

Research on the Construction and Performance Evaluation of an Intelligent Communication Model for Traditional Chinese Medicine Culture from the Perspective of Digital Empowerment

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ABSTRACT This study aims to construct a systematic and evaluable intelligent communication model for Traditional Chinese Medicine (TCM) culture under the framework of digital empowerment. As modern digital communication increasingly relies on electromagnetic information transmission, wireless networking technologies, and intelligent interactive infrastructures to support multimodal content delivery, the efficient dissemination of TCM culture requires an integrated architecture that combines data intelligence with adaptive communication strategies. By integrating communication studies, cognitive science, and information technology, a three-layer intelligent communication architecture consisting of a data support layer, intelligent content generation layer, and precise user interaction layer is proposed, together with a cross-layer governance and compliance mechanism. The key technical contribution lies in the development of a deep recommendation algorithm that incorporates domain knowledge graphs and in the establishment of a comprehensive performance evaluation framework based on the Analytic Hierarchy Process (AHP) and a multi-indicator weighted summation model. Validation using publicly available cases, including the “New Medical Hub” platform and an intelligent herbal dispensing system, demonstrates that the proposed framework effectively expands communication coverage, enhances cultural understanding, and promotes health behavior transformation. The study further identifies critical challenges associated with data standardization, interpretable algorithms, and cross-domain governance, while highlighting the potential of intelligent communication systems operating over electromagnetic information infrastructures to facilitate scalable and reliable digital cultural dissemination.

INDEX TERMS traditional chinese medicine culture, intelligent communication, knowledge graph, electromagnetic information transmission, digital empowerment

I. INTRODUCTION

IN the wave of digitalization and intelligence, the integration of Traditional Chinese Medicine culture with advanced materials science faces a historic opportunity to transform traditional health paradigms into modern, bio-compatible fiber technologies. However, current practices mostly focus on single technology applications or content digitization, lacking a holistic framework that integrates “data-algorithms-evaluation” from a systems engineering perspective. Meanwhile, the measurement of communication effectiveness is often limited to superficial traffic statistics, making it difficult to scientifically quantify the depth of cultural understanding and behavioral transformation effects, resulting in strategy optimization lacking empirical basis [1]. Existing research has paid attention to theoretical discussions and case descriptions, but shows

significant deficiencies in the formal description of key technical pathways and quantitative aggregation methods for evaluation indicators. Related studies have further explored the application of knowledge graphs in TCM.

To fill this gap, the core tasks of this study are: first, to construct an intelligent communication system model with a clear technical stack and well-defined module interfaces; second, to design a multi-dimensional performance evaluation indicator system and quantitative model that combines theoretical rigor with practical operability; third, to conduct preliminary validation of the effectiveness of the model and evaluation methods through publicly available case data. This research focuses on the “how-to” of integrating TCM culture with high-performance engineering, aiming to provide a digital communication solution that balances theoretical foresight with the practical measurement of func-

tional fiber efficacy.

II. THEORETICAL FRAMEWORK FOR INTELLIGENT COMMUNICATION OF TCM CULTURE

A. INTERDISCIPLINARY PERSPECTIVE OF COGNITIVE SCIENCE AND COMMUNICATION STUDIES

The intelligent communication of TCM culture essentially optimizes the complex process from knowledge transmission to meaning construction through technological mediation. Cognitive science points out that audiences face cognitive barriers in understanding holistic thinking modes such as "syndrome differentiation and treatment." One of the core tasks of intelligent communication is to build low cognitive load learning paths through multimodal interactive design. For example, using 3D visualization technology to dynamically demonstrate meridian circulation has been experimentally proven to significantly improve identification accuracy among beginners (Zhao L, 2024) [2].

From a communication studies perspective, digital technology has promoted the decentralization of communication network structures. Intelligent communication systems therefore need to possess networked collaboration and dynamic response capabilities. Their goal is not merely to transmit information, but to build an online cultural community that facilitates meaning negotiation. The system identifies discussion focuses in community interactions through semantic analysis and automatically pushes related knowledge, thereby deepening collective understanding and cultural identity through interaction. This process embodies the paradigm shift in communication from "one-way indoctrination" to "two-way negotiation," providing a theoretical foundation for the digital construction of cultural identity [3].

