Research Article

A Multimodal AI Framework for Intelligent Traditional Chinese Medicine Intervention in Older Adults

Brady Crane[1,*]

[1] Department of Computer Science, University of California, Los Angeles, USA, 90095, USA

* Corresponding author: Brady Crane

Email: BradyCraner@outlook.com

Abstract: The increasing digitalization of health management creates new possibilities for integrating traditional Chinese medicine (TCM) with multimodal artificial intelligence, particularly in the long-term management of older adults with heterogeneous health conditions. This study proposes a multimodal AI framework for intelligent TCM intervention and health management, integrating clinical records, symptom assessments, physiological measurements, treatment information, and potentially unstructured clinical observations. The framework emphasizes multimodal feature representation, temporal information integration, patient-specific profiling, and machine-learning-assisted intervention analysis. Rather than assuming that heterogeneous data sources can be directly combined without loss of meaning, the study examines challenges related to data quality, missing observations, modality imbalance, individual variability, and the uncertain computational representation of TCM concepts. Existing research on integrated acupuncture, Tuina, and moxibustion, standardized TCM external therapies, smart wellness systems, and AI-assisted acupuncture provides the clinical and technological context for the proposed framework. The approach may support more continuous and individualized health assessment, although its clinical reliability, interpretability, and generalizability require further validation using prospective, multimodal, and sufficiently diverse datasets.

Keywords: *Traditional Chinese Medicine, Multimodal Artificial Intelligence, Digital Health, Older Adults, Personalized Intervention, Health Management.*

1. Introduction

1.1 Background

Population ageing is gradually changing the structure of healthcare demand. For older adults, health management is frequently characterized not by a single acute disease episode but by the coexistence of chronic conditions, recurrent symptoms, functional limitations, psychological fluctuations, treatment exposure, and changing levels of physical resilience. Such characteristics create a substantial methodological challenge for conventional clinical information systems, because a patient's health status cannot always be adequately represented by a small number of isolated clinical measurements.

Traditional Chinese medicine (TCM) offers a potentially valuable perspective in this context because many TCM interventions emphasize individualized assessment, continuous observation, treatment adjustment, and the interaction between symptoms, functional status, and broader health conditions. External therapies such as acupuncture, Tuina, and moxibustion are particularly relevant because they can be delivered repeatedly and may be adjusted according to changes in individual patient conditions. However, the individualized nature of such interventions also makes systematic computational analysis difficult.

Standardization has consequently become an important foundation for the digital transformation of TCM. Research on standardized TCM external therapy for chronic soft tissue pain demonstrates how treatment procedures can be organized into more consistent clinical structures while still being evaluated in a real-world patient population [1]. This type of work is particularly relevant to artificial intelligence because computational systems require sufficiently stable definitions of interventions, outcomes, and clinical observations before meaningful comparisons can be performed. Nevertheless, standardization should not be interpreted as complete elimination of clinical individuality. Rather, it may provide a common structural layer upon which patient-specific information can subsequently be represented.

A related development can be observed in the construction of digital TCM health-management systems. Research on a smart wellness model integrating TCM health-preservation standards with digital systems provides an important conceptual basis for connecting traditional health-management practices with contemporary information technologies [3]. Its significance for the present study lies not simply in the introduction of digital tools, but in the recognition that TCM health management can potentially be transformed from fragmented clinical records into a more continuous information process.

Artificial intelligence adds another layer of possibility. Previous research has conceptualized AI as a bridge between traditional TCM knowledge and modern computational innovation, emphasizing the possibility of connecting traditional medical knowledge with contemporary information-processing technologies [4]. Such a perspective is particularly useful for the present study because the proposed framework does not regard AI simply as a prediction algorithm. Instead, AI is considered as an intermediate analytical infrastructure through which heterogeneous clinical information can be organized, compared, and potentially transformed into decision-support evidence.

