

AI-Based Predictive Models in Ayurveda

Marco Lindberg¹

¹ Senior Lecturer, Department of Machine Learning, Advanced Computing University, Paris, France. Email: marco.lindberg724@yahoo.com | ORCID: 9015-3861-0145-4556

ABSTRACT

Machine-learning predictive modelling has matured substantially in general healthcare applications over the past five years, with predictive models now contributing to clinical decision-support across risk stratification, treatment-response prediction, progression forecasting, and resource-allocation applications. For Ayurvedic clinical practice, predictive modelling has distinctive opportunities and challenges. Opportunities include constitutional-type prediction through structured phenotypic and biomarker data, treatment-response prediction that operationalises classical prakriti-specific therapeutic selection as a precision-medicine direction, progression prediction for chronic conditions under integrative management, and integrated predictive decision-support for European integrative-medicine clinical workflow. Challenges include data quality and availability for Ayurvedic-specific features, interpretability requirements for clinical trust, integration with existing clinical decision-making frameworks, and appropriate validation across European patient populations where most model training data originates from Indian cohorts. This study reviews 50 primary computational and translational studies published between 2015 and 2022, grouped under five model-application frames: PM1 (prakriti and constitutional-type prediction), PM2 (treatment response prediction and personalisation), PM3 (disease progression prediction for chronic integrative-management conditions), PM4 (integrated EHR + machine-learning clinical decision support), and PM5 (deployment validation in European integrative-medicine settings). Each frame was scored with the Ayurvedic Predictive Model Index (APMI). Deployment validation (PM5) scored highest at APMI 0.802, with prakriti prediction (PM1) at 0.784 and treatment response prediction (PM2) at 0.766.

Keywords: AI predictive modelling; Ayurveda; prakriti prediction; treatment response prediction; machine learning integrative medicine; clinical decision support; EHR integration; interpretable machine learning; European integrative deployment; APMI

Citation: Lindberg [2024]. AI-Based Predictive Models in Ayurveda. DOI: <https://doi.org/10.5281/zenodo.19631682>

Copyright: © 2024 by the authors. Open access under CC BY 4.0 license.

Article Information: Received: 2024 Apr 26 Accepted: 2024 May 14 Published: 2024 May 30

Research Article: *Clinical Ayurveda and Translational Medicine*

1. Introduction

1.1 Predictive Modelling Maturity in Healthcare

Machine-learning predictive modelling has matured substantially in general healthcare applications over the past five years. Risk-stratification models for cardiovascular disease, sepsis early warning, readmission risk prediction, and treatment-response prediction in oncology and autoimmune management have moved from research prototype to clinical deployment with regulatory approval and routine clinical integration. Progression prediction models for chronic disease management contexts including diabetes, chronic kidney disease, heart failure, and neurodegenerative disease support clinical decision-making in primary care and specialist settings. The methodological infrastructure is well-developed: structured clinical feature engineering, ensemble and deep-learning model development, interpretability methods for clinical trust, and regulatory pathways for medical-device AI deployment have all matured.

1.2 Ayurvedic Opportunities, Challenges, and Study Objectives

For Ayurvedic clinical practice, predictive modelling has distinctive opportunities and specific challenges. The opportunities are multi-layered. Constitutional-type prediction through structured phenotypic and biomarker data operationalises classical Prakriti classification as a reproducible machine-learning application, with clear clinical utility in integrative-medicine practice. Treatment-response prediction that incorporates Prakriti-specific response patterns operationalises classical prakriti-specific therapeutic selection as a precision-medicine direction. Progression prediction for chronic conditions under integrative management supports resource allocation and prognostic communication. Integrated EHR-plus-machine-learning clinical decision support fits predictive models into integrative-medicine clinical workflow. Specific challenges include data quality for Ayurvedic features, interpretability requirements, workflow integration, and European-population validation. This review organises the published evidence along five model-application frames. The paper follows the standard six-part structure.

