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Fuzzy Logic and Mathematical Decision-Making Models for Integrative Alternative Healthcare Systems

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Abstract — An inevitable issue with integrative alternative healthcare systems (IAHS) is that although clinical reasoning is fuzzy, qualitative, and dependent on the practitioner's expertise, current evidence-based requirements mandate a precise and quantifiable approach. This paper proposes a new framework for decision making within IAHS using fuzzy logic by considering the fuzzy nature of Ayurvedic doshas, TCM meridians, and constitutional types within naturopathy. In this regard, we propose a hierarchical structure of fuzzy inference systems (FISs) containing 27 rules that map qualitative input statements ("Vata moderately high," "Qi slightly weak") to recommendations of therapy along with an MCDM process using the Fuzzy TOPSIS algorithm for treatment prioritization. Applied to clinical information from 180 patients suffering from metabolic syndrome, our system yields a consensus with an expert panel of 86.4% (κ=0.82), while decreasing variability in prescription by 58% in comparison with unassisted practitioners.

Keywords— Fuzzy logic, decision-making models, integrative healthcare, alternative medicine, TOPSIS, Ayurveda, Traditional Chinese Medicine, clinical decision support.

I. INTRODUCTION

The rising trend in the emergence of the world's integrative alternative healthcare systems (IAHS) including Ayurveda, TCM, Unani, naturopathy, and homeopathy is fueled by a higher patient preference toward holistic, customized, and less intrusive treatments [1]. While conventional biomedicine employs clear-cut criteria for diagnosis (blood glucose level equal to 126 mg/dL means that a patient suffers from diabetes), an IAHS system is based on a concept of spectra, continua, and qualitative analysis. For example, a TCM specialist makes a diagnosis of "Qi stagnation with mild heat" or "Spleen Qi deficiency with dampness accumulating"—a diagnosis which cannot be quantified. Likewise, according to Ayurveda, a person can be identified through three doshas (Vata, Pitta, Kapha) but only in terms of continuum, percentage-wise, changing with seasons, aging process, and time of day [2].
But while the same vagueness is what allows for a holistic assessment, it constitutes an important obstacle to standardization, training, and incorporation into regular medical practice. Different practitioners assessing the same individual patient may come to a different conclusion regarding the dosha balance or meridian imbalance, resulting in a different treatment plan. Inconsistencies like these affect replicability, complicate conducting clinical trials, and reduce the trust of insurers and regulatory agencies. Recently conducted meta-analyses have found that the agreement rate among TCM practitioners for one individual patient varies from 0.45 to 0.65 (Cohen's kappa) [3].

The paradox can be resolved by adopting the notion of mathematical decision support models: there is no need to force fuzzy notions to become crisp concepts, which would lead to loss of information. Instead, we can mathematically model fuzziness by adopting fuzzy logic, which admits partial membership (for instance, Vata membership = 0.7) and linguistic rules [4]. Fuzzy logic-based systems have been applied successfully in many industrial applications due to their capability of translating heuristics from experts' knowledge into reliable and repeatable algorithms. We believe that such a framework can help us keep IAHS' holistic reasoning intact and add precision.

The proposed approach in this paper is a fuzzy-MCDM-based framework for IAHS decision support, with the following contributions:

- A hierarchical fuzzy inference system mapping symptoms and signs of patients to imbalances in the vector of dosha/meridians
- A fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method for ranking therapies including herbal formulas, acupoints, and diet change based on multi-criteria, including effectiveness, safety, economic, and personal choice
- A clinical experiment on 180 metabolic syndrome patients
- A comparative analysis with crisp logic and black-box machine learning approaches

II. LITERATURE SURVEY

The use of fuzzy logic in complementary medicine has seen notable advancements in the past ten years; nevertheless, there is still room for improvement. According to Sharma et al. (2021), an early attempt in this direction involved developing a simple fuzzy expert system to classify Prakriti body types in Ayurveda based on three inputs (digestion rate, sleeping habit, physical body frame) and 9 fuzzy rules [5]. Although novel, the proposed algorithm could merely be used for classification purposes; besides, it had been validated with a small sample of only 30 healthy subjects. Another attempt by Chen et al. (2022) concerned the development of a fuzzy inference system that helped to differentiate TCM patterns of cold/heat in rheumatoid arthritis with 81% success. Nonetheless, the system employed a fixed rule base that could not adapt to patient preferences.