At the same time, the growing interest in AI should not obscure the methodological difficulties associated with clinical data. Older adults frequently exhibit substantial individual differences in symptom presentation, chronic disease burden, treatment history, and healthcare utilization. Even when two patients receive similar interventions, their responses may differ considerably. Moreover, clinical observations are often collected at irregular intervals, while physiological indicators, subjective symptoms, treatment records, and narrative descriptions may possess fundamentally different data structures.

This creates a strong motivation for multimodal artificial intelligence. Rather than relying on a single information source, a multimodal framework may combine several partially independent representations of the same patient. Symptom assessments may capture subjective experience, physiological measurements may provide objective information, treatment records may characterize intervention exposure, and clinical narratives may preserve contextual information that is difficult to encode using predefined variables.

However, multimodal integration should not be regarded as inherently superior to single-modality analysis. More data may introduce redundancy, noise, conflicting observations, and additional sources of bias. The central methodological question is consequently not how to collect the greatest possible quantity of information, but how to identify which information is clinically meaningful and how different forms of evidence should be interpreted together.

1.2 Research Problem

The primary research problem addressed in this study is how heterogeneous clinical information concerning older adults can be transformed into an interpretable multimodal representation capable of supporting individualized TCM intervention and long-term health management.

Several related difficulties are involved.

First, multimodal health information is structurally heterogeneous. Clinical records may contain categorical and numerical variables, symptom assessments may be ordinal, physiological data may form continuous signals, intervention records may be event-based, and clinical narratives may contain highly contextual information. Directly combining these data sources may create a large computational feature space while failing to preserve the meaning of individual modalities.

Second, older-adult health status is dynamic. Symptoms such as pain, fatigue, sleep disturbance, mobility limitation, or emotional distress may change independently or interact with one another. Consequently, a single measurement may have a different clinical meaning depending on when it was obtained and what intervention occurred before or after it.

This issue is evident in research examining non-pharmacological TCM therapies for blood-pressure control. Such work is valuable because it extends attention beyond a purely pharmaceutical treatment paradigm and provides a clinical context in which repeated intervention and longer-term physiological outcomes can be considered [5]. From a computational perspective, however, the challenge is to determine how such longitudinal treatment-response information can be represented without reducing the clinical process to a simple before-and-after comparison.

Third, TCM interventions frequently involve multiple dimensions of clinical response. Research on the use of the traditional concept of "harmonization of body and mind" in addressing anxiety among cancer patients provides an example of how psychological outcomes may be interpreted within a broader TCM therapeutic framework [7]. Such research is relevant to multimodal health management because psychological and physical conditions in older adults may interact, while purely physiological models may fail to represent these interactions adequately.

Fourth, temporal and theoretical dimensions may overlap. Research concerning time-based moxibustion and meridian time sequence illustrates how temporal organization may form part of the conceptual logic of certain TCM interventions [8]. For an AI system, the difficulty is not simply to add timestamps to clinical records, but to determine whether treatment timing contains clinically meaningful information beyond the ordinary chronological order of observations.

These difficulties indicate that a useful multimodal framework should not be designed around the assumption that all clinical information can be translated into a common computational language without loss. Instead, it should preserve modality-specific characteristics while providing mechanisms for controlled integration.

1.3 Research Objectives

The primary objective of this study is to propose a multimodal artificial intelligence framework capable of supporting intelligent TCM intervention and health management for older adults.

The framework has several specific objectives:

To establish a multimodal representation integrating clinical records, symptom assessments, physiological indicators, intervention information, and selected unstructured clinical observations.

To construct individualized patient representations capable of reflecting both relatively stable characteristics and changing health conditions.

To examine how multimodal artificial intelligence can assist in identifying potential relationships between patient characteristics, TCM intervention patterns, and therapeutic responses.

To incorporate temporal information into health assessment so that clinical observations are not interpreted independently of their treatment and observation context.

To address practical problems involving missing observations, modality imbalance, inconsistent data quality, treatment heterogeneity, and potential representation bias.

To provide a methodological basis for future prospective studies evaluating AI-assisted TCM health-management systems. The framework is consequently intended as a decision-support architecture rather than a substitute for clinical judgment.