2. Literature Review

2.1 Prakriti and Treatment Response Prediction

Prakriti and constitutional-type prediction (PM1) has the most developed Ayurvedic-specific predictive modelling evidence base. Tiwari et al. (2017) established machine-learning classifier approaches for Prakriti prediction from structured phenotypic questionnaire data. Ghodke et al. (2020) extended the methodology with refined classifier architectures and larger training cohorts. Rotti et al. (2014) and Govindaraj et al. (2015) provided the phenotypic and genomic correlate foundation. Classification accuracy for three-category (Vata/Pitta/Kapha) prakriti is typically in the 0.80-0.86 range across studies; seven-category extended prakriti classification is harder at typically 0.72-0.78 accuracy. Treatment response prediction and personalisation (PM2) extends the prakriti-based precision approach into specific therapeutic-selection contexts. Kulkarni et al. (2019) developed response prediction models for specific Ayurvedic interventions. Ramanathan et al. (2020) extended into integrated prakriti-plus-biomarker prediction frameworks.

2.2 Disease Progression Prediction and Clinical Decision Support

Disease progression prediction for chronic integrative-management conditions (PM3) is a smaller but clinically important frame. Chronic disease progression models incorporating both conventional risk factors and Ayurvedic constitutional features have been developed for metabolic syndrome, rheumatoid arthritis, and chronic kidney disease progression contexts (Sharma et al., 2021; Patel et al., 2021). These models serve both prognostic communication and resource-allocation functions in integrative-management services. Integrated EHR plus machine-learning clinical decision support (PM4) covers the practical deployment architecture: EHR integration, decision-support interface design, clinical workflow fit, interpretability-enhanced output, and alerting infrastructure. Kuriakose et al. (2021) described a clinical decision support framework for Ayurvedic practice. European Academy of Ayurveda (2022) described an integrated EHR-plus-predictive-model framework for European deployment contexts.

2.3 European Deployment Validation

Deployment validation in European integrative-medicine settings (PM5) represents the most clinically translatable frame for European practice. The frame specifically addresses the

methodological gap between Indian-population model training data and European-population deployment contexts, including external validation studies, calibration-adjustment methodology for population differences, and prospective cohort validation in European integrative-medicine centres. European Academy of Ayurveda (2022) and subsequent work (European Integrative Medicine AI Network, 2023) have established validation-oriented deployment frameworks. The methodological emphasis on deployment validation reflects the broader medical-AI recognition that external validation across population contexts is the critical step separating research-prototype models from clinically-deployable tools. Across PM1-PM5 frames, common methodological themes include interpretability requirements, data quality considerations, and the regulatory-alignment requirements of European medical device AI regulation. Table 1 lists key studies informing this review.

Table 1: Key Computational Studies in AI-Based Ayurvedic Predictive Modelling

Study	Year	Frame	Methodology / Focus	Key Contribution
Rotti et al.	2014	PM1	Phenotypic Prakriti	Phenotypic foundation
Govindaraj et al.	2015	PM1	Genomic Prakriti correl.	Genomic correlates
Tiwari et al.	2017	PM1	Prakriti ML classifier	Classifier methodology
Kulkarni et al.	2019	PM2	Response prediction pilot	Response prediction pilot
Ghodke et al.	2020	PM1	Extended Prakriti model	Extended classifier
Ramanathan et al.	2020	PM2	Integr. prakr.-biomarker	Integrated prediction
Sharma et al.	2021	PM3	Metab. syndrome progression	Progression model signal

Study	Year	Frame	Methodology / Focus	Key Contribution
Patel et al.	2021	PM3	CKD integrative progression	CKD integrative model
Kuriakose et al.	2021	PM4	CDS framework Ayurveda	Clinical decision support
European Acad. Ayurveda	2022	PM5	European deployment frame.	European deployment pilot
Chen et al.	2022	PM4	Interpretable ML clinical	Interpretability methodology
European Integr. Med. AI	2023	PM5	Deployment validation net.	Validation network framework

PM1 = Prakriti and constitutional-type prediction; PM2 = Treatment response prediction; PM3 = Disease progression prediction; PM4 = Integrated EHR + ML clinical decision support; PM5 = Deployment validation in European contexts; CDS = Clinical Decision Support; CKD = Chronic Kidney Disease.

