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Note-Commentary

Mizaj Metric: A Deep Learning Framework for Unani Temperament Analysis: A Hypothesis

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Abstract

Background: Unani medicine, a Greco-Arabic traditional system, centers on Mizaj (temperament) assessment for diagnosis and treatment. The Ajnas-e-Ashra (ten determinants) provide a comprehensive framework for temperament classification, but their subjective nature challenges systematic computational analysis and integration with modern clinical data.

Hypothesis: We hypothesize that deep learning techniques can effectively encode the hierarchical, context-dependent relationships recognized by Unani practitioners into a quantitative framework for temperament analysis. Specifically, we propose that: (1) a similarity metric learned from practitioner consensus will better preserve clinically meaningful temperamental distinctions than standard distance measures; (2) modern neural network architectures can model complex interactions between the ten determinants; (3) combining multiple data types (structured clinical data, patient descriptions, physiological measurements) will improve accuracy; and (4) the resulting visualizations will align with Unani theoretical principles while providing clinically useful insights.

Evaluation: The hypothesis can be tested by (a) collecting a multi-center dataset of patient profiles with practitioner consensus annotations; (b) training the proposed model and comparing its performance against standard methods using measures of accuracy and practitioner agreement; (c) conducting controlled tests to assess each component's contribution; and (d) validating clinical utility through blinded practitioner evaluation and prospective trials.

Implications: If validated, this approach would provide the first quantitative, reproducible framework for Ajnas-e-Ashra analysis, enabling temperament-based patient stratification, treatment personalization, and integration of Unani concepts with modern biomedical data. The methodology could be adapted to other traditional medicine systems.

Keywords: Unani Medicine; Mizaj; Temperament; Deep Learning; Artificial Intelligence; Hypothesis; Traditional Medicine.

1. Introduction

1.1. *The Centrality of Mizaj in Unani Medicine*

Unani medicine, a comprehensive traditional medical system originating in Greco-Arabic philosophy and extensively developed in South Asia, centers on the concept of individual constitution or temperament, known as Mizaj [1]. Mizaj represents the unique psychosomatic equilibrium resulting from the interaction of four humors (Akhlat); Dam (blood; hot-moist), Balgham (phlegm; cold-moist), Safra (yellow bile; hot-dry), and Sauda (black bile; cold-dry) [2]. As articulated by Ahmer et al. [13], "Mizaj is the fundamental concept upon which the entire edifice of Unani medicine rests, determining not only an individual's physical and psychological characteristics but also their predisposition to specific illnesses and response to treatment."

The theoretical framework for comprehensive temperament assessment is provided by the Ajnas-e-Ashra (ten determinants), systematically codified in classical Unani texts including Ibn Sina's Al-Qanun fi al-Tibb [1]. These ten determinants are:

1. **A'za** (Organs): Structural components of the body
2. **Arwah** (Vital Spirit): The life force mediating physiological functions
3. **Akhlat** (Humors): The four humors in their relative proportions
4. **Quwa** (Faculties): Natural, vital, and psychic powers
5. **Af'al** (Functions): Physiological activities

6. **Mizaj** (Temperament proper): The resultant quality from humor interaction
7. **Ashkal** (Shapes): Morphological characteristics
8. **A'raz** (Accidents): Sensory qualities (color, texture, temperature)
9. **Qad** (Size): Bodily dimensions
10. **Adad** (Number): Numerical parameters (pulse rate, respiratory rate)

Unani practitioners assess these determinants through integrated clinical observation, yielding classifications such as Barid Mizaj (cold temperament), Har Mizaj (hot temperament), Balghami (phlegmatic), Saudavi (melancholic), and their various combinations [4]. While clinically invaluable, this assessment remains inherently subjective, relying on practitioner experience and intuition.

1.2. *The Computational Challenge and Opportunity*

The subjectivity of Mizaj assessment presents both a challenge and an opportunity. The challenge: subjective assessment limits standardization, reproducibility, and integration with modern data-driven approaches. The opportunity: if practitioner expertise could be systematically encoded into a computational framework, it would enable quantitative temperament analysis while preserving the holistic wisdom of classical Unani medicine.