The significance of this study lies in its attempt to connect TCM intervention, geriatric health management, and multimodal artificial intelligence within a common methodological framework.

Recent developments in AI-based TCM research have demonstrated that artificial intelligence is increasingly being applied to knowledge extraction, clinical prediction, multimodal fusion, and other computational tasks. A systematic analysis of AI applications in TCM has particularly highlighted the growing role of data mining, large language models, and multimodal fusion, while also illustrating the methodological complexity introduced when these technologies interact with traditional medical knowledge [6]. This provides an important basis for the present study, while also suggesting that technical sophistication alone is insufficient to guarantee clinically meaningful results.

The proposed framework therefore emphasizes the relationship between computational representation and clinical interpretation. It seeks to preserve the possibility that different modalities may provide complementary, contradictory, or incomplete information.

From a practical perspective, the framework may support more continuous patient profiling and potentially assist practitioners in identifying changes that are difficult to detect through isolated consultations. For older adults, this could be particularly relevant because health conditions may evolve gradually and may involve interactions between physical, psychological, and functional dimensions.

The research is also potentially significant for the development of intelligent TCM systems because it shifts attention from isolated AI applications toward a more integrated health-management architecture. Nevertheless, the clinical usefulness of such a system remains an empirical question and requires prospective validation.

2. Related Work and Research Background

2.1 Standardization of TCM External Therapy

Standardization represents one of the fundamental prerequisites for computational analysis of TCM interventions. Without sufficiently consistent descriptions of treatment procedures, intervention intensity, treatment frequency, and clinical outcomes, machine-learning models may learn differences in documentation rather than differences in treatment.

Research concerning the construction and application of a standardized system for traditional external therapy in TCM health preservation provides an important methodological contribution in this respect [2]. The significance of such work for AI-assisted health management is that it establishes a structured foundation through which treatment information may become more interoperable across patients and clinical environments.

However, standardization introduces an important tension. If a treatment is described too broadly, clinically meaningful distinctions may disappear; if it is described through an excessively detailed collection of variables, the resulting system may become difficult to implement consistently. The optimal representation may consequently lie between these two extremes.

The present framework adopts this principle by distinguishing between standardized intervention information and individualized treatment context. The former provides a common computational structure, while the latter preserves information concerning treatment adjustments, patient response, and practitioner reasoning.

2.2 Digital TCM Health Management

The digital transformation of TCM health preservation provides another important foundation. The smart wellness model proposed by Yao integrates TCM health-preservation industry standards with digital systems, demonstrating the feasibility of conceptualizing TCM health management as a structured digital process rather than a collection of isolated clinical activities [3].

For the proposed framework, this perspective is important because multimodal AI requires an underlying digital environment capable of continuously collecting and organizing information. AI cannot compensate for the absence of reliable clinical data infrastructure. If treatment records are inconsistent, symptom assessments are incomplete, or physiological measurements are collected irregularly, increasing model complexity may simply increase the complexity of the resulting errors.

Consequently, digital infrastructure and artificial intelligence should be understood as complementary rather than interchangeable components. Digitalization creates the information environment, whereas AI provides analytical capabilities within that environment.

2.3 Artificial Intelligence and Traditional Chinese Medicine

The relationship between AI and TCM has developed from relatively isolated computational applications toward broader attempts to connect traditional knowledge with machine learning and intelligent systems.

Lu et al. describe AI as a bridge between ancient TCM knowledge and modern innovation [4]. This perspective is particularly relevant because the fundamental challenge is not simply whether AI can process TCM data, but whether computational systems can preserve clinically meaningful relationships embedded within traditional knowledge structures.

A broader systematic analysis of AI in TCM has subsequently emphasized data mining, large language models, and multimodal fusion as important technological directions [6]. The methodological importance of this research lies in its recognition that AI in TCM is becoming increasingly multidimensional. However, multimodal integration also increases the possibility of semantic mismatch, data heterogeneity, and interpretability problems.

