Research Article

Time-Series Modeling and Intelligent Analysis of Therapeutic Responses to Traditional Chinese Medicine Interventions

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***Abstract*:** Traditional Chinese medicine (TCM) interventions often involve therapeutic responses that evolve over time, whereas conventional clinical analyses may treat repeated observations as relatively independent measurements, potentially obscuring temporal dependencies and heterogeneous response patterns. This study proposes a time-series modeling framework for the intelligent analysis of therapeutic responses to TCM interventions, focusing on longitudinal symptom measurements, physiological indicators, treatment-related variables, and time-dependent intervention characteristics. Building on clinical research involving integrated acupuncture, Tuina, and moxibustion, together with theoretical discussions of time-based qi transformation and meridian time sequence, the proposed framework incorporates temporal feature construction, multivariate time-series analysis, and machine-learning techniques to characterize response trajectories and explore possible relationships between intervention timing and clinical outcomes. Particular attention is given to practical challenges, including irregular observation intervals, missing measurements, individual heterogeneity, and the uncertain translation of traditional theoretical concepts into computable variables. Rather than presuming that a single algorithm can adequately capture therapeutic dynamics, several modeling strategies are considered from complementary perspectives. The framework may provide a computational basis for longitudinal evaluation and personalized TCM intervention, although further validation with sufficiently large and heterogeneous clinical datasets is needed.

Keywords: *Traditional Chinese Medicine, Time-Series Modeling, Machine Learning, Therapeutic Response, Digital Health.*

1. Introduction

Traditional Chinese medicine (TCM) has increasingly attracted attention in the context of chronic disease management, rehabilitation, health preservation, and non-pharmacological intervention. Unlike many pharmacological interventions that can be described relatively conveniently through standardized dosage and administration schedules, TCM interventions may involve a broader combination of therapeutic modalities, treatment frequency, intervention timing, patient constitution, symptom evolution, and practitioner-dependent adjustments. This complexity does not necessarily imply that TCM interventions are unsuitable for quantitative analysis; rather, it suggests that the temporal dimension of therapeutic response deserves more careful computational treatment.

Previous clinical research has examined the effects of integrated acupuncture, Tuina, and moxibustion on chronic multisite musculoskeletal pain through a three-arm assessor-blinded randomized controlled design incorporating biomarkers and pressure pain threshold measurements [2]. Such a design provides a relatively structured clinical environment in which treatment response can be observed from multiple dimensions rather than through a single subjective outcome. At the same time, clinical studies of this type primarily address therapeutic efficacy and clinical assessment, whereas the temporal structure of repeated observations may not itself constitute the central object of computational investigation. Consequently, information concerning the sequence, interval, persistence, fluctuation, and possible delayed response to intervention may remain insufficiently characterized.

The temporal issue becomes particularly interesting when considering theoretical discussions within TCM. Research concerning the standardization of time-based moxibustion with Linggui Bafa has examined intervention timing from the perspectives of time-based qi transformation and meridian time sequence [1]. Such theoretical discussion should not be interpreted as direct empirical evidence for a particular computational relationship between treatment time and therapeutic outcome. Nevertheless, it raises a question that is relevant to computational research: whether intervention time, treatment interval, and longitudinal changes in patient status can be represented as structured temporal variables rather than being treated merely as background information.

A similar consideration arises from theoretical research on elderly patients with chronic musculoskeletal pain. The analysis of combined acupuncture, Tuina, and moxibustion guided by meridian examination discusses the concepts of tendon excess-deficiency and qi-blood stasis [3]. Although these concepts are difficult to translate directly into conventional numerical variables, associated clinical observations may contain information that can potentially be structured through feature engineering, clinical annotation, or multimodal representation. The challenge is not simply to digitize traditional terminology, but to determine which aspects of such information can be represented with sufficient reliability and which should remain contextual rather than computational.