Existing computational approaches to Mizaj classification have primarily employed questionnaire-based scoring systems [5-7] providing standardized but discrete classifications. Siddiqui et al. [5] developed and validated a 48-item Mizaj assessment instrument (Cronbach's $\alpha = 0.82$) in 500 healthy volunteers. Ansari et al. [6] applied similar methodology to correlate Mizaj with biochemical parameters. While valuable for standardization, these approaches reduce complex interactions to summated scores, losing the hierarchical relationships practitioners recognize.

Single-modality analysis has explored pulse waveforms [8] and thermal imaging [10]. Ahmad et al. [8] demonstrated preliminary correlations between pulse parameters and practitioner-assessed Mizaj. Singh et al. [10] found significant temperature differences between Garmi Mizaj and Sue Mizaj individuals using infrared thermography. These approaches provide objective measurements but capture only isolated aspects of the Ajnas-e-Ashra framework.

Notably, Ahmer and Ahmad 9 contributed an innovative approach by investigating objective physiological correlates of temperament. They assessed total body water in Damvi (sanguineous) and Safravi (choleric) Mizaj using non-invasive anthropometric equations, finding significant differences between these types and demonstrating that temperament has measurable physical correlates—a crucial validation of the Unani framework from a biomedical perspective.

Statistical norming studies [12] have established population distributions of Mizaj types. Alam et al. [12] reported Mizaj distribution in 2,500 North Indian adults, providing valuable reference data. However, such approaches lose individual specificity and cannot capture the holistic integration central to Unani practice.

By comparison, Traditional Chinese Medicine has seen over 100 computational publications since 2015, including deep learning for pulse diagnosis [14], tongue analysis [15], and constitution classification [16]. Ayurvedic researchers have similarly explored machine learning for Prakriti assessment [17]. Unani computational research remains nascent, with no published studies applying modern machine learning to Mizaj analysis.

No existing approach simultaneously

(a) integrates all ten Ajnas-e-Ashra determinants,

(b) preserves the hierarchical, context-dependent relationships recognized by practitioners, (c) processes multimodal clinical data, and (d) provides interpretable visualizations of temperamental relationships.

1.3. *The Hypothesis*

Deep learning techniques can effectively encode the hierarchical, context-dependent relationships recognized by Unani practitioners into a quantitative framework for temperament analysis that preserves clinically meaningful distinctions while enabling interpretable visualization.

Specifically, we propose:

Hypothesis 1 (Learned Similarity): A computational model that learns directly from practitioner judgments about which patients have similar or different temperaments will better capture clinically meaningful distinctions than standard mathematical distance measures (like Euclidean distance) that treat all features as equally important.

Rationale: Modern machine learning includes techniques that can learn "what similarity means" in a specific domain by studying examples. These "metric learning" approaches have proven highly effective in medical imaging [18], where they learn to distinguish subtle differences that even experts find challenging. In face recognition [19] and image retrieval [20], such methods achieve human-level performance by learning which visual features matter. By training on pairwise judgments from expert Unani practitioners, the model should learn to weight clinical features according to their true importance in temperament classification—for example, learning that the cold quality shared by Balghami and Saudavi temperaments is clinically significant, while minor variations in less relevant features are not.

Hypothesis 2 (Feature Interaction Modeling): A modern neural network architecture called a "Transformer" (which uses self-attention mechanisms) will capture complex interactions between the ten Ajnas-e-Ashra determinants better than simpler approaches that combine features in a linear fashion.

Rationale: The ten determinants do not operate independently. For example, the type of humor dominance (Akhlat) influences which faculties (Quwa) are strongest, which in turn affects bodily functions (Af'al). A Balghami (phlegmatic) individual's slow digestion is not an isolated finding—it relates to their overall cold-moist constitution. Transformers [21] are specifically designed to model such relationships by allowing each piece of information to "attend to" every other piece, learning which combinations matter. They have revolutionized fields from language translation to medical image analysis [22] precisely because of this ability to capture complex interactions. Moreover, the "attention weights" the model learns can be visualized, potentially revealing which feature combinations the model considers most important—providing interpretability.

Hypothesis 3 (Multimodal Integration): Combining multiple types of patient data—structured clinical observations, unstructured symptom descriptions in the patient's own words, and physiological measurements (thermal imaging of temperature patterns, anthropometric measures as pioneered by Ahmer and Ahmad [9])—will produce more accurate temperament representations than using any single data type alone.

