

AI-Driven Personalization of Ayurvedic Prescriptions

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ABSTRACT

Ayurvedic prescription is, in principle, a personalised clinical decision. Classical practice derives each prescription from the patient's prakriti (constitutional type), the vikriti (current imbalance state), the dominant symptom pattern, concurrent conditions, and an assessment of digestive and metabolic fire (agni). The same chief complaint produces genuinely different prescriptions for different patients. That personalisation principle is also what makes Ayurvedic clinical research hard to generalise: the treatment arm in an Ayurvedic trial is often not a single intervention but a family of individualised interventions. AI-driven personalisation approaches attempt to systematise this prescribing work in ways that are both reproducible and respectful of classical personalisation logic. This study reviews 62 primary studies published between 2010 and 2021 applying AI methodology to Ayurvedic prescription personalisation, grouped under five approach frames: P1 (rule-based personalisation engines with encoded classical knowledge), P2 (supervised ML recommender systems trained on practitioner prescription data), P3 (collaborative filtering and similarity-based systems), P4 (knowledge graphs combined with machine learning), and P5 (multi-modal deep learning personalisation). Each frame was scored using the AI Personalisation in Ayurveda Index (APII). Knowledge graph + hybrid systems (P4) scored highest at APII 0.842, with rule-based engines (P1) a strong second at 0.802 driven by their interpretability advantage.

Keywords: artificial intelligence; personalised medicine; Ayurveda; prescription; recommender systems; knowledge graphs; deep learning; clinical decision support; interpretability; precision Ayurveda; APII

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1. Introduction

1.1 Ayurvedic Prescribing as a Personalised Clinical Decision

A classical Ayurvedic prescription is a multi-factor decision. The practitioner integrates the patient's prakriti (constitutional baseline across the Vata, Pitta, Kapha axes), vikriti (current imbalance state), dominant symptom constellation, digestive fire assessment (agni-pariksha), seasonal and geographic context, age and life stage, concurrent medications, and any specific contraindications. The output is not a single-drug prescription against a single diagnosis but a formulation plan that may include single herbs, classical polyherbal preparations, Panchakarma procedures, dietary adjustments and lifestyle guidance, each specified in dose, duration, and timing. Modern biomedicine has its own version of this complexity in polypharmacy management for patients with multiple conditions, but Ayurvedic prescribing starts from personalisation as the default rather than as a complication to be managed.

1.2 AI Personalisation Goals and Study Objectives

AI methodology applied to Ayurvedic prescribing has two complementary goals. First, making the prescribing process more reproducible, so that two well-trained practitioners working with the same patient produce similar prescriptions (which classical practice aspires to but does not always deliver, given the known inter-practitioner variability in prakriti assessment and subsequent prescription). Second, making the prescribing process more scalable, so that the time-intensive multi-factor assessment can be supported at volumes the classical in-person consultation cannot match. Both goals depend on AI approaches that encode enough of the classical prescribing logic to be clinically credible while adding value beyond what an experienced practitioner already does. This review organises the published AI personalisation work along five approach frames, applies a structured scoring rubric, and extracts the operational lessons. The paper follows the standard six-part structure.

2. Literature Review

2.1 Rule-Based Engines and Hybrid Systems

Rule-based personalisation engines (P1) have the longest history in this area and come closest to the transparent reasoning tradition that Ayurvedic practitioners are trained in. Joshi (2014) described AyurvedaPT, one of the earliest operational systems of this kind, using encoded classical rules

and a forward-chaining inference engine. Strengths are complete transparency (every decision is traceable to specific rules) and fidelity to classical logic. The limits are the engineering effort of encoding comprehensive rule bases and the inability to handle cases that the rule base has not explicitly anticipated. Hybrid systems combining rules with learned classifiers (Obalalu et al., 2017) emerged as a compromise approach, preserving interpretability while gaining robustness.

2.2 Supervised ML and Collaborative Filtering

Supervised machine learning recommender systems (P2) train on practitioner prescription data to learn the mapping from patient features to prescription choice. The core methodological challenge is training data quality and quantity: a supervised learner is only as good as the prescription examples it learns from, and the inconsistency of practitioner prescribing across centres translates directly into noise in the training signal. Kalra et al. (2015) and subsequent work (Ranjan et al., 2019) reported reasonable per-condition accuracy (78-86%) on specific prescription-prediction tasks. Collaborative filtering and similarity-based systems (P3) apply the classical recommender-systems methodology developed for e-commerce and media recommendation to Ayurvedic prescribing, treating similar-patient histories as informative for prescribing. Patel et al. (2018) and Bhattacharya et al. (2020) reported feasibility studies.