B. COLLABORATIVE MECHANISM OF MULTIMODAL CONTENT GENERATION AND USER EXPERIENCE

The advantage of intelligent communication lies in utilizing technologies such as AIGC, VR/AR, etc., to achieve innovative content forms that transform abstract theories into perceptible experiences. However, the effectiveness of technology ultimately depends on its precise matching with user experience needs. This relies on a continuous "perception-decision-feedback" closed loop. The system builds dynamic user profiles by analyzing user interaction data, and accordingly adjusts content strategies and interaction methods. For example, recommending personalized medicinal diet videos to health enthusiasts, or connecting difficult case consultants to intelligent Q&A modules. This data-driven personalized collaboration is key to enhancing user stickiness and communication depth. Research shows that personalized content delivery based on user profiles can effectively improve the acceptance and memory retention of cultural information [4].

III. CONSTRUCTION OF AN INTELLIGENT COMMUNICATION MODEL FOR TCM CULTURE

A. THREE-LAYER ARCHITECTURE MODEL FOR INTELLIGENT COMMUNICATION

This study proposes a three-layer system model comprising a data support layer, intelligent content generation layer, and precise user interaction layer (as shown in Figure 1). These layers exchange data and invoke functions through standardized interfaces, forming an organic whole. To address the critical challenge of adapting this model to new domains, we explicitly introduce a cross-cutting governance and compliance module that interfaces with all three layers, ensuring the system's outputs adhere to relevant regulations and ethical guidelines from the outset.

- *Data Support Layer:* As the foundation of the system, this layer is responsible for the aggregation, governance, and knowledge transformation of multi-source heterogeneous data. Its core is to build a unified TCM culture data platform that integrates digitized ancient texts, modern medical records, user behavior logs, and, in future applications, standardized performance data of functional fibers according to industry protocols, and utilizes blockchain to ensure the immutability of key data (such as Chinese herbal medicine traceability information), providing high-quality, standardized data services for upper-layer applications. This standardization is critical when applying the model to industry contexts, where consistent measurement of fiber performance characteristics must follow established industry protocols. The data governance process of this layer should include critical steps such as data cleaning, entity alignment, and terminology standardization to address the challenge of high heterogeneity in TCM data. This layer is responsible for interfacing with the Governance & Compliance Module to ensure all data, especially sensitive user information, is handled according to privacy laws like GDPR or local equivalents.
- *Intelligent Content Generation Layer:* The task of this layer is to achieve automated, personalized content production. It relies on materials and knowledge provided by the data support layer, invoking large language models (LLMs) fine-tuned with TCM domain knowledge or specialized deep neural networks (DNNs), knowledge graphs, and multimodal generation algorithms to create, adapt, and reorganize content. For example, automatically generating a series of popular science graphics and short videos based on current seasons and epidemiological data. Content generation strategies need to set up cultural accuracy verification modules to ensure that the output content conforms to core TCM theories and avoids misleading [5]. Before any content is pushed to the user layer, the Governance & Compliance Module reviews it for potential violations, such as unsubstantiated health claims or culturally insensitive portrayals.
- *Precise User Interaction Layer:* As the terminal directly facing users, this layer is responsible for deliver-

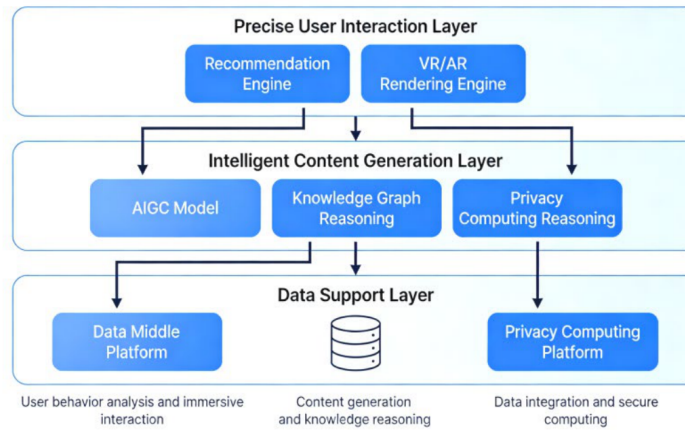


FIGURE 1. Three-layer Architecture Diagram of TCM Culture Intelligent Communication System, including an integrated Governance & Compliance Module

ing content at the right time, through the right channels, and in the right format. It contains two core engines: one is an intelligent recommendation engine based on user profiles and scene awareness; the other is a VR/AR rendering engine that provides immersive experiences. Interaction design should follow the cognitive principle of "from superficial to deep," initially attracting users with interesting, experiential content, and gradually transitioning to content with stronger theoretical and professional characteristics. This layer enforces compliance by, for example, obtaining necessary user consents for data tracking and personalization, as directed by the governance module.