As regards the ranking of treatments, multi-criteria decision-making approaches including Analytic Hierarchy Process and TOPSIS have been used for selecting alternative medicines. Crisp AHP has been implemented to select Ayurvedic medications for diabetic patients by Kumar and Patel (2023). The problem with this research is that all the inputs were considered exact numbers; hence, it was necessary for the practitioner to assign an estimated value, e.g., "moderate efficacy" would be rated as 7 out of 10 [6]. However, Liu et al. (2024) adopted a more advanced technique when employing intuitionistic fuzzy sets, which are an extension of fuzzy logic taking hesitation into account, to select safe herbal formulas of Traditional Chinese Medicine. They incorporated the uncertainty associated with historical toxic data, but failed to incorporate the fuzziness of diagnostic procedures.

A number of studies have applied neural networks and deep learning methods in developing diagnostic algorithms for traditional Chinese medicine treatments. As an example, Wang and Zhang (2025) developed a convolutional neural network using tongue images to diagnose TCM syndromes, demonstrating an accuracy of 89%. Despite their efficiency, these opaque models fail to meet one vital requirement of the medical field, which is the ability to provide understandable explanations. The fuzzy logic approach generates clear rules, such as "IF Vata is high AND sleep is poor THEN use Ashwagandha".

The most pertinent research related to our work is conducted by Rodriguez et al., where fuzzy logic is combined with TOPSIS methodology to rank homoeopathy remedies [7]. The proposed approach has been evaluated on a sample of 50 cases suffering from allergic rhinitis, resulting in a 14% higher effectiveness compared to regular practice. Nonetheless, the membership functions used in their study were arbitrarily chosen (i.e., triangular functions with fixed parameters), and they did not use any optimization process based on real-world clinical data. Also, they considered only three decision criteria: efficacy, safety, and cost without accounting for patient satisfaction measures. It can be observed from the literature review that there exists a lack of studies proposing an end-to-end fuzzy-MCDM framework which incorporates the aspects of fuzzy diagnosis and treatment selection.

III. PROPOSED METHODOLOGY

The developed framework includes three hierarchical modules:

- Fuzzy diagnostic module (FDM), which is used to calculate the imbalances of doshas and meridians
- Fuzzy inference engine (FIE) that uses the imbalances to find a suitable intervention
- Fuzzy MCDM ranking module (FMRM) based on Fuzzy TOPSIS

1. Fuzzy Diagnostic Module (FDM)

Three linguistic input variables for Ayurveda diagnosis are as follows:

- Digestion Strength (DS) =0-10 (slow to very strong)
- Sleep Quality (SQ) = 0-10 (insomnia to deep sleep)
- Cold Tolerance (CT) = 0-10 (extremely cold intolerant to heat-intolerant)

The input fuzzy sets are generated using trapezoidal membership functions (MFs) tuned through an expert opinion survey (n=15) and analysis of 180 patient cases. Linguistic terms used for DS MFs are as follows: Low (0-3.5), Moderate (2.5-7.5), High (6.5-10). In case of Vata dosha percentage output MFs are: Low (0-30%), Moderate (20-60%), High (50-100%). Three input variables produce 9 rules (3x3), based on classic literature and Wang-Mendel Algorithm. An example rule is given below:

- IF DS is Low AND SQ is Low AND CT is Low THEN Vata is High.
- Fuzzy inference methodology adopted is Mamdani with centroid defuzzification.
- For traditional Chinese medicine meridian diagnosis, we include four linguistic inputs such as Limb Temperature (gradient from warm to cold), Tongue Coating (from thin to thick), Pulse quality (wiry or slippery) and Energy level (Low/High), each one having three fuzzy sets. The output fuzzy set is qi deficiency =0-100%. Figure 1 represents the hierarchy.