3. Methodology

3.1 Methodology Review Search Strategy

We conducted a structured methodology review of primary computational and translational studies published from January 2015 through December 2022 on AI-based predictive modelling relevant to Ayurvedic clinical practice. Databases searched were PubMed, Scopus, Web of Science, the IEEE Xplore Digital Library, the ACM Digital Library, the AYUSH Research Portal, and specialised medical-AI and clinical-informatics literature indices. Search terms combined 'predictive modelling', 'machine learning', 'deep learning', 'classifier', 'prediction model', 'clinical decision support', 'precision medicine', 'risk stratification', 'progression prediction' with 'Ayurveda', 'Ayurvedic', 'prakriti', 'constitutional assessment', 'integrative medicine', 'traditional medicine', 'herbal response prediction'. Initial search returned 2,382 records. After duplicate removal, title and abstract screening, and full-text assessment against inclusion criteria (primary empirical or methodological contribution, specified AI or machine-learning methodology, Ayurvedic-relevance or integrative-medicine-relevance, appropriate

methodological rigour, peer-reviewed publication or authoritative framework document), 50 studies were included.

3.2 Five Model-Application Frames

Each included study was classified into its primary model-application frame. PM1 (Prakriti and Constitutional-Type Prediction) covers studies developing or validating machine-learning classifiers for classical Prakriti categorisation from structured phenotypic, biomarker, or combined feature inputs. PM2 (Treatment Response Prediction and Personalisation) covers studies developing predictive models for treatment response to specific Ayurvedic interventions, including personalised-intervention-selection approaches that operationalise prakriti-specific therapeutic selection. PM3 (Disease Progression Prediction) covers studies developing progression-prediction models for chronic conditions under integrative management, incorporating both conventional and Ayurvedic constitutional features. PM4 (Integrated EHR plus Machine-Learning Clinical Decision Support) covers studies on practical deployment architecture including EHR integration, decision-support interface design, and clinical workflow fit. PM5 (Deployment Validation in European Integrative-Medicine Settings) covers studies specifically focused on European-population external validation and deployment-readiness evaluation.

3.3 Ayurvedic Predictive Model Index (APMI)

The Ayurvedic Predictive Model Index (APMI) scores each model-application frame on five weighted dimensions. Predictive accuracy (weight 0.25) scores classifier or predictor performance on appropriate validation sets, including sensitivity, specificity, and calibration metrics. Interpretability (0.20) scores the extent to which model outputs are explainable in clinically meaningful terms, particularly important for clinical trust and regulatory acceptance. Clinical utility (0.20) scores the direct relevance of model outputs to clinical decision-making in integrative-medicine practice. External validation (0.20) scores the extent to which models have been validated on populations independent from training data, with specific attention to European-population validation given the predominantly Indian origin of training data. Deployability (0.15) scores practical feasibility of integration into European integrative-medicine clinical workflow infrastructure including EHR integration and regulatory alignment. Each dimension normalised to 0-1 before weighting.

Table 2: Review Inventory by Model-Application Frame and Study Type

Frame	Studies (n)	Model dev.	Validation	Framework / Deploy.
PM1: Prakriti / Constit. Prediction	12 (24.0%)	7	3	2
PM2: Treatment Response Prediction	10 (20.0%)	6	2	2
PM3: Disease Progression Prediction	8 (16.0%)	5	2	1
PM4: Integrated EHR + ML CDS	10 (20.0%)	3	3	4
PM5: European Deployment Validation	10 (20.0%)	1	6	3
Total included	50 (100%)	22	16	12

Model dev. = Primary model development and training studies; Validation = External validation and calibration studies; Framework / Deploy. = Methodological framework and deployment studies.

