Research Article

AI-Assisted Ayurvedic Pattern Recognition for Personalized Assessment of Prakriti and Therapeutic Response Using Multimodal Health Data

Dr Ravi Rao S[1*], Dr. Ajith Kamath M.[2], Rahul Haridas Gujarathi[3], Dr Asha S Raj[4]

[1*]Professor and Head Department of Dravyaguna , National Institute of Ayurveda, Sector 4D, Mansa Devi Complex, Panchakula, Haryana 134114, Dravyaguna, Email ID: ravisorake@gmail.com, ORCID ID: 0009-0001-9674-2375
[2]Professor and Vice Principal, Department of Agada Tantra evum Vidhi Vaidyaka, Karnataka Ayurveda Medical College, Mangalore, Email Id: ajithagada@gmail.com, ORCID ID: 0009-0003-5055-6189
[3]Professor and Head of Department, Bharati Vidyapeeth (Deemed to be University) College of Ayurved, Pune, India, Email ID: shrigujarathi@gmail.com, ORCID ID: 0000-0002-8248-1412
[4]Associate Professor, Department of Dravyagunavijnana , J S Ayurveda Mahavidyalaya, Nadiad, 387001, MAM UNIVERSITY, Email ID: drashasraj@gmail.com, ORCID ID: 0000-0002-8902-5698

Abstract

Ayurvedic Prakriti represents an individualized constitutional framework with potential relevance to contemporary precision medicine, yet its conventional assessment remains constrained by subjectivity, inter-observer variability, and limited standardization. This review examines the emerging role of artificial intelligence (AI) and multimodal health data in improving Prakriti recognition and predicting personalized therapeutic response. Evidence across clinical characteristics, questionnaires, physiological signals, wearable sensors, imaging, voice features, genomics, metabolomics, proteomics, and microbiome profiles indicates opportunities to construct multidimensional representations of constitutional phenotypes. Machine learning, deep learning, computer vision, natural language processing, and multimodal fusion can integrate these heterogeneous data streams, while explainable AI may improve interpretability and clinical acceptance. Importantly, AI-enabled Ayurveda should progress beyond automated constitutional classification toward prediction of individualized responses to dietary, lifestyle, herbal, yoga, and behavioral interventions. Longitudinal digital phenotyping and causal machine learning may further support dynamic monitoring and estimation of heterogeneous treatment effects. However, clinical translation requires standardized Prakriti definitions, high-quality multicenter datasets, external and cross-population validation, transparent reporting, privacy protection, algorithmic fairness, and regulatory oversight. Future research should prioritize prospective studies demonstrating whether multimodal AI-derived phenotypes provide incremental clinical value, improve therapeutic selection, and enhance patient outcomes within evidence-based personalized healthcare across diverse populations and clinical settings globally.

Keywords: Prakriti, Artificial intelligence, Multimodal health data, Personalized medicine, Ayurveda.

1. Introduction

As new precision and personalized medicine has emerged, there is an increasing need for approaches that can account for intra-individual variability in biological, clinical, behavioral, and environmental factors in healthcare decisions [1]. AI and the new technologies of multi-omics, digital health technologies, wearable sensors and computational analytics offer tremendous potential to uncover complex patterns in diverse health data and to help guide personalized prediction and treatment decisions [2]. These developments are also valuable for computational research into historical medical systems that are traditionally based on individualized assessment.

Ayurveda is a customized healthcare model that speaks of Prakriti (constitutional phenotype) as relatively stable combinations of Vata, Pitta and Kapha. Prakriti is seen to be relevant to physiology, disease susceptibility, lifestyle guidelines, and drug selection, and thus concepts of predictive, preventive and personalized medicine emerge. The

traditional evaluation of Prakriti, however, heavily depends on questionnaires, clinical observation and practitioner judgment, which can cause inter-observer variability and reduce reproducibility. Recent application of emerging deep-learning techniques shows the possibility of a computational classification of Ayurvedic constitution types, and also points out the potential of more objective phenotype recognition [4].