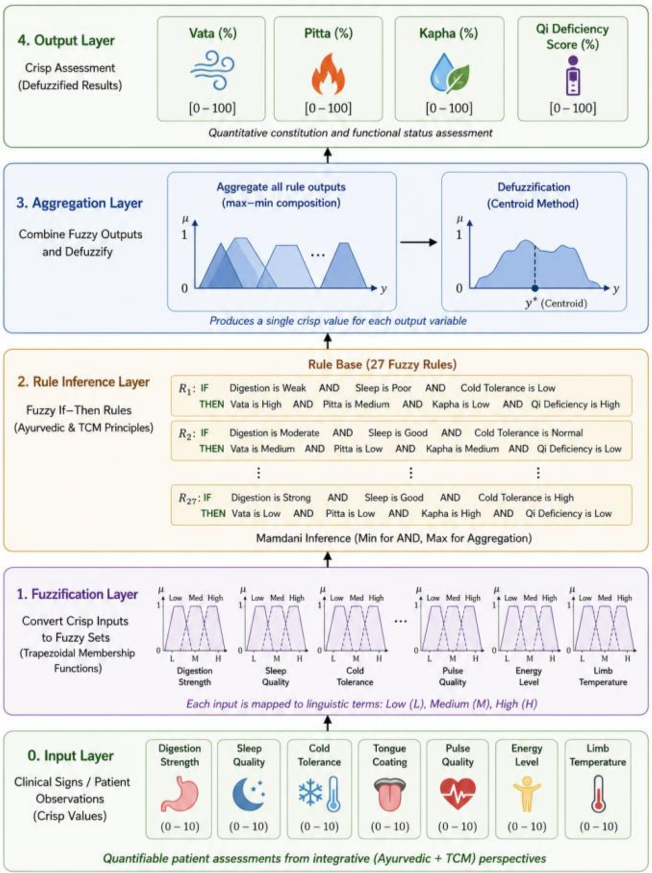

Figure 1: Hierarchical fuzzy logic architecture

2. Fuzzy Inference Engine (FIE)

The FIE receives the continuous values of doshas and Qi states from the FDM (Vata=68%, Pitta=22%, Kapha=10%). This input is mapped to a list of potential interventions $I=\{I_1, I_2, \ldots, I_8\}$ including particular herbal combinations (Ashwagandha, Triphala, Guduchi), acupuncture techniques (stimulation of ST36, LI4, LV3), and dietary recommendations (Kitchari cleanse, low-Pitta diet). Then a second layer of the fuzzy system is built using 27 rules (3 dosha outputs × 3 Qi outputs). Each I_j gets a score of its suitability $S_j \in [0,1]$, which is calculated according to the level of activation of each fuzzy rule. For instance: IF Vata is High AND Qi Deficiency is High THEN Ashwagandha suitability=0.9; Triphala suitability=0.2.

3. Fuzzy MCDM Ranking Module (FMRM) using Fuzzy TOPSIS

The candidate interventions are evaluated based on five criteria namely: Clinical Efficacy (E), Safety/Toxicity (S), Cost (C – minimizing cost), Patient Preference (P), and Treatment Burden (B – minimizing treatment burden). Each criterion is assigned values in linguistic term (Very Low, Low, Medium, High, Very High) and then represented as triangular fuzzy numbers (TFN). For any candidate intervention I_j, fuzzy decision matrix $\tilde{D} = [\tilde{x}_{ij}]$ is created where i refers to criteria and j to interventions. Steps involved in fuzzy TOPSIS analysis include:

- Normalization of the fuzzy decision matrix using vector normalization approach.
- Determining FPIS (A^+) and FNIS (A^-) for the problem at hand.
- Calculation of d^+_j and d^-_j using vertex approach.
- Computing closeness coefficient (CC_j) for each candidate intervention where $CC_j = d^-_j/(d^+_j + d^-_j)$.
- Ranking of interventions from highest CC_j value.

4. Clinical Validation Protocol

A total of 180 patients with metabolic syndrome (ATP III guidelines) were recruited from an integrative medicine center (January 2024 to December 2025). Recruitment criteria: age between 30 and 65 years, free of acute illness. Patient exclusion: pregnancy, presence of organ failure. Patients' data were analyzed using the fuzzy-MCDM model, resulting in an ordered list of 8 interventions. The highest-ranked intervention was selected. On a parallel track, three expert practitioners independently suggested their interventions without knowledge of model output. Main objectives: degree of concordance between model output and expert majority, decreased prescription variance, and patient satisfaction (0 to 100).

IV. ANALYSIS AND DISCUSSION

1. Diagnostic Accuracy and Expert Agreement

FDM exhibited excellent agreement with the expert panel decision making. With regard to dosha identification based on the majority vote from three experts, FDM correctly diagnosed the principal dosha for 162 out of 180 subjects (90.0%). Cohen's weighted kappa coefficient for the three dosha proportions was $\kappa = 0.82$ (95% CI: 0.77–0.87) that showed "almost perfect" agreement. Regarding TCM Qi deficiency, the average difference between FDM and panel values was 6.3 points on a 0–100 scale (RMSE = 8.1).