B. KEY TECHNICAL IMPLEMENTATION PATHWAYS

1) Construction of TCM Knowledge Graph Based on Improved TransE Model

The knowledge graph is the "brain" of the intelligent system. Its construction first requires information extraction from unstructured texts (such as ancient classics). We adopt the BiLSTM-CRF model for entity recognition, which can effectively capture the contextual features of TCM terminology. During model training, we use annotated TCM ancient text corpora, employ the Adam optimizer with a learning rate set to 0.001, and use early stopping to prevent overfitting. Subsequently, an attention-based relation classification model is used to extract relationships between entities. It is important to acknowledge that the high accuracy of this process is contingent upon the quality and standardization of the underlying annotated corpora. The current bottleneck of "low standardization of TCM data" directly impacts the scalability of this approach to broader, uncurated datasets. Therefore, while the technology is effective on existing high-quality corpora, its widespread application requires a parallel, industry-wide effort to create more standardized data. As noted in the literature, the integration of knowledge graphs with ancient TCM classics presents both challenges and future prospects [6].

Building a high-quality knowledge graph representation is crucial. We adopt an improved TransE model for knowledge embedding [7]. The traditional TransE model treats relations as translations from head entity vectors to tail entity vectors, i.e., $h + r \approx t$, where h , r , and t represent the vectors of the head entity, relation, and tail entity, respectively. In the TCM domain, to address the complexity of many-to-many relations, we introduce relation-specific projection matrices, improving the objective function to (1):

$$f(h, r, t) = \|M_r h + r - M_r t\|_2^2. \quad (1)$$

where M_r is a diagonal matrix related to relation r , used for projection transformation before adding relation semantics to entity vectors. By minimizing the loss based on this function, entities and relations can be embedded into a continuous vector space, facilitating subsequent tasks such as semantic search and associative reasoning. This improved model was tested on a self-built dataset of classic TCM formula relationships, with the Hits@10 metric for link prediction improving by approximately 7.5% compared to the original TransE model (the construction process is shown in Figure 2).

2) Deep Recommendation Algorithm Integrating Knowledge Graph and User Behavior

To achieve precise communication, we designed a collaborative filtering recommendation algorithm that integrates knowledge graph embedding and neural networks. This algorithm not only utilizes the user-item interaction matrix but also incorporates the semantic information of items (such as a health preservation article) in the knowledge graph.

The model first obtains the embedding vectors e_i of all items through the method described in the previous subsection ("Construction of TCM Knowledge Graph Based on Improved TransE Model"). For user u , we use the mean of the embedding vectors of items they have interacted with

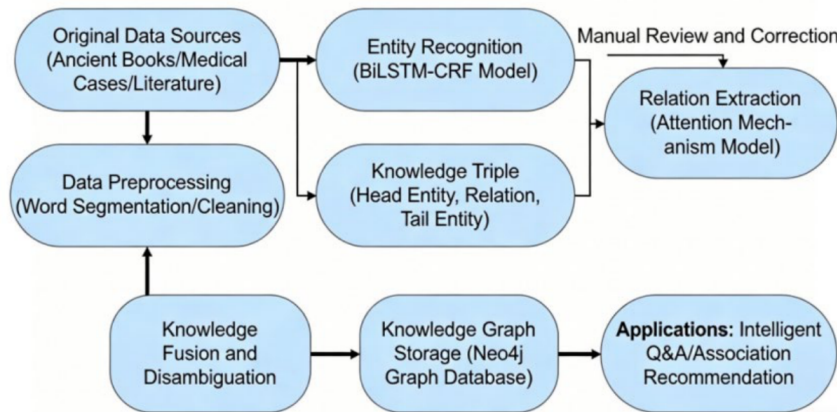


FIGURE 2. Semi-automatic Construction Process of TCM Knowledge Graph

as their initial representation p_u . However, to capture deeper user interests, we input the user vector p_u and item vector e_i together into a multi-layer perceptron (MLP) for interactive learning, predicting the click probability $\hat{y}_{ui}$ of user u on item i (2):

$$\hat{y}_{ui} = \sigma(\text{MLP}(p_u \oplus e_i \oplus (p_u \odot e_i))). \quad (2)$$