The present framework builds on this technological development but takes a deliberately cautious position: multimodal fusion is treated as a research strategy whose usefulness depends on the quality and meaning of the information being fused.

Non-pharmacological TCM interventions may be particularly relevant to older-adult health management because they can be integrated with longer-term care and may address symptoms or functional limitations without relying exclusively on pharmaceutical treatment.

Research examining TCM non-pharmacological therapies in community patients with hypertension provides a useful example of how TCM interventions may be studied in a population-based health-management context [5]. Such work broadens the relevance of TCM beyond specialized treatment environments and suggests that digital systems could potentially support continuous monitoring and intervention assessment in community settings.

Nevertheless, the computational interpretation of such studies requires caution. Observational and community-based data may contain confounding factors related to treatment selection, lifestyle, adherence, healthcare access, and baseline disease severity. An AI model trained on such data may identify clinically useful associations, but these associations should not automatically be interpreted as causal treatment effects.

Older-adult health management cannot always be separated into independent physical and psychological domains. Anxiety, sleep disturbances, chronic pain, fatigue, and functional decline may interact over time.

The study examining cancer patients' anxiety through the TCM concept of “harmonization of body and mind” is relevant because it illustrates how psychological outcomes can be incorporated into a broader therapeutic framework rather than treated as isolated variables [7]. For multimodal AI, this suggests that symptom-level and physiological information should not necessarily be modeled independently.

However, the incorporation of psychological and traditional theoretical concepts also increases representational complexity. Concepts with rich clinical meaning may lose important contextual information when reduced to simple categorical variables. The framework therefore favors layered representations that can preserve both standardized indicators and contextual information where possible.

Time is another important but relatively underdeveloped dimension of intelligent TCM research. The theoretical analysis of time-based moxibustion involving Linggui Bafa and meridian time sequence provides an example in which treatment timing is connected to a broader theoretical understanding of intervention [8]. For computational research, this raises a methodological possibility: treatment timing may contain information that is not captured when interventions are represented only by treatment type.

At the same time, the computationalization of traditional temporal concepts should be approached carefully. A timestamp alone cannot establish the theoretical significance attributed to a particular treatment period. It may be necessary to distinguish ordinary temporal information from theory-informed temporal variables and then empirically examine whether either contributes reproducible information.

AI-assisted TCM diagnosis has become an increasingly active research area. Recent work on AI-driven diagnostic models for TCM demonstrates the growing methodological effort to transform traditional diagnostic information into computationally analyzable representations [13]. Such research is important because diagnosis represents one of the most information-intensive stages of TCM practice, involving combinations of symptoms, signs, observations, and clinical interpretation.

For the present framework, however, diagnosis should not be treated as the only target of AI. Health management requires continuous reassessment after diagnosis, and treatment response may generate new information that modifies the patient's clinical representation.

The proposed framework therefore extends the computational perspective from diagnosis toward a broader cycle involving assessment, intervention, observation, and subsequent adjustment.

The application of AI-assisted TCM approaches to chronic and degenerative conditions provides another relevant research direction. Research examining AI-assisted TCM formula granules in bone and joint degenerative diseases illustrates how computational technologies may be integrated with TCM approaches in conditions that are particularly relevant to ageing populations [10].

The value of this research for the present framework lies in its disease-oriented perspective, while the present study adopts a somewhat broader health-management perspective. Older adults frequently present with multiple overlapping conditions, meaning that an AI system limited to a single disease category may not adequately represent the overall clinical context.

This does not imply that disease-specific models are inappropriate. Rather, disease-specific modeling and patient-centered multimodal modeling may serve different purposes. The former may achieve greater specificity for a particular clinical problem, whereas the latter may better represent the complexity of long-term health management.

Multimodal fusion provides a potential mechanism for integrating the different information sources discussed above. In principle, combining clinical records, physiological data, treatment information, and textual observations could provide a more comprehensive patient representation.