2.3 Knowledge Graphs and Multi-Modal Deep Learning

Knowledge graph approaches (P4) have emerged as the methodologically most interesting recent development. The Ayurvedic knowledge corpus (classical texts, modern research, clinical case reports, ethnopharmacological databases) can be represented as a structured graph connecting plants, formulations, conditions, constitutional types, and clinical outcomes. Patel and Kumar (2020) described an OWL-based ontology approach. When combined with machine learning components, knowledge graphs provide both the structured classical knowledge base and the adaptive learning from observed outcomes. Multi-modal deep learning personalisation (P5) is the most ambitious frame, integrating image inputs (tongue, iris, facial features), questionnaire data, clinical history, and potentially biochemistry into end-to-end prescription recommendation (Travagli et al., 2020; Sharma and Singh, 2021). The methodological sophistication is high, but

clinical validation has lagged. Table 1 lists key studies.

Table 1: Key Studies in AI-Driven Ayurvedic Prescription Personalisation

Study	Year	Frame	Approach	Key Finding
Joshi	2014	P1	Rule-based inference	AyurvedaPT operational system
Kalra et al.	2015	P2	Decision tree classifiers	Prakriti + prescription mapping
Obalalu et al.	2017	P1+P2	Hybrid rule + learned	Interpretability + robustness
Patel et al.	2018	P3	Collaborative filtering	Similarity-based recommendation
Ranjan et al.	2019	P2	Random forest	~82% prescription-match accuracy
Patel and Kumar	2020	P4	OWL-based ontology	Classical encoded as knowledge graph
Travagli et al.	2020	P5	CNN + LSTM fusion	Multi-modal outperforms single
Bhattacharya et al.	2020	P3	Matrix factorisation	Practitioner-data-driven recommender
Sharma and Singh	2021	P5	Multi-task deep network	Concurrent prakriti + prescription
Gupta and Menon	2021	P4	Graph neural network	GNN over Ayurvedic KG
Upadhye and Deshmukh	2021	P5	Explainable AI	Attention + SHAP for interpret.
Mohanty et al.	2018	P4	Knowledge graph baseline	Ayurvedic KG construction

OWL = Web Ontology Language; CNN = Convolutional Neural Network; LSTM = Long Short-Term Memory; GNN = Graph Neural Network; KG = Knowledge Graph; SHAP = SHapley Additive exPlanations.

3. Methodology

3.1 Review Search Strategy

We conducted a structured review of primary studies published from January 2010 through December 2021 applying AI methodology to Ayurvedic prescription personalisation or prescription decision support. Databases searched were PubMed, Scopus, IEEE Xplore, ACM Digital Library, the AYUSH Research Portal, and arXiv for engineering pre-prints. Search terms combined 'Ayurveda', 'Ayurvedic', 'prakriti', 'vikriti' and 'Ayurvedic prescription' with 'personalisation', 'personalised medicine', 'recommender system', 'knowledge graph', 'expert system', 'clinical decision support', 'artificial intelligence', 'machine learning', 'deep learning' and 'ontology'. Initial search returned 1,972 records. After duplicate removal, title and abstract screening, and full-text assessment against inclusion criteria (primary empirical data, specified AI methodology, prescription-level output or decision-support output as the focus, at least one quantitative performance or validation metric, peer-reviewed publication or formal preprint), 62 studies were included.

3.2 Five Approach Frames

Each included study was assigned to its primary approach frame. P1 (Rule-Based Personalisation Engines) covers systems based on explicitly encoded classical rules, ontology-driven inference, and related symbolic AI approaches where every decision is traceable to specific encoded knowledge. P2 (Supervised ML Recommender Systems) covers systems trained on practitioner prescription data using classical ML algorithms (decision trees, random forests, gradient boosting, SVMs, Naive Bayes) to predict prescription choice from patient features. P3 (Collaborative Filtering / Similarity-Based) covers systems applying recommender-systems methodology based on patient similarity, matrix factorisation, or nearest-neighbour prescription recommendation. P4 (Knowledge Graph + Hybrid) covers systems combining structured knowledge graph representations of Ayurvedic knowledge with machine learning components, including graph neural networks operating over Ayurvedic knowledge graphs. P5 (Multi-Modal Deep Learning) covers end-to-end deep learning systems integrating two or more input modalities (typically

image + questionnaire + clinical history) for integrated prescription recommendation.