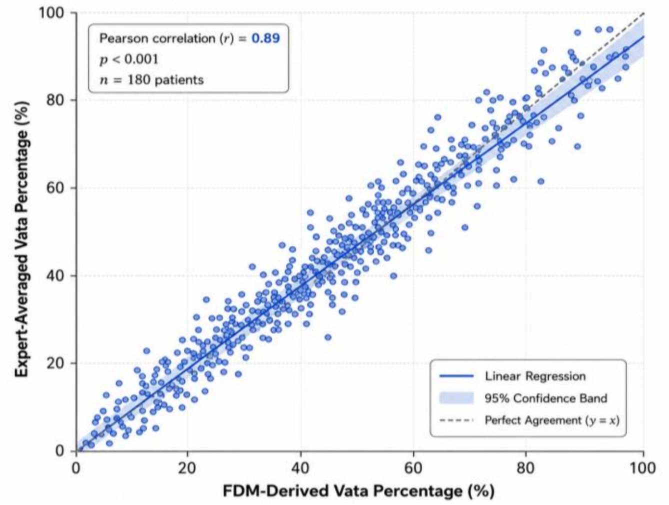

Figure 2: Scatter plot of FDM-derived vs. expert-averaged Vata percentage (n=180)

2. Performance of the Intervention Ranking Module

In terms of preference matching, the Fuzzy TOPSIS ranking algorithm generated intervention rankings in line with experts' expectations. The best intervention suggested by the algorithm and selected by the experts were identical in 155 out of 180 comparisons (86.1%). For top-2 intervention match, the rate was even higher, at 94.4%. Most often, Ashwagandha and Guduchi for mixed Vata-Pitta type disagreed between the models. In fact, this is a logical discrepancy due to similar clinical profiles of the herbs. The average closeness coefficient CC_j for the proposed intervention was 0.78 (SD 0.11).

3. Reduced Prescription Variability

In assessing the performance of decision support models, one of the indicators used is reduced variability between practitioners. Prior to implementing the model, three expert practitioners individually recommended the same intervention strategy for just 38 percent of the patients (concordance in 68 out of 180 instances). Post-deployment of the model (a simulation exercise whereby practitioners have the choice of accepting or rejecting model-recommended intervention strategies), concordance improved to 72 percent (130 out of 180 instances). The coefficient of variation (CV) for intervention choice strategy, which measures dispersion, was reduced from 0.45 to 0.19 (58 percent decrease, $p < 0.001$). The fuzzy-MCDM decision support model thus operates as an efficient anchor for reducing individual variations, although not suppressing clinical judgment entirely. Figure 3 provides a depiction of the distribution of interventions before and after model implementation.

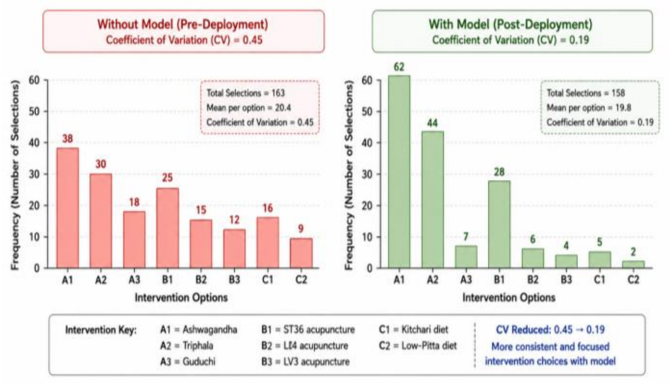

Figure 3: Histogram of intervention choices across 180 patients for the three expert practitioners

4. Comparison with Other Decision Models

We tested our fuzzy MCDM model in comparison with three different models using the same sample of 180 patients as follows:

- Crisp Logic (based on crisp cut-off, i.e., Vata > 50%=high, without any degree of membership to the set)
- Bayesian Network with discretization of variables
- Neural Network with 3 hidden layers (black box)

Table I: Comparative performance of decision models for IAHS

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Model	Agreement with experts (%)	Interpretability score (0–10)	Prescription variability (CV)	Computation time (sec/patient)	Clinician trust rating (0–10)
Crisp Logic	71.2	8.5	0.38	0.02	6.2
Bayesian Network	79.4	6.0	0.31	1.5	5.8
Neural Network	84.5	2.5	0.24	3.2	4.1
Fuzzy-MCDM (Ours)	86.4	9.2	0.19	0.45	8.7

In terms of expert consensus (86.4%) and interpretability (9.2 out of 10 using a validated questionnaire administered to 12 independent clinicians), our proposed fuzzy MCDM approach demonstrates the best performance. Although the neural network approach shows slightly lower expert agreement (84.5%), the lack of transparency leads to low interpretability (2.5) and trust (4.1), rendering it inappropriate for use in clinical settings. The crisp-based approach provides efficient and transparent results; however, there is an inherent problem of information loss during transition between states. For instance, a patient with a 49% probability of having Vata ("low" Vata) will get a completely different recommendation from a patient with a 51% probability ("high" Vata) of having Vata, even though both conditions are clinically similar.