It is therefore becoming an important interdisciplinary research field when combining AI with traditional, complementary and integrative medicine [5,6]. Multimodal AI systems, incorporating clinical data, questionnaires, physiological data, imaging, data from wearables, lifestyle factors, and molecular data, could help to create more complete representations of Prakriti. The growing field of AI and integrative medicine research suggests a greater focus on the use of computing tools for traditional healthcare, and holistic health-record infrastructures could support such integrative approaches [7].

However, the potential clinical applications of AI in Ayurveda need to move beyond the simple process of automated constitutional typing to predict personalized therapeutic outcomes. Hence, in this review, the biological and computational basis of Prakriti recognition, multimodal health-data integration, AI methodologies, model validation and explainability are discussed, with a focus on the connection of constitutional phenotypes with therapeutic outcomes. It additionally examines methodological, ethical and translational issues, and key areas of research needed to build robust and interpretable AI models for personalized Ayurvedic healthcare.

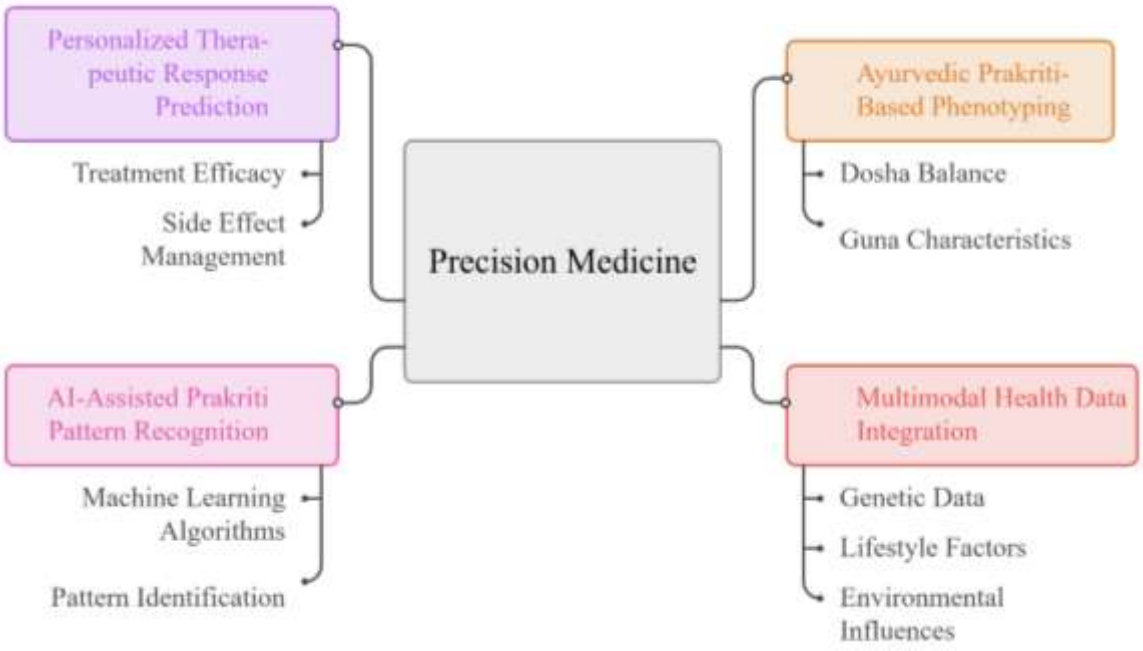


Figure 1. AI-Enabled Precision Medicine Framework Integrating Ayurvedic Prakriti, Multimodal Health Data, and Therapeutic Response

The framework illustrates the integration of Ayurvedic *Prakriti* phenotyping, multimodal genetic, lifestyle, and environmental data, and AI-assisted pattern recognition within precision medicine to facilitate individualized therapeutic-response prediction, improved treatment efficacy, and effective management of adverse effects.

Review Objectives

1. To evaluate AI approaches for accurate and objective *Prakriti* pattern recognition.

2. To examine the integration of multimodal health data for personalized *Prakriti* assessment.
3. To assess the potential of AI-derived *Prakriti* profiles for predicting individualized therapeutic response.
4. To identify key methodological, validation, and translational gaps and future research priorities.