where $\oplus$ represents vector concatenation, $\odot$ represents element-wise multiplication, and σ is the sigmoid activation function. The model's loss function employs cross-entropy loss with negative sampling. By introducing the structured semantic information of the knowledge graph into the recommendation system, it can effectively alleviate the data sparsity problem and improve the accuracy and interpretability of recommendations (for example, by displaying explanation paths such as "recommended based on your attention to the 'qi deficiency' theme and the correlation between this article and the classic formula 'Sijunzi Decoction' in therapeutic principles"). This algorithm design draws on the idea of neural collaborative filtering [8]. During model training, we set the MLP hidden layers to [64, 32, 16], use

Dropout (rate=0.2) to reduce overfitting, and on simulated datasets, the AUC metric reached 0.852, which is a relative improvement of approximately 7.3% compared to the 0.794 AUC achieved by a traditional collaborative filtering baseline (Matrix Factorization) on the same simulated dataset. This comparative experiment provides preliminary evidence that the integration of knowledge graph semantics helps to mitigate the data sparsity problem by leveraging item-side information, leading to more accurate recommendations in a TCM context.

IV. DESIGN OF THE INTELLIGENT COMMUNICATION PERFORMANCE EVALUATION SYSTEM

A. MULTI-DIMENSIONAL EVALUATION INDICATOR SYSTEM

The evaluation system is constructed from four dimensions: communication breadth, depth, conversion rate, and sustainability. Breadth measures coverage, depth evaluates the degree of cognitive and identity internalization, conversion rate focuses on behavioral changes, and sustainability examines the long-term operational capability of the system itself. Specific indicators are shown in Table 1.

TABLE 1. Comprehensive Evaluation Indicator System for TCM Culture Intelligent Communication Performance

Primary Indicators	Secondary Indicators	Measurement Methods	Example Weights (Source: AHP Calculation)
Communication Breadth	Cumulative reached users	Backend data statistics, third-party monitoring	0.50
Communication Breadth	Channel coverage	Backend data statistics, third-party monitoring	0.30
Communication Breadth	Audience structure diversity	User profile analysis	0.20
Communication Depth	Content interaction depth index	Text mining (e.g., comment sentiment, semantic complexity)	0.40
Communication Depth	Knowledge gain	Standardized pre-post questionnaires	0.35
Communication Depth	Cultural identity	Likert scale	0.25
Conversion Rate	Health behavior adoption rate	Backend behavioral data tracking (e.g., online course completion, in-app feature usage, purchase of recommended wellness products) with minimal reliance on subjective reporting	0.60
Conversion Rate	Service utilization conversion rate	Backend behavioral data tracking (e.g., appointment bookings, teleconsultation usage).	0.40
Sustainability	Long-term user retention rate	User lifecycle analysis (e.g., next-month retention rate)	0.40
Sustainability	Content ecosystem health	UGC analysis (e.g., proportion of original content, interaction quality)	0.35
Sustainability	System operation efficiency ratio	System monitoring and ROI calculation	0.25

(Note: The example weights in Table 1 were calculated using the AHP method described in the following subsection("Indicator Weight Determination Method Based on AHP"), based on expert scoring, and are used to illustrate model application. In actual applications, recalculation is required based on the specific evaluation object and expert opinions.)

B. INDICATOR WEIGHT DETERMINATION METHOD BASED ON AHP

To scientifically determine the weights of each indicator, this study adopts the Analytic Hierarchy Process. First, 15 experts from the fields of TCM, communication studies, and data science were invited to conduct pairwise comparisons of indicators at each level, constructing judgment matrices $A = (a_{ij})_{n \times n}$, where a_{ij} represents the importance scale of indicator i relative to indicator j . It is crucial to clarify that the role of these experts is to assign weights to the indicators based on their perceived relative importance, not to define what constitutes "success." The "success" itself is defined by the multidimensional indicators (e.g., knowledge gain, behavior change). Therefore, while expert input is subjective, the final evaluation score E is an objective aggregation of standardized performance data against these weighted criteria, mitigating the risk of a self-fulfilling prophecy. The maximum eigenvalue $\lambda_{\max}$ of the judgment matrix and its corresponding eigenvector w are calculated. After normalizing w , the weight vector of each indicator is obtained. To ensure judgment consistency, the consistency ratio $CR = CI/RI$ needs to be calculated, where $CI = (\lambda_{\max} - n)/(n - 1)$, and RI is the average random consistency index. Usually, $CR < 0.1$ is required. The example weights in this paper (as shown in Table 1) were calculated through this process using Yaahp 12.0 software, with all judgment matrix CR values less than 0.1, meeting consistency requirements. For example, in the calculation

of the judgment matrix fragment for the three secondary indicators under "Communication Breadth," the resulting example weights were 0.50, 0.30, and 0.20 respectively.