Rationale: Unani practitioners naturally integrate diverse information sources. They observe (skin texture, body habitus), they listen (patient descriptions of symptoms, preferences, experiences), and they measure (pulse rate and quality, temperature, anthropometrics). Ahmer and Ahmad's [9] demonstration that total body water differs significantly between Damvi and Safravi temperaments exemplifies how objective physiological measurements can provide meaningful correlates of traditional classifications. Structured questionnaires capture standardized observations but may miss nuances. Patient narratives provide rich contextual information that checklists cannot capture [23]. Thermal imaging offers an objective measure of the "warmth" and "coldness" central to Mizaj theory [24]. A computational model that similarly integrates multiple data streams should more faithfully represent the holistic assessment practitioners perform [25].

Hypothesis 4 (Interpretable Visualization): When the learned similarities between patients are used to create a two-dimensional map (using a technique called multidimensional scaling, or MDS), this visualization will (a) reflect Unani theoretical principles (e.g., hot and cold temperaments appearing in opposite regions), (b) show continuous transitions between related types (e.g., the gradual shift from Balghami to Saudavi as moisture decreases), and (c) highlight unusual patients whose temperaments do not fit clearly into standard categories.

Rationale: MDS [26] is a well-established technique for creating "maps" of complex data where distances on the map reflect similarities between items. When guided by a similarity metric that captures clinical judgment (from Hypothesis 1), the resulting map should place patients according to how practitioners actually perceive their temperaments. Such visualizations have proven valuable in other medical contexts for understanding patient populations and identifying unusual cases [27]. We predict, for example, that patients with predominantly cold temperaments (Sue Mizaj) will cluster separately from those with hot temperaments (Garmi Mizaj), while the related cold types (Balghami and Saudavi) will show overlapping but distinct regions—visually representing both their shared cold quality and their differing moisture.

Hypothesis 5 (Clinical Utility): When shown these visualizations, Unani practitioners will (a) agree with the model's temperament classifications in the majority of cases, (b) find the maps useful for identifying patients with complex or mixed temperaments, and (c) report that the visualizations provide insights beyond what they could glean from individual patient assessment alone.

Rationale: If the model successfully encodes practitioner consensus, its outputs should align with expert judgment. Based on previous studies of clinician-AI agreement in diagnostic support systems [28], we consider 85% or higher agreement clinically acceptable. Moreover, by revealing relationships between patients—showing, for instance, that a particular patient falls in a transitional zone between Balghami and Saudavi—the visualization may alert practitioners to complexity they might otherwise miss. The ability to see where a patient lies relative to hundreds of previously seen cases could provide a form of "augmented intuition" that enhances clinical judgment.

2. The Proposed Framework: Mizaj metric (Conceptual Overview)

2.1. *What the Framework Would Do*

Mizaj Metric is a proposed computational framework designed to:

1. **Take in diverse patient data:** structured clinical assessments (like standardized forms), unstructured symptom descriptions in the patient's own words, thermal images of the face and palms, and anthropometric measurements (building on work by Ahmer and Ahmad [9] showing their relevance to temperament).
2. **Learn what similarity means** by studying thousands of pairwise judgments from expert Unani practitioners about which patients have similar or different temperaments.
3. **Create a visual map** where each patient appears as a point, and the distance between points reflects how similar their temperaments are according to practitioner consensus.
4. **Highlight patterns:** showing where different temperament types cluster, where transitions occur between types, and which patients are unusual.

2.2. *How It Would Work (Conceptually)*

Step 1: Processing Different Types of Data

Different data types require different handling:

- **Structured clinical data** (like answers to a 48-item questionnaire) would be processed by a neural network that learns which combinations of answers are most informative.
- **Patient symptom descriptions** in Urdu or Arabic would be processed by a language model (similar to

those that power translation services) that converts text into numerical representations capturing meaning.

- **Thermal images** would be processed by a vision model that learns to extract temperature patterns relevant to temperament—for example, the temperature difference between central face and extremities that might indicate warm or cold constitution.
- **Anthropometric measurements** (height, weight, body circumferences, and derived measures like total body water [9]) would be processed as structured numerical data, with the model learning their correlations with temperament.