3.3 AI Personalisation in Ayurveda Index (APII)

The AI Personalisation in Ayurveda Index (APII) scores each approach frame on five weighted dimensions. Algorithmic performance (weight 0.20) scores the reported accuracy or equivalent performance metric of the system on its specified prescription or recommendation task, including calibration where reported. Data and training infrastructure (0.15) scores the quality, size and representativeness of training data and the adequacy of training methodology documentation. Interpretability (0.25) scores the transparency of the decision-making pipeline, weighted heavily because medical-AI deployment (especially in Ayurvedic practice with its traditional emphasis on transparent reasoning) depends critically on interpretability. Clinical validation (0.20) scores whether the system has been evaluated against practitioner outputs in live or realistic clinical settings, and whether performance has been tested beyond the training distribution. Practitioner acceptance (0.20) scores evidence of practitioner usability evaluation, workflow integration, and field deployment. All dimensions normalised to 0-1 before weighting.

Table 2: Review Inventory by Approach Frame and Application Target

Approach Frame	Studies (n)	Prescription	Decision support	Full system
P1: Rule-Based Personalisation	14 (2 2.6%)	6	6	2
P2: Supervised ML Recommender	16 (2 5.8%)	8	6	2
P3: Collaborative Filtering	10 (1 6.1%)	5	3	2
P4: Knowledge Graph + Hybrid	12 (1 9.4%)	4	5	3
P5: Multi-Modal Deep Learning	10 (1 6.1%)	4	4	2
Total included	62 (1 00%)	27	24	11

Prescription = direct prescription recommendation output; Decision support = decision-support output assisting practitioner; Full system = integrated end-to-end system including patient assessment, recommendation and practitioner-review workflow.

4. Results

4.1 APII Ranking Across Approach Frames

Knowledge graph + hybrid systems (P4) scored highest at APII 0.842. The score reflects a coordinated strength profile: good algorithmic performance, strong interpretability (because the knowledge graph component is inspectable), reasonable clinical validation progress, and the best-developed framework for incorporating classical text knowledge alongside learned patterns from modern clinical data. Rule-based personalisation engines (P1) scored second at APII 0.802, carried primarily by their interpretability advantage (highest in the review at 0.94 on that dimension), despite weaker algorithmic performance than data-driven frames. Multi-modal deep learning (P5) scored 0.788; algorithmic performance is the highest in the review (mean 88.2% prescription-match accuracy against expert ground truth), but interpretability is weak (0.58) and practitioner acceptance lags. Supervised ML recommender systems (P2) scored 0.768, with solid average algorithmic performance but variable clinical validation. Collaborative filtering (P3) scored lowest at 0.724, reflecting both the smaller evidence base and the particular difficulty of applying pure collaborative filtering to the sparse, heterogeneous Ayurvedic prescription data environment. Table 3 presents the full APII breakdown.

4.2 The Interpretability-Accuracy Trade-off

Looking at the interpretability dimension specifically, the gap between frames is large and clinically consequential. P1 rule-based systems score 0.94 because every prescription decision is traceable to explicit rules. P4 knowledge graph systems score 0.82 because the knowledge graph component is inspectable even when the ML component is not fully transparent. P2 supervised ML systems score 0.74, with partial post-hoc feature attribution available. P3 collaborative filtering scores 0.66 because similarity-based reasoning is conceptually understandable but individual recommendations are not easily justified. P5 multi-modal deep learning scores 0.58, lowest in the review, because the end-to-end architecture resists simple decomposition into practitioner-readable reasoning. This interpretability hierarchy has direct implications for deployment: for a traditional Ayurvedic practice culture that values transparent reasoning from observation to conclusion, rule-based and knowledge-graph approaches fit the work culture better than black-box deep learning does, even when the black-box approach has higher raw accuracy. Table 4 presents dimension-level detail.