The development of digital technologies provides another important dimension for this research. A smart wellness model integrating TCM health-preservation industry standards with digital systems suggests that traditional health-management knowledge can increasingly be connected with digital infrastructures [4]. More broadly, recent research has considered the modernization of TCM diagnosis and treatment through artificial intelligence and other emerging technologies [5], while research specifically addressing artificial intelligence in acupuncture has explored the possibility of connecting traditional knowledge with precision integrative medicine [8]. These developments indicate that computational methods are becoming increasingly relevant to the transformation of TCM-related knowledge into structured digital applications, although the translation from clinical knowledge to computational representation remains methodologically demanding.

Recent work has also emphasized multimodal and data-driven approaches in acupuncture research, highlighting both the methodological opportunities and challenges associated with integrating heterogeneous forms of clinical information [9]. This perspective is particularly relevant to time-series analysis because therapeutic response is rarely represented adequately by a single variable. Symptoms, physiological measurements, treatment records, practitioner observations, and patient-reported outcomes may evolve according to different temporal patterns. A computational framework capable of preserving these differences may provide a richer representation of therapeutic dynamics than a simple pre-treatment and post-treatment comparison.

The standardization of TCM external therapy provides another important methodological consideration. Multicenter observational research has examined standardized TCM external therapy for chronic soft tissue pain [11], while another study has focused on the construction and application of a standard system for traditional external therapy and TCM health preservation [12]. These studies suggest that standardized intervention descriptions can improve the consistency of clinical observation and potentially facilitate subsequent computational analysis. However, standardization itself does not eliminate individual variation or guarantee that patients will exhibit similar response trajectories. From a computational perspective, this distinction is important: a standardized intervention protocol may improve comparability between observations, but a useful time-series model still needs to account for patient-specific trajectories.

Artificial intelligence has also begun to extend beyond diagnostic assistance toward knowledge discovery in TCM. Research on AI-enabled target discovery has described a pathway from computational prediction to experimental validation [10]. Although target discovery and longitudinal therapeutic-response prediction represent different computational problems, this work illustrates a broader transition from static digital representation toward computationally assisted inference. The present study focuses on a different layer of this process, namely the analysis of how patient conditions change over time in relation to intervention characteristics.

Clinical research on non-pharmacological TCM therapies and blood pressure control provides another example of a condition in which temporal variation may be particularly relevant [6]. Blood pressure can fluctuate naturally and may be affected by numerous behavioral, physiological, and environmental factors. Likewise, research concerning the intervention of cancer patients' anxiety through the concept of harmonization of body and mind suggests that psychological outcomes may also evolve over time rather than remaining static during an intervention period [7]. These studies do not by themselves establish a general computational model of therapeutic dynamics, but they illustrate why longitudinal representation may be useful across different clinical contexts.

Against this background, the present study proposes a time-series modeling framework for intelligent analysis of therapeutic responses to TCM interventions. The emphasis is not on proving a particular traditional theoretical proposition, but on exploring how longitudinal clinical observations can be represented, processed, and analyzed computationally. The framework considers temporal feature construction, irregular observations, missing measurements, individual heterogeneity, intervention timing, and several machine-learning-based time-series strategies.

Particular attention is given to the possibility that therapeutic response may not follow a simple monotonic pattern and that apparent treatment effects may partly reflect natural symptom fluctuation, behavioral changes, measurement variability, regression toward the mean, or differences in treatment adherence. The study consequently approaches TCM intervention from a computational rather than purely theoretical perspective. Its central concern is how a sequence of clinical observations can be transformed into meaningful temporal representations without excessively simplifying the clinical context. Such an approach may provide a foundation for longitudinal evaluation and personalized intervention, although the validity and generalizability of the proposed framework ultimately depend on the quality, scale, and heterogeneity of future clinical datasets.

2. Related Work and Research Background

2.1 Longitudinal Evaluation of TCM Interventions

The evaluation of TCM interventions has traditionally relied on clinical outcomes, symptom scores, physiological indicators, practitioner assessment, and patient-reported measures. These variables can provide clinically meaningful evidence, but their interpretation becomes more complicated when observations are collected repeatedly over time. A patient's symptom level at one observation point is not necessarily independent of the previous observation, and the change between two observations may depend not only on the intervention but also on sleep, physical activity, medication use, psychological status, environmental conditions, and ordinary fluctuation in disease severity.

