Review Article

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DECODING PRAKRITI: A SYSTEMATIC REVIEW OF MACHINE LEARNING AND AI APPROACHES TO AYURVEDIC DOSHA CLASSIFICATION

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ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly integrated with Ayurveda, the ancient Indian system of personalised medicine, to automate and standardise the assessment of Prakriti (individual constitutional typology) and Tridosha (Vata, Pitta, Kapha). This systematic review synthesises 80 bibliographic records published 2009-2026, of which 18 constitute core computational studies identified through a PRISMA 2020-compliant three-tier screening framework. Supervised ML classifiers-including ensemble methods, deep learning, Retrieval-Augmented Generation (RAG)-based conversational agents, and IoT-integrated physiological sensing pipelines-consistently achieve Dosha/Prakriti classification accuracies of 92-99% on internal test sets. Critical limitations include: absence of a universally validated Prakriti assessment instrument (only 2 of 64 tools satisfy ≥7/9 psychometric criteria); small, single-institution datasets with limited cross-population generalizability (only one cross-cultural India-USA validation study exists); near-total absence of computational efficiency benchmarking (reported by only 1 of 18 studies); and minimal use of Explainable AI (XAI). India dominates the research landscape (73.9% of attributable records). The review outlines a scientific research roadmap involving multimodal data fusion, standardisation of open datasets, Clinical interpretability using XAI methods, and regulatory alignment with India's digital health initiative, NAMASTE/Ayush Grid.

Keywords: Ayurveda, Prakriti, Personalised Medicine, Preventive Healthcare, Dosha Classification, Explainable AI, Digital Health, Ayur genomics

INTRODUCTION

According to Ayurveda's fundamental principle, it is a personalised medicine[1] and one of the oldest codified systems of medicine, practised for more than 5000 years. Philosophically and clinically, the Prakriti is derived from the Tridosha concept of everyone being constitutionally bound by the three bioenergetic principles (Vata, Pitta and Kapha)[1,2]. A person's predominant dosha combination (called Prakriti in Ayurveda) dictates the entities of illness, treatment and food and lifestyle needs.

Even with this theoretical advancement, Prakriti assessment, so far, has been experience-dependent, practitioner-subjective and standardisation was not easy. In a systematic review conducted from 1987-2024, 64 instruments (Prakriti Assessment Tools-PATs) were identified; of these, only two instruments, CCRAS-PAS and ACPI, had 7 of 9 recommended psychometric validations, and the use of biotech and AI to speed product development[3,4]. This lack of basic information directly affects model reliability; AI/ML models trained with unvalidated questionnaire inputs would inherit the same unreliability in the annotation.

Since the advent of AI/ML and the greater digitisation of healthcare, enormous technological changes have begun shifting paradigms to overcome this methodological gap. Prescriptive characterisation of Prakriti, from structured questionnaires to physiological sensor streams to diagnostic nail images, has achieved excellent accuracy in automated Dosha prediction using ML classifiers[5-8]. At the same time, Prakriti gives Molecular and genomic correlates for Ayurgenomics - a transdisciplinary approach that paves the way for the integration of artificial intelligence in precision medicine. The policy landscape is becoming more conducive to the integration of AI-Ayurveda with the launch of nationwide digital health platforms - NAMASTE: standardised AI-Ayurveda terminology with ICD frameworks and Ayush Grid: cross-system interoperability infrastructure.

Yet, no systematic review has kept pace with these new developments in AI/ML methodologies, datasets, performance metrics, research gaps, and technological constraints in this nascent body of literature. This paper aims to fill this gap. The objective is to: (1) map the thematic range of AI/ML application in Ayurveda using an inventory of 80 records; (2) combine important methods, data sets, attributes, and performance measures; (3) disclose a severity gap analysis; (4) paint a picture of the reporting gap in computational efficiency; and (5) propose a systematic research agenda.

METHODOLOGY

Search Strategy and Corpus Assembly

This study conducted a structured keyword search in a large-scale, interdisciplinary bibliographic database of peer-reviewed journals, conference proceedings, edited books, and book chapters on 23 July 2026. The search had no year restrictions, and the seven-term Boolean search string used was: Ayurveda, Artificial Intelligence, Machine Learning, Personalised

Healthcare, Preventive Healthcare, and Tridosha, which yielded 80 articles from 2009 to 2026.

Publication-type composition: Edited Book (n = 55, 68.75%), Article (n = 11, 13.75%), Proceeding (n = 5, 6.25%), Monograph (n = 5, 6.25%), Chapter (n = 4, 5.0%). Open-access status: Closed (n = 56, 70%), Gold OA (n = 17, 21.25%), Bronze OA (n = 5, 6.25%), Hybrid OA (n = 1), Green OA (n = 1). Of all records, 85% (n = 68) were published in 2021- 2026, with 2025 as the peak year (n = 20), confirming an accelerating publication rate.

