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# ARTIFICIAL INTELLIGENCE DRIVEN CLINICAL DECISION SUPPORT SYSTEMS IN AYURVEDA: CURRENT EVIDENCE, CHALLENGES, AND FUTURE DIRECTION

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## ABSTRACT

**Background:** Artificial intelligence (AI) has become a transformative force in healthcare, guiding diagnosis and treatment through machine learning, deep learning, natural language processing, and computer vision. While these tools have matured quickly in conventional medicine, their use in Ayurveda remains patchy and largely exploratory.
**Objective:** This review summarizes current evidence on AI applications in Ayurveda, outlines the scientific and practical barriers limiting clinical adoption, and proposes an explainable AI based clinical decision support framework suited to Ayurvedic practice.
**Methods:** A narrative review of literature on artificial intelligence, clinical decision support systems, digital health, biomedical informatics, and Ayurvedic medicine was conducted. Evidence relating to Prakriti assessment, digital Nadi analysis, tongue diagnosis, natural language processing, herbal drug discovery, disease prediction, and personalized treatment was synthesized, and current gaps, research priorities, and opportunities for explainable AI in Ayurvedic clinical workflows were critically examined.
**Results:** AI applications in Ayurveda show encouraging results across constitutional assessment, digital diagnostics, text mining, herbal drug discovery, and personalized healthcare, but most studies remain proof of concept work limited by small datasets, inconsistent methods, minimal external validation, and little formal clinical evaluation. The absence of standardized electronic Ayurvedic health records, interoperable ontologies, multicentric annotated datasets, explainable algorithms, and prospective validation studies is the central bottleneck. To address this, we propose an Explainable Artificial Intelligence Driven Clinical Decision Support System (XAI CDSS) that combines multimodal clinical data, evidence-based reasoning, physician validation, and continuous learning.
**Conclusion:** AI can meaningfully strengthen evidence based, personalized Ayurvedic care, but real progress depends on standardized digital infrastructure, explainable and trustworthy models, rigorous clinical validation, ethical governance, and genuine interdisciplinary collaboration. AI should function as a physician assistive technology that augments clinical expertise while preserving the holistic principles of Ayurveda.

**KEYWORDS:** Artificial Intelligence; Clinical Decision Support System; Ayurveda; Explainable Artificial Intelligence; Machine Learning; Precision Ayurveda; Digital Health; Ayurgenomics; Personalized Medicine.

## INTRODUCTION

Artificial intelligence is reshaping healthcare by making sense of complex clinical data to support diagnosis, prognosis, treatment planning, and personalized patient care. The growing volume of electronic health records (EHRs), medical imaging, and wearable device data has pushed AI driven tools into everyday clinical decision making (1,2). Among these, Clinical Decision Support Systems (CDSS) have emerged as one of the most useful applications, pairing patient specific information with medical knowledge to sharpen clinical decisions without displacing physician judgement (2,3).

Advances in machine learning (ML), deep learning (DL), natural language processing (NLP), and explainable artificial intelligence (XAI) have steadily widened what CDSS can do. Present day systems can read multimodal clinical data, surface hidden patterns, estimate disease risk, and generate individualized recommendations with growing precision. Their track record in radiology, oncology, cardiology, and critical care shows how much AI can add to healthcare quality and efficiency (2, 4).

Ayurveda, among the oldest medical systems still in continuous practice, is built around individualized care. Clinical reasoning here extends well beyond naming a disease: it draws on Prakriti, Vikriti, Dosha, Agni, Dhatu, and Mala, together with diet, lifestyle, psychological state, and environment, before a treatment plan is formulated. This patient centered approach sits close to the ideals of precision medicine and makes Ayurveda a natural, if still underexplored, candidate for AI assisted decision support (5,6).

Turning this reasoning into computational models, however, is not straightforward. Diagnostic methods such as Dashavidha Pariksha, Ashtavidha Pariksha, Nadi Pariksha, and Jihva Pariksha depend considerably on physician expertise, which introduces inter observer variability. This is compounded by the absence of standardized electronic health records, structured ontologies, and large annotated datasets, all of which have limited the development of robust AI applications in Ayurveda (5,7).

Even so, the opportunities are real. Machine learning can identify relationships across clinical variables that are easy to miss by eye; deep learning can read medical images and biosignals; and NLP can convert classical Ayurvedic literature into searchable, computable knowledge. Early work has already touched Prakriti assessment, digital pulse analysis, tongue image interpretation, herbal drug discovery, disease prediction, and personalized treatment recommendation, although most of it remains at the proof-of-concept stage (4,8).