The three-arm assessor-blinded randomized controlled study of integrated acupuncture, Tuina, and moxibustion for chronic multisite musculoskeletal pain provides a useful example of multidimensional clinical assessment [2]. The incorporation of biomarkers and pressure pain threshold measurements extends evaluation beyond a single subjective pain score and creates opportunities for computational analysis. However, the methodological strength of multidimensional measurement also introduces a modeling difficulty: different variables may evolve at different rates and may respond differently to treatment. A biomarker may exhibit a relatively rapid change, whereas perceived pain or functional status may change more gradually. Treating these variables as interchangeable indicators of a common therapeutic trajectory could consequently lead to oversimplification.

Research on non-pharmacological TCM therapies and blood pressure control similarly illustrates the potential importance of longitudinal clinical observation [6]. Blood pressure is intrinsically dynamic and may be influenced by numerous factors beyond the intervention under investigation. Consequently, computational models that analyze blood pressure trajectories should ideally distinguish treatment-associated changes from ordinary physiological variation. This observation is relevant to the broader framework proposed in this study because temporal modeling should not automatically transform temporal association into therapeutic attribution.

The intervention of cancer patients' anxiety through the TCM concept of harmonization of body and mind provides another example of an outcome that may possess substantial temporal variability [7]. Psychological indicators can be affected by disease progression, treatment burden, social support, and individual coping mechanisms, making it difficult to interpret short-term changes as direct consequences of a particular intervention. From a computational perspective, this reinforces the need to consider response trajectories rather than relying exclusively on isolated outcome measurements.

2.2 Temporal Characteristics and TCM Intervention

The temporal dimension has a particular conceptual relevance to TCM research. Theoretical work concerning time-based moxibustion has considered the relationship between intervention timing, time-based qi transformation, and meridian time sequence [1]. From a computational standpoint, the significance of such work does not necessarily lie in directly validating its theoretical assumptions.

Instead, it provides a conceptual motivation for examining treatment timing as an explicit research variable.

For example, the interval between interventions, the time elapsed before an observable response, the persistence of improvement, and the recurrence of symptoms may all contain clinically relevant information. A conventional pre-intervention versus post-intervention comparison can capture overall change while overlooking intermediate patterns. A time-series approach, by contrast, can potentially examine whether a response appears immediately, gradually, intermittently, or after a delayed period.

This distinction is particularly important because temporal association can have several possible explanations. A delayed improvement may reflect a genuine delayed treatment response, cumulative intervention effects, changes in patient behavior, regression toward the mean, or simply the natural course of the condition. Accordingly, temporal modeling should be regarded as a means of describing and investigating response patterns rather than as an automatic mechanism for establishing causality.

2.3 Standardization and Digital Representation

Standardization is an important prerequisite for meaningful longitudinal computation. Multicenter observational research on standardized TCM external therapy for chronic soft tissue pain indicates the importance of consistent intervention descriptions and clinical observations [11]. The construction and application of a standard system for traditional external therapy and TCM health preservation further emphasizes the role of structured standards in TCM health management [12].

Nevertheless, standardization and personalization may appear to pull in different directions. A highly standardized data structure can improve comparability between patients, but excessive standardization may remove clinically relevant contextual information. Conversely, highly individualized records may preserve clinical richness while making computational comparison substantially more difficult.

The smart wellness model integrating TCM health-preservation industry standards and digital systems provides a broader context for this issue [4]. Digital health infrastructure can potentially connect standardized knowledge with longitudinal patient information, but the quality of resulting analysis remains dependent on how the underlying information is collected and represented. Digital availability should not be confused with analytical validity.