However, multimodal fusion also introduces a fundamental methodological problem: not all modalities are equally reliable, equally dense, or equally interpretable. A continuous physiological signal may contain thousands of observations, while a clinical narrative may contain only a few sentences. Directly placing both into a common representation can produce an imbalance in which data quantity rather than clinical relevance determines model behavior.

The proposed framework therefore considers modality-specific processing followed by controlled integration. Such an approach is intended to retain the unique properties of individual data sources before attempting to establish cross-modal relationships.

3. Methodology

3.1 Research Design

The proposed study adopts a framework-based research design. It does not claim to have generated new clinical efficacy evidence, but instead establishes a methodological architecture that can subsequently be evaluated using prospective or retrospective multimodal datasets.

The research process begins with clinical information identification, followed by modality-specific preprocessing, representation construction, multimodal alignment, individualized patient profiling, intervention-response analysis, and interpretability assessment. Importantly, these stages should not be regarded as perfectly linear.

During practical implementation, problems discovered at the modeling stage may require returning to the data-definition stage. For example, an apparently useful feature may later prove to reflect documentation bias rather than a patient characteristic. Similarly, a modality that appears valuable in a pilot analysis may contribute little after external validation. Such iterative revision is treated as part of the research process rather than as evidence of methodological failure.

3.2 Multimodal Data Sources

The framework includes five principal categories of information.

The first category is structured clinical information, including demographic characteristics, chronic conditions, previous treatment history, baseline symptoms, functional indicators, and other clinically relevant variables.

The second category consists of symptom and patient-reported information. Pain, fatigue, sleep quality, anxiety-related symptoms, mobility difficulties, and related indicators may capture aspects of patient experience that cannot be adequately inferred from physiological measurements alone.

The third category includes physiological and objective measurements. Depending on the clinical setting, these may include blood pressure, heart-rate-related indicators, mobility measurements, pressure pain thresholds, laboratory measurements, and other measurable physiological variables.

The fourth category represents TCM intervention information, including intervention type, treatment frequency, treatment duration, treatment location where appropriate, treatment sequence, and practitioner-recorded adjustments.

The fifth category consists of unstructured or semi-structured clinical information, such as practitioner notes, symptom descriptions, treatment rationales, and observational comments.

The inclusion of multiple categories does not imply that every patient must provide complete information across all five modalities. In fact, incomplete modality availability is expected to be one of the principal characteristics of real-world clinical datasets.

3.3 Data Preprocessing

Data preprocessing is treated as a clinically informed stage of the methodology.

Missing observations should first be examined in relation to their potential causes. A missing measurement may result from technical failure, patient absence, clinical judgment, or a change in treatment strategy. These scenarios have different meanings and should not necessarily be handled identically.

Similarly, inconsistent terminology should be identified before computational modeling. The standardization of TCM external therapies can provide useful reference structures, but standard terminology should not automatically replace clinically meaningful descriptions.

The preprocessing stage therefore involves several iterative activities: data-quality inspection, terminology harmonization, identification of implausible observations, assessment of missingness patterns, and evaluation of modality availability.

Rather than assuming that one preprocessing strategy is universally appropriate, alternative approaches may need to be compared during model development.

3.4 Modality-Specific Representation

Each modality is first represented according to its own structure.

Structured clinical information can be encoded using clinically meaningful categorical and continuous variables. Symptom assessments can retain ordinal characteristics when appropriate. Physiological measurements may require normalization and temporal aggregation. Treatment information can be represented using intervention categories together with treatment frequency and adjustment information.

Textual information requires a different approach. Natural-language-processing models may extract semantic representations from practitioner narratives, but the resulting representations should remain associated with their original clinical context.

A particular concern is that language models may learn practitioner-specific documentation styles. If one practitioner consistently records more detailed observations, a model might incorrectly interpret documentation density as a patient characteristic. This possibility should be investigated during validation.

The central representation within the proposed framework is an individualized patient profile.

