SCIENXT
ISSN: 3048-9407; SJRTDDS
Scienxt Journal of Recent Trends in Drug Delivery System

Artificial intelligence and digital technologies in homeopathy: A comprehensive review of clinical decision support, digital case analysis, individualised remedy selection, research applications, and future perspectives

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DOI: 10.5281/zenodo.23100368

Abstract:

Artificial intelligence (AI) and digital health technologies are increasingly being used to organise clinical information, analyse free-text records, support prediction, automate repetitive tasks, and extend access to healthcare. Homeopathy presents a distinctive digitalisation problem because its clinical workflow commonly depends on longitudinal narratives, symptom descriptors, individualisation, repertorisation, materia medica consultation, and repeated follow-up assessment. Digital tools can therefore be relevant to case documentation, structured symptom extraction, repertory search, clinical decision support, remote consultation, outcome monitoring, research data management, and evidence synthesis. At the same time, the existence of a technically feasible AI application should not be confused with proof of clinical efficacy of the underlying therapy. Contemporary reviews and evidence assessments continue to report limited or uncertain evidence for homeopathy as an effective treatment for specific health conditions, while individualised homeopathy research has produced heterogeneous findings and ongoing methodological debate. Consequently, AI should be evaluated as a technology for information processing and decision support rather than as evidence that validates homeopathic efficacy.

This review examines the potential and current state of digital technologies in homeopathy, including electronic case records, repertory software, natural language processing, machine learning, large language models, multimodal data capture, patient-facing applications, teleconsultation, research informatics, and AI-assisted evidence synthesis. Published research on repertory software demonstrates meaningful uptake among practitioners, while recent multicentre Indian clinical data work shows that internet-based systems can capture symptoms, diagnoses, prescriptions, and longitudinal outcomes at scale. A 2026 comparative retrospective study also illustrates a key limitation of generative AI in this domain: remedy recommendations from chatbots were not consistently aligned with live practitioners or stable across repeated inputs.

For safe implementation, homeopathic AI should therefore follow established health-AI principles: clinically meaningful problem definition, representative datasets, traceable model development, external validation, transparent reporting, cybersecurity, privacy protection, human oversight, monitoring after deployment, and explicit management of uncertainty. The most credible near-term role is as a human-in-the-loop infrastructure that improves information quality, reproducibility, research efficiency, and longitudinal record keeping while leaving accountable clinical decisions with qualified professionals and

ensuring timely conventional assessment for urgent, serious, or diagnostically uncertain conditions. Future progress will depend less on simply adding AI features and more on building high-quality, standardised, auditable datasets and testing whether digital support produces measurable improvements in decision quality, patient safety, workflow, and patient-centred outcomes.

Keywords:
Artificial intelligence; digital health; homeopathy; clinical decision support; natural language processing; machine learning; repertorisation; individualised remedy selection; telehealth; large language models; research informatics; patient monitoring

1. Introduction:

Artificial intelligence has moved from a largely experimental field into a practical component of modern digital health. Contemporary systems can classify data, identify patterns, retrieve information, generate language, summarise records, support prediction, and assist professionals with selected tasks. The clinical value of these systems depends not only on technical performance but also on the quality of the problem being solved, the data used to build the system, the way the output reaches a clinician, and the ability to measure whether the tool improves care. Reviews of healthcare AI have repeatedly emphasised this connection between computational capability, workflow integration, and human judgement (Jiang et al., 2017; Yu et al., 2018; Topol, 2019).

Digital transformation is relevant to homeopathy because much of homeopathic practice generates information that is difficult to manage manually. A detailed consultation can contain a long narrative, changing symptoms, modalities, mental and emotional descriptions, generalities, past medical history, family history, lifestyle factors, previous remedies, treatment responses, and follow-up observations. Traditional paper notes preserve some of this information but make longitudinal retrieval, structured comparison, aggregation, and research use difficult. Electronic records and search tools can reduce these limitations by converting a case from a one-time written document into a longitudinal information object that can be queried, compared, and analysed.

However, technological feasibility does not settle questions about clinical validity. Homeopathy remains scientifically and clinically contested. Evidence assessments vary in their methods and conclusions, but recent systematic reviews and government evidence summaries continue to describe the evidence for specific clinical efficacy as limited, uncertain, or not convincing enough to support homeopathy as an established treatment for defined diseases (Shang et al., 2005; Hamre et al., 2023; NCCIH, 2026). The role of AI in this context must therefore be framed carefully. An AI system may improve the organisation of homeopathic information without demonstrating that the proposed remedy produces a specific therapeutic effect. It may also introduce new risks if its fluent language creates unwarranted confidence.

The purpose of this review is to bring these two strands together: the emerging digital and AI opportunities for homeopathy and the methodological requirements that should govern their use. The review focuses on clinical decision support, digital case analysis, individualised remedy selection, potency and follow-up support, remote care, research applications, ethics, governance, validation, and future perspectives. A recurring principle throughout is that AI should function as support infrastructure rather than an autonomous prescriber, and that any clinical innovation should be evaluated against patient safety, transparency, evidence quality, and measurable outcomes.

2. Scope and Review Approach:

This is a literature-informed narrative review focused on the intersection of AI, digital technologies, homeopathic clinical practice, and research. Sources were identified from current biomedical literature, authoritative health-technology guidance, and recent publications specifically addressing

repertory software, digital case collection, and AI in homeopathy. The review prioritises sources that provide methodological guidance or empirical information. Because the homeopathy-specific AI literature is still small, the article also draws on established medical-AI principles and then translates them cautiously into the homeopathic setting rather than implying that general medical AI findings have already been demonstrated in homeopathy.

The scope intentionally separates three kinds of evidence. First, there is evidence about the technology itself, such as natural language processing, electronic records, predictive modelling, large language models, and human-in-the-loop clinical decision support. Second, there is evidence about digital technology already used within homeopathic practice, including repertory software and internet-based longitudinal data collection (Gray et al., 2023; Kaur et al., 2025). Third, there is evidence about the clinical efficacy and safety of homeopathy as a therapeutic system. These evidence streams answer different questions and should not be merged. An AI tool can be reliable for extracting text from a case while still being unable to establish that a selected remedy is clinically effective.

The review therefore uses a deliberately conservative interpretation of emerging AI applications. Where a technology has only been proposed conceptually, it is described as a future or research opportunity. Where a study has reported an observational association, it is not presented as proof of causation. Where generative AI has produced a recommendation in a benchmark or retrospective exercise, that performance is described as a demonstration of capability rather than a clinical endorsement. This distinction is especially important because modern AI systems are capable of generating plausible language even when their factual or clinical foundations are weak (Thirunavukarasu et al., 2023; Clusmann et al., 2023).