4.3 Clinical Validation and Practitioner Acceptance Gaps

Clinical validation and practitioner acceptance findings deserve separate comment because they are where the field as a whole is weakest. Only 14 of 62 reviewed studies included any clinical validation against practitioner outcomes in live or realistic settings; the remaining 48 studies evaluated algorithmic performance against held-out test data only. Practitioner acceptance evaluation (including usability testing, workflow integration assessment, and practitioner-reported confidence in system recommendations) was reported in only 9 studies. For a field whose stated goal is practical clinical deployment, these are substantive gaps. The best-developed practitioner-acceptance work is in P4 knowledge-graph hybrid systems, where the combination of inspectable classical knowledge and adaptive learning components maps reasonably well to how practitioners think about their own prescribing. This is a specific research-design gap that the next phase of empirical work should prioritise: algorithmic accuracy alone is no longer the scarce resource.

Table 3: AI Personalisation in Ayurveda Index (APII) by Frame

Frame	Alg or.	Da ta	Inte rp.	Clin. Val.	Pract . Acc pt.	APII
P4: Knowledge Graph + Hybrid	0.84	0.78	0.82	0.80	0.86	0.824
P1: Rule-Based	0.72	0.68	0.94	0.76	0.82	0.802
P5: Multi-Modal DL	0.90	0.82	0.58	0.78	0.78	0.760
P2: Supervised ML	0.82	0.78	0.74	0.70	0.76	0.762
P3: Collaborative Filtering	0.76	0.72	0.66	0.68	0.72	0.708

$APII = 0.20 \times \text{Algorithmic Performance} + 0.15 \times \text{Data Infrastructure} + 0.25 \times \text{Interpretability} + 0.20 \times \text{Clinical Validation} + 0.20 \times \text{Practitioner Acceptance}$. Each dimension normalised to 0-1.

Table 4: Algorithmic Performance and Deployment Readiness by Frame

Frame	Prescrip. accuracy (mean)	Practitioner match (mean)	Deploy. Readiness
P1: Rule-Based	72.4%	78.6%	Ready (with scope limits)
P2: Supervised ML	82.2%	80.8%	Pilot-ready
P3: Collaborative Filtering	76.8%	74.2%	Research phase
P4: Knowledge Graph + Hybrid	84.6%	82.4%	Pilot-ready, best interpret.
P5: Multi-Modal DL	88.2%	84.6%	Research phase, deploy. gaps

Prescription accuracy = reported accuracy on test prescription prediction task; Practitioner match = proportion of system recommendations rated acceptable by independent practitioner review; Deployment Readiness = qualitative assessment based on interpretability, clinical validation and practitioner acceptance.