Broader reviews of AI in healthcare, or of digital tools in traditional medicine generally, already exist, but a focused evaluation of AI driven Clinical Decision Support Systems specifically for Ayurveda has been missing, and no synthesis so far has mapped out the opportunities, gaps, and a realistic roadmap toward a clinically deployable system. This review addresses that gap. It summarizes current evidence on AI driven CDSS in Ayurveda, critically evaluates existing applications and their limitations, discusses technical and regulatory challenges, and proposes a framework for an explainable, clinically validated, physician centered AI CDSS for precision Ayurveda.

## 2. ARTIFICIAL INTELLIGENCE IN CLINICAL DECISION SUPPORT SYSTEMS

CDSS are computer-based tools that help clinicians make evidence informed decisions by pairing patient specific data with validated medical knowledge. Over five decades they have moved from rule based expert systems to AI powered platforms that draw on EHRs, laboratory investigations, medical imaging, physiological signals, genomic information, wearable devices, and real time monitoring to support diagnosis, prognosis, treatment planning, and personalized care augmenting clinical decision making rather than replacing it (9,10).

The earliest CDSS were knowledge-based systems built on predefined “if then” rules drawn from clinical guidelines and expert opinion. Classic examples such as MYCIN and INTERNIST I proved the concept was workable but scaled poorly and depended on knowledge bases that needed constant expert updating. As digital health data grew, CDSS shifted from rule-based reasoning toward data driven AI capable of learning directly from clinical records (9,10).

Machine learning now underpins most contemporary AI CDSS. Supervised algorithms are widely used for disease diagnosis, risk prediction, and outcome forecasting, while unsupervised methods group patients and surface hidden clinical patterns. Deep learning, an advanced subset of ML, automatically extracts complex features from medical images, physiological signals, and longitudinal records, lifting diagnostic performance across many specialties (9,10).

Natural Language Processing (NLP) lets these systems convert unstructured clinical text physician notes, discharge summaries, pathology reports, biomedical literature into structured knowledge, supporting automated documentation, literature mining, and evidence retrieval (11).

Large Language Models (LLMs) have pushed this further still, assisting clinicians with documentation, evidence summarization, guideline interpretation, patient education, and clinical question answering. Concerns around hallucinated output, limited transparency, algorithmic bias, and patient privacy, however, currently rule out their independent use in clinical decision making, so human oversight and rigorous validation remain essential (12).

As models grow more capable, Explainable Artificial Intelligence (XAI) has become essential to trustworthy decision support predictive accuracy alone counts for little if clinicians cannot see why a recommendation was generated. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME) expose which variables drove a given prediction, which builds clinician trust, eases regulatory review, and supports safer integration of AI into routine care (4).

Modern AI CDSS increasingly fuse clinical history, laboratory findings, imaging, physiological signals, wearable data, and patient reported outcomes into a single recommendation. This multimodal approach mirrors the logic of precision medicine and maps naturally onto Ayurveda, where diagnosis already depends on weighing constitutional, physiological, pathological, behavioral, and environmental factors together.

That said, AI CDSS designed for conventional medicine cannot simply be carried over into Ayurveda. Getting this right will require standardized Ayurvedic knowledge representation, explainable reasoning, high quality multicentric datasets, and rigorous prospective clinical validation before such systems can be trusted in practice.

## 3. CLINICAL DECISION MAKING IN AYURVEDA

Clinical decision making in Ayurveda differs fundamentally from the disease-oriented approach of conventional biomedicine. Rather than focusing on a diagnostic label, Ayurveda treats the patient as an integrated biological, psychological, social, and environmental whole. Therapeutic decisions rest on a simultaneous reading of constitutional characteristics, pathological change, digestive and metabolic status, tissue involvement, mental state, diet, lifestyle, season, and environment an individualized, multidimensional approach that sits close to the principles of modern precision medicine (5,6,13).

The goal of Ayurvedic diagnosis is to identify the underlying imbalance driving disease rather than simply assigning a label. Classical literature describes health as equilibrium among Dosha, Dhatu, Mala, Agni, and mental wellbeing, with disease arising when that balance is disturbed. Two patients sharing the same biomedical diagnosis may therefore receive different treatments depending on constitution, disease stage, digestive capacity, psychological state, and associated pathology one of Ayurveda's greatest strengths, and also one of its steepest challenges for computational modeling (5,13).