2. Prakriti as a Biological and Personalized Health Phenotype

Prakriti is an elemental principle in Ayurveda that represents the individual's constitutional phenotype where Vata, Pitta and Kapha are the relative predominance of these three elements. It has been defined as the difference in physiological functions, metabolism, morphology, behavioral characteristics, disease susceptibility and response to therapy among individuals. With the rise in the interest about precision medicine, there has been a spate of research on Prakriti as a biologically relevant stratification model. But traditional assessment relies heavily on clinical evaluation and questionnaires, meaning there is a degree of subjectivity when it comes to practitioners and which assessment tools they use. Existing tools show differences in scoring, validation and classification methods, highlighting the importance of scientific and standardized methods [9].

Modern studies reveal that Prakriti could be the measureable biological variation. The gut microbiome has been studied in various constitutional types, which indicates that the features of the microbiome may be useful for understanding Prakriti associated biological heterogeneity [10]. However, Ayurgenomics also combines constitutional typology with genomic and molecular data and proposes a framework for the discovery and therapeutic stratification of drugs at a genomic-molecular level, according to a personalized approach [11]. Association of molecular investigation of the KCNJ11 gene with Prakriti-based stratification and type 2 diabetes has also been demonstrated, thus requiring further investigation of constitutional phenotypes in terms of metabolic risk assessment [12]. Likewise, the variations in the coronary artery disease risk predicting biomarkers between Prakriti groups indicate the relevance of individual cardiovascular risk characterization [13].

Inter-individual differences in psychophysiological responses to environmental and occupational stressors have also been found and are indicative of the general significance of dynamic physiological measurements for personalized phenotyping [14]. In total, these findings strongly suggest a computational approach for integrating clinical, physiological, molecular, microbial and behavioral data to characterize Prakriti. However, more robust multicenter validation and common ground truth definitions are necessary to ensure these phenotypes can be effectively used in supporting the AI-driven personalized assessment and prediction of therapeutic response.

Table 1. Biological and Personalized Health Dimensions of Prakriti

Dimension	Key evidence/relevance to Prakriti	Reference
Assessment and classification	Current Prakriti tools vary in scoring, validation, and classification, indicating a need for standardization.	[9]
Gut microbiome	Differences in microbial composition suggest potential constitution-associated biological variation.	[10]
Genomics/Ayurgenomics	Integrates Prakriti with molecular information for personalized drug discovery and therapeutic stratification.	[11]

Metabolic susceptibility	KCNJ11-related findings support investigation of Prakriti in type 2 diabetes risk stratification.	[12]
Cardiovascular biomarkers	Prakriti groups show variation in biomarkers associated with coronary artery disease risk.	[13]
Psychophysiological variation	Individual variability in physiological stress responses supports incorporating dynamic biomarkers into personalized phenotyping.	[14]

3. Multimodal Health Data for Ayurvedic Phenotyping

A multimodal health data offers a critical ground for the shift of the phenotyping of Ayurveda from the mostly qualitative mode to objective and reproducible characterization with the help of computational methods. The integration of heterogeneous information is especially important in the assessment of Prakriti as it involves physical, physiological, behavioural, psychological and possibly molecular aspects of the human constitution. Clinical and demographic data, such as age, gender, anthropometric measures, metabolic markers, medical history, dietary pattern, lifestyle, and socioeconomic factors, can be used to give background information. Strong linkages between the socio-demographic characteristics, lifestyle, obesity, and health status have highlighted the need to take these into account when developing personal health profiles [15]. Information gained from the questionnaire and patient-reported data can also help capture eating habits, sleep, stress, behavioural tendencies and symptoms, and perceived health characteristics that may not be well captured by clinical measurements alone.

Physiological and wearable technologies extend this by continuously measuring heart rate, heart-rate variability, electrodermal activity, physical activity, sleep, temperature and other dynamic signals. Objective physiological measures linked to self-reported stress and mental health states have been shown to be measurable via wearable sensors and mobile-phone derived behavioral measures [16]. Thus, the combination of physiological and neurocognitive biomarkers using machine-learning models could aid in more comprehensive and nuanced health profiling [17]. Image-based phenotyping could also include facial morphology, tongue morphology, skin texture, pigmentation and other visually observed characteristics, and voice and acoustic biomarkers might include complementary information in terms of speech rhythm, pitch, spectral characteristics and vocal dynamics.

