



Narrative Review:

Artificial Intelligence in Allied Health Practice: Current Evidence, Emerging Applications, And Implications for Patient Safety

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ABSTRACT: Artificial intelligence (AI) is moving from experimental research into routine healthcare workflows, including diagnostic support, clinical documentation, rehabilitation, laboratory medicine, medical imaging, patient education, and service management. Allied health professionals are increasingly involved in these AI-enabled pathways, yet evidence and implementation guidance are often concentrated in physician-led specialties. This narrative review synthesises current evidence on the use of AI across allied health practice and examines implications for patient safety, professional accountability, education, and health equity. Literature from peer-reviewed journals and authoritative guidance was considered, with emphasis on clinical applications, implementation barriers, bias, explainability, human-AI interaction, and generative AI. Current evidence supports potential benefits such as workflow support, image interpretation, pattern recognition, personalised rehabilitation, laboratory decision support, documentation assistance, and improved access to health information. However, technical performance alone does not establish clinical effectiveness or safety. Dataset shift, hidden bias, automation bias, inaccurate generated content, privacy risks, poor interoperability, insufficient local validation, and unclear responsibility can introduce new failure modes. Safe adoption should include a defined intended use, representative validation, transparent performance monitoring, user training, incident reporting, privacy safeguards, human oversight, and periodic re-evaluation after deployment. The review concludes that AI has meaningful potential across allied health practice, but sustainable adoption depends on evidence-based governance and continuous patient-safety monitoring rather than technology adoption alone.

KEYWORDS: artificial intelligence, allied health, machine learning, generative AI, patient safety, clinical decision support, digital health, rehabilitation, laboratory medicine, healthcare professionals.

1. INTRODUCTION

Artificial intelligence (AI) refers to computational methods that can perform tasks associated with human cognitive functions, including pattern recognition, prediction, classification, language processing, and decision support. Machine learning (ML), deep learning, natural language processing (NLP), computer vision, and generative AI are important components of the broader AI landscape. In healthcare, these technologies are increasingly used with electronic health records, medical images, laboratory results, physiological signals, rehabilitation data, and clinical text. The attraction of AI lies not only in automation but also in its ability to analyse large and complex datasets at a scale that is difficult to reproduce manually. [1-3]

Although much public discussion about healthcare AI focuses on physicians and diagnostic medicine, allied health professionals are integral to AI-enabled care. The allied health workforce includes professionals working in laboratory medicine, medical imaging, physiotherapy, occupational therapy, speech and language therapy, nutrition and dietetics, respiratory care, rehabilitation, health information management, and other diagnostic and therapeutic services. AI can influence each stage of these pathways, from data acquisition and quality assurance to interpretation, treatment planning, documentation, monitoring, and follow-up.

Evidence from radiology, pathology, ophthalmology and other image-intensive disciplines demonstrates that deep-learning systems can achieve high performance on selected, well-defined tasks. [4-8] However, evidence of technical accuracy should not be confused with evidence of improved patient outcomes. Reviews have highlighted limitations in study design, external validation,



reporting, and clinical translation. [9-12] A model may perform well on a carefully curated dataset but behave differently when patient populations, equipment, disease prevalence, documentation patterns, or clinical workflows change.

The patient-safety dimension is therefore central. WHO guidance places human autonomy, safety, transparency, accountability, equity, and appropriate governance at the centre of AI for health. [13] More recent WHO guidance on large multimodal models highlights additional concerns associated with generative AI, including inaccurate outputs, privacy, automation, and the need for oversight. [14] For allied health professionals, these principles translate into practical questions: What is the intended use? What information does the system use? How accurate is it for the local population? What happens when it is wrong? Who verifies the output? How is an error documented and reported?

This narrative review describes current evidence and emerging applications of AI in allied health practice and examines the principal patient-safety implications. It also proposes a practical framework for responsible adoption that can be used by allied health departments and multidisciplinary healthcare organisations.

2. OBJECTIVES

- To summarise current evidence on AI applications relevant to allied health practice.
- To describe emerging applications of machine learning, computer vision, NLP, generative AI, and predictive analytics across selected allied health domains.
- To identify patient-safety risks associated with AI-enabled clinical workflows.
- To outline practical requirements for human oversight, validation, governance, training, and post-deployment monitoring.