C. COMPREHENSIVE PERFORMANCE EVALUATION MATHEMATICAL MODEL

To obtain an overall performance score, we establish a multi-indicator weighted summation model. First, due to different dimensions of each indicator, standardization processing is required. For positive indicators (such as reached user numbers), extreme value standardization is used (3):

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)}. \quad (3)$$

For satisfaction and other scale indicators, direct normalization can be applied.

Assuming there are n evaluation indicators, the standardized value of the i indicator is s_i , and its weight determined through AHP is w_i , then the comprehensive performance evaluation value E is (4):

$$E = \sum_{i=1}^n w_i \cdot s_i, \quad \sum_{i=1}^n w_i = 1. \quad (4)$$

This model aggregates multidimensional indicators into a comprehensive score within the $[0, 1]$ interval, facilitating longitudinal comparisons of the performance of the same platform at different times, or horizontal comparisons of the performance of different platforms. To further enhance the robustness of the evaluation, sensitivity analysis could be introduced in the future to explore the impact range of key indicator weight variations on the comprehensive score E [9]. The execution process of this evaluation model is shown in Figure 3.

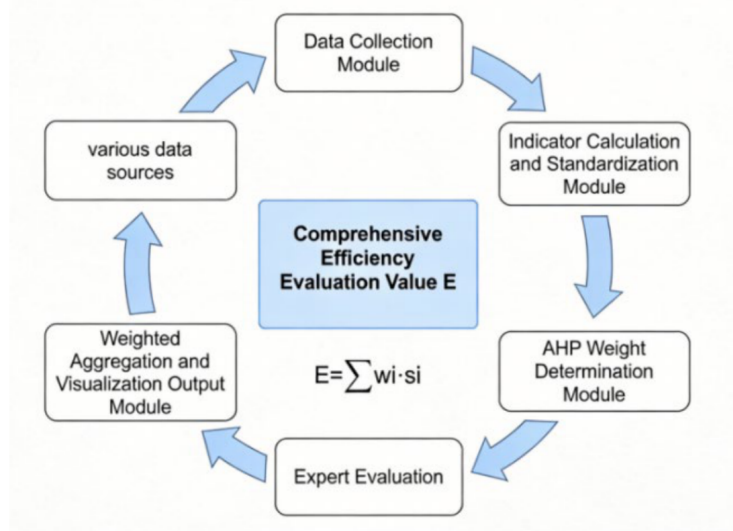


FIGURE 3. Execution Process Diagram of Intelligent Communication Performance Evaluation Model

V. EMPIRICAL ANALYSIS AND CASE VERIFICATION

A. MODEL EFFECT VERIFICATION BASED ON PUBLIC DATA

We selected two representative public cases and verified them by inputting into the evaluation framework. It is important to note that these cases were chosen to validate the core TCM cultural communication model. The industry adaptation represents a distinct application domain that will require further validation in future research. The subsequent section on future challenges will explicitly discuss the modifications and data requirements—such as the integration of "fiber data standardization" and the development of "interpretable algorithms for high-speed manufacturing"—for extending this model to the industry, thereby bridging the current empirical analysis with the stated research objectives.

1) Case One: China Traditional Chinese Medicine Holdings' "New Medical Hub" platform

This platform embodies comprehensive application of the three-layer architecture. Its development aligns with policy encouragement for digital TCM [10] and specific policy documents promoting digital TCM development [11]. Public data shows: in terms of communication breadth, it has reached over 300 counties and cities nationwide, benefiting more than 500,000 people; in terms of conversion rate, it has directly served over 50,000 grassroots doctors [12,13]. If its data is input into the evaluation model, assuming good standardized scores across dimensions, its comprehensive performance score E would mainly benefit from outstanding performance in breadth and conversion rate, reflecting the value of platform-based comprehensive strategies.