The genomics, epigenomics, transcriptomics, proteomics, metabolomics, metagenomics and phenomics provide complimentary layers at the molecular level for the characterization of biological heterogeneity [18]. The molecular profiles can now be integrated with clinical, imaging, wearable and patient reported information to enable deeper exploration of biological signatures of Prakriti. Multimodal datasets, however, vary greatly in dimensionality, scale, temporal resolution, completeness and noise. Rigorous processing, harmonization of data across different processing modules, management of missing data, and cross-modal integration are thus essential for effective computational phenotyping. Shared latent representations from multimodal learning methods can be used to find common representations in multiple information sources [19] which forms the methodological underpinning of AI systems that can represent Prakriti as an integrated phenotype, not individual indicators.

4. Artificial Intelligence for Prakriti Pattern Recognition

AI provides a computational route towards more objective, reproducible and scalable evaluation of the Prakriti, by

identifying complex patterns in the diverse Ayurvedic health indicators. In the realm of Ayurveda, AI is also being used in emerging applications, such as automated constitutional assessment and personalized clinical decision support; however, further standardization of methods and rigorous validation are required to capitalize on these opportunities [20]. Structured clinical, physiological and questionnaire features can be classified into constitutional phenotypes using conventional machine-learning algorithms such as logistic regression, support vector machines, decision trees, random forests and ensemble approaches. These techniques are especially useful where the data sets are not too large and an interpretable relationship between the predictor and outcome variables is desired [21].

Conventional approaches can be extended by learning hierarchical representations from high dimensional data automatically using deep learning, thus eliminating the need for handcrafted features [22]. This is important in the context of image-based Ayurvedic evaluation, as the morphology of the face, skin, tongue, and body shape could include complex phenotypic information. Computer-vision based classification of Prakriti types has already been attempted by researchers for the classification of different Prakriti types, proving the feasibility of extracting constitution-specific information from visual attributes [23]. Another complementary approach is to use natural language processing to transform unstructured clinical notes, symptom descriptions, and patient-reported data into computational representations. The fact that it has been successfully applied to clinical notes shows its ability to extract clinically relevant information from complex textual records [24].

Recognizing the Prakriti may be more complex and involve a multimodal AI that can combine various information such as clinical, imaging, physiological, wearable, behavioral, and molecular. Representation learning and multimodal fusion can learn many complementary and common pieces of information from different modalities, which may lead to richer representations of patients than single modality models [25]. However, such predictive accuracy is not enough for clinical translation. Therefore, it is important to have explainable AI that supports Prakriti classification based on feature attribution, interpretable decision pathways, uncertainty estimation and transparent relationships between computational features and Ayurvedic characteristics. This may allow clinicians to understand the logic behind the creation of a specific constitutional classification, to identify influential features and to identify poor predictions. Thus, clinically interpretable multimodal AI could revolutionize the way Prakriti is recognized, moving beyond mere classification to an evidence-based approach for personalized Ayurvedic evaluation and personalized treatment.

Table 2. AI Approaches for Prakriti Pattern Recognition

AI approach	Application to Prakriti assessment	Key advantage	Reference
AI in Ayurveda	Automated constitutional assessment and clinical decision support	Improves objectivity and scalability	[20]
Conventional machine learning	Classification using clinical, physiological, and questionnaire data	Suitable for structured, moderate-sized datasets	[21]

Deep learning	Automated extraction of complex phenotypic features	Reduces manual feature engineering	[22]
Computer vision	Classification from facial and other visual characteristics	Enables image-based Prakriti recognition	[23]
Natural language processing	Extraction of features from clinical narratives and symptom descriptions	Utilizes unstructured textual data	[24]
Multimodal AI	Fusion of clinical, imaging, physiological, behavioral, and molecular data	Generates comprehensive patient representations	[25]
Explainable AI	Interpretation of model predictions and influential features	Supports transparency and clinical trust	[20]

5. AI-Based Personalization and Prediction of Therapeutic Response

The aim of Prakriti recognition is not only to identify one's constitutional type, but also to have an idea about what interventions might be most likely to assist a person.Clinical value of Prakriti recognition goes beyond the constitutional type classification and is also useful for knowing which interventions are likely to help a person. One of the reasons for the consideration of Prakriti as a personalised-medicine framework is the fact that there might be a constitutional difference between individuals that could drive heterogeneity in terms of disease susceptibility, treatment needs and therapeutic outcomes [26]. AI can do this by integrating the concept of Prakriti along with clinical, genomic, physiology, behavioural and lifestyle data, to produce personal predictions of response to treatment. Similar precision medicine uses illustrate the potential of using AI-based analysis of genomic biomarkers to enable patient stratification and treatment optimization, offering a methodological model for constitution informed therapeutic modelling [27].