Data Extraction

For each of the 18 Tier-1 core studies, the following data items were extracted: (i) algorithmic approach(es); (ii) dataset size and characteristics; (iii) performance metrics (accuracy, F1, AUC, ROUGE, BERT Score); (iv) validation methodology; (v) explainability approach; (vi) runtime /latency benchmarking; and (vii) stated limitations.

PRISMA 2020 Screening and Relevance Stratification

Because the database matches keywords across full-text fields, the raw export contains records with highly variable relevance. Evidence-based integrative platform so Ayurveda and modern medicine can be used together[9]. AI in Personalised Ayurveda review[10]. All 80 records were independently classified into three relevance tiers by two authors with consensus resolution, following the PRISMA 2020 framework[11]. The complete screening flow is presented in Figure 1.

THEMATIC LANDSCAPE OF THE CORPUS

Corpus-Wide Thematic Distribution (n = 80)Figure 2 visualises the thematic distribution across all 80 records, with exact counts and percentages in Table 1. Phytochemistry, Pharmacognosy and Natural Product Research constitutes the largest single domain (26.2%, n = 21). AI/ML-Enabled Ayurvedic Diagnostics and Personalised Healthcare, the primary domain of this review, is second (17.5%, n = 14). The Ayurgenomics and Precision Medicine cluster (3.8%, n = 3) is smallest but most translationally significant. The temporal distribution is strongly right-skewed: 85% of records were published 2021-2026, with 2025 the peak year (n = 20).

Sub-Themes within the Core AI/ML-Ayurveda Cluster (n = 18)
Figure 3 shows the sub-theme distribution within the 18 core studies, with representative works in Table 2. AI/ML Dosha Classification Models are dominant (22.2%, n = 4). AI-based Digital Health Applications and Ayurgenomics/Precision Medicine each represent 11.1% (n = 2). The remaining nine sub-themes each represent a single study (5.6%), spanning RAG-based conversational AI, deep-learning diagnostic imaging, IoT physiological monitoring, disease prediction, rural telehealth, HTA of traditional medicine, Prakriti assessment review, ethnobotany/wellness, clinical dermatology, and AI-driven drug design.

CORE AI/ML METHODOLOGIES AND RESULTS

Supervised Classification for Prakriti/Dosha Prediction

SMOTE class balancing and SelectKBest feature selection, the model achieved 99.15% training, 98.93% validation, and 92.44% external test accuracy (AUC = 1.00)-the largest dataset and most rigorous ensemble design in the corpus. The 6.7 pp accuracy drop on external test data is key evidence for Gap 2 (Section VI).

Tripathi *et al*.[6] integrated validated psychometric assessments (emotional quotient, risk-taking inventory, personality scale, Raven's Progressive Matrices) with seven ML models (LR, DT, RF, SVM, XGBoost, CatBoost, MLP) plus a hand-tuned stacked ensemble (MR-CAT). Cross-cultural validation on a combined India-USA cohort (n = 406: India 202, USA 204) achieved 0.97 accuracy (India-trained) and 0.99 (USA cross-validation). SHAP explainability revealed Dosha-specific psychometric signatures: Vata-high resilience and self-motivation; Pitta-high calmness and ethical courage; Kapha-high emotional stability but reduced leadership initiative[6]. This is the only cross-cultural validation study in the entire corpus.

Bheemavarapu and Usha Rani[7] evaluated 11-12 ML algorithms, including ANN models and ensembles, on Prasna Pariksha nominal questionnaire data, with SMOTEN class balancing and PCA vs MCA dimensionality reduction. A hyperparameter-tuned Logistic Regression with MCA reduction and 80:20 split achieved accuracy = 1.00 with latency = 0.05 s-the only quantitative runtime figure in the corpus[7]. Manishramar *et al*.[8] demonstrated a Decision Tree achieving 94.74% accuracy (recall = 85.71%, F1 = 87.88%) on symptom-based classification[8].

Deep Learning and Computer Vision

Aggarwal and Sheikh[15] pioneered deep learning for Ayurvedic nail analysis-a traditional diagnostic modality in which nail colour, texture, and shape encode Dosha information. Nail images from two Indian institutes were preprocessed via normalization and Adaptive Thresholding segmentation before DL classification, achieving 95.14% validation accuracy and 96.33% test accuracy[15]. This establishes proof-of-concept for computer-vision-based Ayurvedic diagnostics, though single-country sampling limits generalizability.