3.Conceptual Foundations: What AI Means in a Homeopathic Workflow:

3.1. Artificial intelligence, machine learning, and generative AI:

Artificial intelligence is an umbrella term for computational systems that perform tasks associated with functions such as pattern recognition, inference, language processing, prediction, or decision support. Machine learning is a subset in which model behaviour is learned from data rather than determined entirely by manually coded rules. Deep learning uses multilayer neural networks to learn complex representations. Natural language processing (NLP) focuses on analysing and generating language, while generative AI produces new text, images, audio, or other content from prompts or structured inputs. Modern large language models (LLMs) are a prominent form of generative AI and can process free-text questions and generate context-sensitive responses (Thirunavukarasu et al., 2023; Teo et al., 2025).

For homeopathy, these distinctions matter because different problems require different technical approaches. A rule-based repertory engine may be sufficient to map a selected rubric to a remedy database. An NLP model may help convert a patient narrative into candidate symptom concepts. A supervised machine-learning model could estimate a predefined outcome from historical cases. An LLM may summarise a longitudinal case or retrieve information from a curated corpus. These functions should not be treated as interchangeable. The most sophisticated model is not necessarily the safest or most useful model for a given task. In clinical environments, a narrow, auditable system that performs one well-defined function can be preferable to an open-ended conversational model.

3.2. Clinical decision support is not autonomous clinical practice:

Clinical decision support (CDS) means providing clinicians with information, assessments, reminders, predictions, or recommendations intended to assist decision making. A safe CDS design preserves human responsibility for the final decision, provides enough context to interpret the output, and makes uncertainty visible. Modern health-AI guidance emphasises the need to define the clinical role of the system, evaluate its interaction with professionals, and study actual performance in the setting where it will be used rather than relying only on technical benchmarks (Vasey et al., 2022; Lekadir et al., 2025).

In homeopathy, CDS can be conceptualised as a layered assistant. The first layer manages data entry and completeness. The second converts narrative information into structured symptom features. The third performs repertory retrieval or other knowledge-base operations. The fourth presents ranked

possibilities and supporting evidence. The fifth records the practitioner decision and subsequent outcome. Such a system can help reduce clerical burden without assuming that a numerical ranking is synonymous with a correct remedy. It can also preserve an audit trail showing which symptoms were entered, which repertory version was used, which assumptions were made, and whether the final prescription differed from the software suggestion.

3.3. Digital Transformation of Homeopathic Practice

The move from paper-based to digital homeopathic records has several consequences. At a minimum, structured electronic records make it easier to retrieve earlier consultations, compare baseline and follow-up symptoms, identify previous remedy exposure, and organise longitudinal outcomes. They also allow researchers to create de-identified datasets for service evaluation and observational research. The multicentre Indian study by Kaur and colleagues is important in this respect because it demonstrates that homeopathic outpatient data can be collected through an internet-based system containing registration, presenting complaints, case totality, repertorisation, prescriptions, follow-up information, and outcome assessments (Kaur et al., 2025).

Repertory software is already more established than AI itself within homeopathic practice. An international survey reported regular software use among a substantial proportion of respondents and highlighted both perceived value and barriers such as insufficient training and cost (Gray et al., 2023). These findings suggest that digital repertorisation is not merely a theoretical idea. Yet software usage alone does not show that software improves clinical outcomes. It shows that practitioners find digital organisation and searching useful. The next research question is whether specific digital features improve reproducibility, documentation quality, decision time, agreement between practitioners, patient follow-up, or clinical outcomes in controlled evaluations.

A mature digital system should therefore be designed around the entire consultation rather than a single repertorisation screen. It should support identity and consent management, structured history, free-text notes, document upload, relevant examination or investigation fields, remedy history, follow-up scheduling, outcome capture, and longitudinal visualisation. It should also distinguish factual patient information from practitioner interpretation and from machine-generated suggestions. This separation helps preserve the provenance of the information and prevents a generated statement from quietly becoming part of the clinical record as though it were an observed fact.

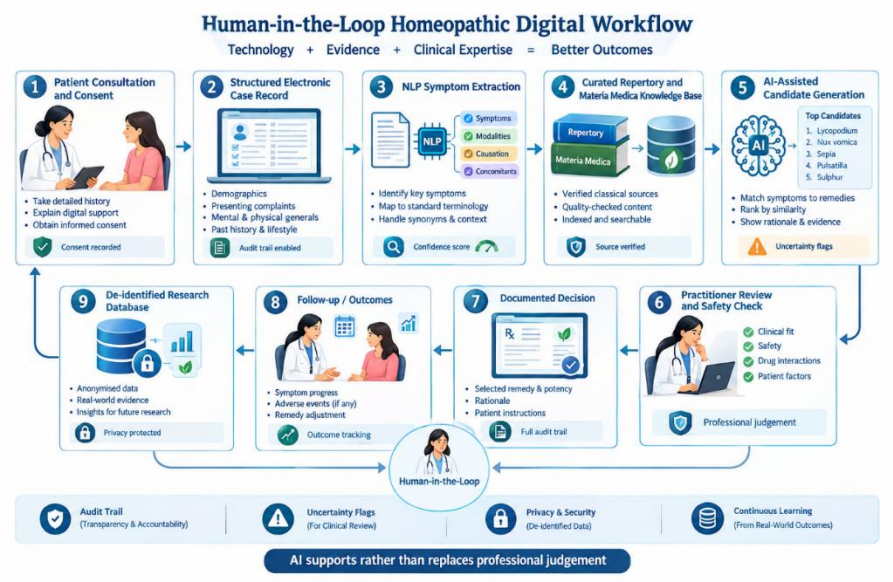


Figure.1: Integrated AI-enabled digital workflow for homeopathic clinical decision support

4. Digital Case Analysis: From Narrative Consultation to Structured Data:

4.1. Why case narratives are difficult for computers:

Homeopathic case records are primarily language-rich rather than laboratory-rich. The same clinical concept can be described with multiple expressions, and the meaning of a symptom may depend on context, timing, intensity, modality, associated features, or the patient's own words. A statement such

as “headache after missing lunch, relieved by pressure, worse in a warm room” contains several attributes that are useful only when preserved together. Naive keyword matching could fragment the sentence into isolated terms and lose the relationship between symptom, trigger, and modality. NLP systems attempt to preserve more of that semantic structure.

A practical digital case model can represent each symptom as a structured object with fields for body location, sensation, intensity, onset, duration, frequency, triggers, relieving factors, aggravating factors, concomitants, patient-reported language, and confidence. It can also store whether the feature was spontaneous, directly observed, prompted, inferred, or copied from a prior record. Such provenance is essential. An AI model should not silently transform an ambiguous patient statement into a highly specific rubric and present the result as if the patient had explicitly reported it.

4.2. Natural language processing:

NLP can assist by identifying entities, symptoms, negations, temporal expressions, modifiers, and relationships in clinical text. Tokenisation and sentence segmentation are basic steps; more advanced systems use contextual language representations or transformer architectures to identify meaning across a sentence or consultation. In a homeopathic setting, an NLP pipeline could highlight candidate symptom concepts and ask the practitioner to confirm the most appropriate rubric wording. This design is more defensible than allowing automatic translation from narrative to rubric without review, because rubric selection is itself part of clinical interpretation.