Recent research on multimodal and data-driven approaches in acupuncture has emphasized the need to integrate heterogeneous information while also recognizing methodological challenges associated with data quality, representation, and interpretation [9]. This perspective supports a layered digital representation in which standardized clinical variables coexist with contextual information that may not yet be suitable for direct numerical encoding.

2.4 Artificial Intelligence and Computational Approaches in TCM

The increasing application of artificial intelligence to TCM provides an important computational background for the proposed framework. Research on AI-assisted acupuncture has discussed the potential for artificial intelligence to bridge traditional knowledge with precision integrative medicine [8]. Such approaches may involve knowledge extraction, pattern recognition, decision support, or patient-specific analysis. Their relevance to time-series research lies partly in the possibility of combining traditional clinical knowledge with longitudinal patient data.

At a broader level, research on TCM modernization has considered the use of artificial intelligence and nanotechnology in diagnosis and treatment [5]. While such work encompasses technological areas beyond the present study, it reflects a broader movement toward computational transformation of TCM research and clinical practice.

AI-enabled target discovery represents another direction in this modernization process [10]. Computational prediction followed by experimental validation provides a framework for connecting data-driven hypotheses with biological investigation. Although target discovery differs substantially from therapeutic-response modeling, the methodological principle of combining computational inference with subsequent empirical validation is relevant here. A time-series model should similarly be regarded as a tool for identifying potentially meaningful temporal patterns rather than as an independent source of clinical truth.

2.5 Machine Learning and Time-Series Analysis

Machine learning provides several possible approaches for modeling longitudinal clinical data. Conventional statistical time-series methods can be useful when temporal structures are relatively stable and interpretable, whereas tree-based machine-learning approaches may offer greater flexibility when nonlinear relationships and heterogeneous clinical variables are involved. Deep-learning architectures, including recurrent and attention-based models, may capture more complex temporal dependencies, although they generally require larger datasets and may be more difficult to interpret.

For TCM intervention research, the choice of algorithm should consequently be determined by the characteristics of the data rather than by the assumption that greater model complexity necessarily represents methodological improvement. In a small clinical dataset, a highly parameterized neural model may identify patterns that do not generalize beyond the training sample. Conversely, a relatively simple model may fail to represent delayed or nonlinear responses when the dataset is sufficiently rich.

Recent multimodal research in acupuncture also suggests that heterogeneous data sources may require different analytical strategies [9]. Consequently, the proposed framework remains open to several computational approaches rather than assigning a predetermined model as universally optimal.

3. Methodology

3.1 Research Design

The proposed research adopts a longitudinal computational framework in which patient observations are treated as temporally ordered records rather than as isolated clinical measurements. Each patient's observation sequence may contain intervention information, symptom assessments, physiological indicators, treatment intervals, and other clinically relevant variables. The framework is designed to accommodate repeated observations collected before, during, and after a course of TCM intervention.

The research process is not assumed to proceed through a perfectly linear sequence of data collection, preprocessing, modeling, and interpretation. In practical clinical datasets, the initial data structure may reveal irregular observation intervals, incomplete records, inconsistent terminology, or variables that appear clinically meaningful but cannot be reliably quantified. Such difficulties require iterative adjustment of the feature representation and may lead to the exclusion, reclassification, or contextual preservation of certain variables.

The framework therefore begins with clinical data characterization rather than immediate algorithm selection. The temporal distribution of observations, measurement frequency, missingness patterns, intervention intervals, and variability among patients should first be examined. Only after these characteristics become sufficiently clear should the appropriate modeling strategy be selected.

3.2 Data Representation and Temporal Feature Construction

A central methodological issue is the representation of time. A simple observation date provides only limited information. More informative temporal variables may include the elapsed time since treatment initiation, the interval between interventions, the duration of treatment exposure, the period between intervention and subsequent assessment, and the persistence of an observed response.

Clinical variables may also be divided according to their temporal behavior. Some variables are relatively stable characteristics, such as age or baseline condition. Others change gradually, such as functional status. Still others may fluctuate considerably between adjacent observations, including pain intensity, blood pressure, or subjective fatigue. Distinguishing these temporal behaviors can improve model interpretation and reduce the risk of treating fundamentally different variables as equivalent.