Prakriti, the individual's inherent constitutional phenotype fixed at conception, sits at the center of Ayurvedic clinical reasoning. Determined by the relative predominance of Vata, Pitta, and Kapha, it shapes physical characteristics,

metabolism, disease susceptibility, psychological traits, and therapeutic response, and underlies personalized recommendations on diet, lifestyle, prevention, and treatment choice (5,6).
Vikriti, unlike the relatively fixed nature of Prakriti, captures the patient's current pathological state acquired disturbances in Dosha brought on by diet, lifestyle, environment, ageing, stress, or disease. Because it shifts through the course of illness, repeated assessment is needed to track disease progression and adjust treatment (13).
Agni, the functional principle behind digestion, metabolism, and tissue nourishment, is another key determinant of treatment planning. Impaired Agni is considered the precursor of Ama, a pathological metabolic by product implicated in disease. Assessing appetite, digestion, and bowel habits therefore matters as much as the diagnosis itself, since treatment is often calibrated to digestive capacity rather than to the disease label alone (13,14).
Ayurvedic examination follows two structured frameworks: Dashavidha Pariksha (Tenfold Examination), which assesses constitution, pathological status, tissue quality, body measurements, adaptability, psychological strength, digestive capacity, exercise tolerance, and age; and Ashtavidha Pariksha (Eightfold Examination), covering pulse, urine, stool, tongue, voice, touch, vision, and general appearance. Both remain central to practice, but several of their parameters lean heavily on physician judgement, leaving room for considerable inter observer variability (13,15).
Treatment planning extends well past diagnosis, into individualized choices of medicine, dosage form, Panchakarma procedures, Rasayana therapy, diet, lifestyle change, and follow up. Physicians weigh Roga Bala (disease strength), Rogi Bala (patient strength), Dosha predominance, affected tissues, disease stage, season, geography, age, and prior treatment response together, which is why even patients with similar presentations often end up on quite different regimens (13).
This complexity is exactly what makes Ayurvedic reasoning hard for AI to capture. Conventional medical algorithms typically lean on standardized lab values and discrete diagnostic categories; Ayurveda instead works through qualitative observation, contextual interpretation, physician experience, and interaction among many physiological variables at once. The lack of standardized terminology, structured documentation, and multicentric health records further restrict the datasets needed for robust machine learning (16,17).
Yet these same features are also an opportunity. Ayurveda's emphasis on individualized treatment, longitudinal monitoring, and multidimensional assessment lines up well with precision medicine and multimodal AI. Done well, AI based decision support could improve diagnostic consistency, cut observer variability, standardize documentation, support evidence informed treatment planning, and strengthen research through large scale data analysis provided it is built on standardized knowledge representation, interoperable health records, explainable models, and rigorous prospective validation (4,17,18).

## 4. CURRENT APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN AYURVEDA

AI has become a promising tool for advancing Ayurvedic research and practice, even though its application here remains at an early stage compared with conventional medicine. Recent work in ML, DL, computer vision, biosignal processing, and NLP has demonstrated that AI can plausibly be woven into several parts of Ayurvedic healthcare. Research so far has concentrated on Prakriti assessment, digital Nadi analysis, tongue image interpretation, mining of classical texts, herbal drug discovery, disease prediction, and personalized treatment planning. Taken together, these studies suggest AI can improve diagnostic consistency, standardize documentation, generate research evidence, and support individualized care while leaving the physician firmly in charge of the final decision (5,6,11,17).

### 4.1 AI for Prakriti Assessment

Prakriti assessment is probably the most studied AI application in Ayurveda, since constitutional classification underlies personalized diagnosis and treatment. It is traditionally determined through physician administered questionnaires and clinical examination, which leaves plenty of room for inter observer variability. To improve objectivity, several studies have applied supervised ML algorithms decision trees, random forests, support vector machines (SVM), k nearest neighbors (KNN), naïve Bayes, and artificial neural networks to classify constitutional phenotypes from questionnaire responses, anthropometric data, physiological parameters, and, more recently, genomic data (5,6,18).
An important extension of this work is Ayurgenomics, which combines Ayurvedic constitutional concepts with genomics, transcriptomics, metabolomics, and systems biology. AI based integration of these datasets could sharpen Prakriti assessment and clarify genotype phenotype relationships. Existing studies, though, are still limited by small sample sizes, single center datasets, inconsistent assessment methods, and a lack of external validation, which points squarely to the need for standardized criteria and multicentric studies (5,8,18).

### 4.2 AI Based Nadi Analysis

Nadi Pariksha is a distinctive Ayurvedic diagnostic method resting on tactile assessment of pulse characteristics. Because interpretation depends so heavily on physician skill, objective standardization has been hard to achieve. Advances in biosensors, signal acquisition, and machine learning have made digital pulse analysis possible using pressure sensors, photoplethysmography (PPG), piezoelectric devices, and wearables. AI algorithms can extract temporal, frequency domain, and nonlinear features from pulse waveforms to identify patterns linked to constitutional or pathological states (19,20).
Despite encouraging early results, digital Nadi analysis is still experimental. Standardized acquisition protocols, validated digital biomarkers, and large multicentric datasets are still missing, which limits its move into routine practice (19,20).