All these different representations would then be combined into a single "patient profile" that integrates information from all sources.

Step 2: ***Learning from Practitioner Expertise***

Senior Unani practitioners would be asked a simple question about hundreds of pairs of patients: "On a scale of 1 to 5, how similar are these patients' temperaments?" Their answers would train the model to understand what similarity means in clinical practice.

The model learns by adjusting itself so that patients judged similar end up close together in its internal representation, while those judged dissimilar end up far apart. This is analogous to learning a new language by seeing many examples—the model gradually develops an intuition for which features matter and how they combine.

Step 3: ***Creating a Visual Map***

Once the model has learned a good representation, a standard technique called multidimensional scaling (MDS) creates a two-dimensional map. This map preserves the learned similarities as faithfully as possible—patients who should be similar appear near each other; those who should be different appear far apart.

The result is an intuitive visualization where:

- Hot and cold temperaments appear in opposite regions
- Related types (like Balghami and Saudavi) appear in neighboring regions with some overlap
- Mixed temperaments appear in transitional zones
- Unusual cases appear as isolated points, flagged for clinical attention

Step 4: ***Making It Practical for Clinical Use***

For real-world use, the model would be compressed into a small, efficient version that can run on a smartphone or tablet. This "edge deployment" means patient data never leaves the clinic—addressing critical privacy concerns. A practitioner could collect the necessary data, run the analysis locally, and see the patient's position on the temperament map within seconds.

2.3. *What the Framework Would Not Do*

It is important to be clear about what Mizaj Metric is not intended to do:

- **It would not replace practitioner judgment.** The map is a decision support tool, not a diagnosis. The practitioner remains the expert.
- **It would not reduce Unani medicine to numbers.** As Ahmer et al. [13] emphasize, Mizaj is a holistic concept that encompasses physical, psychological, and spiritual dimensions. The goal is to augment, not replace, this holistic understanding.
- **It would not mandate a single "correct" classification.** By showing continuous relationships and transitional zones, the framework acknowledges that temperament exists on spectra, not in discrete boxes.
- **It would not work without practitioner expertise.** The entire framework depends on practitioner annotations to learn what matters. It is a tool for encoding and extending their expertise, not for replacing it.

3. How the Hypothesis would be tested

3.1. *What Data Would Be Needed*

To test these hypotheses, a research study would need to collect:

- **At least 1,000 patients** (calculated to provide statistically reliable results) from multiple Unani centers across different regions
- **Complete data for each patient:** structured clinical assessment (48-item form), verbatim symptom descriptions, thermal images of face and palms, and anthropometric measurements (including those validated by Ahmer and Ahmad [9] for assessing total body water)
- **Expert annotations:** at least five senior Unani practitioners would independently rate the similarity of 500 carefully selected patient pairs (choosing which pairs to annotate strategically to maximize learning)
- **"Ground truth" labels:** each patient's primary Mizaj type as determined by practitioner consensus (for validation purposes)

Handling rare types: Since some temperament types are uncommon, the study would need to ensure adequate representation—potentially by over-sampling unusual cases or generating synthetic examples for training.

3.2. *How Each Hypothesis Would Be Evaluated*

Hypothesis 1 (Learned Similarity): The proposed model would be compared against standard approaches that use simple distance measures (Euclidean distance) or popular visualization techniques (t-SNE, UMAP). Three measures would assess performance:

- How well the model preserves the original practitioner similarity judgments

- How cleanly patients with the same temperament type cluster together
- How well independent practitioners (not involved in training) rate the model's outputs (on a 0-100 scale)

Prediction: The proposed model will significantly outperform all standard approaches on all three measures.

Hypothesis 2 (Feature Interaction Modeling): A simplified version of the model (without the Transformer architecture) would be compared against the full version. If the full version performs better, this supports the hypothesis that modeling feature interactions matters.

Hypothesis 3 (Multimodal Integration): Versions of the model trained on single data types (e.g., questionnaires only, thermal images only, anthropometrics only) would be compared against the full multimodal version. If the full version performs best, this supports the hypothesis that integrating multiple data sources improves accuracy.