Conversational AI and Retrieval-Augmented Generation

Sendhilkumar *et al*.[14] developed a two-stage pipeline: a Transformer classifier (96.83% Dosha accuracy; precision/recall/F1 > 0.95) coupled with a RAG+LLM response generation stage (ROUGE-1 = 0.7931, ROUGE-2 = 0.6071, ROUGE-L = 0.7931, BERT Score F1 = 0.9677)[14]-the first generative AI architecture for Ayurvedic consultation in the corpus. AyuMonk[12] and Medi-Compass[13] translate Dosha classification into user-facing digital health products, though neither reports algorithmic identity or performance metrics.

IoT-Enabled Real-Time Physiological Monitoring

Pawaskar *et al*.[16] proposed an IoT-ML system integrating heart rate, ECG, body temperature, and SpO2 sensing with Random Forest and SVM classifiers for real-time Prakriti identification and personalised lifestyle advice. Qualitative "high accuracy, low latency" was reported-no numeric validation dataset size or quantitative latency figures provided[16]. This is the sole IoT-integrated Prakriti classification system in the corpus and exemplifies the computational efficiency reporting gap analysed in Section VII.

Ayurgenomics and Precision Medicine Frameworks

Mukerji[9] (28 citations; highest-cited core study) presented Ayurgenomics enabling: (i) molecular Prakriti correlate discovery; (ii) early-intervention biomarker identification; (iii) Ayurvedic drug mechanism elucidation for repurposing; (iv) P4 medicine network perspectives; (v) non-invasive population stratification; and (vi) evidence-based integrative medicine[9]. Pathak *et al*.[10] synthesised ML-based Prakriti classification, Ayurgenomics, and NAMASTE/Ayush Grid digital health integration[10]. (Table 3)

GEOGRAPHIC DISTRIBUTION AND RESEARCH COLLABORATION

Author-affiliation data were extractable from 18 of the 80 records (22.5%); the remaining 62 records-predominantly Edited Book and Monograph container entries-list only volume editors. Figure 4 illustrates the country-wise distribution. India is the clear geographic hub, accounting for 17 of 23 attributable records (73.9%). The USA contributed to 3 records through institutions including Harvard, Johns Hopkins, Massachusetts General Hospital, UT MD Anderson, UCSF, Maharishi International University, and Jhpiego Corp. The UK (Imperial College London/Healthcare NHS Trust) and Germany (Charité Berlin) each co-authored the Prakriti review[4]. Canada (University of Ontario Institute of Technology) contributed to one co-authored record.

Author-affiliation data extractable for only 18/80 records (22.5%). The remaining 62 records list only volume editors and could not be attributed without adding external information. Only one study-Tripathi *et al.* [6] was designed as a cross-country comparative study (India N=202; USA N=204).

RESEARCH GAPS: SEVERITY- RATED ANALYSIS

Table 5 presents all ten research gaps with severity ratings (Critical > High > Medium > Low) and direct evidential grounding in the corpus.

Critical Gap

[CRITICAL] Gap 1 - No Universally Validated Prakriti/Dosha Assessment Instrument: Of 64 identified PATs (1987-2024), only 2 (CCRAS-PAS, ACPI) met 7 of 9 validation criteria under the Scale Development and Validation framework; most lack dimensionality testing, test-retest reliability, and population diversity[4].

High-Severity Gaps

The Nail-image DL study was conducted independently by two local institutions and showed an out-of-scope test image generalisation of 92.44%[15]. The research used triple classifiers (Tridosha[5]), and train/val accuracy was approximately 99%.

Gap 3 - Data Standardisation and Interoperability Still Nascent - Although in the field of AI-in-Ayurveda[10] has mentioned that NAMASTE/Ayush Grid 'initiative' efforts exist, some issues related to small datasets, lack of standardisation, and standardisation of data comparability among datasets still exist.

Rarely Tested: Out of 18 key research[6] that collected data from more than a single nation/institution, only one of them tested a model in two (INDIA=202; USA=204).

It has seen "data privacy and ethics" as one of the unanswered questions, along with cultural integrity and comparability of datasets in the Fifth Gap aspect and appeared in the AI-in-Ayurveda review[10], but till now there is a lack of any significant study to suggest a framework for governance.

Medium-Severity Gaps

Few studies gave thresholds for runtimes and/or efficiencies: one quantitative (QT) threshold (0.05 s) [7] and one qualitative (qualitative means there is no value (QV)) [16]. The other sixteen papers (seen above in Section VII) were not able to communicate any runtime or efficiency metrics.

One classification experiment of the 18 experiments[6] reported accuracy and F1 scores, but it did not analyse interpretability. This means that there is no application of XAI (Explainable AI) - gap [7]. Explainability is a requirement for clinical adoption.