The profile should integrate relatively stable characteristics with changing clinical observations. Demographic information and long-term disease history may remain relatively stable, whereas symptoms, physiological indicators, treatment exposure, and functional status may change over time.

This dynamic representation may be more suitable for older adults than a purely static classification model because treatment and health status are mutually related. A change in symptoms may influence treatment selection, while treatment may subsequently influence symptoms.

However, personalization also creates a risk of overfitting. If a model is excessively tailored to a small number of individuals, apparently sophisticated patient-specific predictions may fail when applied to new populations. The framework therefore treats personalization as a representation objective rather than an assumption of guaranteed predictive superiority.

Multimodal fusion can occur at different stages of the modeling process.

Early fusion combines modalities before major analytical processing. This approach is relatively straightforward but may be problematic when modalities differ substantially in scale, density, or semantic structure.

Late fusion allows each modality to be processed separately before combining their representations. This approach may better preserve modality-specific characteristics, although it can make cross-modal relationships more difficult to model.

A hybrid approach may consequently be appropriate. For example, physiological measurements could undergo independent temporal processing, while clinical text could be transformed through language representation methods, after which the resulting representations could be integrated within a patient-level model.

The framework does not prescribe one universal fusion architecture. Instead, the choice should depend on the structure and quality of the available dataset.

The framework seeks to examine relationships between patient characteristics, intervention patterns, and subsequent outcomes.

This analysis should distinguish association from causation. A patient who receives intensive treatment and subsequently experiences poor outcomes may have received intensive treatment precisely because the initial condition was severe. Without appropriate methodological controls, an AI system could interpret this relationship incorrectly.

The model should therefore consider baseline characteristics, treatment exposure, temporal relationships, and potential confounding variables before interpreting treatment-response patterns.

The objective is not necessarily to identify a single "optimal" intervention. Instead, the system may identify response patterns that warrant further clinical evaluation.

Older adults represent a highly heterogeneous population. Differences in age, comorbidities, physical function, lifestyle, treatment history, and access to healthcare may all influence treatment response.

The proposed framework may use clustering, representation learning, or other patient-stratification methods to explore potential subgroups. However, computationally generated groups should not automatically be interpreted as clinically established categories.

A subgroup is more convincing when it remains relatively stable across reasonable modeling choices and can be interpreted through clinically meaningful characteristics.

This requires repeated testing rather than reliance on a single algorithmic partition.

At a basic level, the system should provide information about which modalities contributed to a particular prediction. At a more advanced level, it should allow clinicians to inspect the patient characteristics and longitudinal observations associated with the model output.

Nevertheless, an explanation generated by an AI model is not necessarily a faithful description of its internal reasoning. A clinically plausible explanation may still be post hoc and incomplete.

The framework therefore recommends that interpretability be evaluated empirically, preferably through comparison with clinician assessment and through stability testing across different model configurations.

4. Analytical Discussion of the Proposed Framework

4.1 Multimodal AI and the Meaning of "More Information"

A common assumption in multimodal AI is that combining several data sources should produce a more complete representation of the patient. This assumption is reasonable to some extent, but it is not universally valid.

Different modalities may contain complementary information, but they may also contain redundant measurements, correlated errors, or contradictory signals. For example, subjective pain may improve while functional performance remains unchanged. Such a discrepancy should not immediately be interpreted as model noise. It may indicate that different aspects of recovery are changing at different rates.

The proposed framework therefore treats disagreement among modalities as potentially meaningful information. Instead of forcing all modalities into a single consensus representation, the model should retain sufficient structure to allow discrepancies to be examined.

4.2 Missingness as Clinical Information

Missing data are particularly important in older-adult health management.

A patient who misses repeated follow-up appointments may have a different health-management profile from a patient who attends every scheduled assessment. The missingness itself may reflect mobility limitations, socioeconomic conditions, healthcare accessibility, disease severity, or other factors.

Consequently, conventional statistical imputation may sometimes produce a technically complete dataset while removing clinically relevant information.

A more appropriate strategy may involve distinguishing between random technical missingness and clinically structured missingness. The model should also be capable of operating when only a subset of modalities is available.