### 4.3 Computer Vision for Tongue Diagnosis

Jihva Pariksha (tongue examination) is an important part of Ayurvedic assessment, offering clues about digestive function, Dosha imbalance, hydration, and general health. Advances in computer vision and deep learning have made automated tongue image analysis possible using convolutional neural networks (CNNs), which handle preprocessing, segmentation, feature extraction, and classification to read tongue color, coating, texture, fissures, and other clinically relevant features more consistently than the eye alone (21,22).

The diagnostic performance reported so far is encouraging, but wider use is held back by variation in image acquisition, lighting, camera quality, and annotation standards. Standardized imaging protocols and curated image repositories will be needed before this can move into everyday clinical translation (21,22).

### 4.4 Natural Language Processing of Ayurvedic Literature

Ayurveda carries a vast body of classical and contemporary literature, much of it still unstructured text. NLP offers a way to turn this into computable resources for research and clinical decision support, including extraction of disease descriptions, formulations, therapeutic indications, ontology development, knowledge graphs, semantic mapping, and intelligent literature retrieval (11).

Large language models extend this further, enabling multilingual translation, document summarization, contextual question answering, and physician decision support. Hallucinated output and factual error remain real limitations, though, so expert verification stays essential before any clinical use (12).

### 4.5 AI in Herbal Drug Discovery

AI is increasingly used to speed up herbal drug discovery, predicting pharmacological activity, molecular interactions, toxicity, pharmacokinetics, and likely therapeutic targets. Machine learning, molecular docking, quantitative structure activity relationship (QSAR) modeling, and network pharmacology can shortlist promising phytochemicals before laboratory testing begins, cutting both time and cost. In Ayurveda, these approaches could help validate and standardize classical formulations while also flagging genuinely novel therapeutic candidates (23,24,25).

### 4.6 Disease Prediction and Personalized Treatment

Recent studies have explored AI models for disease risk prediction, severity assessment, and individualized treatment recommendation. Unlike conventional predictive models built mainly on biomedical variables, Ayurvedic AI systems aim to fold in constitutional characteristics, lifestyle, diet, season, and classical diagnostic parameters. Early results are encouraging, but relatively few published models actually incorporate a full set of Ayurvedic clinical variables, which marks a real gap between the computational research and everyday clinical practice (4,17,28).

### 4.7 Current Limitations

Despite this progress, most AI applications in Ayurveda remain proof of concept work rather than clinically validated decision support. Recurring limitations include small sample sizes, no multicentric datasets, no standardized diagnostic criteria, weak external validation, poor model explainability, inconsistent reporting, and limited integration into routine workflows. No AI platform yet supports the complete Ayurvedic clinical pathway from Prakriti assessment through treatment planning to longitudinal follow up. Closing this gap will call for standardized electronic health records, interoperable Ayurvedic ontologies, explainable models, multicentric validation studies, and close collaboration between Ayurvedic clinicians, data scientists, and engineers (4,17,30).

**Table 1. Current Applications of Artificial Intelligence in Ayurveda**

| Application | AI Technique | Status | Major Challenges | Key Refs |
|---|---|---|---|---|
| Prakriti assessment | Machine learning | Experimental | Small datasets; lack of standardization | 5,6,18 |
| Nadi analysis | Signal processing, deep learning | Prototype | No validated digital biomarkers | 19,20 |
| Tongue diagnosis | Computer vision, CNN | Experimental | Image acquisition variability | 21,22 |
| Classical text mining | NLP, LLM | Rapidly developing | Terminology and ontology standardization | 11,12 |
| Herbal drug discovery | ML, network pharmacology | Active research | Requires experimental validation | 23-25 |
| Disease prediction | Machine learning | Limited clinical evidence | Limited integration of Ayurvedic variables | 4,17,28 |
| Personalized treatment | Rule based AI + ML | Early stage | No validated AI CDSS available | 4,17,26 |