3. REVIEW APPROACH

This article was prepared as a narrative evidence review rather than a systematic review or meta-analysis. Peer-reviewed literature was considered from biomedical and multidisciplinary sources, together with authoritative guidance from the World Health Organization and recognised reporting frameworks for AI research. Priority was given to reviews, clinical evaluation studies, methodological papers, reporting standards, and publications directly relevant to AI safety, implementation, rehabilitation, pathology/laboratory medicine, medical imaging, and generative AI. The literature was synthesised thematically under four domains: current applications, emerging applications, patient-safety implications, and implementation requirements. Published numerical findings quoted in this manuscript are findings reported by the cited studies and are not presented as original data from the authors.

4. CURRENT APPLICATIONS OF AI IN ALLIED HEALTH PRACTICE

4.1 Medical imaging and radiography

Medical imaging is one of the most mature areas of clinical AI. Computer vision and deep-learning models can assist with image classification, detection, segmentation, prioritisation of examinations, quality control, and quantitative measurements. Research has demonstrated strong performance for selected tasks such as chest radiograph interpretation, mammographic abnormality detection, retinal image analysis, and other image-based assessments. [4-8] AI may help radiography departments prioritise urgent examinations, identify technically inadequate images, standardise measurements, and reduce repetitive workload. In practice, however, the radiographer or radiologist remains responsible for assessing image quality, clinical context, and whether the AI output is plausible. A model trained using one scanner, protocol, or population may not generalise reliably to another setting.

4.2 Laboratory medicine and pathology

Laboratory medicine provides multiple opportunities for AI because clinical laboratories generate large volumes of structured and image-based data. Potential applications include result interpretation, flagging abnormal patterns, quality assurance, specimen and workflow management, image analysis, morphology classification, and decision support. Reviews describe applications in digital pathology, tumour classification, prognosis, haematology image analysis, and clinical laboratory workflows. [15-18] AI can support repetitive recognition tasks and may help laboratory professionals identify patterns requiring further review. It should not be treated as an independent diagnostic authority. Pre-analytical errors, specimen quality, instrument variation, reference-range differences, contamination, and clinical context can all influence interpretation.



4.3 Physiotherapy and physical rehabilitation

AI-enabled rehabilitation has expanded through wearable sensors, computer vision, mobile applications, robotic systems, gaming environments, and predictive models. A systematic review identified 9054 records and included 28 projects spanning apps, robotics, gaming systems and wearables; only five randomised controlled trials were identified and clinical effects were inconsistent. [19] Potential uses include movement analysis, exercise feedback, adherence monitoring, functional assessment, and prediction of rehabilitation trajectories. AI may support home-based rehabilitation by providing structured feedback between professional appointments. Nevertheless, therapy goals should remain patient-centred, and automated exercise recommendations require clinical review.

4.4 Occupational therapy

Occupational therapy can use AI for activity recognition, adaptive interfaces, functional assessment, environmental analysis, assistive technology, rehabilitation planning, and educational support. AI may be useful where repeated measurements are required, but functional performance is multidimensional and cannot always be represented by a single algorithmic score. Human assessment remains necessary to integrate functional, social, environmental and patient-preference information. [33]

4.5 Speech and language therapy

Speech and language services may benefit from speech recognition, acoustic analysis, language modelling, automated transcription, communication-assistance technologies, and personalised digital exercises. NLP can support documentation and longitudinal analysis of language features. Generative systems can also produce educational material or communication prompts. However, speech disorders vary with age, language, accent, culture, neurological condition, and context. Systems developed using limited language datasets may therefore perform unevenly across patient groups. [34]

4.6 Nutrition and dietetics

AI can assist nutrition professionals through dietary pattern analysis, food recognition, personalised educational content, risk prediction, and monitoring of adherence. Mobile tools can estimate dietary intake from photographs or patient-entered records. Predictive analytics may help identify patients at nutritional risk. Yet nutrition decisions are influenced by medical status, cultural practices, affordability, food availability, allergies, preferences, and social circumstances. AI-generated advice must therefore be checked by qualified professionals before clinical use. [35]

5. EMERGING APPLICATIONS

Emerging AI applications are broader than conventional classification systems. Generative AI and multimodal models can process or produce text, images, audio, and other forms of information. Potential uses include patient education, clinical communication, research support, translation, simulation-based education, structured documentation, and multidisciplinary information synthesis. WHO guidance published in 2025 specifically addresses large multimodal models and emphasises the need for governance, safety and evidence before clinical deployment. [14]

Predictive analytics is another emerging area. AI models may estimate the probability of deterioration, readmission, falls, treatment response, or rehabilitation outcomes. The value of prediction depends on whether the prediction changes care appropriately. A highly accurate model that produces alerts clinicians cannot act upon may create alert fatigue rather than improve safety. An imperfect model may still be useful if it is integrated into a well-designed workflow with clear thresholds, human verification, and escalation pathways. [9-12,32]

Synthetic data and privacy-preserving approaches are also developing. Synthetic data may support education, model development and proficiency testing, but it can introduce data-quality limitations, malicious-use concerns and ethical bias. [21] Federated approaches may reduce the need to centralise sensitive data, although they do not automatically eliminate privacy, security, or bias concerns.