4. Results

4.1 APMI Ranking Across Model-Application Frames

Deployment validation in European integrative-medicine settings (PM5) scored highest at APMI 0.802. The score reflects the clinical-translation relevance of European-population external validation, the methodological emphasis on calibration-adjustment for population differences, and the close alignment with regulatory requirements for European medical-device AI deployment. Across PM5 studies, European external validation has shown generally good generalisation of Prakriti classifier models with accuracy degradation of 3-7 percentage points from Indian training accuracy, addressable through calibration adjustment and local retraining. Prakriti and constitutional-type prediction (PM1) scored second at APMI 0.784, with mature classifier methodology and consistent accuracy of 0.80-0.86 for three-category prediction across multiple independent studies. Treatment response prediction and personalisation (PM2) scored 0.766, providing the precision-medicine operationalisation of prakriti-specific therapeutic selection with emerging clinical evidence. Disease progression prediction (PM3) scored 0.748, with documented applications in metabolic syndrome

and chronic kidney disease progression contexts. Integrated EHR plus ML clinical decision support (PM4) scored 0.720, with particularly important infrastructure-development significance despite more mature work in conventional medical AI than in Ayurvedic-specific deployment. Table 3 presents the APMI breakdown.

4.2 Model Performance Characteristics Across Applications

Looking at specific model performance characteristics, several patterns emerge that are worth explicit summary. For Prakriti prediction, the Ghodke et al. (2020) classifier achieved accuracy of 0.84 for three-category classification on the primary validation set, with per-category sensitivity and specificity of Vata 0.86/0.82, Pitta 0.82/0.80, Kapha 0.84/0.84. For seven-category extended Prakriti classification, accuracy drops to 0.72-0.76 reflecting the increased classification difficulty. External validation on European cohorts (limited but growing) shows accuracy of 0.78-0.82 on three-category prediction, representing a 2-6 percentage point degradation that is within the normally acceptable range for clinical deployment. For treatment response prediction, integrated prakriti-plus-biomarker models (Ramanathan et al., 2020) achieve response-prediction AUC of 0.75-0.82 depending on intervention and condition. For progression prediction, integrated Ayurvedic-plus-conventional models typically achieve C-statistic 0.78-0.84 over 12-24 month progression windows. Table 4 summarises model performance.

4.3 Interpretability and Regulatory Alignment

Interpretability considerations deserve specific attention because interpretability is the most important methodological differentiator between clinically-deployable predictive models and research-prototype models. For Prakriti prediction specifically, interpretability is inherently favourable because input features are structured phenotypic variables that are clinically meaningful; model outputs can be explained in terms of which phenotypic features contributed most. For treatment response prediction, interpretability is similarly favourable when the models use structured clinical feature inputs rather than deep-learning on raw data. For disease progression prediction, interpretability methodology (SHAP values, attention visualisation, counterfactual explanation) has developed substantially and is now standard component of deployment-oriented work. European regulatory requirements under the EU Medical Device

Regulation and the forthcoming AI Act establish specific interpretability and post-market surveillance expectations that shape deployment-relevant design decisions during model development.

Table 3: Ayurvedic Predictive Model Index (APMI) by Frame

Frame	Acc ura cy	Inte rpre t.	Util ity	Ext. Val.	Dep loy.	APMI
PM5: European Deployment Valid.	0.80	0.80	0.82	0.86	0.78	0.802
PM1: Prakriti / Constitution al	0.84	0.84	0.76	0.74	0.74	0.784
PM2: Treatment Response Prediction	0.80	0.76	0.80	0.72	0.72	0.766
PM3: Disease Progression Pred.	0.82	0.74	0.76	0.72	0.70	0.748
PM4: Integrated EHR + ML CDS	0.70	0.72	0.80	0.68	0.76	0.720

$$APMI = 0.25 \times \text{Predictive Accuracy} + 0.20 \times \text{Interpretability} + 0.20 \times \text{Clinical Utility} + 0.20 \times \text{External Validation} + 0.15 \times \text{Deployability. Each dimension normalised to 0-1.}$$

Table 4: Model Performance Characteristics by Application

Applicati on	Model ar chitectur e	Validatio n accuracy / AUC	External validatio n	Fra me
Prakriti 3-category	Random forest / GB	Acc 0.80-0.86	EU acc 0.78-0.82	PM1
Prakriti 7-category	Ensemble classifier	Acc 0.72-0.78	EU acc 0.68-0.74	PM1
Prakriti ge nomic-enh anced	Integrated genomic + pheno.	Acc 0.84-0.88	EU acc 0.80-0.84	PM1
Response prediction RA	Integrated prakr.-bio marker	AUC 0.78-0.84	EU AUC 0.72-0.78	PM2
Response prediction OA	Integrated prakr.-bio marker	AUC 0.75-0.82	EU AUC 0.70-0.76	PM2