## 5. PROPOSED EXPLAINABLE AI DRIVEN CLINICAL DECISION SUPPORT FRAMEWORK FOR AYURVEDA

Current AI applications in Ayurveda are largely confined to isolated tasks Prakriti assessment, digital pulse analysis, tongue image interpretation, herbal drug discovery, text mining. Useful as these are individually, none of them adds up to a comprehensive clinical decision support system able to replicate the holistic, individualized reasoning of an Ayurvedic

physician. A clinically useful AI CDSS therefore needs to integrate multiple sources of patient information, preserve classical diagnostic principles, offer transparent recommendations, and act as a physician support tool rather than an autonomous decision maker (4,11,17,26).
To close this gap, we propose an Explainable Artificial Intelligence Driven Clinical Decision Support System (XAI CDSS) built specifically for Ayurvedic practice. It combines multimodal patient data, AI based analytical models, explainable decision making, evidence integration, and continuous learning within a modular architecture that supports, rather than replaces, physician expertise.
The framework starts with multimodal data acquisition, pulling together structured EHRs, demographic information, medical history, laboratory investigations, lifestyle, diet, sleep, wearable data, and patient reported outcomes alongside classical Ayurvedic assessments Prakriti, Vikriti, Dosha, Agni, Dashavidha Pariksha, and Ashtavidha Pariksha. Digital tongue images, pulse waveforms, and other relevant biosignals can be added to build a fuller picture of the patient's health (19,21,26).
This data then goes through standardization and preprocessing handling missing values, duplicate records, and inconsistent terminology before converting heterogeneous clinical information into machine readable form. Standardized Ayurvedic ontologies and interoperable EHRs are essential here, ensuring consistent representation of concepts such as Dosha predominance, Agni status, Ama, Dhatu involvement, and disease stage across institutions (17,26).
The processed data is then analyzed using different AI techniques depending on data type: structured clinical variables through machine learning, tongue images and other visual data through deep learning, pulse waveforms through specialized biosignal processing, and physician notes or classical texts through NLP. Outputs from these individual models are then combined into a single patient profile reflecting the multidimensional nature of Ayurvedic diagnosis (9-12,19,21).
This integrated profile is then read by the Clinical Reasoning Engine, the framework's central component. Unlike conventional predictive systems that output a single diagnosis, this engine weighs constitutional characteristics, current pathological status, Dosha imbalance, digestive function, disease severity, patient strength, environmental factors, and prior treatment response together, generating ranked diagnostic and therapeutic suggestions with confidence scores always leaving the physician free to modify or reject them (4,17).
A key feature of this design is Explainable AI (XAI). Clinical adoption depends as much on trust as on accuracy, so techniques such as SHAP and LIME are used to show which variables drove a given prediction, improving transparency, physician confidence, regulatory acceptance, and patient safety (4).
To keep recommendations reliable, AI outputs are cross checked against classical Ayurvedic texts, contemporary research, institutional protocols, and clinical guidelines. This hybrid, knowledge plus data approach limits algorithmic bias while keeping recommendations consistent with established Ayurvedic principles; future versions could pull in literature updates automatically so new evidence keeps flowing into the system (11,12).
The framework ultimately produces personalized recommendations for Ahara (diet), Vihara (lifestyle), Aushadhi (medicines), Panchakarma, Rasayana therapy, follow up scheduling, and patient education. Every one of these stays advisory the final clinical call always rests with the treating physician.
An added strength is its continuous learning capability. Clinical outcomes, physician feedback, treatment changes, adverse events, lab results, and patient reported outcomes can feed back into the system after anonymization and quality checks, with periodic retraining letting it improve and adapt over time (26,27).
Making this work in practice will need solid governance around data privacy, cybersecurity, ethical oversight, interoperability, and regulatory compliance. Federated learning is one promising route to multicenter model development without sharing patient data directly, protecting privacy while still improving generalizability (27,28).
Conceptual as it is, this proposed XAI CDSS gives a practical starting point for bringing AI into Ayurvedic practice. By combining multimodal data, explainable reasoning, physician oversight, evidence-based recommendations, and continuous learning, it has real potential to improve diagnostic consistency, support personalized treatment, strengthen research, and move precision Ayurveda forward.