6. SELECTED PUBLISHED EVIDENCE

The following examples illustrate the scale and type of evidence currently available. They are not pooled estimates and should not be interpreted as a meta-analysis.

Table 1. Examples of published evidence and guidance relevant to AI-enabled allied health practice.

Evidence source	Reported evidence	Application	Interpretation
Conversational LLM systematic review [20]	820 records screened; 65 included	Summarisation, knowledge, prediction, administration	Rapidly expanding evidence; reliability and bias remain concerns.
Physical rehabilitation systematic review [19]	9054 records; 28 projects included; 5 RCTs	Apps, robotics, gaming, wearables	Clinical effects were inconsistent and implementation evidence remains limited.
CONSORT-AI [28]	AI-specific reporting extension	AI clinical trials	Adds reporting requirements for AI interventions and human-AI interaction.
SPIRIT-AI [29]	AI-specific protocol extension	AI clinical trial protocols	Improves transparency and pre-specification.
WHO AI ethics guidance [13]	Six ethical principles	AI across health systems	Emphasises autonomy, safety, transparency, accountability, equity and governance.

These examples show why simple claims that AI is accurate are insufficient. The clinically important question is whether the complete human-AI system improves patient outcomes without creating unacceptable new risks. Clinical evaluation should include workflow effects, false-positive and false-negative consequences, usability, equity, patient experience, and post-deployment performance.

7. PATIENT-SAFETY IMPLICATIONS

7.1 Data quality and dataset shift

AI systems learn patterns from historical data. Missing values, incorrect labels, inconsistent measurements, and differences in clinical practice can affect model performance. Dataset shift occurs when the population or environment in which a model is used differs from its development data. Local validation and continuous monitoring are therefore necessary. [9-12, 32]

7.2 Algorithmic bias and health equity

Bias can arise from under-representation, historical inequalities, proxy variables, measurement differences, or unequal access to digital services. A widely cited study showed that an algorithm used in population health management could reproduce racial bias because healthcare expenditure was used as a proxy for need. [22] Reviews also identify fairness, transparency, privacy and accountability as important considerations for clinical AI. [23,24]

7.3 Automation bias and professional judgement

Automation bias occurs when users give excessive weight to a computer-generated recommendation. Allied health professionals should treat AI output as decision support rather than an unquestionable instruction. Human review should be especially strong when AI outputs conflict with clinical findings. [31]

7.4 False reassurance and missed abnormalities

An AI system may fail to identify a clinically important abnormality. In imaging and laboratory settings, false-negative results can delay diagnosis; in rehabilitation, inappropriate risk predictions can lead to unsuitable progression; in documentation, an omitted symptom can alter downstream decisions. Clear escalation rules and override procedures are required. [9-12, 31, 32]

7.5 Generative AI errors and hallucinations

Generative AI can produce fluent but incorrect information. Reviews of healthcare LLMs identify reliability, bias, privacy and acceptability as recurring concerns. [20,25] Generated content should be verified against the clinical record and trusted references before clinical use.



7.6 Privacy and confidentiality

AI systems may process highly sensitive health information. Privacy risks can arise during collection, storage, model training, vendor integration, secondary use, or transmission. Institutions should establish clear rules for what information may be entered into external AI services. [13,14,36]

7.7 Explainability and transparency

Users need sufficient information to understand intended use, limitations, input variables, output meaning and uncertainty. Explainability can support trust and accountability, but recent literature shows that the appropriate level of explanation can be context-dependent. [26,27]

7.8 Interoperability and workflow failure

An AI model can be technically accurate but clinically unsafe if its output is delivered at the wrong time, to the wrong user, or without information needed for interpretation. Integration with electronic health records, laboratory systems, radiology systems and rehabilitation platforms should be tested before clinical deployment.