The highest-value use of NLP may be selective rather than total automation. The system can automatically extract obvious administrative facts and recurring clinical terms, but it can flag ambiguous descriptions for confirmation. It can also suggest synonyms and show the original patient phrase beside the proposed structured term. This retains traceability and gives the practitioner a clear opportunity to reject or edit the transformation. Large language models make these interactions easier because they can work with long free-text inputs, but their fluent outputs can hide uncertainty, so every generated concept should remain visibly labelled as machine-generated until verified (Thirunavukarasu et al., 2023; Teo et al., 2025).

4.3. Multimodal case analysis:

Future systems may combine text, structured forms, images, audio, and longitudinal measurements. A consultation could include a transcribed patient narrative, photographs of a skin lesion or other visible finding when clinically appropriate, medication lists, laboratory data, wearable measurements, and follow-up questionnaires. Multimodal AI can combine different data types, but its usefulness depends on the quality and clinical meaning of each modality. More data is not automatically better data. A large multimodal dataset containing inconsistent labels, incomplete follow-up, or non-representative patient populations may produce a model that appears sophisticated while remaining clinically unreliable.

A particular caution is required for emotion and behavioural inference. Voice tone, facial expression, gesture, and posture are influenced by culture, language, disability, privacy concerns, and the consultation environment. Inferring a psychological state from such signals can be inaccurate and ethically sensitive. Therefore, multimodal features should be treated as optional contextual information, not as hidden determinants of remedy choice. The practitioner should be able to see what the model used and disable modalities that are not validated for the task.

5.AI-Assisted Repertorisation and Individualised Remedy Selection:

5.1. From manual repertorisation to computational ranking:

Repertorisation can be understood computationally as a retrieval and ranking problem: selected symptom descriptors are matched against a knowledge base linking rubrics to remedies, and the system calculates some form of correspondence or weight. Digital repertory software has made this process faster and easier to reproduce than manual searching in printed repertories. The international survey by Gray and colleagues indicates that practitioners use software for this practical purpose, although training and feature utilisation remain uneven (Gray et al., 2023).

AI could extend this process in several ways. It could help identify candidate rubrics from free text, detect related terminology, compare the current case with prior cases, highlight unusual combinations

of symptoms, and generate ranked candidate remedies. It could also allow more sophisticated weighting schemes than a simple symptom count. For example, a research prototype might test whether certain features add incremental predictive value beyond common symptoms. However, the act of ranking remedies remains a computational representation of the chosen knowledge base and algorithm. A higher score means only that the input matched the system's internal rules or learned patterns more strongly; it does not establish clinical correctness.

5.2. Individualisation and the problem of hidden assumptions:

Individualised remedy selection introduces a key modelling challenge: the definition of what counts as a relevant symptom is partly conceptual and partly clinical. Two practitioners may read the same narrative differently, select different rubrics, and assign different importance to generalities, modalities, mental symptoms, or local complaints. If an AI system is trained from historical prescriptions, it may learn these practitioner habits rather than an independently verified therapeutic signal. In machine-learning terms, the model can reproduce the labels present in the training data even when those labels contain systematic variation or bias (Wiens et al., 2019).

This creates an important distinction between imitation and validation. A model that predicts what experienced practitioners would prescribe may achieve strong agreement with the reference prescriber while offering no evidence that either the model or the reference prescriber is selecting a remedy that causes better outcomes. Such a model may still have legitimate educational or standardisation value, but its claim must be framed accurately. Research should therefore compare multiple targets: agreement with practitioners, reproducibility between practitioners, calibration of the model, usefulness in real workflow, and patient-centred outcomes. These are related but different endpoints.

5.3. Human-in-the-loop remedy selection:

A safer architecture places the practitioner between algorithmic candidate generation and the final prescription. The software can show the selected symptoms, their weights, the remedies supported by each input, and any conflicting evidence. The practitioner can then accept, reject, edit, or add symptoms and record the reasoning for the final choice. This creates a transparent chain from patient statement to clinical action. Such traceability is consistent with broader AI governance frameworks that emphasise fairness, traceability, usability, robustness, and explainability (Lekadir et al., 2025).

Human-in-the-loop design also enables disagreement analysis. When the practitioner chooses a different remedy from the model, the system can record the difference without treating it as an error. Later research can examine whether disagreement is associated with case complexity, missing data, ambiguity, training differences, or model limitations. This turns routine practice into a source of learning while preserving professional accountability. It may ultimately be more informative than forcing agreement between the system and the practitioner.

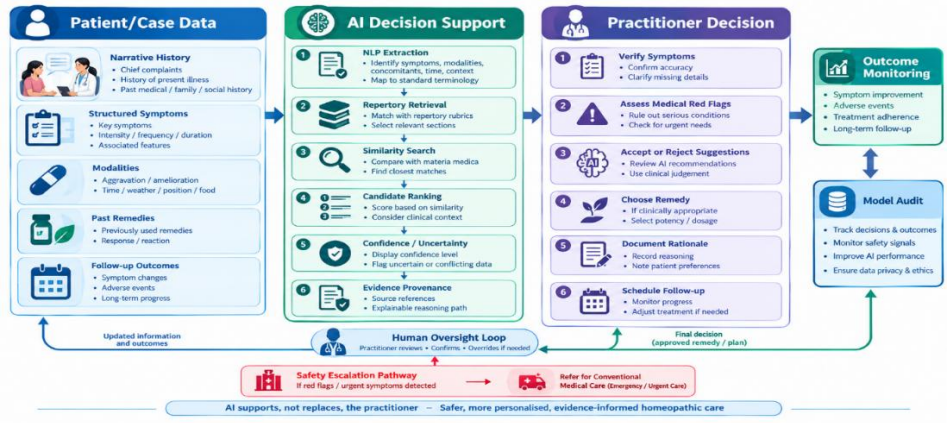


Figure.2: Human-in-the-loop architecture for individualised remedy selection and follow-up

6.Clinical Decision Support Beyond Remedy Ranking:

Clinical decision support in a digital homeopathy system should not be reduced to a remedy list. A broader system can improve information completeness, identify missing fields, flag drug interactions

or contraindication concerns related to non-homeopathic medicines and supplements, remind clinicians about follow-up, and prompt documentation of referrals and investigations. Where a patient presents with potentially serious symptoms, the system could generate a safety prompt directing the practitioner to appropriate medical evaluation rather than encouraging reliance on a remedy suggestion. Such safety layers are especially important because AI systems may otherwise optimise the local task of answering the user while neglecting the wider clinical context. Decision support can also be used for differential information organisation. For example, when a case contains symptoms that could reflect more than one common diagnosis, an AI system could organise the available history and highlight which additional information or conventional assessment might be useful. The purpose should be to improve clinical reasoning and information completeness, not to claim that the AI has established a diagnosis. A health-AI tool that operates safely should know when it does not have enough information and should make that limitation visible. Another useful function is longitudinal change detection. Rather than repeatedly reading several pages of notes, the clinician could receive a structured summary of symptoms that have improved, worsened, newly appeared, or remained unchanged. This is especially valuable for chronic cases. However, summaries should preserve patient-reported uncertainty and avoid converting subjective language into artificial precision. For example, a statement that pain "feels a little less intense" should not automatically become a numerical change unless the measurement method has actually been specified.