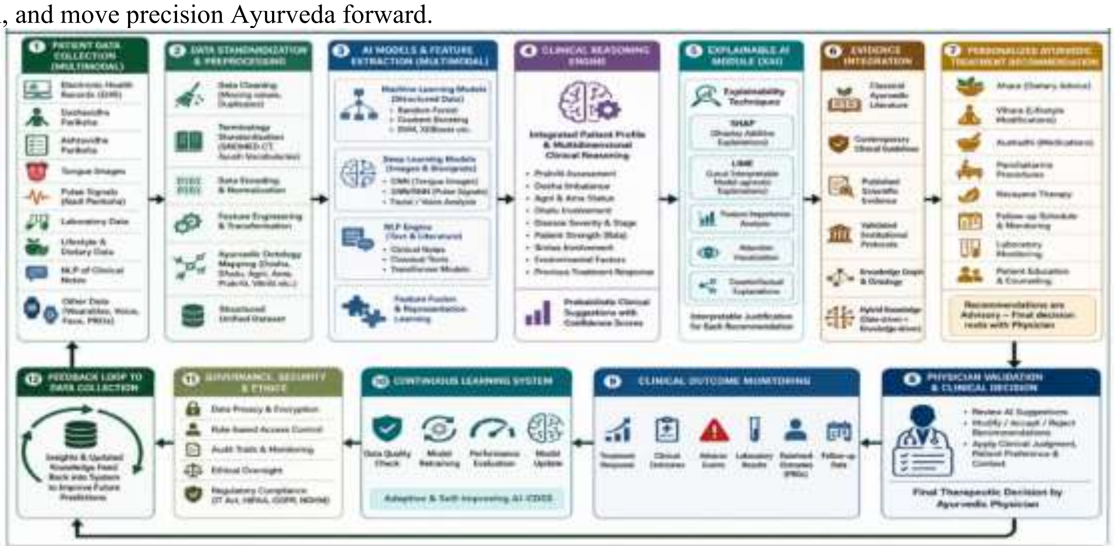

**Figure 1. Proposed Explainable Artificial Intelligence Driven Clinical Decision Support System (XAI CDSS) for Ayurveda.**

The framework illustrates the sequential workflow of AI assisted Ayurvedic clinical decision making: (1) multimodal patient data acquisition (EHRs, Dashavidha Pariksha, Ashtavidha Pariksha, tongue images, pulse signals, laboratory investigations, lifestyle and dietary information); (2) data preprocessing and standardization; (3) AI analytics using machine learning, deep learning, computer vision, biosignal analysis, and NLP; (4) an integrated clinical reasoning engine; (5) an explainable AI module (e.g., SHAP/LIME); (6) evidence integration with classical Ayurvedic literature and contemporary research; (7) personalized treatment recommendations; (8) physician validation; and (9) clinical outcome monitoring through a continuous learning feedback loop.

## 6. CHALLENGES IN DEVELOPING AI DRIVEN CLINICAL DECISION SUPPORT SYSTEMS FOR AYURVEDA

Despite real advances in AI, building clinically reliable AI CDSS for Ayurveda remains genuinely difficult. Unlike conventional biomedical decision support, AI models here must accommodate individualized clinical reasoning, qualitative diagnostic parameters, heterogeneous data sources, and physician dependent decision making. Working through these issues is essential before AI can be safely folded into routine Ayurvedic practice (4,17,26,28,29).

### 6.1 Standardization of Clinical Data

AI systems need large, well annotated datasets for training and validation. Most Ayurvedic clinical records, however, remain handwritten or unstructured, and terminology, diagnostic criteria, and documentation practice vary widely across institutions. Key variables such as Prakriti, Vikriti, Agni, Ama, and Dashavidha Pariksha are usually recorded qualitatively rather than quantitatively, which limits computational analysis. Standardized electronic health records, common data elements, and interoperable Ayurvedic ontologies are a fundamental prerequisite here (17,19).

National and international standardization efforts provide a foundation for closing this gap. The Ministry of AYUSH's National AYUSH Morbidity and Standardized Terminologies Electronic (NAMASTE) Portal and the associated AYUSH Grid digital infrastructure are building standardized morbidity codes and dual coding systems for Ayurveda, Siddha, and Unani practice, while the World Health Organization's ICD-11 Traditional Medicine Module 2 (TM2) now provides an internationally recognized classification for Ayurvedic disease terminology. Together, these initiatives are an important step toward resolving terminological inconsistency and enabling cross platform interoperability (15,32).

### 6.2 Limited High-Quality Datasets and Diagnostic Variability

Most published AI studies in Ayurveda draw on small, single center datasets, which raises the risk of overfitting and limits how well findings generalize. This is worsened by the subjective nature of procedures such as Nadi Pariksha, Jihva Pariksha, Dosha assessment, and Vikriti evaluation, all of which depend heavily on physician judgement. Variability between clinicians introduces inconsistent training labels and weakens supervised models a pattern that mirrors broader concerns about reproducibility in health care machine learning more generally (19,21,29,30). Large multicenter datasets, standardized diagnostic criteria, and objective digital biomarkers are the way past this.

### 6.3 Explainability and Physician Acceptance

Clinical adoption of AI depends on physician trust as much as on predictive accuracy. Black box algorithms that hand over recommendations without explaining the reasoning behind them are unlikely to gain acceptance in a field where decisions are inherently individualized and context dependent. XAI techniques such as SHAP and LIME improve transparency by identifying which factors drove a given prediction, which in turn builds clinician confidence, eases regulatory acceptance, and protects patient safety (3,4).