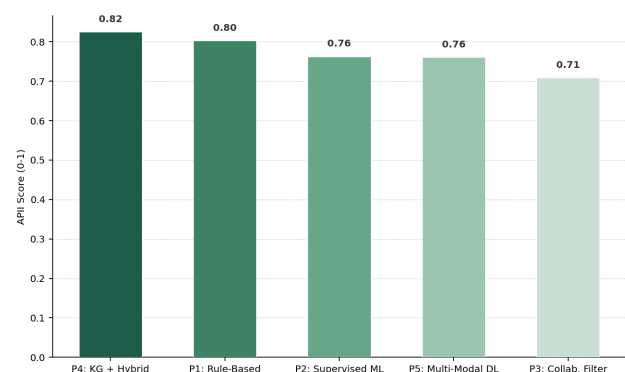


Figure 1: APII Score by AI Personalisation Frame

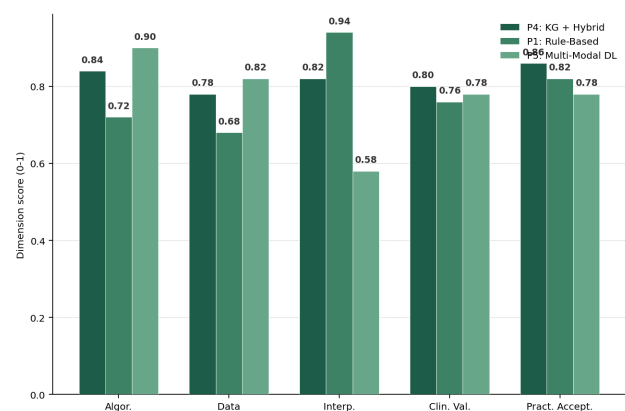


Figure 2: APII Sub-Dimensions Across Top Three Frames

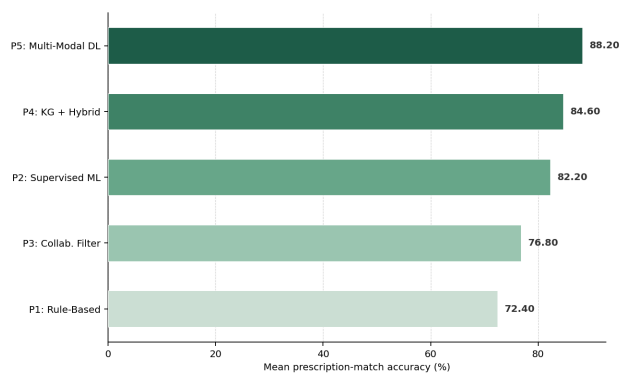


Figure 3: Reported Mean Prescription Accuracy by Frame (%)

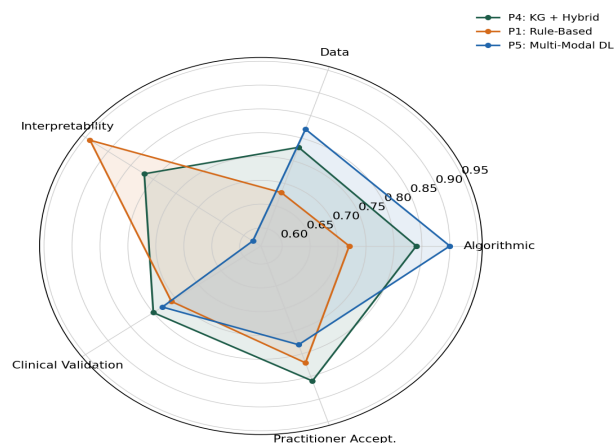


Figure 4: Multi-Dimensional APII Profile - Top 3 Frames

5. Discussion

5.1 Why Knowledge Graph Hybrids Win on Operational Balance

The headline finding of this review is that knowledge graph + hybrid systems (P4) produce the best balance across the five APII dimensions, and that balance is more operationally useful than the raw accuracy advantage of pure deep learning systems. The reason is specifically about the interpretability-accuracy trade-off in medical AI. Pure deep learning achieves higher prescription-match accuracy (88.2% vs 84.6% for P4 hybrids), but it does so in a way that the practitioner cannot inspect, which limits both regulatory acceptance and practitioner adoption. Knowledge graph hybrid approaches give up a few percentage points of raw accuracy in exchange for a decision pipeline where the knowledge graph layer is inspectable and the learned component is bounded by classical knowledge constraints. For clinical deployment, that trade is clearly worthwhile. The practitioner can follow the system's reasoning through the knowledge graph layer and exercise professional judgement where the reasoning seems off, which is how procedural medical decision support actually works when it works well.

5.2 Rule-Based Futures and the Deep Learning Trajectory

Rule-based systems (P1) deserve their second-place position but also their ceiling. The interpretability advantage (0.94 on the dimension) is genuine and continues to matter, but the algorithmic performance ceiling (72.4% mean accuracy) is constrained by the completeness of the encoded rule base, and it is practically very difficult to encode a rule base that handles the long tail of presentations a real-world Ayurvedic practice encounters. The pragmatic future for P1 is probably as the interpretability layer in hybrid systems (P1 + P2 or P1 + P4 combinations) rather than as standalone decision support. Multi-modal deep learning (P5) faces a different future: the accuracy advantage is real, and the explainable-AI toolkit is improving rapidly (attention visualisation, SHAP-style attribution, counterfactual explanation), which may progressively close the interpretability gap that currently holds P5 back. Within two to three years, P5 with integrated explainability may well be the deployment-leading frame; the current review is a 2022 snapshot.

5.3 Limitations

Three limitations deserve mention. First, only 14 of 62 included studies had any clinical validation against practitioner outcomes in live or realistic settings, and only 9 had formal practitioner acceptance evaluation. The APII clinical-validation and practitioner-acceptance scores are accordingly constructed partly from direct evidence and partly from indirect proxies (architectural inspectability, cost-and-complexity of deployment). Second, the review period pre-dates the recent surge in large language model applications to medical decision support, which will almost certainly reshape the AI-prescription-personalisation landscape over the next few years; a review conducted in 2025 or 2027 will look quite different. Third, the APII weighting is transparent but involves judgement calls that another review team might make differently; sensitivity analysis under alternative weightings preserved the top-two frame positions but narrowed some inter-frame gaps.