Dietary and lifestyle interventions are especially appropriate targets, since recommendations for this have been prescribed on an individual basis, based on health and constitution in accordance with Ayurveda. An AI-driven personalized nutrition approach will allow combining metabolic, behavioral, clinical and lifestyle data to forecast individual dietary needs and tailor individual nutrition recommendations [28]. Dietary or lifestyle responses could be analysed with models similar to this that make use of Prakriti as an extra phenotypic layer. Therapeutic-response modelling might also be applied to Ayurvedic herbal interventions, by combining constitutional traits with molecular signatures, disease traits, exposure to treatment and observed outcomes, but large longitudinal data sets will be needed first for reliable predictions to be made.

Another opportunity for multimodal personalisation comes in the form of yoga and behavioural interventions. The

measurable therapeutic outcomes of integrated yoga and behavioral programs demonstrate the measurable therapeutic effects that may be endpoints in models of individual prediction [29]. Continuous monitoring via wearable devices and digital phenotyping could also record sleep, activity, autonomic parameters, symptoms and behavior changes during therapy. Repeated real-world measurements of a patient's digital phenotype are being explored as a marker of treatment non-response and are seen to be useful in identifying different treatment courses [30].

It is important to note that the predictive association does not necessarily imply treatment benefit. Causal machine learning offers techniques for estimating “heterogeneous treatment effects” and determining which treatment the machine should suggest to a specific patient for improved outcomes, rather than just predicting prognosis [31]. Combined with causal AI, the multimodal longitudinal monitoring and the Prakriti-based phenotyping, it can thus aid in adapting therapeutic selection and gradually move the application of AI in Ayurveda from constitutional categorization to evidence-based prediction of treatment-responses on an individual basis.

6. Clinical Validation, Translation, and Responsible AI

A non-predictive approach to clinical translation of AI-assisted Prakriti assessment must also include proper validation, standardization of the phenotype definitions and proper governance. One of the critical problems is the reliable ground-truth Prakriti labelling. There is a significant level of variation in the domains covered, scoring methods, psychometric properties, and levels of validation of existing tools for assessment [32]. For the generation of reliable labels for AI development, consensus-based assessment protocols, validated questionnaires and the consensus among trained Ayurvedic practitioners are therefore essential. Subsequent to modeling, models should then be subjected to thorough testing and assessment on discrimination, sensitivity, specificity, calibration, and clinically meaningful performance measures, with independent external validation emphasized over model performance based on data set internal to the model.

Consider also the importance of population diversity, as a filter that can be applied to algorithms that have been created in a narrow demographic or biological range that might not work in other groups if applied. The results from the gene expression prediction illustrate that there is no guarantee that the underlying biological architectures and data distributions are the same across populations, and this can result in model performance differences [33]. Prakriti-based systems should then be validated in different geographic, demographic, socio-economic and clinical population before a wide implementation. Validation may also be further supported by the introduction of longitudinal digital phenotyping, which is able to detect temporal patterns linked to therapeutic response and non-response, in addition to a cross sectional measurement [30]. In addition, causal machine-learning methods can be used to identify potential differences among treatment groups, which may enhance the clinical usefulness and relevance of individualized recommendations [31].