Internet of Things (IoT) is still in its infancy as far as continuous/real-time (CRT) monitoring is concerned. One crucial study[16] considered only ML for Dosha classification and used IoT only for physiological sensing, without quantifying the size of the validation set.

Position 9: No multimodal data fusion: Models using many modalities of data (user-provided images, questionnaires, IoT, text/chat, etc.) are not explored in any of the studies in the corpus.

Low-Severity Gap

[LOW] Gap 10: Open as opposed to Data Sharing/Repositories-Limited: No datasets were provided from open repositories and/or data sharing repositories were not available; all datasets were acquired and/or requested from authors/institutions.

TECHNOLOGICAL GAPS AND RUNTIME ANALYSIS

In the literature, a comprehensive search based on Key AI/ML principles and Ayurveda found no report to date that discusses technological uniqueness and improved computing efficiency. Of the nine core studies implementing predictive computational models, only Bheemavarapu and Usha Rani[7] report a quantitative latency figure (0.05 s for the best Logistic Regression configuration); Pawaskar *et al.* [16] reference latency only qualitatively ("low latency"). The remaining seven-covering stacked ensembles, Transformer-based RAG-LLM pipelines, DL image segmentation, and multi-model benchmark suites spanning 11-12 algorithms-report no training time, inference latency, memory footprint, or hardware configuration. Table 6 documents this gap for each study.

Across 18 core AI/ML-Ayurveda studies: only 1 reports a quantitative runtime/latency figure7 and 1 reports qualitative latency only16; the remaining 16 do not address computational efficiency at all. This is the single largest technological reporting gap in the corpus, limiting assessment of real-world/edge deployability of Ayurveda-AI systems.

NOVEL CONTRIBUTIONS AND FUTURE RESEARCH DIRECTIONS

A. Novel Contributions of This Review

This review makes five original contributions to the AI-Ayurveda literature:

1. **Three-Tier Relevance Stratification Framework:** First application of a structured three-tier stratification to the AI-Ayurveda bibliographic corpus, enabling transparent separation of core computational studies from tangential keyword matches.
2. **Severity-Rated Research Gap Taxonomy:** First severity-rated gap taxonomy (Critical/High/Medium/Low) grounded in direct evidential mapping to specific studies and quantitative findings.
3. **Computational Efficiency Gap Identification:** First characterisation of the near-total absence of computational efficiency reporting as a standalone technological gap, distinct from and as consequential as dataset-size and validation gaps.
4. **Cross-Cultural Generalizability Synthesis:** First synthesis identifying Tripathi *et al*.[6] as the sole cross-national validation study and documenting SHAP-confirmed cross-cultural feature drift across Vata, Pitta, and Kapha psychometric signatures.
5. **Emerging Frontier Mapping:** Mapping of Ayurgenomics[9] and RAG/LLM[14] sub-fields as high-potential frontiers with unresolved validation, standardisation, and efficiency benchmarking challenges.

B. Future Research Directions

Direction 1 - Standardised Prakriti Benchmark Dataset: Develop and publicly release a multi-site, cross-population Prakriti dataset using a validated instrument (building on CCRAS-PAS or ACPI), incorporating questionnaire responses, physiological

measurements, and, where available, genomic/metabolomic profiles, to enable multimodal model development and fair cross-study benchmarking.

Direction 2 - Multimodal Data Fusion Architectures: Design Transformer-based or graph neural network architectures that fuse questionnaire, imaging (nail/tongue), IoT physiological, and genomic data. No existing study in this corpus attempts any cross-modal fusion despite its clear clinical logic.

Direction 3 - Mandatory Computational Efficiency Reporting: Mandate training time, inference latency (mean ± SD), model parameter count, and hardware configuration in all future studies. For chatbot/RAG and IoT edge-deployment systems, power consumption and minimum device specifications should additionally be provided.

Another application of ExA는 its use in clinical interpretability. All research involving dosha classification includes SHAP, LIME, attention visualisation, and counterfactual explanations. The evidence requirement is very high, as it must also be interpretable; clinical organisations and Ayurvedic practitioners must be able to use it accurately.

Direction 5: Multi-Country Validation Studies: Follow the same procedure as Tripathi *et al.* to validate the assessment instruments in other countries, such as Southeast Asian countries, the Middle East, and African and European countries, and adopt the predetermined analysis strategy.

Sixth Direction: Digital Health Infrastructure Interoperability: The AI-Ayurveda system should be interoperable with Digital Health Infrastructure (DHI) platforms like NAMASTE and Ayush Grid to enable regulatory approval, interoperability with eHR, and deployment of the AI-Ayurveda system at the population level.