7.9 Accountability and medico-legal responsibility

AI does not remove professional accountability. The clinical workflow must define who reviews AI output, who acts on it, who documents the decision, and who manages errors. Governance should include incident reporting, audit trails, version control, and procedures for withdrawing an unsafe model. [13,36]

8. PRACTICAL PATIENT-SAFETY FRAMEWORK FOR ALLIED HEALTH AI

A practical implementation pathway can be organised around seven stages: define the clinical problem; evaluate the evidence; validate locally; prepare users and workflows; deploy with human oversight; monitor outcomes and incidents; and periodically reassess or retire the system. Reporting standards such as SPIRIT-AI, CONSORT-AI and DECIDE-AI provide complementary approaches for transparent development and clinical evaluation. [28-30] [36]

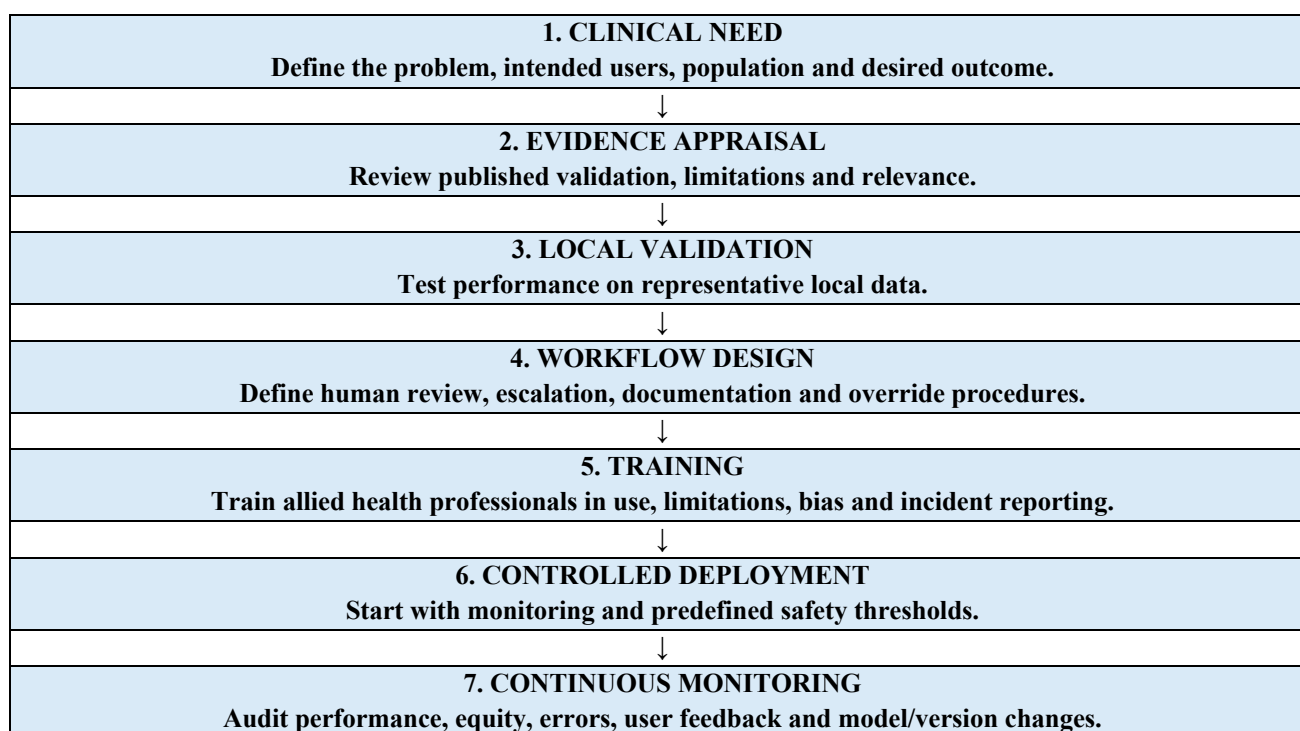


Figure 1. Proposed patient-safety pathway for implementation of AI in allied health practice.

9. ROLE OF ALLIED HEALTH PROFESSIONALS IN RESPONSIBLE AI

Allied health professionals should be involved in AI development and procurement rather than being introduced only after a system has been purchased. Their practical knowledge can identify workflow hazards that may not be visible to software developers. A laboratory professional can recognise specimen-related limitations, a radiographer can identify image-acquisition issues, and a physiotherapist can recognise movement patterns that an algorithm may misclassify. Such expertise is necessary for meaningful validation.