7.Potency, Repetition, and Treatment-Plan Support:

Homeopathic practice commonly includes decisions about potency, repetition, timing of follow-up, and whether to continue, change, or stop a remedy. These decisions are difficult to study because practice styles vary and because the evidence base does not establish a universally validated algorithm for potency selection. AI can nevertheless support documentation and comparative research by recording the options considered, the reasoning supplied by the practitioner, the time between doses, the subsequent clinical observations, and any treatment changes.

In research settings, machine learning could be used to explore whether patterns in historical data are associated with different outcomes under predefined treatment strategies. Such work should be regarded as hypothesis generation unless supported by prospective validation. A model that discovers an association between a particular potency pattern and improvement may reflect confounding by indication, practitioner preference, patient characteristics, concurrent treatment, or regression to the mean. Predictive accuracy alone cannot establish a causal treatment effect.

An especially useful research design would compare decision-support strategies rather than assume that one algorithm is correct. For example, researchers could test a standard electronic repertory workflow against a human-in-the-loop AI assistant and measure decision time, documentation completeness, reproducibility, user confidence calibration, and patient follow-up quality. Only after these process outcomes are understood should investigators ask whether any change in clinical outcomes is attributable to the digital intervention. This sequence follows the broader logic of staged evaluation in clinical AI, including early-stage evaluation of usability and safety before claims of benefit (Vasey et al., 2022).

8.Telehomeopathy, Mobile Health, and Patient-Facing Technologies:

Digital technologies also allow homeopathic consultations and follow-up to occur remotely. Video consultation, secure messaging, electronic forms, mobile questionnaires, appointment reminders, and symptom diaries can support continuity when in-person visits are difficult. From a digital-health perspective, the value of remote care is greatest when it improves access without weakening communication, documentation, privacy, or escalation pathways. WHO digital-health strategy documents emphasise that technology should be integrated with organisational, human, financial, and governance resources rather than deployed as a standalone technical intervention (WHO, 2025). For homeopathic practice, a patient-facing app could collect symptom updates at predefined intervals, record adherence to the prescribed plan, prompt users to document changes, and alert the practitioner when a follow-up response has not been received. It could also provide plain-language summaries of

the patient's recorded history. Such tools can reduce memory bias and make repeated observations more systematic. However, app-based self-prescribing is a different and more hazardous use case. Recent evidence from AI chatbots shows that generative systems can provide variable remedy recommendations for the same case, which illustrates why consumer-facing recommendations require strong safety boundaries and should not be treated as autonomous clinical care (Doherty et al., 2026). Remote consultations also have limitations. Physical examination may be incomplete, visual quality may be inadequate, and serious symptoms can be missed when the consultation is framed too narrowly around homeopathic treatment. A responsible digital workflow should therefore include explicit screening for urgent symptoms, mechanisms for referral, and a clear statement that digital convenience does not replace necessary diagnostic assessment. Technology should strengthen access to qualified care, not create a separate information pathway in which patients receive confident but weakly validated advice.

9.Large Language Models and Generative AI in Homeopathy:

9.1. Potential uses:

Large language models are particularly relevant to homeopathy because the clinical record is narrative and because much of the supporting literature is text based. An LLM can summarise a long case, generate a structured history template, convert jargon into patient-friendly language, compare two text passages, draft a follow-up summary, or help a researcher screen and organise articles. In educational settings, it can create case-based questions and explanations. In administrative settings, it can prepare draft letters, referral summaries, or appointment messages. These uses are broadly consistent with the expanding literature on generative AI in medicine (Thirunavukarasu et al., 2023; Teo et al., 2025).

Within homeopathy, a carefully constrained LLM could be connected to a curated knowledge base and used for retrieval rather than free generation. Instead of answering from general model memory, it could quote or summarise only documents selected by the system, while displaying source provenance. Retrieval-augmented generation can also help keep answers within a defined corpus. Even then, the output should remain subject to professional verification because a language model can misinterpret context, omit important caveats, or combine unrelated information into a fluent but unsupported conclusion (Clusmann et al., 2023).

9.2. Current empirical warning signs:

The most directly relevant recent evidence comes from a 2026 comparative retrospective study that entered notes from 100 acute homeopathic cases into four publicly accessible AI chatbots and compared their suggestions with initial practitioner recommendations and other tools. The initial practitioner-selected remedy appeared among chatbot recommendations in 36.5% of cases on average and was the top recommendation in 20.8%; the study also reported that the systems were not routinely consistent with one another or with repeated inputs of the same case (Doherty et al., 2026). These findings do not establish that practitioners are correct or that a remedy is effective. They do show that generative AI recommendations are not stable enough to be treated as a deterministic substitute for clinical judgement. The practical implication is that reproducibility should be tested explicitly. A homeopathy AI system should be evaluated using repeated runs, different phrasings of the same case, incomplete cases, contradictory inputs, and cases outside the training distribution. If its recommendation changes substantially when the wording changes but the clinical facts remain the same, the system may be unsuitable for high-stakes use. A safety-oriented interface should expose uncertainty and encourage verification instead of hiding variability behind a single confident answer.

9.3. Prompting is not validation:

Prompt engineering can change the output of an LLM, but changing prompts is not equivalent to improving the underlying evidence. A prompt may force a model to be more cautious, more structured, or more explicit about uncertainty, yet the final content can still be incorrect. The system should therefore be evaluated independently of the exact prompt used. Reporting should describe model version, prompt structure, knowledge sources, sampling behaviour where relevant, evaluation

cases, and failure modes. Transparent reporting frameworks developed for clinical prediction and AI studies provide a useful foundation for this discipline (Liu et al., 2020; Collins et al., 2024).

10.Research Applications: Building a Digital Evidence Ecosystem:

10.1. Research data capture:

A major opportunity may be the creation of high-quality, standardised research datasets rather than the immediate deployment of sophisticated AI. The multicentre Indian data-collection study demonstrates that structured digital systems can aggregate clinical information across multiple sites and preserve detailed records of symptoms, rubrics, prescriptions, and follow-up assessments (Kaur et al., 2025). Such datasets can support descriptive epidemiology, care-pattern analysis, quality improvement, and future model development. They can also reveal where the underlying data are incomplete, inconsistent, or biased. Research-ready datasets should preserve provenance at every stage. The original patient language, structured symptom representation, repertory version, practitioner identity or coded site, remedy choice, potency, timing, follow-up status, and outcome definition should be distinguishable. When possible, the dataset should also contain information about missingness, reasons for treatment change, conventional co-treatment, and referral events. Without this detail, a model may learn apparent patterns that are actually created by differences in documentation or follow-up availability.