Collaborative research programs will be initiated under Direction 7 - Ethical, Governance Framework on topics such as: Data Governance, Algorithmic Bias, Informed Consent, Cultural Integrity and Regulatory Framework. The development of these programmes will be guided by the WHO's and the National Digital Health Mission in India's recommendations on the ethics and Governance of AI usage in health.

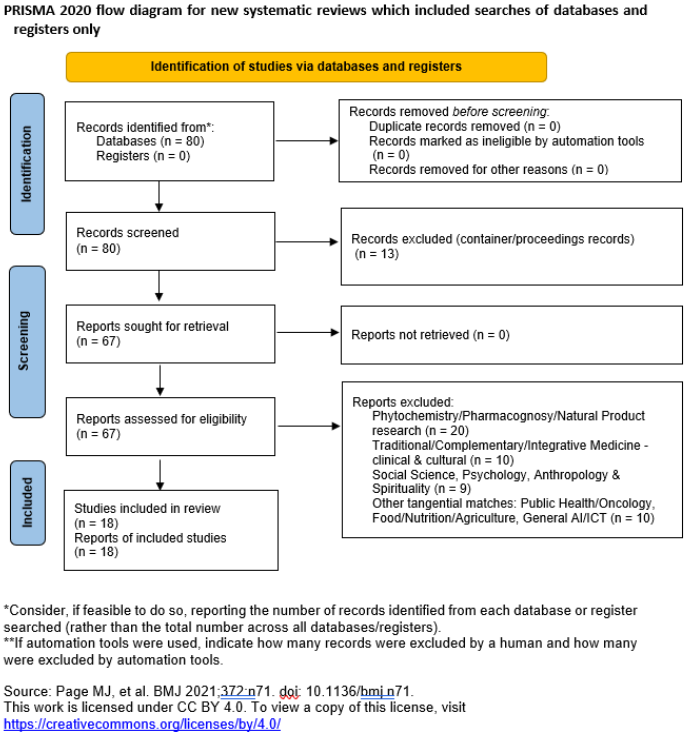

Figure 1

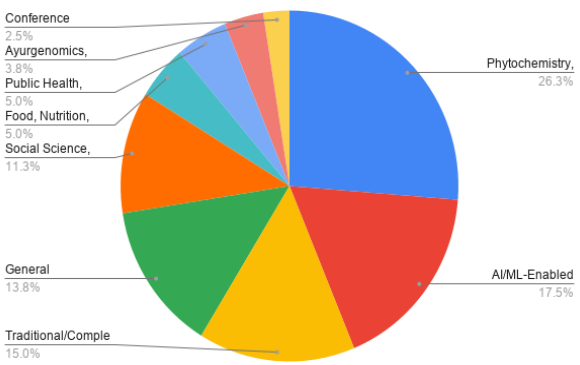

Figure 2: Corpus-wide thematic distribution (n = 80 records). AI/ML-Enabled Ayurvedic Diagnostics and Personalised Healthcare (17.5%) is the second-largest domain, confirming the rapid growth of computational approaches to Prakriti/Tridosha assessment. Minor rounding: chart shows 26.3% for Phytochemistry vs. 26.2% in Table 1.

Table 1: Corpus-Wide Thematic Distribution (n = 80)

Thematic Domain	Records	% of Corpus
Phytochemistry, Pharmacognosy and Natural Product Research	21	26.2%
AI/ML-Enabled Ayurvedic Diagnostics and Personalized Healthcare	14	17.5%
Traditional/Complementary/Integrative Medicine (Clinical and Cultural)	12	15.0%
General AI/ICT/Engineering (Non-Ayurveda-specific)	11	13.8%
Social Science, Psychology, Anthropology and Spirituality	9	11.2%
Food, Nutrition, Agriculture and Biodiversity	4	5.0%
Public Health, Oncology and Global Health Policy	4	5.0%
Ayurgenomics, Precision and Integrative Medicine	3	3.8%
Conference Abstract Supplements (no substantive abstract)	2	2.5%
Total	80	100%

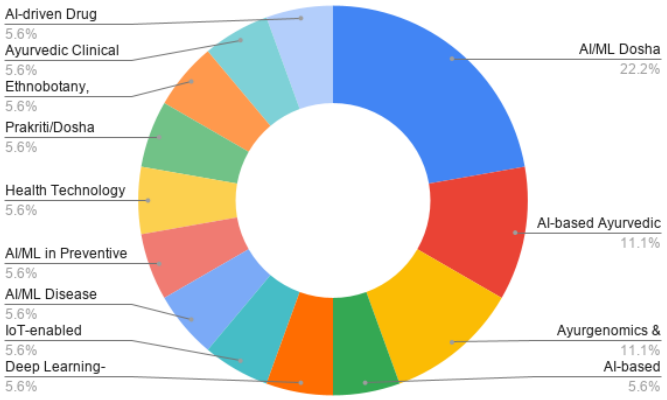

Figure 3: Fresh and reliable identification of Sub-themes for the 18 Core AI/ML-Ayurveda studies. Dominant (22.2%) is the most common AI/ML Dosha classification observed. Both the role of digital health applications based on AI and Ayurgenomics are at 11.1% each. The remaining 11 sub-themes (with one study each or 5.6%) indicate a rapidly expanding but very highly fragmented area of computational research.