The proposed framework also considers the representation of intervention timing. Rather than encoding treatment simply as a binary indicator of whether an intervention occurred, the system may preserve information regarding intervention category, frequency, sequence, and temporal proximity to subsequent measurements. Such representation could allow the model to investigate whether certain response patterns are associated with treatment timing, while recognizing that association alone does not establish causation.

The multimodal perspective emphasized in recent acupuncture research [9] further suggests that temporal features should not necessarily be restricted to conventional numerical observations. Where appropriate, clinical text, practitioner assessments, and other structured or semi-structured information could potentially be transformed into additional representations, although the reliability of such transformations would require independent validation.

3.3 Handling Irregular Observations and Missing Data

Irregular observation intervals represent one of the more substantial practical difficulties in longitudinal clinical research. Patients may return for follow-up at different times, some observations may be postponed, and certain physiological measurements may only be collected when clinically indicated. Consequently, forcing all patients into an identical observation schedule may introduce artificial information that was not present in the original records.

Several strategies may be considered, including temporal interpolation, resampling, missingness indicators, and models capable of directly accommodating irregular observations. The appropriate strategy depends on the nature of the missing data and the clinical meaning of the observation process. For example, an absent measurement may indicate technical failure, patient non-attendance, or the fact that the clinician did not consider the measurement necessary at that time. These situations are not necessarily statistically equivalent.

For this reason, missing data should not be treated solely as a technical inconvenience. The pattern of missingness itself may contain information about patient behavior, disease severity, or clinical decision-making. At the same time, using missingness as a predictive feature without careful interpretation could introduce unwanted bias. Further investigation is needed to determine which missing-data mechanisms are most appropriate for different TCM intervention datasets.

3.4 Time-Series Modeling Strategy

The proposed framework considers several levels of computational modeling. Conventional statistical time-series methods may first be used to establish interpretable temporal patterns and provide baseline comparisons. Machine-learning methods can then be introduced to explore nonlinear relationships between patient characteristics, intervention timing, and therapeutic response.

Tree-based models may be useful where heterogeneous clinical features are available and nonlinear interactions are expected. Recurrent neural networks may be considered when longer sequential dependencies become important, while attention-based architectures may provide another possibility when the relative importance of different historical observations needs to be examined.

Recent research on AI-assisted acupuncture [8] and broader TCM modernization [5] suggests that computational methods may increasingly become part of TCM research infrastructures. However, the availability of sophisticated algorithms does not eliminate the need for careful model selection. A computationally advanced model may not necessarily provide a more clinically meaningful representation of therapeutic dynamics.

Model complexity should consequently be increased cautiously. A model that performs well on a limited clinical dataset may simply be learning patient-specific characteristics rather than clinically transferable response patterns. In particular, random splitting of sequential observations can create information leakage if measurements from the same patient appear in both training and evaluation subsets. A patient-level separation strategy would consequently be more appropriate for assessing generalization to previously unseen patients.

3.5 Therapeutic Response Characterization

The proposed system does not restrict therapeutic response to a single endpoint. Instead, response may be represented through several complementary dimensions, including symptom trajectories, physiological changes, functional indicators, and persistence of improvement.

This multidimensional perspective is consistent with clinical research incorporating subjective outcomes and objective indicators, such as biomarkers and pressure pain thresholds [2]. Nevertheless, different indicators may not move in the same direction. A patient could report reduced pain while a physiological indicator remains relatively stable, or an objective measure could improve before the patient notices a substantial subjective change. Such discrepancies should not automatically be regarded as measurement failure; they may represent different temporal components of recovery.

The framework may consequently allow multiple response trajectories to coexist. Clustering or representation-learning techniques could potentially identify different temporal patterns, such as rapid responders, gradual responders, fluctuating responders, and patients with limited observable change. These categories should be regarded as computationally derived patterns rather than fixed clinical classifications until independently validated.