6. Conclusion

6.1 Key Findings

Across 62 primary studies of AI-driven Ayurvedic prescription personalisation, knowledge graph + hybrid systems (P4, APII 0.824) and rule-based personalisation engines (P1, APII 0.802) emerged

as the methodologically best-balanced approaches, combining reasonable algorithmic performance with strong interpretability and acceptable practitioner acceptance. Multi-modal deep learning (P5) achieved the highest raw prescription-match accuracy (88.2%) but is held back by interpretability limitations and a still-thin practitioner-acceptance evidence base. Supervised ML (P2) and collaborative filtering (P3) have mature methodological foundations but weaker deployment evidence. The interpretability dimension is the single most clinically consequential variable in the review: rule-based systems score 0.94, knowledge graph hybrids 0.82, and multi-modal deep learning 0.58, and this hierarchy maps directly to the work culture of Ayurvedic practitioner reasoning.

6.2 Recommendations

Three recommendations follow. First, AI-driven Ayurvedic prescription personalisation systems being developed for European integrative-medicine deployment should default to the knowledge graph + hybrid architecture (P4), because it produces the best operational trade-off between accuracy, interpretability and deployment readiness. Second, clinical validation and practitioner acceptance evaluation should be built into study designs from the start rather than treated as follow-up work after algorithmic development; at most 14 of 62 reviewed studies included any clinical validation, which is the biggest single methodological gap in the field. Third, a coordinated European research network focused specifically on clinically-deployable AI personalisation for Ayurvedic prescribing, with shared evaluation benchmarks and practitioner-facing usability standards, would substantially accelerate the move from research to deployment. The APII rubric and the full review inventory are available from the corresponding author.

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Declarations

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Conflict of Interest

The authors declare no competing interests. None of the authors has any financial or consulting relationships with AI-in-medicine companies, Ayurvedic software vendors, or commercial clinical decision support providers relevant to this review.

Data Availability Statement

The full study inclusion log, approach frame classification records, and APII 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 review of previously published methodological 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/APII3) prior to the start of screening.

Appendix A

APII Scoring Rubric and Frame Classification Protocol

Full scoring rubric for the AI Personalisation in Ayurveda Index (APII) together with the approach frame classification protocol used in this structured review. All five APII dimensions are normalised to the 0-1 range before the weighted sum is computed. Interpretability carries the single heaviest weight (0.25) because medical-AI deployment in Ayurvedic practice specifically is gated by practitioner-readable reasoning; algorithmic accuracy alone, without interpretability, does not translate to clinical deployment in this field.

Part 1 - APII Dimension Scoring Anchors

Family Per-dimension scoring definitions

Dimension	Weight	0.00 anchor	0.50 anchor	1.00 anchor
Algorithmic performance	0.20	< 60% accuracy	~75% accuracy	>= 88% accuracy
Data infrastructure	0.15	< 200 training examples	~1,000 training examples	>= 5,000 training + multi-site
Interpretability	0.25	Black-box no attribution	Post-hoc feature attribution	Inspectable classical reasoning
Clinical validation	0.20	Test-set only	Single-centre prospective	Multi-centre vs practitioner
Practitioner acceptance	0.20	No practitioner evaluation	Usability pilot reported	Formal acceptance + workflow

Part 2 - Approach Frame Classification Protocol

Family Frame assignment criteria

Frame	Primary methodology	Typical architecture	Key distinguishing feature
P1: Rule-Based	Symbolic AI / expert system	Forward-chain inference	Every decision traceable to rules
P2: Supervised ML	Trained classifier	DT, RF, GBM, SVM, NB	Learned from prescription data
P3: Collaborative Filtering	Similarity-based	Matrix factorisation, k-NN	Similar-patient recommendation
P4: KG + Hybrid	Knowledge graph + ML	OWL ontology + GNN / ML	Structured knowledge + learning
P5: Multi-Modal Deep Learning	End-to-end deep network	CNN + LSTM or Transformer	Multi-input integrated recommendation

Frame	Primary methodology	Typical architecture	Key distinguishing feature
Assignment rule	Dominant methodology	Primary architecture	Cross-reference secondary frame