Table 2: The sub-themes that fall under the Core AI/ML-Ayurveda Cluster (n=18) with agreement representative

Sub-Theme	n	%	Representative Works
AI/ML Dosha (Tridosha) Classification Models	4	22.2%	Ensemble Tridosha Prediction[5]; Psychometric+ML Prakriti[6]; Multiclass Prasna Pariksha[7]; AI in Personalized Ayurveda review[10]
AI-based Ayurvedic Digital Health Applications	2	11.1%	AyuMonk web companion[12]; Medi-Compass recommendation system[13]
Ayurgenomics and Precision/Integrative Medicine	2	11.1%	Ayurgenomics translational frameworks[9]; Nutriomics
AI-based Conversational/Generative AI (RAG)	1	5.6%	RAG-based Dosha Chatbot[14]
Deep Learning-based Diagnostic Imaging	1	5.6%	Nail image analysis + DL and segmentation[15]
IoT-enabled Personalized Health Systems	1	5.6%	Prakriti IoT+ML lifestyle system[16]
AI/ML Disease Prediction and Ayurvedic Guidance	1	5.6%	Disease Prediction and Ayurvedic Guidance (2025)[8]
AI/ML in Preventive and Rural Healthcare	1	5.6%	ML for Rural Healthcare[1]
Health Technology Assessment of Traditional Medicine	1	5.6%	HTA in Ayurvedic insights[2]
Prakriti/Dosha Assessment Frameworks (Review)	1	5.6%	Critical review of Prakriti assessment tools[4]
Ethnobotany, Phytochemistry and Wellness Industry	1	5.6%	Ethnobotany and Ayurveda in Global Wellness[3]
Ayurvedic Clinical Applications (Dermatology)	1	5.6%	Skin infections under Ayurvedic protocols[17]
AI-driven Drug Design from Traditional/Herbal Knowledge	1	5.6%	Sustainable Healthcare, Traditional Knowledge[20]

Table 3: Core AI/ML-Ayurveda Studies: Methodologies, Datasets, and Reported Performance Metrics (n = 18)

Study (Year) [Ref]	Technique(s)	Dataset / Sample	Key Reported Metric
Ensemble Tridosha Prediction (2026)[5]	RF + Gradient Boosting stacked; SMOTE; SelectKBest	6,615 records; 25 physical/behavioral features	99.15% train / 98.93% val / 92.44% ext. test; AUC = 1.00
Prakriti IoT+ML (2026)[16]	Random Forest and SVM on real-time IoT streams (HR, ECG, Temp, SpO2)	Not specified (real-time sensor stream)	Qualitative: "high accuracy, low latency"-no numeric values given
RAG-based Dosha Chatbot (2026)[14]	Transformer classifier + RAG + LLM	Practitioner-validated questionnaire (size NR)	96.83% clf. acc.; ROUGE-1 0.79; ROUGE-2 0.61; BERTScore F1 0.9677
Nail Image Analysis + DL (2024)[15]	Adaptive-thresholding segmentation + DL classifier	Nail images from 2 local Indian institutes (size NR)	95.14% validation / 96.33% test accuracy
Psychometric ML Prakriti (2025)[6]	7 ML models + MR-CAT stacked ensemble; SHAP XAI	N=406 (India 202 + USA 204); cross-cultural cohort	0.97 acc. (India-trained) / 0.99 (USA cross-val)-only cross-cultural study
Multiclass Prasna Pariksha Classification (2025)[7]	11-12 ML algorithms + ANN + ensembles; SMOTEN; MCA/PCA; 5-fold CV	Nominal questionnaire dataset (size NR)	LR+HPT best: acc. = 1.00; latency = 0.05 s-only numeric runtime in corpus