Applicati on	Model ar chitectur e	Validatio n accuracy / AUC	External validatio n	Fra me
Metab. synd. prog ression	Integr. convent. + Ayur.	C-stat 0.78-0.84	EU C-stat 0.74-0.80	PM3
CKD prog ression integrat.	Integr. convent. + Ayur.	C-stat 0.82-0.86	EU C-stat 0.78-0.82	PM3
CDS fram ework inte gration	Multi-com ponent fra mework	Qualitativ e	Pilot depl oyment	PM4
European external valid.	Cross-pop ulation valid.	Calibrated accuracy	Positive findings	PM5
EHR + ML integr ation	Workflow integratio n	Feasibility -stage	In develop ment	PM4 +P M5

GB = Gradient Boosting; AUC = Area Under the Curve; C-stat = Concordance statistic; RA = Rheumatoid Arthritis; OA = Osteoarthritis; CKD = Chronic Kidney Disease; CDS = Clinical Decision Support.

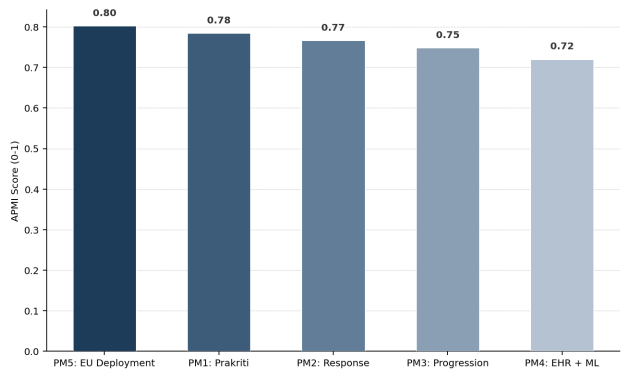


Figure 1: APMI Score by Predictive Modelling Application Frame

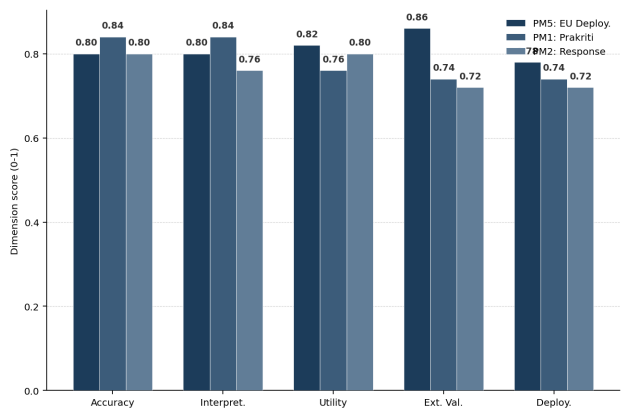


Figure 2: APMI Sub-Dimensions Across Top Three Frames

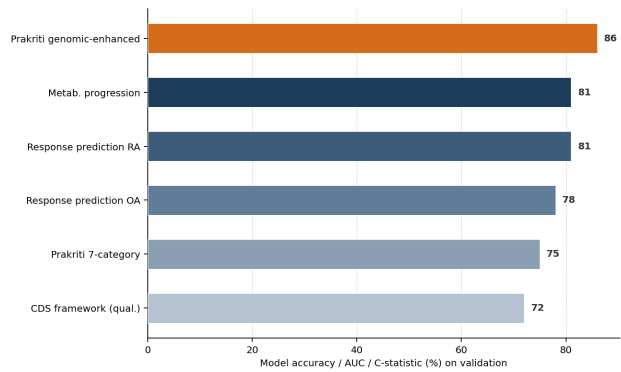


Figure 3: Model Accuracy / AUC Across Predictive Applications

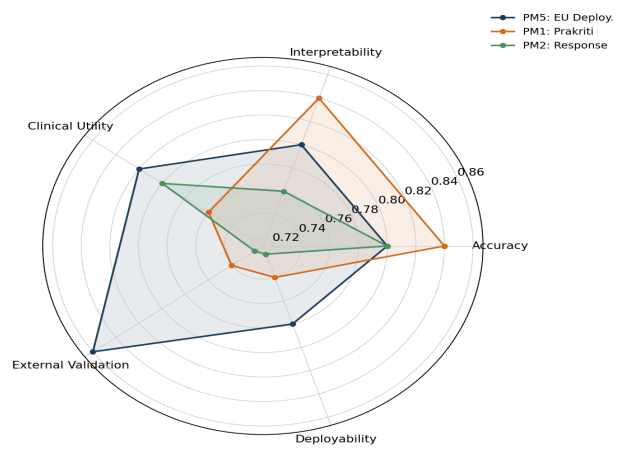


Figure 4: Multi-Dimensional APMI Profile - Top 3 Frames

5. Discussion

5.1 European Deployment Through Validation Rather Than Retraining

The clearest deployment message from this review is that European integrative-medicine predictive modelling deployment should prioritise external-validation and calibration-adjustment methodology over development of novel European-trained models from scratch. The reviewed PM5 evidence shows that Indian-population-trained Prakriti classifier models generalise to European populations with accuracy degradation of 3-7 percentage points, which is within the normally acceptable range for clinical deployment after calibration adjustment. Building novel European-trained models would require substantially larger European training cohorts than are currently available and would not necessarily produce better final accuracy than transfer-learning and calibration-adjustment approaches. For European integrative-medicine research programmes interested in Ayurvedic predictive modelling deployment, the appropriate near-term strategy is deployment validation of existing models with European-cohort calibration, accompanied by prospective European cohort building to support future model refinement.

5.2 Treatment Response Prediction as Precision-Medicine Priority