The clinical decision-support systems into which the translation is included should keep meaningful human oversight. While AI can support interpretation and communication in healthcare settings, there is a need to consider accuracy, contextual reliability, and potential risks of implementation in a systematic way before widespread adoption. Responsible AI for Ayurveda also needs to consider privacy and security, as multimodal systems can integrate genomic, physiological, behavioral, imaging, and longitudinal health data. Therefore, it is essential that consent is transparent, data infrastructures are secure, access is controlled, and data governance is accountable. Algorithmic bias should be assessed for relevant patient subgroups and explainability and uncertainty reporting should allow practitioners to critically assess the recommendations made. The results from the intervention research studies also highlight the need to assess personalized interventions in terms of their clinical impact, not just technological performance (Tanksale et al., 2021). In conclusion, the future of using AI for personalizing Ayurvedic medicine hinges on regulatory oversight, fairness, transparency, privacy protection, and prospective clinical validation, all of which must keep pace with the innovations and predictions of AI.

7. Current Challenges, Research Gaps, and Future Directions

However, while there is growing interest in the use of AI tools for Ayurvedic phenotyping, there are several hurdles to its use in a clinically viable personalized health care system. One of the big challenges is that there are no large, standardized multimodal data sets that combine validated Prakriti labels with clinical, physiological, imaging, molecular, lifestyle and therapeutic-response data. Studies conducted to date often report on small sample sizes, different assessment and computation procedures, and inconsistent methods of assessing outcomes, which makes it challenging to reproduce and apply results to other populations. Model development is further complicated by mixed-Prakriti phenotypes, which may have a more complex state than can be adequately captured by a categorical approach, as there is uncertainty and continuality concerning the phenotype. Probabilistic phenotyping and a standardized reference framework with multicenter and longitudinal validation should thus be used in future studies.

Combining multi-omics profiles with wearable sensors and digital phenotyping is an important avenue for the collection of stable biological characteristics and health trajectories. However, these high-dimensional datasets pose significant privacy, interoperability and interpretability issues. Federated learning and other privacy-preserving architectures might enable collaborative model building without having to centralize sensitive health information and explainable AI is largely vital to creating clinical transparency and practitioner trust. More importantly, research needs to move beyond the replication of the traditional Prakriti classifications. Future systems should identify if there is a benefit to disease-risk stratification, therapeutic selection and individualized response prediction using multimodal constitutional phenotypes. Prospective clinical trials, causal modelling, adaptive monitoring, representation of diverse populations and human-in-the-loop decision support will therefore be key to the future of making AI-powered Ayurveda a scientifically valid precision-health system.

8. Conclusion

Overall, the integration of AI with multimodal health data and Ayurvedic constitutional medicine holds great potential for more objective and personalized healthcare. Traditionally, inter-individual differences in physiological, metabolic, behavioural and therapeutic attributes are described by Prakriti, which may offer a useful phenotypic-based framework for computational personalisation. A combination of clinical data, questionnaires, physiological signals, wearable measurements, imaging, voice signals, lifestyle data, and multi-omics analyses can be used to establish complex patterns of constitution and identify those that might not be detected by the standard assessment.AI can reinforce this framework using clinical data, questionnaires, physiological signals, wearable measurements, imaging, voice characteristics, lifestyle data, and multi-omics profiles. Importantly, such systems must be clinically relevant, not just in the sense of automated Prakriti classification, but also in their ability to predict disease-susceptibility, therapeutic response, and personalized therapeutic strategies. Dynamic and clinically interpretable personalization can be achieved by using multimodal learning, explainable AI, longitudinal digital phenotyping, and causal machine learning. However, definitions of Prakriti in routine healthcare will need to be standardized, good multi-center data collection, external validation, diversification of patient cohorts, clear algorithmic consistency and strict assessment of clinical applicability. Meaningful practitioner involvement, privacy, fairness, cultural integrity and regulatory oversight need to be embedded throughout system development as well. Thus, future studies should focus on prospective studies that examine incremental value of AI-generated constitutional phenotypes in treatment decisions and patient outcomes and create an evidence-based link between Ayurvedic knowledge and modern precision medicine.

References

1. Johnson, K. B., Wei, W. Q., Weeraratne, D., Frisse, M. E., Misulis, K., Rhee, K., ... & Snowdon, J. L. (2021). Precision medicine, AI, and the future of personalized health care. Clinical and translational science, 14(1), 86-93.