Disease Prediction and Ayurvedic Guidance (2025)[8]	Decision Tree on user-reported symptoms	Not specified	94.74% accuracy; 85.71% recall; 87.88% F1
AyuMonk Web Companion (2024)[12]	AI chatbot + unspecified ML classification	Not specified	Not reported (system/product description only)
Medi-Compass Recommendation System (2024)[13]	ML-based symptom-to-recommendation mapping (algorithm NR)	Not specified	Not reported
AI in Personalized Ayurveda-Review (2026)[10]	Narrative synthesis: ML Prakriti + Ayurgenomics + digital health	N/A (review)	N/A-identified: small datasets, absent standards, governance concerns
Prakriti Assessment Tools-Review (2025)[4]	SANRA-aligned narrative review; Boateng Scale Dev. and Validation framework	94 studies synthesized from 635 records identified	Only 2/64 PATs met 7/9 validation criteria (CCRAS-PAS, ACPI)
ML for Rural Healthcare (2022)[1]	Applied review: ML for telehealth, remote monitoring, imaging	N/A (review)	N/A
HTA in Ayurvedic Insights (2026)[2]	Narrative/conceptual review using WHO HTA and HTAIn (India) frameworks	N/A (review)	N/A
Ayurgenomics Translational Frameworks (2023)[9]	Conceptual/translational synthesis (non-computational)	N/A	N/A- 28 citations; highest-cited core study in corpus
Ethnobotany and Ayurveda in Wellness Industry (2025)[3]	Critical/narrative analysis (non-computational)	N/A	N/A
Skin Infections under Ayurvedic Protocols (2026)[17]	Descriptive clinical case analysis	Registered patient cohort (size NR)	Qualitative improvement reported (no numeric AI/ML metric)
AI-driven Drug Design-Traditional Knowledge (2026)[18]	Conceptual: AI in phytoformulation and OMICS drug development	N/A	N/A
ASO special article: Proceedings of the inaugural joint US-India cancer dialogue[19]	strengthened genomics and data-sharing infrastructure	N/A	N/A
Nutriomics/Ayurgenomics Chapter (2026)[20]	Conceptual case-study of omics tools applied to Tridosha theory	N/A	N/A

NR = Not Reported; HPT = Hyperparameter Tuning; clf = classification; acc. = accuracy; val = validation; ext. = external test set; CV = cross-validation.

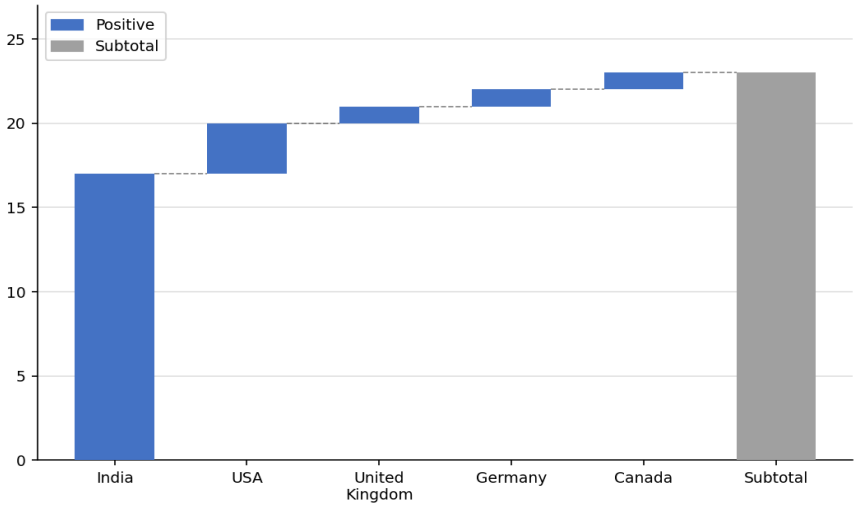

Figure 4: Country-wise distribution of core AI/ML-Ayurveda studies (n = 23 attributable records from 18 of 80 total). Cumulative waterfall: India (17), +USA (3=20), +UK (1=21), +Germany (1=22), +Canada (1=23). India accounts for 73.9% of all attributable records. Author-affiliation data were unavailable for 62/80 records (predominantly Edited Book container entries listing only volume editors).

Table 4: Country-Wise Distribution with Institutional Affiliations

Country	Records	Key Affiliated Institutions
India	17	Amrita Vishwa Vidyapeetham; IITs (Jodhpur, Mandi, Roorkee); AIIMS New Delhi; SRM Institute; VIT University; Manipal Academy; Bennett University; GIET University; Anna University; and others
USA	3	Harvard University; Johns Hopkins University; Massachusetts General Hospital; UT MD Anderson Cancer Center; UCSF; Maharishi International University; Jhpiego Corp
United Kingdom	1	Imperial College London / Imperial College Healthcare NHS Trust (co-authorship on Prakriti review[4])
Germany	1	Charité - University Medicine Berlin (co-authorship on Prakriti review[4])
Canada	1	University of Ontario Institute of Technology (co-authorship)