10.2. Natural language processing for evidence synthesis:

Researchers can use AI to assist literature searching, abstract screening, citation organisation, data extraction, and manuscript drafting. These tasks are generally less risky than autonomous treatment decisions because errors can be reviewed before publication or clinical use. However, the same problem of fluent misinformation applies. Researchers should verify extracted study characteristics against the source, especially population, intervention, comparator, outcome, sample size, and risk-of-bias information. Generative models should not be assumed to have performed a systematic review simply because they can produce a polished summary. A particularly useful application is semantic deduplication and terminology mapping. Homeopathy literature may use multiple spellings, historical terms, abbreviated remedy names, or inconsistent terminology. NLP could normalise these variants while preserving the original text. It could also identify which articles describe randomised trials, observational studies, case reports, repertory methods, or conceptual frameworks. This could make evidence landscapes easier to navigate, although the final inclusion decision should remain governed by a predefined protocol and human verification.

10.3. AI-assisted systematic review and evidence mapping:

AI can support evidence mapping by grouping studies into intervention categories, extracting outcome domains, identifying overlapping datasets, and highlighting gaps in geographical or population coverage. It can also generate draft evidence tables that researchers then verify. The main benefit is speed and organisation. The main risk is automation bias: once a model proposes an interpretation, human reviewers may unconsciously accept it because it is coherent. The safest workflow is therefore “machine suggests, human confirms,” with the source text always accessible.

10.4. Digital Drug Proving, Materia Medica Mining, and Knowledge Management:

Homeopathic drug proving records and materia medica texts are information-rich sources that can be analysed computationally. NLP can detect recurring symptom phrases, remedy relationships, anatomical locations, modalities, and temporal patterns. Researchers could create searchable concept maps linking historical texts with modern terminology. This may improve retrieval and educational access even when the clinical meaning of the historical material remains open to interpretation. Knowledge management can also help distinguish source types. A digital system should separate proving reports, materia medica entries, repertory references, clinical case reports, clinical trials, systematic reviews, regulatory documents, and patient narratives. Mixing these sources into one undifferentiated knowledge base can cause an AI system to treat a historical assertion, an uncontrolled case report, and a randomised trial as though they were equivalent evidence. Evidence provenance must therefore be built into the database and surfaced in the interface. AI may also assist in identifying inconsistencies within large repertory or materia medica corpora. If a symptom appears under different labels, or if a remedy-source relationship is duplicated or contradictory, automated quality

checks can flag the record for editorial review. This is a concrete and scientifically testable use of AI that does not require assumptions about whether homeopathic remedies have specific therapeutic effects. It focuses on the integrity and usability of the information system.

11.Patient Monitoring, Outcomes, and Real-World Data:

Digital follow-up systems can make outcome assessment more systematic. Patients may complete standardised questionnaires, symptom severity ratings, quality-of-life instruments, treatment adherence questions, and free-text comments. The system can then present change over time to the clinician. This reduces reliance on memory and makes it easier to distinguish "no follow-up documented" from "no change reported," an important distinction in observational practice. For research, outcome definitions should be fixed before analysis. The use of patient-reported improvement alone can be informative for service evaluation but is vulnerable to expectancy effects, regression to the mean, concurrent interventions, selection effects, and loss to follow-up. A digital platform should therefore capture multiple dimensions where feasible: patient-reported outcomes, objective measurements when relevant, treatment exposure, co-interventions, referrals, adverse events, and reasons for discontinuation. The purpose of digital monitoring is not to manufacture precision but to improve the completeness of the evidence.

Longitudinal data can also support patient-safety surveillance. A system can identify repeated reports of suspected adverse reactions, unexpectedly severe symptoms, or patterns suggesting delayed referral. Even when causality is uncertain, signal detection can help determine whether a safety event deserves human review. This is an important area where AI may contribute without assuming a therapeutic claim: it can help identify patterns in data that warrant investigation.

12.Data Quality, Interoperability, and Dataset Design:

The quality of an AI system is bounded by the quality of its data. Homeopathic records may contain spelling variation, missing modalities, different rubric conventions, incomplete follow-up, unstructured remedy names, and inconsistent recording of potency and repetition. If these variations are ignored, model performance may reflect documentation habits rather than clinically meaningful patterns. Data quality checks should therefore be part of the system itself, not an afterthought before model training.

Interoperability is another priority. A homeopathic record may need to coexist with conventional clinical information such as diagnoses, investigations, allergies, medications, and hospital encounters. If the systems cannot exchange structured information reliably, the clinician may be forced to maintain parallel records, increasing duplication and the risk of omission. Interoperability should support semantic clarity: a diagnosis, symptom, medication, and practitioner comment should remain distinguishable even when displayed in one interface.

Dataset governance should define who can create, view, modify, export, and delete records. Version control is essential for repertories and knowledge bases because content changes over time. A study should be able to reproduce which version of the knowledge source was used. Likewise, machine-learning models should have version identifiers, training-data descriptions, and documented update procedures. These practices make a digital system auditable and help prevent silent model drift.

13.Privacy, Security, Consent, and Ethical Governance:

Clinical AI involves sensitive personal information, and homeopathic case notes can contain highly personal narrative details. WHO guidance has emphasised that AI in health should place ethics and human rights at the centre of design and use, with attention to autonomy, privacy, safety, accountability, and equity (WHO, 2021). These principles are directly relevant to digital homeopathy because the richness of the case history can increase both the usefulness and the privacy risk of the dataset. Consent should be understandable and purpose-specific. Patients should know when a digital system is used for documentation, decision support, research, or automated communication. Where data may later be reused for model development, the governance process should describe the scope of reuse rather than assuming that a single clinical-consent statement covers all future purposes. De-

identification should remove obvious identifiers, but researchers should also consider the possibility of re-identification from rare combinations of symptoms, dates, locations, or narrative details. Security controls should include authentication, least-privilege access, encryption in transit and at rest, audit logs, backup and recovery processes, and incident response. Cloud-based AI services introduce an additional question: where are the data processed, who may retain them, and whether patient information is used for provider-side model improvement. A clinical application should not transmit identifiable case material to an external model simply because the API is easy to use. Data minimisation and approved workflows are safer.

Ethical governance also concerns the patient's relationship with the clinician. Patients may interpret an AI-generated recommendation as authoritative, especially if it is presented with confidence or a numerical score. Interfaces should clearly identify machine-generated content, avoid deceptive anthropomorphic design, and explain that professional review remains necessary. Where an AI contribution materially affects communication or decision support, transparency helps preserve informed choice and trust.