2. Ho, D., Quake, S. R., McCabe, E. R., Chng, W. J., Chow, E. K., Ding, X., ... & Zarrinpar, A. (2020). Enabling technologies for personalized and precision medicine. Trends in biotechnology, 38(5), 497-518.
3. Khatua, D., Sekh, A. A., Kutum, R., Mukherji, M., Prasher, B., & Kar, S. (2023). Classification of Ayurveda constitution types: a deep learning approach. Soft Computing, 27(9), 5309-5317.
4. Sharma, R., & Prajapati, P. K. (2020). Predictive, preventive and personalized medicine: leads from ayurvedic concept of Prakriti (human constitution). Current Pharmacology Reports, 6(6), 441-450.
5. Ng, J. Y., Cramer, H., Lee, M. S., & Moher, D. (2024). Traditional, complementary, and integrative medicine and artificial intelligence: Novel opportunities in healthcare. Integrative medicine research, 13(1), 101024.
6. Cramer, H. (2023). Artificial intelligence, complementary and integrative medicine: a paradigm shift in health care delivery and research?. Journal of integrative and complementary medicine, 29(3), 131-133.
7. Ali, N., & Shah, W. (2025). Integrative Systems and Holistic Health Records: A New Paradigm in Personalized Medicine.
8. Liu, H., Bilc, M. I., & Ng, J. Y. (2025). Research at the Intersection of Traditional, Complementary, and Integrative Medicine and Artificial Intelligence: A Bibliometric Analysis. medRxiv, 2025-12.
9. Venkatesh, A., Johansson, L., Sivanandan, P. V., Gopakumar, S. P., Sankaranarayanan, K., Kessler, C. S., ... & Puthiyedath, R. (2025). Prakriti (constitutional typology) in Ayurveda: a critical review of Prakriti assessment tools and their scientific validity. Frontiers in Medicine, 12, 1656249.
10. Jnana, A., Murali, T. S., Guruprasad, K. P., & Satyamoorthy, K. (2020). Prakriti phenotypes as a stratifier of gut microbiome: A new frontier in personalized medicine?. Journal of Ayurveda and integrative medicine, 11(3), 360-365.
11. Huang, Z., Chavda, V. P., Bezbaruah, R., Uversky, V. N., P, S., Patel, A. B., & Chen, Z. S. (2022). An ayurgenomics approach: prakriti-based drug discovery and development for personalized care. Frontiers in pharmacology, 13, 866827.
12. Singh, S., Gehlot, S., Agrawal, N. K., Singh, G., Singh, D., Kaur, P., ... & Singh, R. (2024). Molecular study of the KCNJ11 gene and its correlation with Prakriti to preventing and managing type 2 diabetes. Journal of Traditional and Complementary Medicine, 14(5), 494-500.
13. Dua, P., Prasher, B., Seth, S., Pandey, S., Maulik, S. K., & Reeta, K. H. (2025). Prakriti elucidates the inter-individual variability in coronary artery disease risk-predicting biomarkers: A tertiary care hospital-based case control study. Journal of Ayurveda and Integrative Medicine, 16(5), 101178.
14. Stergiou, M., Robles-Pérez, J. J., Rey-Mota, J., Tornero-Aguilera, J. F., & Clemente-Suárez, V. J. (2023, December). Psychophysiological responses in soldiers during close combat: implications for occupational health and fitness in tactical populations. In Healthcare (Vol. 12, No. 1, p. 82). MDPI.
15. Al-Raddadi, R., Bahijri, S. M., Jambi, H. A., Ferns, G., & Tuomilehto, J. (2019). The prevalence of obesity and overweight, associated demographic and lifestyle factors, and health status in the adult population of Jeddah, Saudi Arabia. Therapeutic advances in chronic disease, 10, 2040622319878997.
16. Sano, A., Taylor, S., McHill, A. W., Phillips, A. J., Barger, L. K., Klerman, E., & Picard, R. (2018). Identifying objective physiological markers and modifiable behaviors for self-reported stress and mental health status using wearable sensors and mobile phones: observational study. Journal of medical Internet research, 20(6), e210.
17. Bhardwaj, N., Singh, A., Sharma, R., Chaudhary, G., Chandel, A., Bhavsar, A., & Dutt, V. (2025). Machine Learning Framework for Individualised Health Profiling Using Multimodal Physiological and Neurocognitive Biomarkers.
18. Srivastava, U., Kanchan, S., Kesheri, M., Gupta, M. K., & Singh, S. (2024). Types of omics data: genomics, metagenomics, epigenomics, transcriptomics, proteomics, metabolomics, and phenomics. In Integrative omics (pp. 13-34). Academic Press.
19. Song, G., Wang, S., Huang, Q., & Tian, Q. (2019). Harmonized multimodal learning with Gaussian process