Table 5: Research Gaps: Severity Ratings and Evidence from the Corpus

Gap	Severity	Evidence from Dataset
No universally validated Prakriti/Dosha assessment instrument	Critical	Of 64 PATs (1987-2024), only 2 (CCRAS-PAS, ACPI) met 7/9 validation criteria; most lack dimensionality testing, test-retest reliability, population diversity[4]
Small, single-institution datasets; limited external validation	High	Nail-image DL[15] from 2 local institutes only; ensemble Tridosha[5] dropped ~99%→92.44% on external test-clear generalization gap
Data standardization and interoperability still nascent	High	Explicitly noted in 2026 AI-in-Ayurveda review[10]: small datasets, absent standards, comparability issues; NAMASTE/Ayush Grid not yet adopted
Cross-population/cross-cultural generalizability rarely tested	High	Only 1/18 studies[6] validated across 2 national cohorts (India N=202; USA N=204); all others single-country/single-institution
Data privacy, ethics and governance frameworks under-addressed	High	Flagged as open concern in[10] alongside cultural-integrity issues; no core study proposes a concrete governance mechanism
Runtime/computational-efficiency benchmarking rarely reported	Medium	1/18 studies[7] reported numeric latency (0.05 s); 1/18[16] qualitative only; remaining 16/18 report no runtime/efficiency data at all
Limited use of Explainable AI (XAI)	Medium	SHAP in only 1/18 studies[6]; other classification studies report accuracy/F1 without any interpretability analysis
IoT-based continuous/real-time monitoring still exploratory	Medium	Only 1 core study[16] integrates IoT sensing with ML Dosha classification; reports no quantitative validation dataset size
No multimodal fusion (image + questionnaire + genomic + IoT)	Medium	Each core study uses a single data modality only; no study combines modalities in a single model
Open-data/reproducibility practices limited	Low	Datasets author-collected or "on request"-none published as open/shared repositories

Table 6: Technological Gaps and Runtime Reporting Status Across Core AI/ML-Ayurveda Studies

Study [Ref]	Algorithm(s)	Runtime Reported?	Technological Gap Noted
Ensemble Tridosha Prediction (2026)[5]	RF + Gradient Boosting + LR meta-learner (stacked)	No	No inference-time / hardware benchmarking; scalability to larger populations untested
Prakriti IoT+ML (2026)[16]	Random Forest, SVM on IoT streams	Qualitative only ("low latency")	No numeric latency/throughput figures; edge-device deployment feasibility not evaluated
RAG-based Dosha Chatbot (2026)[14]	Transformer classifier + RAG + LLM	No	No response-time/inference-latency benchmarking for LLM-based chatbot despite real-time context
Nail Image DL (2024)[15]	Adaptive thresholding segmentation + DL classifier	No	No image-processing throughput or model-size/efficiency data reported
Psychometric ML Prakriti (2025) [6]	7 ML models + stacked ensemble (MR-CAT) + SHAP	No	No training/inference time reported despite 7+ models across 2 cohorts
Multiclass Prasna Pariksha Classification (2025)[7]	11-12 ML algorithms + ANN + ensembles	Yes - 0.05 s (best configuration only)	Latency for single best configuration only; not systematic across all 12+ models tested
Disease Prediction - Decision Tree (2025)[8]	Decision Tree	No	No runtime/scalability analysis for real-time symptom-triage use case
AyuMonk Web Companion (2024)[12]	Unspecified ML + chatbot	No	Algorithm identity and computational performance both unspecified
Medi-Compass (2024)[13]	Unspecified ML	No	Algorithm identity and computational performance both unspecified

CONCLUSION

This review provides the latest evaluation of the current research status, gaps, and future directions in Ayurvedic medicine and Artificial Intelligence. It followed the PRISMA 2020 guidelines and used a three-step process to synthesise 18 studies from 269, focusing on computational AI/ML and Ayurveda studies published from 2009 to 2026. Some supervised classifier ensembles, deep learning approaches, or conversational agents with physiological sensing through IoT have achieved consistently high Prakriti/Dosha classification accuracy, ranging from 92% to 99% on their own test sets. This is certainly an area of promise and potential. Ayurgenomics is innovative and important because it bridges precision genomics and classical constitutional medicine. Unfortunately, due to the lack of a globally validated Prakriti evaluation tool, a robust, non-generalised dataset, an inefficient computational process, and a lack of explainable AI, clinical translation has been limited. To address these research gaps, researchers must embrace multi-modal, multi-site study designs; report computational methods' performance; make XAI the standard in research; and develop regulatory and governance frameworks. That's where Artificial Intelligence (AI) and Ayurveda (the science of life-sustaining medicine) can bring a revolution and make health care truly individualistic, scalable, and culturally and sensibly relevant to the “home-remedies” practising world's 1.4 billion population.

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