14.Bias, Fairness, and Cultural Representation:

Bias can enter an AI system through the population from which cases are collected, the language used in records, the clinicians who generate labels, the software taxonomy, or the outcome definition. Homeopathic practice is especially vulnerable to linguistic and cultural variation because symptom descriptions often depend on idiom, local vocabulary, and consultation style. A model trained on English-language urban records may perform differently for regional languages, dialects, or different documentation conventions. Fairness evaluation should therefore be part of development. Model performance can be stratified by age, sex, language, region, socioeconomic context, data completeness, and other variables that are relevant and ethically appropriate. The aim is not to force identical predictions for all groups, but to identify systematic differences that could create unequal reliability or safety. More broadly, health-AI literature has shown that apparently neutral algorithms can reproduce inequities when the target variable or training data encode existing differences in care (Wiens et al., 2019).

Cultural representation is also important for NLP. A patient may use a culturally specific phrase that does not map neatly onto a standard rubric. The system should preserve the original wording and allow the clinician to select a broader or alternative concept rather than inventing a precise translation. Future datasets should be deliberately diversified by language and setting, with documented performance rather than assumed generalisability.

15.Explainability, Traceability, and Trustworthy AI:

Trustworthy AI is not the same as highly accurate AI. A clinically useful system must be understandable enough for users to recognise when its output does not fit the case. The FUTURE-AI framework identifies fairness, universality, traceability, usability, robustness, and explainability as core principles for healthcare AI across the lifecycle (Lekadir et al., 2025). These principles are especially relevant to a system that proposes homeopathic remedies because clinicians need to understand which features drove the ranking and what evidence source supports each relationship. Explainability can be implemented at several levels. At the input level, the system should show the symptoms and weights it used. At the knowledge level, it should show the repertory or reference sources that support the candidate. At the model level, it should indicate confidence, uncertainty, or important limitations. At the outcome level, it should permit users to compare predictions with observed follow-up. This layered explanation is more useful than a generic statement that an AI model is "confident." Traceability is equally important for research. If a paper reports that an AI system selected a remedy, readers should be able to understand which dataset, software version, knowledge base, algorithm, prompt, and decision pathway produced the result. Clinical prediction reporting standards such as TRIPOD+AI provide a broader model for transparent reporting of model development and evaluation, while CONSORT-AI and DECIDE-AI support structured reporting of

clinical trials and early-stage clinical evaluation involving AI (Liu et al., 2020; Vasey et al., 2022; Collins et al., 2024).

16.Validation: What Should a Homeopathy AI Study Actually Measure?:

Validation should begin with the exact question the technology is intended to answer. If the objective is symptom extraction, the primary metrics should measure extraction accuracy, omission, false positives, and agreement with a predefined reference standard. If the objective is repertory retrieval, evaluation should examine retrieval relevance, ranking stability, and reproducibility. If the objective is outcome prediction, researchers should evaluate discrimination, calibration, clinical utility, and external validation. If the objective is workflow improvement, time, documentation completeness, user burden, and error rates become relevant. A sensible development pathway contains several stages. First is technical verification using controlled test cases. Second is silent evaluation on retrospective data without influencing care. Third is early-stage prospective evaluation under human supervision, focusing on safety, usability, and workflow interaction. Fourth is larger comparative evaluation to test whether the tool changes clinically meaningful processes or outcomes. This staged approach parallels the rationale of DECIDE-AI, which stresses that early clinical evaluation is necessary to understand actual performance, human factors, and safety before large-scale deployment (Vasey et al., 2022). External validation is essential. A model trained in one clinic can appear strong because of local documentation habits, repertory choices, or clinician-specific prescribing patterns. Testing it across institutions, regions, practitioners, and patient populations reveals whether the model learned a generalizable pattern or simply memorised local behaviour. The multicentre data work from India provides a useful demonstration of the infrastructure needed for this kind of distributed evidence base, even though it is not itself a validation study of AI efficacy (Kaur et al., 2025). Prospective studies should also be designed to avoid circular evaluation. A model trained to reproduce practitioner prescriptions should not be judged solely by agreement with those same prescriptions. If the research question concerns patient outcomes, outcome measures must be independent of the model's training target. This is one reason that "AI agreed with the expert" can be an insufficient endpoint. Agreement can be useful for measuring consistency, but it does not independently establish clinical benefit.

17.Research Reporting Standards and Reproducibility:

Poor reporting can make an AI study appear stronger than it is. Researchers should document the data source, inclusion criteria, outcome definition, preprocessing, model architecture or rule system, hyperparameters where relevant, software versions, reference standards, missing-data handling, train-test separation, validation strategy, and error analysis. TRIPOD+AI was developed to improve reporting of prediction models that use regression or machine-learning methods, and its principles are applicable to homeopathy AI research when the study involves prediction (Collins et al., 2024). For intervention studies, the CONSORT-AI extension encourages reporting details that explain how an AI system interacts with participants and professionals, including the AI intervention itself and deviations or errors associated with its use (Liu et al., 2020). For early-stage clinical evaluation, DECIDE-AI emphasises reporting of the technology, users, clinical environment, workflow integration, safety, and human factors (Vasey et al., 2022). Applying these standards would make homeopathy AI research easier to reproduce and compare across settings. Reproducibility also requires versioned knowledge bases. A repertory may change, a language model may be updated, or a vendor may modify the scoring algorithm without obvious changes to the interface. Studies should therefore archive or document the exact software environment and reference materials used. If proprietary components cannot be fully inspected, that limitation should be stated explicitly. Scientific conclusions should not depend on undocumented software behaviour.

18.Regulatory and Clinical Governance Considerations:

The regulatory status of an AI system depends on what it does, how its output is used, and the jurisdiction in which it is deployed. A software product that merely stores notes or provides educational search is different from one that makes recommendations intended to influence clinical management. The higher the clinical consequence of the output, the stronger the requirements for validation, risk management, documentation, change control, and post-deployment monitoring. This

principle is consistent with the broader lifecycle approach to trustworthy AI described by international guidance (WHO, 2021; Lekadir et al., 2025). Clinical governance should assign responsibility clearly. A named clinical lead should oversee the use case, a technical team should maintain model and infrastructure quality, and an information-governance function should manage privacy and access controls. Users should know how to report an unsafe or misleading output. There should also be a defined process for model updates, temporary suspension, and rollback when a defect is identified.

A homeopathy AI system should also integrate with escalation pathways. If the digital record contains red-flag symptoms, severe deterioration, pregnancy-related emergencies, suspected poisoning, acute neurological deficits, significant breathing difficulty, or other urgent concerns, the workflow should support prompt medical evaluation. This is not a limitation of homeopathic AI alone; it is a general safety requirement for any clinical decision-support system operating in a real patient population.