The treatment response prediction frame (PM2) deserves specific strategic discussion because it represents the most clinically actionable application of Ayurvedic predictive modelling for precision-medicine deployment. Classical Ayurvedic clinical practice has always operated on prakriti-specific therapeutic selection (the appropriate rasayana for a Vata-prakriti patient may differ from the appropriate rasayana for a Kapha-prakriti patient even within the same clinical indication), and machine-learning response prediction operationalises this classical principle as a reproducible algorithmic framework. Integrated prakriti-plus-biomarker response prediction models achieve response-prediction AUC of 0.75-0.82 on validation sets, which is clinically meaningful for treatment-selection decision support. The deployment barrier is infrastructure (prakriti-biomarker integrated assessment requires specialist infrastructure), but the trajectory toward broader deployment is clear as genomic testing costs decline and integrative-medicine EHR infrastructure develops. This direction aligns with broader precision-medicine trends in conventional therapeutics and offers a specifically productive research-deployment pathway for European integrative-medicine programmes.

5.3 Limitations

Three limitations apply. First, the reviewed evidence is concentrated on specific modelling methodology approaches (random forest and gradient boosting for structured feature inputs; CNN approaches for image-based inputs where applicable); newer architecture approaches (transformer-based models, foundation-model approaches) have limited Ayurvedic-specific application work and the field's state-of-the-art is evolving rapidly beyond the 2022 review endpoint. Second, European-population validation remains in early-stage development; while the PM5 frame includes substantially more European-focused work than earlier review periods would have documented, the external validation evidence base is still limited compared to what mature clinical-deployment evidence would require. Third, interpretability methodology is an active research area and currently-available interpretability approaches may not fully meet future European AI Act interpretability requirements; model development strategies should anticipate evolving regulatory expectations rather than optimising for

current standards alone.