The same principle may be relevant when extending the framework to outcomes such as blood pressure or psychological status, for which existing TCM research already suggests potentially complex intervention-response relationships.

Evaluation should extend beyond predictive performance. In clinical applications, interpretability, temporal robustness, calibration, and generalization may be at least as important as a single performance metric.

A model that predicts a patient's future symptom level with reasonable accuracy but cannot explain which temporal observations contribute to the prediction may have limited practical value for clinical decision support. Conversely, a highly interpretable model may provide useful insight even when its predictive performance is modest.

Accordingly, the framework considers model comparison from several perspectives, including predictive stability, sensitivity to missing observations, robustness across patient groups, and interpretability of temporal features. Where possible, validation should be conducted using independent patient groups or temporally separated datasets.

This emphasis on validation is also consistent with the broader development of AI in TCM, where computational prediction increasingly needs to be connected with empirical or experimental verification rather than treated as sufficient evidence in itself [10]. Such evaluation would help determine whether identified patterns reflect generalizable therapeutic dynamics or merely characteristics of a particular dataset.

4. Analytical Discussion of the Proposed Framework

The proposed time-series framework offers a different way of understanding TCM intervention outcomes by shifting attention from isolated before-and-after comparisons toward the evolution of patient states. This shift is conceptually important, but it also introduces several interpretive difficulties that should not be overlooked.

First, an observed temporal association between an intervention and subsequent improvement cannot by itself demonstrate that the intervention caused the change. Chronic pain, blood pressure, anxiety, and other clinical outcomes may naturally fluctuate, and patients may modify their behavior during treatment. Regression toward the mean may also produce apparent improvement when individuals enter treatment during periods of unusually severe symptoms. The clinical studies underlying the present framework provide important empirical contexts, but their findings should not be mechanically transformed into causal assumptions for computational models.

Second, the theoretical temporal concepts discussed in TCM require careful computational interpretation. The discussion of time-based qi transformation and meridian time sequence provides a conceptual motivation for examining intervention timing [1], but this does not mean that these theoretical constructs can simply be encoded as validated numerical variables. A computational representation may capture only one aspect of a much broader theoretical system. Premature numerical formalization could create an appearance of precision without corresponding empirical validity.

A more cautious approach would be to treat such concepts as candidate contextual variables or hypotheses for temporal analysis. If a measurable association emerges, subsequent studies could examine whether the finding persists across independent populations and alternative measurement strategies. If no stable association is observed, this would also be informative, since it could indicate that the proposed computational representation is inadequate or that the underlying relationship is more context-dependent than initially assumed.

Third, patient heterogeneity is likely to be a major source of variation. The theoretical discussion of elderly chronic musculoskeletal pain emphasizes meridian examination, tendon excess-deficiency, and qi-blood stasis [3]. From a computational perspective, patients described using similar conventional clinical variables may nevertheless exhibit substantially different temporal response patterns. Age, disease duration, baseline severity, concurrent treatment, adherence, lifestyle, and practitioner-specific intervention strategies may all contribute to this heterogeneity.

This suggests that a single population-level model may not adequately represent all patients. Personalized models or hierarchical modeling strategies could potentially address this problem, although such approaches introduce their own risks of overfitting, particularly when individual patient records are limited. Further research with larger longitudinal datasets would be needed to determine whether stable subgroups of temporal response can actually be identified.

Fourth, standardization remains both an opportunity and a limitation. Research concerning standardized external therapy [11] and the construction of standard systems for TCM health preservation [12] provides a useful foundation for computational data organization. Yet excessive standardization could remove information about clinical adaptation, which may itself be relevant to therapeutic outcomes. A treatment that appears identical at the protocol level may be implemented differently depending on patient characteristics and practitioner judgment.

The integration of TCM standards with digital systems, as discussed in research on smart wellness models [4], may provide a possible solution by allowing standardized variables to coexist with flexible contextual records. Such a structure would preserve comparability while reducing the pressure to convert every clinical observation into a rigid numerical format.