19.Current Evidence: What Is Established and What Remains Uncertain?:

The current evidence base supports several narrow conclusions. Digital repertory software is used in practice and is perceived by many practitioners as useful, although barriers to training and cost exist (Gray et al., 2023). Large-scale digital case collection is feasible and has been demonstrated across multiple homeopathic outpatient sites in India (Kaur et al., 2025). Conceptual publications propose AI-assisted case-taking, multimodal recording, NLP, and machine-learning support in homeopathy, but these proposals remain early and require empirical validation (Anpat et al., 2026). The evidence becomes much weaker when moving from information management to claims of clinical superiority. Homeopathy-specific AI studies are too limited to conclude that AI improves the accuracy of remedy selection, potency selection, or patient outcomes. The 2026 chatbot study instead highlights variability in generative AI recommendations (Doherty et al., 2026). This is an important signal for cautious evaluation, not a final judgment on all possible AI systems. A purpose-built, rules-based, evidence-linked tool could behave differently from a general chatbot, and that possibility itself is an empirical question.

The therapeutic evidence for homeopathy must also remain separate from the technology question. Historical and contemporary evidence reviews have reached different conclusions depending on inclusion criteria and analytical approach, but there is continuing debate about bias, methodological quality, heterogeneity, and the extent to which observed effects are specific to the homeopathic intervention. The 2023 systematic review of meta-analyses illustrates this continuing debate, while major evidence summaries state that convincing evidence of efficacy for specific conditions is lacking or limited (Shang et al., 2005; Hamre et al., 2023; NCCIH, 2026; EASAC, 2017).

Therefore, a responsible article about AI and homeopathy should avoid a common category error: “AI can process individualised information, therefore individualised homeopathy is validated.” The first proposition concerns computing and workflow; the second concerns clinical efficacy. They require different forms of evidence. AI can help make a clinical method more explicit and reproducible without proving that the therapeutic theory behind the method is correct.

20.Practical Applications with Near-Term Feasibility:

Several applications are relatively tractable because they improve information management without requiring autonomous clinical prescribing. These include digital intake forms, structured follow-up, searchable records, automatic summarisation with human verification, repertory navigation, appointment reminders, longitudinal timelines, and research data extraction. They can often be evaluated using operational metrics such as time saved, completeness, user satisfaction, and error rates before any claim about patient benefit is attempted.

A second group includes semi-automated clinical support: symptom concept extraction, candidate rubric suggestions, remedy ranking, differential comparison, and follow-up alerts. These functions require stronger validation because the output can influence a clinical decision. Human confirmation and clear audit trails should be mandatory. The system should preserve the original patient narrative and show how the candidate output was produced. A third group includes high-risk applications such as autonomous prescribing, unsupervised patient triage, and consumer-facing symptom-to-remedy

recommendations. These functions should require substantially stronger evidence and governance. The 2026 chatbot study shows why: identical case information does not guarantee stable recommendations across systems or even repeated runs (Doherty et al., 2026). Until reliability and safety are demonstrated prospectively, such outputs should not be treated as substitutes for qualified clinical evaluation.

21.Future Perspectives:

21.1. Personalised digital phenotyping:

Future systems may create a longitudinal digital phenotype that combines symptoms, treatment history, patient-reported outcomes, lifestyle factors, laboratory information when available, and patterns of follow-up over time. The scientific challenge will be to determine whether any such profile improves prediction of a clinically meaningful outcome. The mere ability to integrate many variables is not evidence that those variables contain a valid therapeutic signal. Research should begin with clearly defined outcomes and prospective validation rather than technology-first enthusiasm.

21.2. Retrieval-grounded and source-aware AI:

The next generation of clinical AI in homeopathy may rely more heavily on retrieval-grounded systems than on unconstrained chatbots. A source-aware assistant could answer only from an approved corpus and attach source provenance to every substantive statement. This approach does not eliminate errors, but it reduces the risk of treating an invented sentence as though it were a documented fact. Generative AI research increasingly emphasises the importance of rigorous validation, transparency, privacy, and domain-specific data curation (Teo et al., 2025).

21.3. Privacy-preserving learning:

Federated learning and other privacy-preserving approaches could allow multiple clinics to contribute to model development without centralising all raw patient records. Such systems are attractive for rare cases or geographically distributed research networks. Nevertheless, federated learning does not automatically solve bias, label quality, or governance questions. Participating sites must still harmonise data definitions and agree on how models, updates, and research outputs are governed.

21.4. Digital twins and simulation:

A longer-term research possibility is the use of patient-specific simulation models to explore trajectories under different monitoring strategies. In a rigorous scientific context, a “digital twin” would not be a virtual patient that proves a remedy will work; it would be a computational representation used to test hypotheses about information, monitoring, or decision pathways. Such models could help researchers explore follow-up schedules, data collection burden, or referral triggers before testing them in real clinical environments.

21.5. Multilingual and culturally responsive systems:

For widespread use in India and other multilingual settings, future systems should support local languages while maintaining semantic consistency. The original patient expression should remain visible, and translation confidence should be tracked. This is particularly important for symptoms that are culturally expressed or for which literal translation changes the meaning. Multilingual AI should be validated separately rather than assuming that an English model will behave equally well across languages.

21.6. Implementation Roadmap for Responsible Homeopathy AI:

A practical programme can begin with the least risky high-value functions. The first step is to standardise digital case recording and outcome capture. The second is to introduce rule-based search and retrieval with visible provenance. The third is to add limited NLP assistance for terminology mapping and summarisation. The fourth is to develop machine-learning or LLM features in a research environment with retrospective evaluation. Only after safety, reproducibility, and usability are demonstrated should the tool be evaluated prospectively as a clinical decision-support intervention.

- Phase 1 – Infrastructure: establish structured records, consistent terminology, consent processes, role-based access, audit logs, and version-controlled knowledge sources.
- Phase 2 – Assisted workflow: add search, summarisation, symptom extraction, repertory navigation, and follow-up tools with mandatory human verification.

- Phase 3 – Research models: develop and internally validate predictive or ranking models using de-identified data, with explicit outcomes and error analysis.
- Phase 4 – Prospective evaluation: test safety, workflow, usability, reliability, and decision impact in real clinical settings using independent oversight.
- Phase 5 – Continuous governance: monitor model drift, user behaviour, adverse events, subgroup performance, software updates, and patient feedback after deployment.

This roadmap reflects a broader lesson from health AI: the greatest benefit may come from better problem definition and data governance rather than from using the most complex model available. Technology should be selected because it solves a demonstrated problem, not because the technology itself is novel. This approach is consistent with responsible machine-learning guidance and the wider movement toward trustworthy, traceable, human-centred healthcare AI (Wiens et al., 2019; Lekadir et al., 2025).

22.Conclusion:

Artificial intelligence and digital technologies have clear potential to change how homeopathic information is recorded, searched, summarised, monitored, and studied. Electronic case systems can create longitudinal records; repertory software can accelerate structured search; NLP can help transform narrative language into candidate structured concepts; machine learning can explore patterns in large datasets; and generative AI can assist with communication, education, and research tasks. Current homeopathy-specific literature demonstrates that digital repertory use and multicentre data collection are already feasible, while emerging 2026 research shows that general-purpose AI chatbots remain variable in their remedy recommendations (Gray et al., 2023; Kaur et al., 2025; Doherty et al., 2026).