Hypothesis 4 (Interpretable Visualization): Independent practitioners would be shown the visual maps and asked whether they reflect clinical expectations. Quantitative measures would assess how well-separated different temperament types are and whether unusual cases (outliers) correspond to clinically recognized rare presentations.

Prediction: Hot and cold types will show clear separation (measurable by standard clustering metrics); related types (Balghami/Saudavi) will show partial overlap; outliers will match clinically documented rare types.

Hypothesis 5 (Clinical Utility): Independent practitioners would evaluate 50 test patients. For each, they would first provide their assessment, then see the model's visualization, and answer:

- Does this match your assessment? (yes/no)
- Does this provide additional insight beyond your initial assessment? (1-5 scale)

Prediction: At least 85% agreement with model classifications; at least 75% of cases where practitioners report additional insights.

4. What would it Mean if the Hypothesis is Supported?

4.1. *Implications for Unani Medicine*

First quantitative framework for Ajnas-e-Ashra: For the first time, the ten determinants could be analyzed systematically and reproducibly, enabling research that was previously impossible.

Validation of core concepts: Studies like Ahmer and Ahmad's [9] demonstration of objective physiological correlates of temperament could be greatly extended, potentially revealing the biological basis of Mizaj.

Patient stratification: Researchers could identify patient subgroups based on temperament and study how they respond to different treatments, enabling more personalized approaches.

Training tool: Trainees could see how their assessments compare to expert consensus, accelerating learning.

Quality assurance: Practitioners could review their assessments against the model, identifying cases where they deviate from peer consensus.

Integration with modern medicine: As Ahmer et al. [13] argue, "Understanding Mizaj is essential for integrating Unani medicine with contemporary biomedical science." Temperament classifications could be correlated with genomic, proteomic, or metabolic data, potentially revealing biological correlates of traditional concepts.

4.2. *Implications for Other Traditional Medicine Systems*

The same approach could be adapted to:

- **Ayurveda:** Prakriti assessment (Vata, Pitta, Kapha) [17]
- **Traditional Chinese Medicine:** Constitution types (Yang deficiency, Yin deficiency, Phlegm-dampness) [16]
- **Greek humoral theory:** The original four humors system

Cross-system comparisons could reveal whether these different traditions are describing universal dimensions of human variation or culture-specific constructs.

4.3. *Implications for Personalized Medicine*

If temperament correlates with treatment response, the framework could guide therapy selection—not replacing clinical judgment but providing probabilistic guidance: "Patients with profiles similar to this one typically respond well to these interventions."

5. What if the Hypothesis is Not Supported?

Several alternative explanations would need investigation:

Possibility 1: Not Enough Data or Poor Data Quality

- Practitioner agreement might be lower than expected (if they disagree significantly, there may be no consistent "ground truth" to learn)
- The dataset might not include enough examples of rare types
- **Solution:** Collect more data; train practitioners to reach higher consensus; use active learning to focus on most informative cases

Possibility 2: Wrong Architecture Choice

- Transformers might not be optimal for this type of data
- **Alternative:** Try graph neural networks that explicitly model known relationships between determinants; or Bayesian models that incorporate prior knowledge

Possibility 3: Fundamental Incommensurability

- Ajnas-e-Ashra might simply not be reducible to quantitative representation without losing essential information
- Temperament might be inherently holistic in ways that resist decomposition
- As Ahmer et al. [13] note, "Mizaj is not merely a sum of parts but an emergent property of their interaction" this emergent property may resist reduction
- **Implication:** Focus on measurable components rather than full framework; accept that some aspects of Unani medicine may remain qualitative

Possibility 4: Practitioner Disagreement Is Itself Informative

- If inter-rater reliability is low, this highlights areas of diagnostic uncertainty needing clarification
- This would be a valuable finding in itself, guiding efforts to refine diagnostic criteria

Possibility 5: Technical Implementation Challenges

- The proposed approach might require computational resources beyond typical research settings
- **Solution:** Explore simpler architectures; prioritize clinical feasibility over state-of-the-art complexity

6. Predictions for Specific Mizaj Types

Based on Unani theoretical principles and empirical findings like those of Ahmer and Ahmad [9] (who demonstrated total body water differences between Damvi and Safravi types), we predict:

1. **Sue Mizaj (cold) and Garmi Mizaj (hot)** will occupy opposite regions in the visual map, with clear separation between clusters.
2. **Balghami (phlegmatic; cold-moist) and Saudavi (melancholic; cold-dry)** will show partial overlap but distinct clustering centers, reflecting their shared cold quality but differing moisture. The transition zone between them will contain patients with mixed features.
3. **Damvi (sanguineous; hot-moist) and Safravi (choleric; hot-dry)** will similarly show overlap with separation, and their positions should correlate with measurable physiological parameters like total body water [9].
4. **Mixed temperaments** will appear in transitional zones between pure types, not as distinct clusters.
5. **Rare or complex cases** will appear as outliers—patients whose distance to all clusters exceeds typical variation. These should correspond to documented conditions like *Su-e-Mizaj Maddi* (material temperamental imbalance).

7. Challenges and Mitigations

Challenge	Mitigation
Annotation cost: Having senior practitioners rate hundreds of patient pairs is expensive and time-consuming	Active learning to select most informative pairs; crowdsourcing with expert validation
Interpretability: Deep learning models can be "black boxes"	Attention visualization; feature attribution methods; simplified versions for clinical use
Clinical adoption: Practitioners may resist "AI telling them what to do"	Co-design with practitioners; emphasize assistive role; demonstrate clear clinical utility
Data privacy: Patient data must be protected	Edge deployment (model runs locally); federated learning for multi-center training
Regulatory approval: Clinical use requires clearance	Engage regulators early; plan prospective validation studies
Cost in resource-limited settings: Sensors may be expensive	Smartphone-based alternatives; focus on most informative, lowest-cost modalities (e.g., anthropometrics as validated by Ahmer and Ahmad [9]

8. Next Steps

If this hypothesis generates interest, we propose a phased approach:

Phase 1 (Proof-of-Concept): Collect 200 patients from one center; train initial model; assess feasibility; refine protocols. Estimated timeline: 12 months. Estimated cost: ≈ ₹1.25 crore ($150,000).

Phase 2 (Multi-center): Expand to 3-5 centers across South Asia; collect 1,200+ patients; establish practitioner consensus. Estimated timeline: 24 months. Estimated cost: ≈ ₹4.15 crore ($500,000).

Phase 3 (Validation): Blinded practitioner evaluation; prospective observational study correlating model outputs with clinical outcomes. Estimated timeline: 18 months. Estimated cost: ≈ ₹2.49 crore ($300,000).

Phase 4 (Clinical Trial): Randomized trial comparing treatment outcomes with vs. without Mizaj Metric assistance. Estimated timeline: 36 months. Estimated cost: ₹12.45 crore ($1.5 million).

9. Conclusion

Mizaj Metric represents a hypothetical but theoretically grounded framework for integrating the Ajnas-e-Ashra system of Unani medicine with modern deep learning. By learning directly from practitioner expertise what makes temperaments similar or different, modeling the complex interactions between the ten determinants, combining multiple data types (including anthropometric measures that have already shown promise in differentiating temperaments [9]), and creating intuitive visualizations, the proposed approach aims to encode the holistic wisdom of Unani temperament assessment into a quantitative, reproducible, and clinically useful computational tool.

As Ahmer et al. [13] eloquently state: "The theory of Mizaj is not merely a historical artifact but a living framework that continues to guide clinical practice. Its integration with modern scientific methods holds the promise of revealing new insights into human health and disease." The five hypotheses presented are testable through systematic data collection and rigorous evaluation. If validated, Mizaj Metric would provide the first computational framework for Ajnas-e-Ashra analysis, enabling temperament-based patient stratification, treatment personalization, and integration of Unani concepts with modern biomedical research. Even if not fully supported, the attempt to formalize Unani temperament assessment computationally will clarify the framework's assumptions, identify areas of practitioner disagreement, and advance the broader project of bridging traditional and modern medical knowledge.

We invite collaboration from Unani practitioners, computational researchers, and traditional medicine scholars to test these hypotheses and collectively advance this important agenda. The goal is not to replace practitioner judgment but to augment it providing tools that enhance training, support clinical decisions, and enable integration of Unani concepts with contemporary science.

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