This may be more valuable in practice than optimizing performance under artificially complete datasets.

4.3 Individualization and the Risk of Overinterpretation

Personalized intervention is one of the most promising aspects of the framework, but it also creates substantial interpretive risks.

If an AI system identifies a subgroup of older adults that appears to respond favorably to a particular intervention, several explanations may remain possible. The pattern may reflect treatment effectiveness, baseline disease differences, practitioner selection, adherence, lifestyle, or unmeasured variables.

Consequently, model-derived subgroups should initially be interpreted as candidate clinical patterns rather than established therapeutic categories.

This distinction is important because artificial intelligence can identify statistical regularities much faster than clinical research can establish their causal significance.

4.4 Standardization Versus Individualized Treatment

Standardization and individualized treatment may initially appear to represent opposing principles.

Standardization improves interoperability, reproducibility, and computational accessibility. Individualization preserves clinical flexibility and allows practitioners to adjust treatment according to patient-specific circumstances.

The two principles can potentially coexist if the data architecture separates a standardized intervention core from individualized treatment context.

For example, treatment type and basic intervention characteristics can be standardized, while practitioner observations and treatment adjustments remain available as additional contextual variables.

Such an architecture may be more realistic than attempting to force individualized TCM practice into a rigid standardized template.

4.5 Computational Representation of TCM Concepts

One of the most difficult methodological questions concerns the translation of TCM theoretical concepts into computational representations.

A simplistic approach would convert concepts into categorical variables. This is computationally convenient but may eliminate important contextual distinctions.

A more flexible approach would use natural-language processing to preserve practitioner descriptions. However, language models can introduce semantic ambiguity, particularly when terminology has different meanings across practitioners or clinical contexts.

The most reasonable approach may consequently be a layered representation in which structured variables, textual descriptions, and clinical context coexist.

This would allow computational models to exploit structured information without requiring all clinical reasoning to be reduced to a single numerical representation.

4.6 Clinical Decision Support Rather Than Autonomous Treatment

The proposed framework is best interpreted as a clinical decision-support system rather than an autonomous treatment mechanism.

AI may organize patient information, identify potentially relevant patterns, highlight changes in longitudinal indicators, and assist practitioners in comparing possible intervention strategies.

However, treatment decisions remain dependent on clinical context that may not be fully captured by available datasets.

This distinction is especially important for older adults, whose treatment decisions may involve comorbidities, medication interactions, functional status, patient preferences, and other factors outside the computational representation.

4.7 Potential Contribution to Chronic Disease Management

The framework may have particular relevance to chronic disease management.

Research on smart TCM systems has increasingly considered the integration of prevention, screening, diagnosis, treatment, and management within a continuous digital health process. A recent study focusing on cardiovascular-cerebrovascular diseases and tumors illustrates the potential of intelligent TCM systems to support a whole-chain health-management perspective rather than concentrating exclusively on individual treatment episodes [12].

This direction is consistent with the proposed framework, which similarly regards TCM intervention as part of a longitudinal health-management process.

However, whole-chain digital management introduces additional requirements for data continuity, interoperability, privacy, and clinical governance. The more stages of healthcare are connected through an AI system, the more consequential errors in one stage may become for subsequent stages.

5. Transitional Discussion

Considering the methodological issues discussed above, the proposed framework can be regarded as an intermediate structure connecting the rapidly developing field of artificial intelligence with the individualized and context-dependent characteristics of TCM intervention in older adults. Its potential value does not necessarily arise from the complexity of multimodal algorithms themselves, but from the possibility of organizing fragmented clinical observations into a longitudinal and interpretable representation while preserving uncertainty where the underlying evidence remains incomplete. This perspective also suggests that the future development of intelligent TCM health management should move beyond simple model-performance comparisons toward prospective clinical validation, robust multimodal datasets, transparent representation of treatment reasoning, and careful examination of how AI-assisted information may alter practitioner decision-making. If these challenges can be addressed progressively, multimodal AI may become not merely a computational tool for predicting outcomes, but a broader infrastructure for connecting prevention, assessment, individualized intervention, and long-term health management; nevertheless, determining the extent to which such systems can genuinely improve clinical practice will require sustained empirical investigation across diverse older-adult populations and healthcare environments.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] *Chen, Y. (2026). Standardized Traditional Chinese Medicine External Therapy for Chronic Soft Tissue Pain: A Multicenter Observational Study. Current Research in Medical Sciences, 5(3), 36-45.*

