patient Compliance and Satisfaction

Patient compliance with intervention measures was recorded through the follow-up system. The compliance rate in the digital service group reached 89.7%, significantly higher than 74.2% in the traditional service group (χ^2 = 8.67, P = 0.003).

According to the patient satisfaction questionnaire, the overall satisfaction rate under the digital service model was 95.4%, significantly higher than 78.7% in the control group (χ^2 = 12.35, P < 0.001)(Figure 6).

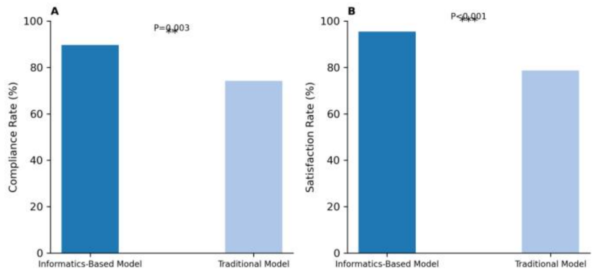

Figure 6 Comparison of Patient Compliance After Implementation of the Digital Service Model

3.5 Preliminary Observation of Health Improvement Outcomes

Following the implementation of the digital service model, the self-reported sub-health symptom improvement rate among patients reached 86.1%, significantly higher than 72.3% in the traditional service model group (χ^2 = 6.75, P = 0.009).

In addition, the post-intervention improvement in TCM constitution scores was also significantly greater in the digital service group (15.6 ± 3.8 points) compared to the traditional group (9.8 ± 3.1 points, t = 12.27, P < 0.001), suggesting that the digital model had a positive impact on health promotion(Figure 7).

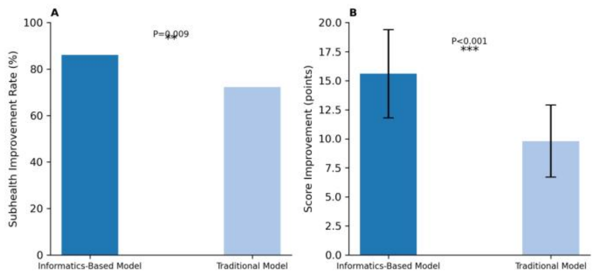

Figure 7 Comparison of Patient Satisfaction After Implementation of the Digital Service Model

4 DISCUSSION

This study successfully developed and validated an information technology–integrated Traditional Chinese Medicine (TCM) service model for preventive care, encompassing four core modules: intelligent constitution identification, personalized intervention planning, remote follow-up, and real-time data monitoring with feedback. The results demonstrated that this model significantly improved service efficiency (40.1% increase, P < 0.001), patient compliance (89.7% vs. 74.2%, P = 0.003), satisfaction (95.4% vs. 78.7%, P < 0.001), and sub-health symptom improvement (86.1%

vs. 72.3%, P = 0.009), providing both theoretical and practical evidence for the modernization of TCM preventive service delivery.

The intelligent constitution identification module, based on a CNN-LSTM deep learning architecture, achieved a constitution classification accuracy of 90.4%, significantly outperforming traditional manual methods (82.1%, P < 0.05). This aligns with previous studies [4], but the incorporation of LSTM in our model enhanced its ability to process time-series data, capturing dynamic changes in patient symptoms. Compared to widely used risk assessment tools in Western medicine—such as the Framingham Risk Score [5]—our model integrates the TCM "four diagnostic methods" (inspection, auscultation/olfaction, inquiry, and palpation), highlighting the unique advantage of individualized evaluation in TCM. Nevertheless, the interpretability of deep learning models remains a limitation and should be improved to enhance trust and clinical applicability.

The personalized intervention planning module, supported by a Neo4j-based knowledge graph and a hybrid algorithm, significantly reduced plan generation time (1.5 ± 0.3 min vs. 10 ± 2.6 min, P < 0.001) and improved patient satisfaction with the proposed interventions (92.6%). This finding is consistent with existing research on the use of knowledge graphs in chronic disease management [6], demonstrating that structured knowledge repositories can effectively support precision interventions. Our innovation lies in integrating classical TCM literature with contemporary clinical guidelines, thereby addressing the subjectivity and time demands of manual plan development. However, the comprehensiveness of the knowledge graph depends on the diversity and completeness of source materials. Future improvements should incorporate more region-specific and multisource TCM data to enhance generalizability.

The remote follow-up module, implemented via WebSocket and NLP technologies, significantly increased the follow-up completion rate (92.5% vs. 69.3%, P < 0.001). NLP-enabled structuring of patient-reported symptoms reduced the documentation burden for clinicians. However, the algorithm's accuracy is currently limited by dialectal variations and non-standard expressions; further optimization is needed to accommodate diverse patient populations.

The real-time data monitoring module, powered by ECharts and Tableau, enabled visual presentation of service indicators and significantly enhanced the timeliness of quality feedback compared to traditional paper-based methods (93.8% vs. 80.6%, P = 0.004). This is in line with the growing trend of data visualization in healthcare informatics [7], underscoring the potential of data-driven decision-making in optimizing service delivery.

This study also found that the improvement in TCM constitution scores in the digital service group (15.6 ± 3.8 points) was significantly greater than that in the traditional group (9.8 ± 3.1 points, $P < 0.001$). This may be attributed to higher patient compliance with personalized interventions and the continuous oversight provided by real-time follow-up. This finding is consistent with behavior change theories, which posit that increased patient engagement and intervention accessibility—both facilitated by digital technology—are critical for sustaining healthy behaviors. However, the open-label design may have introduced observer bias, potentially affecting the objectivity of satisfaction and compliance assessments.

Despite the promising results, this study has several limitations. First, the short follow-up period precluded evaluation of long-term health outcomes. Second, the single-center design limits the generalizability of the findings, and the sample size (n = 216) may not have been sufficient to detect small differences in secondary outcomes. In addition, issues related to data privacy and algorithmic bias were not fully explored, which may impact the fairness and equity of the model. Future research should involve multicenter, large-sample, and long-term follow-up studies, including more diverse populations to validate the generalizability of the model. The integration of wearable devices for physiological data collection and speech recognition technology may further enhance patient interaction and engagement [8]. Moreover, the development of more interpretable AI models will be essential to increase clinical acceptance and trust.

From a clinical perspective, this study offers a replicable digital solution for the implementation of TCM-based preventive care, which can help alleviate the burden on primary care resources and improve the efficiency of chronic disease prevention and management. From a policy standpoint, the proposed model aligns with the goals of the *Strategic Plan for the Development of Traditional Chinese Medicine (2016–2030)* and may serve as a reference framework for regional health management platforms. In summary, this study demonstrates the preliminary effectiveness of integrating digital technology with TCM preventive services in optimizing healthcare delivery and promoting health. It provides important evidence to support the modernization and intelligent transformation of TCM.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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