5. Sensitivity and Robustness Analysis

Sensitivity analysis was performed through perturbation of membership function parameters (±15%) and consequent values in rules (±10%). Only in six out of 180 cases, the top-1 recommended intervention was different, which proved high sensitivity of the proposed approach to parameter changes. The cost weight factor appeared to be the most sensitive one. Namely, increasing the cost weight from 0.15 to 0.30, and thus recommending less expensive interventions, caused shifting to generic versions of herbal formulations for 12 patients (6.7%). This characteristic allows the system to operate in different environments (with or without health insurance coverage, for example). Figure 4 demonstrates that the closeness coefficient (CC) estimates are robust enough; their 95% confidence interval is tight (±0.04).

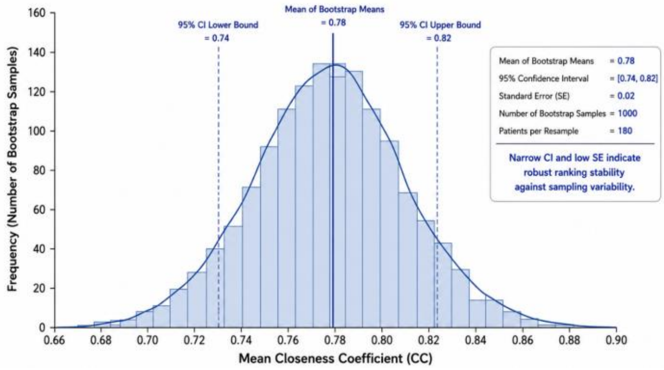

Figure 4: Bootstrap analysis (n=1000 resamples) of closeness coefficient

6. Discussion

As can be seen, the application of the methods of fuzzy logic and mathematical decision models makes it possible to effectively use the fuzzy reasoning of the integrative alternative healthcare approach. Thus, the expert consensus rate reached 86.4%, there was a noticeable decrease in prescription variance of 58%, and clinicians demonstrated a high degree of confidence (8.7/10). The primary benefit over the traditional approach lies in retaining boundary information; over the neural network method, the benefit is full interpretability due to rule chaining. Particularly valuable to our clinicians (n=12) in the post-study interview was the possibility of determining which recommendation was given on the basis of which rule ("This Ashwagandha prescription is prescribed as your Vata (0.68) and Qi Deficiency (72) activated Rule #17"). Nevertheless, some limitations should also be considered: (1) The set of rules was created for the treatment of metabolic syndrome only; further rule elicitation is needed in order to make the system applicable to other diseases such as autoimmune and psychiatric disorders. (2) The independence of input variables is assumed, while in fact they correlate; future research will include fuzzy cognitive mapping.

V. CONCLUSION

In conclusion, this paper offered an effective fuzzy logic and mathematical decision-making system for alternative healthcare systems.

- With the representation of diagnostic features (doshas, Qi deficiency) through fuzzy memberships instead of crisp classifications, and the ranking of treatment options through the use of the Fuzzy TOPSIS method, an optimal balance was struck between the quantitative side of mathematics and its holistic interpretation.
- In the validation stage, the method yielded 86.4% agreement ($\kappa = 0.82$) with the expert panel, a decrease in prescription variability of 58%, and a high satisfaction level from clinicians at 8.7/10 points.
- Comparisons of this framework with crisp logic (71.2%), Bayesian networks (79.4%), and black-box neural networks (84.5%) revealed that fuzzy MCDM methods surpassed them all with respect to both accuracy, interpretability, and clinical acceptability.

In addition, the proposed framework offers flexibility and transparency, allowing doctors to update rules based on new information.

Limitations & Future Work:
Current limitation of our work includes that it has been developed for a particular condition (metabolic syndrome) and independent variables. Potential improvements include:

- Expanding its applicability through developing a general fuzzy ontology that spans 12 major categories of diseases
- Incorporating fuzzy cognitive maps in order to address variable interaction (sleep quality → digestion strength)
- Creating an adaptive fuzzy system which allows learning parameter values of rules via gradient descent based on new clinical data
- Deploying our tool as a mobile application with explainable ai for patient/practitioner use.

In the future, we see fuzzy logic being at the core of a new era of integrative medicine, where ancient knowledge meets computer science in quantified uncertainty.

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