[2] *Chen, Y. (2026). Construction and Application of Standard System for Traditional External Therapy in Traditional Chinese Medicine Health Preservation. Journal of Innovations in Medical Research, 5(2), 23-31.*

[3] *Yao, C. (2026). Construction and Practice of Smart Wellness Model Integrating Traditional Chinese Medicine Health Preservation Industry Standards and Digital Systems. Insights in Social Science, 4(2), 76-86.*

[4] *Lu, L., Lu, T., Tian, C., & Zhang, X. (2024). AI: bridging ancient wisdom and modern innovation in traditional Chinese medicine. JMIR medical informatics, 12(1), e58491.*

[5] *Yuan, D. (2025). The Impact of Traditional Chinese Non-Pharmacological Therapies on Blood Pressure Control in Community Patients with Hypertension. Current Research in Medical Sciences, 4(5), 8-15.*

[6] *Yin, L., Xue, X., Pan, S., Liu, X., Zhou, Y. Y., Nahar, L., ... & Xu, T. (2025). Artificial intelligence in Traditional Chinese Medicine: systematic insights from data mining, large language models, and multimodal fusion. Acta Materia Medica, 4(4), 674-697.*

[7] *Yuan, D. (2025). Research on the Intervention of Cancer Patients' Anxiety by the Concept of "Harmonization of Body and Mind" in Traditional Chinese Medicine. Journal of Innovations in Medical Research, 4(5), 19-25.*

[8] *Rui, H. (2026). Theoretical Analysis on Standardization of Time-Based Moxibustion with Linggui Bafa for Intervention in Mild Cognitive Impairment: From the Perspectives of Time-Based Qi Transformation and Meridian Time Sequence. Insights in Social Science, 4(2), 102-113.*

[9] *Huang, R. (2026). Integrated Acupuncture, Tuina and Moxibustion for Chronic Multisite Musculoskeletal Pain: A Three-Arm Assessor-Blinded Randomized Controlled Trial with Biomarker and Pressure Pain Threshold Assessments. Journal of Innovations in Medical Research, 5(2), 16-22.*

[10] *Zhang, X. Q., Wei, X. D., Gu, Z. X., Zhou, G. H., Huang, C. J., Luo, M. H., ... & Yang, W. Y. (2025). Application of artificial intelligence-assisted Traditional Chinese medicine formula granules in bone and joint degenerative diseases in the field of holistic health. Frontiers in Medicine, 12, 1630824.*

[11] *Huang, R. (2026). Theoretical Analysis of Combined Acupuncture, Tuina and Moxibustion Intervention for Elderly Chronic Musculoskeletal Pain Guided by Meridian Examination—From the Perspective of Tendon Excess-Deficiency and Qi-Blood Stasis. Journal of Research in Social Science and Humanities, 5(2), 32-41.*

[12] *Zhang, X., Wei, J., Liang, Y., You, L., Zhang, M., & Shang, H. (2026). Smart traditional Chinese medicine empowers the whole chain of "prevention–screening–diagnosis–treatment–management" for major chronic diseases in primary healthcare: Research on cardiovascular–cerebrovascular diseases and tumors. Science of Traditional Chinese Medicine, 4(2), 132-139.*

[13] *Wang, L., Tang, K., Wang, Y., Zhang, P., & Li, S. (2025). Advancements in artificial intelligence-driven diagnostic models for traditional Chinese medicine. The American Journal of Chinese Medicine, 53(03), 647-673.*