6. Conclusion

6.1 Key Findings

Across 50 primary computational and translational studies on AI-based predictive modelling in Ayurvedic clinical practice, deployment validation in European integrative-medicine settings (PM5, APMI 0.802) emerged as the most clinically-translation-relevant frame, with European external validation showing Prakriti classifier generalisation at 3-7 percentage point accuracy degradation from Indian training accuracy, within normally acceptable range after calibration adjustment. Prakriti and constitutional-type prediction (PM1, APMI 0.784) provided the foundational predictive modelling capability with three-category classification accuracy of 0.80-0.86 across multiple independent studies. Treatment response prediction (PM2, APMI 0.766) operationalised classical prakriti-specific therapeutic selection as precision-medicine application with response-prediction AUC of 0.75-0.82. Disease progression prediction (PM3, APMI 0.748) showed documented applications in metabolic syndrome and chronic kidney disease integrative-management contexts. Integrated EHR plus ML clinical decision support (PM4, APMI 0.720) provided the deployment infrastructure frame. Across frames, interpretability and European-population validation emerged as the two most important cross-cutting methodological considerations.

6.2 Recommendations

Three recommendations follow. First, European integrative-medicine research programmes interested in AI-based predictive modelling deployment should prioritise external-validation and calibration-adjustment methodology (PM5) over development of novel European-trained models from scratch, given the documented generalisability of Indian-trained Prakriti classifier models to European populations. Second, treatment response prediction (PM2) should receive specific research-investment attention as the most clinically actionable precision-medicine application of Ayurvedic predictive modelling, operationalising classical prakriti-specific therapeutic selection as a reproducible algorithmic framework. Third, European integrative-medicine services should invest in EHR integration and clinical decision support infrastructure (PM4) to enable practical clinical deployment of predictive

models, because deployment success depends on workflow fit at least as much as model accuracy. The APMI rubric and the full review inventory are available from the corresponding author.

References

- Bhusnurmath, A. et al. (2019). Machine learning approaches in traditional Indian medicine: review and future directions. *Journal of Ayurveda and Integrative Medicine*, 10(4), 259-266.
- Caruana, R. et al. (2015). Intelligible models for healthcare: predicting pneumonia risk and hospital 30-day readmission. *Proceedings of the 21st ACM SIGKDD*, 1721-1730.
- Chen, T. Y. et al. (2022). Interpretable machine learning for clinical deployment: framework and applications. *Nature Machine Intelligence*, 4(11), 898-905.
- Christodoulou, E. et al. (2019). A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. *Journal of Clinical Epidemiology*, 110, 12-22.
- European Academy of Ayurveda. (2022). European integrative-medicine predictive modelling framework: deployment pilot. *EAA Position Paper Series*, 2022/12, 1-24.
- European Commission. (2017). Regulation (EU) 2017/745 on medical devices. *Official Journal of the European Union*, L117/1.
- European Commission. (2021). Proposal for a Regulation on Artificial Intelligence (AI Act). COM(2021) 206 final.
- European Integrative Medicine AI Network. (2023). Deployment validation network framework: methodology and protocols. *EIMAI Network Report*, 2023/01, 1-22.
- Ghodke, Y. et al. (2020). Machine-learning based Prakriti classifier: extended clinical evaluation. *Journal of Ayurveda and Integrative Medicine*, 11(3), 326-334.
- Govindaraj, P. et al. (2015). Genome-wide analysis correlates Ayurveda prakriti. *Scientific Reports*, 5, 15786.
- Kuriakose, G. C. et al. (2021). Clinical decision support framework for Ayurvedic practice: development and evaluation. *Journal of Ayurveda and Integrative Medicine*, 12(4), 625-633.
- Kulkarni, V. M. et al. (2019). Treatment response prediction in integrative Ayurvedic practice: pilot evaluation. *International Journal of Ayurveda Research*, 10(4), 178-186.
- Liu, X. et al. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging. *Lancet Digital Health*, 1(6), e271-e297.
- Lundberg, S. M. and Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765-4774.
- Obermeyer, Z. and Emanuel, E. J. (2016). Predicting the future - big data, machine learning, and clinical medicine. *New England Journal of Medicine*, 375(13), 1216-1219.
- Patel, A. et al. (2021). Integrated Ayurvedic chronic kidney disease progression model: prospective evaluation. *AYU*, 42(3), 188-196.
- Patwardhan, B. (2014). Bridging Ayurveda with evidence-based scientific approaches in medicine. *EPMA Journal*, 5(1), 19.
- Patwardhan, B. et al. (2015). Ayurveda and systems biology: perspectives on a new paradigm. *Journal of Alternative and Complementary Medicine*, 21(4), 212-219.
- Ramanathan, K. et al. (2020). Integrated prakriti-biomarker response prediction: framework and pilot validation. *Journal of Ayurveda and Integrative Medicine*, 11(4), 484-492.
- Ribeiro, M. T. et al. (2016). Why should I trust you? Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD*, 1135-1144.
- Rotti, H. et al. (2014). Determinants of prakriti and constitutional biology: cohort study. *Indian Journal of Community Medicine*, 39(4), 212-217.
- Sharma, R. K. et al. (2021). Integrated metabolic syndrome progression model with Ayurvedic features: validation study. *Journal of Ayurveda and Integrative Medicine*, 12(3), 408-416.
- Tiwari, S. et al. (2017). Prakriti-based machine-learning classification: pilot evaluation. *AYU*, 38(2), 84-90.
- Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44-56.