Professional education should include basic AI literacy. Clinicians do not need to become programmers, but they should understand training and validation datasets, sensitivity, specificity, predictive values, calibration, overfitting, dataset shift, algorithmic bias, and model drift. They should also know how to interpret uncertainty and report AI-related incidents.

10. EDUCATION, RESEARCH AND PROFESSIONAL DEVELOPMENT

AI literacy should become part of continuing professional development across allied health disciplines. Education can be organised around four competencies: understanding AI fundamentals; evaluating evidence; safe clinical use; and ethical and legal practice. Students should learn to critically appraise AI-generated information rather than treating generated text as a substitute for primary literature or professional reasoning.

Research should increasingly move beyond retrospective accuracy studies. Clinical effectiveness, implementation science, human factors, cost-effectiveness, patient-reported outcomes, and health-equity assessments are needed. SPIRIT-AI and CONSORT-AI provide standards for transparent reporting of AI interventions, while DECIDE-AI addresses early-stage clinical evaluation and human factors during real-world implementation. [28-30]

11. PROPOSED MONITORING INDICATORS

Table 2. Suggested indicators for monitoring AI-enabled allied health services.

Domain	Example indicator	Why it matters	Suggested action
Clinical performance	Sensitivity, specificity, calibration or task-specific accuracy	Detects degradation	Review model and workflow
Safety	AI-related incidents, near misses, override frequency	Identifies harm or unsafe reliance	Root-cause analysis and corrective action
Equity	Performance across relevant patient subgroups	Detects unequal benefit or harm	Targeted validation/retraining
Usability	User workload, trust, alert burden	Identifies workflow problems	Redesign interface or thresholds
Governance	Version changes, audit logs, approval status	Supports accountability	Document and revalidate changes
Privacy	Unauthorised access or disclosure events	Protects confidentiality	Security review and incident response

12. DISCUSSION

The current evidence suggests that AI can provide useful augmentation across several allied health domains, particularly where large volumes of structured, image-based, physiological, or textual data are available. The strongest evidence is generally found in narrowly defined tasks rather than broad autonomous clinical decision-making. Imaging and digital pathology provide examples of high technical performance, while rehabilitation research demonstrates a growing range of wearable, robotic, app-based, and computer-vision approaches. [4-8,15-19]

At the same time, the literature repeatedly identifies a gap between algorithm development and real-world clinical benefit. Reviews of AI studies have noted weaknesses in external validation, reporting, and study design. [9-12] Implementation is also affected by interoperability, regulation, workflow redesign, user acceptance, and local data quality. These limitations are especially



important in allied health because care is often longitudinal, multidisciplinary, context-dependent, and closely connected to patient behaviour and function. [36]

Generative AI adds a different risk profile. Unlike conventional predictive models that usually provide a numerical or classification output, generative systems can produce apparently coherent language that may contain unsupported claims. [14,20,25] This makes verification particularly important. Such tools may be useful for drafting patient education material, summarising information, or assisting administrative work, but final content should be reviewed by an appropriately qualified professional.

Patient safety should therefore be considered a property of the entire socio-technical system rather than of the algorithm alone. The same model can be relatively safe in one workflow and unsafe in another depending on how its output is presented, interpreted, and acted upon. WHO principles of autonomy, safety, transparency, accountability, equity, and responsible governance provide a useful foundation for this broader view. [13,14]

13. CONCLUSION

Artificial intelligence is becoming relevant to allied health practice through medical imaging, laboratory medicine, pathology, rehabilitation, occupational therapy, speech and language services, nutrition, documentation, and clinical workflow support. The evidence indicates substantial potential for improving efficiency, consistency, access, and personalised care in selected tasks. However, technical performance alone does not establish safety or clinical effectiveness.

Responsible implementation requires clearly defined clinical use cases, representative validation, transparent limitations, human oversight, professional training, privacy protection, equity assessment, incident reporting, and continuous post-deployment monitoring. Allied health professionals should participate actively in the selection, evaluation, implementation, and governance of AI systems. The appropriate model for most current applications is augmentation: AI supports professional work, while qualified healthcare professionals retain responsibility for clinical interpretation and patient-centred decision-making.

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Cite this Article: Ramya, S., Baskaran, R., Somasundaram, L. (2026). Artificial Intelligence in Allied Health Practice: Current Evidence, Emerging Applications, And Implications for Patient Safety. International Journal of Current Science Research and Review, 9(10), pp. 5264-5272. DOI: <https://doi.org/10.47191/ijcsrr/V9-i10-04>