latent variable models. IEEE transactions on pattern analysis and machine intelligence, 43(3), 858-872.
20. Shaumya, S., & Kumar, R. (2025). Artificial Intelligence in Ayurveda: A Systematic. Journal of Ayurveda and Naturopathy, 2(2), 05-19.
21. Lee, S., & El Naqa, I. (2022). Conventional Machine Learning Methods. In Machine and Deep Learning in Oncology, Medical Physics and Radiology (pp. 27-50). Cham: Springer International Publishing.
22. Dara, S., & Tumma, P. (2018, March). Feature extraction by using deep learning: A survey. In 2018 Second international conference on electronics, communication and aerospace technology (ICECA) (pp. 1795-1801). IEEE.
23. Gadre, G. (2019). Classification of humans into Ayurvedic Prakruti types using computer vision.
24. Sheikhalishahi, S., Miotto, R., Dudley, J. T., Lavelli, A., Rinaldi, F., & Osmani, V. (2019). Natural language processing of clinical notes on chronic diseases: systematic review. JMIR medical informatics, 7(2), e12239.
25. Zhang, C., Yang, Z., He, X., & Deng, L. (2020). Multimodal intelligence: Representation learning, information fusion, and applications. IEEE Journal of Selected Topics in Signal Processing, 14(3), 478-493.
26. Coffin, J. D., Rao, R., & Lurie, D. I. (2018). Translational potential of ayurveda prakriti: concepts in the area of personalized medicine. In Translational Ayurveda (pp. 21-32). Singapore: Springer Singapore.
27. Kumar, A., & Metta, D. (2024). AI-driven precision oncology: predictive biomarker discovery and personalized treatment optimization using genomic data. Int J Adv Res Publ Rev, 1(3), 21-38.
28. Agrawal, K., Goktas, P., Kumar, N., & Leung, M. F. (2025). Artificial intelligence in personalized nutrition and food manufacturing: a comprehensive review of methods, applications, and future directions. Frontiers in Nutrition, 12, 1636980.
29. Tanksale, R., Sofronoff, K., Sheffield, J., & Gilmour, J. (2021). Evaluating the effects of a yoga-based program integrated with third-wave cognitive behavioral therapy components on self-regulation in children on the autism spectrum: A pilot randomized controlled trial. Autism, 25(4), 995-1008.
30. Hammelrath, L., Brose, A., Heinrich, M., Zagorscak, P., Burchert, S., Langhammer, T., & Knaevelsrud, C. (2025). PREACT-digital: study protocol for a longitudinal, observational multicentre study on digital phenotypes of non-response to cognitive behavioural therapy for internalising disorders. BMJ open, 15(7), e102392.
31. Feuerriegel, S., Frauen, D., Melnychuk, V., Schweisthal, J., Hess, K., Curth, A., ... & van der Schaar, M. (2024). Causal machine learning for predicting treatment outcomes. Nature Medicine, 30(4), 958-968.
32. Gupta, A., Singh, V., Chandra, S., & Garg, R. (2025). Towards standardization of Prakriti evaluation: A scoping review of modern assessment tools and their psychometric properties in Ayurvedic medicine. Journal of Ayurveda and integrative medicine, 16(4), 101157.
33. Keys, K. L., Mak, A. C., White, M. J., Eckalbar, W. L., Dahl, A. W., Mefford, J., ... & Gignoux, C. R. (2020). On the cross-population generalizability of gene expression prediction models. PLoS genetics, 16(8), e1008927.
34. Genovese, A., Borna, S., Gomez-Cabello, C. A., Haider, S. A., Prabha, S., Forte, A. J., & Veenstra, B. R. (2024). Artificial intelligence in clinical settings: a systematic review of its role in language translation and interpretation. Annals of Translational Medicine, 12(6), 117.