The principal scientific opportunity is therefore not to build an autonomous AI prescriber but to develop a transparent, human-in-the-loop digital ecosystem. Such an ecosystem can make case analysis more explicit, preserve provenance, improve longitudinal measurement, support safer documentation, and generate higher-quality research data. At the same time, AI cannot by itself resolve the underlying evidence questions about homeopathy. Reviews and evidence summaries continue to report substantial uncertainty or limited support for specific clinical efficacy, and this therapeutic evidence must remain conceptually separate from the performance of digital tools (Hamre et al., 2023; NCCIH, 2026). Future research should prioritise standardised datasets, multilingual capability, external validation, reproducible algorithms, prospective evaluation, privacy-preserving infrastructure, and patient-safety safeguards. Studies should report not only accuracy but also calibration, workflow effects, subgroup performance, failure modes, and clinically meaningful outcomes. When these principles are followed, digital technology can become a tool for disciplined information management and scientific investigation rather than a source of false certainty. The future of AI in homeopathy will be determined less by how convincingly a system speaks and more by how transparently it handles evidence, uncertainty, human oversight, and measurable clinical consequences.

23.References:

(1) Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol. 2017;2(4):230-243. doi:10.1136/svn-2017-000101.
(2) Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. Nat Biomed Eng. 2018;2:719-731. doi:10.1038/s41551-018-0305-z.
(3) Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56. doi:10.1038/s41591-018-0300-7.
(4) Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J. 2019;6(2):94-98. doi:10.7861/futurehosp.6-2-94.
(5) Rajkomar A, Dean J, Kohane I. Machine learning in medicine. N Engl J Med. 2019;380(14):1347-1358. doi:10.1056/NEJMra1814259.

(6) Wiens J, Saria S, Sendak M, Ghassemi M, Liu VX, Doshi-Velez F, et al. Do no harm: a roadmap for responsible machine learning for health care. Nat Med. 2019;25:1337-1340. doi:10.1038/s41591-019-0548-6.
(7) Liu X, Cruz Rivera S, Moher D, Calvert MJ, Denniston AK, SPIRIT-AI and CONSORT-AI Working Group. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. Nat Med. 2020;26:1364-1374. doi:10.1038/s41591-020-1034-x.
(8) World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance. Geneva: World Health Organization; 2021. ISBN 978-92-4-002920-0.
(9) Vasey B, Nagendran M, Campbell B, Clifton DA, Collins GS, Denaxas S, et al. Reporting guideline for the early stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. BMJ. 2022;377:e070904. doi:10.1136/bmj-2022-070904.
(10) Thirunavukarasu AJ, Ting DSJ, Elangovan K, Gutierrez L, Tan TF, Ting DSW. Large language models in medicine. Nat Med. 2023;29(8):1930-1940. doi:10.1038/s41591-023-02448-8.
(11) Clusmann J, Kolbinger FR, Muti HS, Carrero ZI, Eckardt JN, Ghaffari Laleh N, et al. The future landscape of large language models in medicine. Commun Med (Lond). 2023;3:141. doi:10.1038/s43856-023-00370-1.
(12) Collins GS, Moons KGM, Dhiman P, Riley RD, Beam AL, Van Calster B, et al. TRIPOD+AI statement: updated guidance for reporting clinical prediction models that use regression or machine learning methods. BMJ. 2024;385:e078378. doi:10.1136/bmj-2023-078378.
(13) Lekadir K, Frangi AF, Porras AR, Glocker B, Cintas C, Langlotz CP, et al. FUTURE-AI: international consensus guideline for trustworthy and deployable artificial intelligence in healthcare. BMJ. 2025;388:e081554. doi:10.1136/bmj-2024-081554.
(14) Teo ZL, Thirunavukarasu AJ, Elangovan K, Cheng H, Moova P, Soetikno B, et al. Generative artificial intelligence in medicine. Nat Med. 2025;31:3270-3282. doi:10.1038/s41591-025-03983-2.
(15) World Health Organization. Global strategy on digital health 2020-2027. Geneva: World Health Organization; 2025. ISBN 978-92-4-011687-0.
(16) Shang A, Huwiler-Muntener K, Nartey L, Juni P, Dorig S, Sterne JAC, et al. Are the clinical effects of homoeopathy placebo effects? Comparative study of placebo-controlled trials of homoeopathy and allopathy. Lancet. 2005;366(9487):726-732. doi:10.1016/S0140-6736(05)67177-2.
(17) Mathie RT, Lloyd SM, Legg LA, Clausen J, Moss S, Davidson JRT, et al. Randomised placebo-controlled trials of individualised homeopathic treatment: systematic review and meta-analysis. Syst Rev. 2014;3:142. doi:10.1186/2046-4053-3-142.
(18) Mathie RT, Ramparsad N, Legg LA, Clausen J, Moss S, Davidson JRT, et al. Randomised, double-blind, placebo-controlled trials of non-individualised homeopathic treatment: systematic review and meta-analysis. Syst Rev. 2017;6:63. doi:10.1186/s13643-017-0445-3.
(19) Hamre HJ, Glockmann A, von Ammon K, Riley DS, Kiene H. Efficacy of homoeopathic treatment: systematic review of meta-analyses of randomised placebo-controlled homoeopathy trials for any indication. Syst Rev. 2023;12:191. doi:10.1186/s13643-023-02313-2.
(20) National Center for Complementary and Integrative Health. Homeopathy: what you need to know [Internet]. Bethesda (MD): NCCIH; 2026 [cited 2026 Oct 2]. Available from: https://www.nccih.nih.gov/health/homeopathy.
(21) European Academies Science Advisory Council. Homeopathic products and practices: assessing the evidence and ensuring consistency in regulating medical claims in the EU. Halle (Saale): EASAC; 2017.
(22) Gray AC, Pracjek P, Straiges D. Attitudes to and uptake of repertory software in homeopathy clinical practice-results of an international survey. Homeopathy. 2023;112(2):97-106. doi:10.1055/s-0042-1748841.
(23) Kaur H, Jain S, Katarmal D, Sachdeva J, Ponnam HB, Muraleedharan KC, et al. The patient population at homeopathic outpatient clinics across India: a clinical data collection study. Homeopathy. 2025;114(2):74-84. doi:10.1055/s-0044-1782221.

(24) Doherty R, Pracjek P, Luketic CD, Straiges D, Gray AC. Comparing AI chatbots to live practitioners of homeopathy: a comparative retrospective study. Healthcare (Basel). 2026;14(7):909. doi:10.3390/healthcare14070909.
(25) Anpat AV, Jayant PS, Tukaram IM, Haribhahu KM. Artificial Intelligence [AI] and Homoeopathy: Applicability, Reliability, Validity and Limitations of an AI-Aided Homoeopathic Clinic. J Drug Deliv Ther. 2026;16(1):143-145. doi:10.22270/jddt.v16i1.7505.