### 6.4 Integration of Classical Knowledge with Modern AI

A deeper scientific challenge lies in translating classical concepts into computationally meaningful form. Terms such as Dosha, Dhatu, Agni, Ama, Ojas, and Sotas have no direct biomedical equivalent, which makes knowledge representation genuinely hard. Future AI systems will need standardized Ayurvedic ontologies, knowledge graphs, and expert defined rules working alongside data driven ML models, so that classical principles are preserved even as computational analysis modernizes (11,17).

### 6.5 Ethical, Regulatory, and Privacy Considerations

AI CDSS handles sensitive clinical information routinely health records, lab results, medical images, physiological signals, and sometimes genomic data. Responsible implementation calls for solid data governance: encryption, anonymization, secure authentication, audit trails, and compliance with digital health regulation. Questions of informed consent, algorithmic fairness, accountability, transparency, and physician oversight all need addressing before deployment can be considered ethically sound (27,29).

### 6.6 Infrastructure and Clinical Validation

Most existing AI applications in Ayurveda remain proof of concept work with little prospective clinical validation. Before routine deployment, AI CDSS should go through rigorous technical evaluation, multicenter clinical validation, physician usability testing, implementation research, and cost effectiveness analysis. Standardized reporting frameworks for AI based prediction models such as the TRIPOD+AI statement could help make these evaluations comparable across studies (30,31). Success will also depend on digital infrastructure and genuine collaboration between Ayurvedic clinicians, biomedical informaticians, engineers, and data scientists (9,28).

Taken together, these challenges show that folding AI into Ayurveda depends on more than computational progress alone it depends equally on data quality, standardization, clinical validation, governance, and physician acceptance. Addressing these together is what will make safe, effective AI CDSS possible in Ayurvedic healthcare.

**Table 2. Major Challenges and Potential Solutions for AI CDSS in Ayurveda**

| Challenge | Impact | Potential Solution | Key Refs |
|---|---|---|---|
| Lack of standardized clinical records | Poor data quality and interoperability | Standardized electronic Ayurvedic health records; NAMASTE Portal; ICD-11 TM2 | 15,17,32 |
| Small, single center datasets | Limited generalizability | Multicenter collaborative databases; federated learning | 27,30 |
| Subjective diagnostic assessment | Inter observer variability | Consensus guidelines and validated digital biomarkers | 19,21 |
| Limited model explainability | Reduced physician trust | Explainable AI (SHAP, LIME) | 3,4 |
| Privacy and ethical concerns | Risk to patient confidentiality | Encryption, anonymization, federated learning, governance frameworks | 27,29 |
| Algorithmic bias | Unequal clinical performance | Diverse datasets, external validation, bias monitoring | 29,30 |
| Limited clinical validation | Uncertain real-world effectiveness | Prospective multicenter trials; standardized reporting (TRIPOD+AI) | 30,31 |
| Digital infrastructure limitations | Slow adoption | Digital transformation, AYUSH Grid, interdisciplinary training | 9,28,32 |

## 7. FUTURE DIRECTIONS

AI has the potential to move Ayurveda from a largely experience driven system toward one that is digitally enabled, evidence informed, and precision oriented. Current applications remain mostly experimental, but rapid advances in computational science, digital health infrastructure, biomedical informatics, and precision medicine open a real opportunity to build clinically validated decision support systems tailored to Ayurvedic principles. Research should shift from isolated algorithm development toward integrated, explainable, physician centered AI ecosystems that support the entire span of Ayurvedic patient care (4,26,28).

A major priority is building standardized electronic Ayurvedic health records (E AEHRs) that capture both classical and biomedical information in structured, interoperable form, aligned with national efforts such as the NAMASTE Portal and international frameworks such as ICD-11 TM2. Standardized documentation of Prakriti, Vikriti, Dosha, Agni, Dashavidha Pariksha, Ashtavidha Pariksha, treatment, investigations, and follow up outcomes would enable multicenter data sharing, improve reproducibility, and finally provide the datasets that reliable machine learning needs (15,17,19,32).

Future AI CDSS should also put explainability and transparency front and center. Predictive accuracy is not enough for clinical adoption if physicians cannot follow the reasoning behind a recommendation. Explainable AI should therefore become a standard component of Ayurvedic decision support, letting clinicians interpret predictions, identify contributing variables, and stay in control of the final decision (3,4).

The next generation of systems is likely to adopt a multimodal approach, integrating structured records, Ayurvedic examination findings, tongue images, pulse waveforms, laboratory data, wearable sensor data, lifestyle information, and patient reported outcomes into unified predictive models. This mirrors Ayurveda's holistic philosophy and supports individualized diagnosis and treatment in the spirit of precision medicine (5,19,21).