Fifth, the increasing application of AI to TCM introduces both opportunities and methodological risks. Research on AI in acupuncture has emphasized the possibility of connecting traditional knowledge with precision integrative medicine [8], while broader work on TCM modernization has considered AI as part of a larger technological transformation of diagnosis and treatment [5]. These developments suggest that intelligent systems may become increasingly useful in organizing and interpreting complex clinical information. However, computational sophistication should not be confused with clinical validity.

The recent emphasis on multimodal and data-driven acupuncture research [9] is particularly relevant here. Combining clinical text, physiological measurements, treatment records, and other information may improve representation of patient states, but multimodal integration also introduces additional sources of noise and uncertainty. Different data types may have different sampling frequencies, reliability levels, and semantic meanings. A model that integrates all available information without considering these differences could potentially become more complex without becoming more informative.

Sixth, model interpretability remains an important concern. Deep-learning approaches may potentially identify complex temporal relationships that conventional methods fail to capture, but increased predictive complexity does not necessarily correspond to increased clinical understanding. In the context of TCM intervention, where theoretical concepts and clinical observations may already involve substantial contextual interpretation, an opaque computational model could make the relationship between prediction and clinical reasoning even more difficult to evaluate.

For this reason, model explanation should be treated as part of the analytical objective rather than as an optional technical supplement. Temporal feature importance, trajectory visualization, sensitivity analysis, and patient-level explanation may help researchers understand why a model generates a particular prediction. Nevertheless, explanation techniques themselves can be imperfect, and their outputs should not be interpreted as direct evidence of causal mechanisms.

Seventh, computational prediction should remain connected to empirical validation. Research on AI-enabled target discovery in TCM illustrates a broader methodological pathway in which computational prediction is followed by experimental validation [10]. Although the present study addresses clinical time-series rather than molecular target discovery, the underlying principle is relevant: computationally identified patterns should ideally generate testable hypotheses rather than be regarded as definitive clinical findings.

The proposed framework also has implications for chronic disease and health-management research beyond the specific TCM interventions considered here. Previous work on TCM non-pharmacological approaches to blood pressure control [6] and the intervention of anxiety among cancer patients through the concept of harmonization of body and mind [7] suggests that different clinical outcomes may exhibit different temporal structures. A computational framework developed around time-dependent response may consequently be adaptable to multiple conditions, although such generalization should be empirically examined rather than assumed.

Considering these factors, the value of time-series modeling in TCM research may ultimately lie less in producing a single highly accurate predictive model and more in providing a structured language through which treatment timing, longitudinal response, patient heterogeneity, and uncertainty can be examined simultaneously. Such an approach may gradually narrow the distance between clinical observation and computational analysis without requiring either domain to be reduced entirely to the conceptual vocabulary of the other.

5. Transitional Discussion

The methodological considerations above suggest that intelligent analysis of TCM intervention should not be understood simply as an exercise in applying increasingly sophisticated algorithms to clinical records. The more fundamental issue concerns how temporal clinical experience is represented, what information is necessarily lost during digital transformation, and whether computationally identified patterns remain meaningful when returned to the clinical setting. Time-series modeling may reveal response trajectories that are difficult to recognize through isolated observations, while simultaneously exposing uncertainties arising from irregular follow-up, heterogeneous patients, incomplete measurements, and the distinction between temporal association and therapeutic causation. The growing application of artificial intelligence, multimodal analysis, and digital standardization in TCM further suggests that future computational systems may need to integrate not only numerical observations but also contextual clinical knowledge, while maintaining appropriate boundaries between computational inference and clinical interpretation. This tension provides a basis for further consideration of how computational models might support rather than replace clinical reasoning, particularly when traditional theoretical concepts are introduced as contextual hypotheses rather than predetermined computational truths. Future research may consequently need to move toward larger longitudinal datasets, prospective validation, multimodal clinical information, and more transparent human, AI interaction, allowing the proposed framework to develop from a methodological possibility into a more empirically grounded approach to personalized and digitally supported TCM intervention.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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