2) Case Two: Beijing University of Chinese Medicine's intelligent Chinese herbal medicine dispensing system

This case demonstrates deep empowerment in vertical scenarios. Data shows its conversion rate is extremely high—cumulatively serving over 1.05 million times, with 100% accuracy and satisfaction rates [14,15]. In the evaluation model, this system would receive extremely high scores on indicators related to "conversion rate" and "service precision," although its direct communication breadth may not match mass platforms, its effectiveness in specific dimensions is significant. This proves the evaluation model's ability to distinguish the effectiveness differences of different communication strategies.

Comparative analysis of the two cases indicates that the application of intelligent communication models can be configured with different emphases according to objectives (mass popularization or professional deepening).

VI. DISCUSSION AND FUTURE OUTLOOK

A. CHALLENGES IN TECHNICAL IMPLEMENTATION AND CULTURAL ADAPTABILITY

The successful deployment of this model faces dual challenges. At the technical level, the low standardization of TCM data remains a bottleneck for improving algorithm

model effectiveness. In the future, it is necessary to promote industry-wide co-construction of high-quality annotated datasets and standard terminology sets. Additionally, the current algorithms (such as recommendation models) lack interpretability, making it difficult to convincingly explain why specific cultural content is recommended, which is particularly crucial in healthcare-related fields. Developing explainable artificial intelligence (XAI) frameworks suitable for TCM is a necessary direction, such as using knowledge graphs to provide reasoning paths, or employing attention mechanisms to visualize model decision-making bases [16]. When adapting this model to the industry, this challenge manifests as the need for "interpretable algorithms for high-speed weaving" to ensure quality control and process optimization can be understood and trusted by engineers. These algorithms must process manufacturing data at rates exceeding 200 samples per second while maintaining explainability of quality decisions. Furthermore, this adaptation critically depends on "fiber data standardization," requiring the creation of unified databases for material properties—a prerequisite as fundamental as standardized TCM terminology. Such standardization requires adherence to international testing protocols (e.g., ISO 139 for conditioning and testing environments) to ensure cross-border applicability.

At the cultural level, balancing cultural authenticity and communication effectiveness is a core issue. When using algorithms for cross-cultural adaptation, ethical boundaries must be established to prevent core concepts from being improperly simplified or distorted. It is recommended to draw on WHO ICTM standards to establish multi-modal interpretation norms, maintaining cultural essence while innovating expression. A "cultural accuracy review-user feedback-algorithm iteration" collaborative mechanism could be established to ensure that communication content is both vivid and easy to understand while maintaining professional essence [17].

B. FUTURE RESEARCH DIRECTIONS

Future research can be deepened in three aspects: first, algorithm innovation, exploring few-shot learning and causal inference models that integrate TCM syndrome differentiation thinking to enhance AI's cultural understanding ability; second, evaluation deepening, introducing sensitivity analysis based on the comprehensive evaluation model to explore the impact of different weight allocations on results, enhancing evaluation robustness; third, ecosystem construction, promoting the establishment of an open and collaborative innovation ecosystem, encouraging the development of modular tools based on unified data standards and interfaces, lowering the threshold for small and medium organizations to apply intelligent communication technology. Additionally, the construction of interdisciplinary research teams is crucial, requiring deep collaboration between TCM experts, data scientists, communication researchers, and product designers. For the industry, future work must focus

on developing the foundational "fiber data standardization" pro-protocols and creating "interpretable AI models" that can provide real-time insights into complex manufacturing parameters, thereby translating the principles of intelligent TCM communication into tangible advancements in smart fiber technology.

VII. CONCLUSION

This study constructed a three-layer system model for the intelligent communication of TCM culture, integrating sensory data into a technical chain that formally describes knowledge graph construction and personalized recommendation algorithms. Simultaneously, the research designed a quantifiable mathematical model to evaluate performance across health indicators, weight assignment, and comprehensive calculation. Through analysis of publicly available cases, the rationality and practicality of this framework were verified.

The research results show that intelligent communication is not simply a pile of technologies, but a systems engineering project requiring alignment of data, algorithms, evaluation, and humanistic values. Future work should focus on promoting open data standards and interpretable algorithms that bridge TCM knowledge with advanced material properties, establishing interdisciplinary collaborative governance frame-works to achieve the "culturally authentic digital empowerment" of TCM culture through smart fiber digital technology.

AUTHOR CONTRIBUTIONS

Jiandong Liu designed, collected and analyzed the data, and drafted the manuscript. Jiandong Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jiandong Liu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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