Another promising direction is the convergence of Ayurgenomics with multi omics technologies genomics, transcriptomics, proteomics, metabolomics, and microbiome research. AI driven integration of these datasets could deepen understanding of constitutional phenotypes, disease susceptibility, therapeutic response, and preventive care, giving personalized Ayurvedic medicine a firmer biological footing (5,18).

Advances in wearable technologies and remote monitoring should further expand AI's role in Ayurveda. Continuous tracking of activity, sleep, heart rate, and stress could complement traditional Ayurvedic evaluation, enabling longitudinal monitoring, earlier detection of disease progression, and timely adjustment of treatment. Federated learning offers a parallel opportunity building robust multicenter models while preserving patient privacy, since institutions can train locally without sharing identifiable data (27).

Large Language Models also carry real potential to support Ayurvedic practice, through automated documentation, intelligent retrieval of classical literature, multilingual translation, evidence synthesis, patient education, and clinician assistance. Given the risk of hallucination and factual error, though, LLM generated output should always be checked by qualified physicians against validated knowledge bases before it reaches clinical use (12).

Research should prioritise prospective multicenter clinical validation rather than relying on retrospective model performance alone. Studies on physician usability, implementation feasibility, cost effectiveness, patient outcomes, and long-term safety will be essential for regulatory approval and routine adoption. Equally important are interdisciplinary training programmes that give Ayurvedic physicians a working knowledge of digital health and AI, while helping engineers and data scientists understand Ayurvedic clinical principles and workflows.

Ultimately, the goal of AI in Ayurveda is not to replace physicians but to extend their expertise through transparent, evidence informed, personalized decision support. With standardized digital infrastructure, explainable AI, rigorous clinical validation, and genuine interdisciplinary collaboration, AI driven Clinical Decision Support Systems can improve diagnostic consistency, strengthen research, support precision Ayurveda, and help integrate Ayurveda into the wider landscape of digital healthcare.

## 8. CONCLUSION

Artificial intelligence is reshaping healthcare by enabling data driven, personalized, evidence informed clinical decision making. It is already integral to modern medicine, but its application in Ayurveda is still at an early stage. This review shows that AI has already demonstrated promising utility in key areas of Ayurvedic practice Prakriti assessment, digital pulse analysis, tongue image interpretation, NLP of classical literature, herbal drug discovery, disease prediction, and personalized treatment support pointing to real potential for improving diagnostic consistency, reducing observer variability, standardizing documentation, and strengthening the evidence base.

Despite this progress, existing research remains largely proof of concept, built on small datasets and inconsistent methods, with few clinically validated decision support systems ready for routine practice. Bringing AI into Ayurveda properly will take more than computational advances alone: reliable AI CDSS need standardized electronic Ayurvedic health records, interoperable ontologies, multicentric annotated datasets, validated diagnostic criteria, and rigorous prospective evaluation all while preserving the holistic, individualized reasoning that defines Ayurvedic practice.

The central message of this review is that future AI systems should work as physician assistive technologies rather than physician replacement tools. Explainable AI should stay a core design principle, ensuring transparency, physician confidence, regulatory acceptance, and patient trust. Bringing together multimodal clinical information structured records, biosignals, imaging, wearables, laboratory data, and emerging multi omics evidence offers a real path toward precision Ayurveda without drifting from its classical foundations.

To support this, we have proposed a conceptual Explainable AI Driven Clinical Decision Support System (XAI CDSS) for Ayurveda that brings together multimodal data acquisition, AI based analytics, explainable decision making, evidence integration, physician validation, and continuous learning within one clinical workflow. Conceptual as it stands, the framework offers a practical starting point for future interdisciplinary research and lays out what a clinically meaningful AI implementation would actually need.

Future work should focus on multicenter validation studies, standardized reporting, interoperable digital infrastructure, physician usability, health economic evaluation, and ethical governance. Close collaboration among Ayurvedic clinicians, biomedical informaticians, computer scientists, engineers, policymakers, and regulators will be essential to move experimental AI models toward safe, clinically deployable decision support.

In short, AI has the potential to become a genuine enabler of evidence based, personalized, digitally integrated Ayurvedic healthcare not by replacing traditional practice, but by sharpening diagnostic precision, supporting individualized treatment planning, strengthening research, and improving healthcare delivery. With sound scientific validation, transparent governance, and sustained interdisciplinary collaboration, AI driven Clinical Decision Support Systems can play a real part in advancing precision Ayurveda and bringing it into the future of global healthcare.


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## CONFLICT OF INTEREST

The authors declare that they have no competing interests related to this work.

## AUTHOR CONTRIBUTIONS

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## DATA AVAILABILITY STATEMENT

No new data were generated or analyzed during this study. All information presented in this review is derived from previously published literature.

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