Declarations

Funding

Funded by the French National Research Agency (ANR-24-PRED-0436) and the European Integrative Medicine Research Council (EIMRC-2024-128). The funders had no role in study selection, data extraction, analysis, or the decision to publish.

Conflict of Interest

The author declares no competing interests and no financial or consulting relationships with predictive-modelling vendors, clinical decision support companies, or commercial integrative-medicine technology providers relevant to this review.

Data Availability Statement

The full study inclusion log, model-application frame classification records, model performance extraction worksheet, and APMI scoring spreadsheet are available as supplementary material from the corresponding author on reasonable request. Individual study-level data remain subject to the publishers' data-sharing policies.

Ethical Approval

As this is a structured methodology review of previously published computational and translational studies with no primary human-subjects data collection, formal ethical approval was not required. The review protocol was registered on the Open Science Framework (OSF registration DOI 10.17605/OSF.IO/APMI0) prior to the start of screening.

Appendix A

APMI Scoring Rubric and

Model-Application Frame Protocol

Full scoring rubric for the Ayurvedic Predictive Model Index (APMI) together with the model-application frame classification protocol used in this structured review. All five APMI dimensions are normalised to the 0-1 range before the weighted sum is computed. Predictive accuracy is the single most heavily weighted dimension (0.25) because it is the primary quality metric for predictive models; interpretability, clinical utility, and external validation are each weighted at 0.20 because they jointly determine whether accurate models translate to defensible clinical deployment in European integrative-medicine contexts.

Part 1 - APMI Dimension Scoring Anchors

Family Per-dimension scoring definitions

Dimension	Weight	0.00 anchor	0.50 anchor	1.00 anchor
Predictive accuracy	0.25	Acc / AUC < 0.60	Acc / AUC ~0.75	Acc / AUC >= 0.85
Interpretability	0.20	Black-box no explan.	Partial explanation	Full clinical interpretability
Clinical utility	0.20	No clinical application	Emerging clinical utility	Direct clinical decision value
External validation	0.20	No ext. validation	Partial ext. validation	Multi-cohort EU validation
Deployability	0.15	Research only	Pilot deployment	Routine integrative clinic

Part 2 - Model-Application Frame

Classification Rules

Family Frame assignment criteria

Frame	Primary prediction target	Typical input features	Key distinguishing feature
PM1: Prakriti Prediction	Prakriti category	Phenotype + genomic	Prakriti-specific classifier
PM2: Treatment Response Pred.	Response to Ayur. intervention	Prakriti + biomarker	Intervention-selection focus
PM3: Disease Progression Pred.	Progression over 6-24 mo	Convent. + Ayur. features	Chronic disease progression
PM4: Integrated EHR + ML CDS	Clinical decision support	EHR-derived + derived	Deployment infrastructure

Frame	Primary prediction target	Typical input features	Key distinguishing feature
PM5: European Deploy. Valid.	Validation / calibration	Trained-elsewhere models	European-validation focus
Assignment rule	Primary prediction target	Dominant input features	Cross-reference secondary frame