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Artificial Intelligence – Assisted Clinical Decision-Making: Progress and Perspectives with Applications in Thyroid Disease Stratification and Personalized Medication

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ABSTRACT

Artificial intelligence (AI) is increasingly used in clinical decision-making to improve prediction, risk assessment, and interpretation of complex medical data. Thyroid disease, especially thyroid nodules, is a representative setting because diagnostic uncertainty and management variability remain common. Recent advances in machine learning, deep learning, and multimodal data integration have expanded the role of AI in thyroid evaluation.This review summarizes progress in AI-assisted clinical decision-making with emphasis on thyroid disease stratification and individualized management. We discuss clinical decision support systems, deep learning for ultrasound-based thyroid nodule diagnosis, multimodal integration of imaging and clinical data, and the potential of reinforcement learning and predictive modeling in adaptive management. We also review emerging digital platforms for thyroid care and the challenges of implementation, including data quality, interpretability, regulation, and workflow integration. Overall, AI-assisted systems may improve diagnostic consistency and support precision medicine in thyroid disease, but safe clinical translation will require continued collaboration among clinicians, data scientists, and regulators.

KEYWORDS

Artificial intelligence; Clinical decision support systems; Thyroid nodules; Precision medicine; Multimodal data integration; Machine learning in healthcare

1 Introduction

Artificial intelligence (AI) is becoming increasingly important in healthcare, especially in settings that require complex data interpretation and individualized judgment. Compared with rule-based systems, current AI methods can analyze heterogeneous medical data, identify nonlinear patterns, and support diagnosis, risk estimation, and treatment planning [1-3].

The growth of digital medicine has accelerated this trend by expanding access to electronic health records, imaging archives, laboratory data, and longitudinal follow-up information. However, clinical usefulness depends not only on model performance, but also on validation, interpretability, and clinician acceptance [1-3].

Thyroid disease is a useful setting in which to examine these issues. Thyroid nodules are common, and their detection has increased with wider use of imaging. Because most nodules are benign, the central challenge is not detection alone, but identifying which lesions require further evaluation or treatment and which can be managed conservatively [4-5].

Current pathways still rely mainly on ultrasound and selective fine-needle aspiration (FNA). Although guideline-based systems have improved standardization, ultrasound remains partly operator-dependent, and indeterminate cytology continues to complicate management [6-7]. In practice, decisions also depend on laboratory findings, clinical characteristics, and follow-up context. Thyroid disease therefore provides a useful model for studying how AI may support risk stratification, multimodal integration, and individualized decision-making [1-7].

This review summarizes recent progress in AI-assisted clinical decision-making, using thyroid disease as a representative application scenario. Particular attention is given to AI-supported risk stratification, ultrasound-based diagnosis, multimodal integration, and intelligent systems for individualized management [1-7].

2 Clinical Decision-Making Challenges in Thyroid Diseases

2.1 Epidemiology and Clinical Burden

Thyroid nodules are among the most common endocrine disorders. Their detection has increased with widespread imaging, yet most nodules are benign. The main clinical task is therefore to identify which lesions require further evaluation or treatment and which can be managed conservatively [4-5].

The burden of thyroid disease extends beyond malignancy risk. Increased detection has contributed to repeated

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imaging, surveillance, patient anxiety, and overdiagnosis. Current guidelines therefore favor selective, risk-stratified management rather than indiscriminate investigation [5].

2.2 Diagnostic Limitations of Current Pathways

Ultrasound remains the cornerstone of thyroid nodule assessment. Structured reporting systems have improved standardization, but interpretation remains partly operator-dependent, and differences in scanning technique and reader experience still cause substantial interobserver variation [4].

FNA is essential for suspicious nodules, but uncertainty remains. Many nodules yield indeterminate cytology, leaving clinicians between surveillance and surgery, even though a large proportion prove benign [4]. This uncertainty continues to complicate counseling and treatment planning.

2.3 Variability in Treatment Decisions

Clinical decisions in thyroid disease are rarely based on a single finding. Physicians integrate ultrasound features, cytology, symptoms, age, comorbidity, and feasibility of follow-up when deciding on surveillance, biopsy, or treatment. Although guidelines offer a framework, real-world decisions still vary across clinicians and institutions.

This variation matters clinically because similar nodules may be managed conservatively in one setting but more aggressively in another. The challenge is to balance missed malignancy against unnecessary procedures [5].

2.4 Why Thyroid Disease Is a Suitable Model for AI-Assisted Decision Support

Thyroid nodule management is well suited to AI-assisted decision support because it is high-volume, heavily imaging-based, and frequently affected by intermediate-risk uncertainty. More broadly, thyroid care reflects a common problem in modern medicine: improving diagnostic precision while avoiding overtreatment. Recent multicentre studies suggest that deep learning can support ultrasound interpretation and reduce some subjectivity in assessment [6-7]. Thyroid disease has therefore become both a target application for AI and a practical model for studying clinical integration.

3 Artificial Intelligence in Clinical Decision Support Systems

AI has expanded clinical decision support systems from static rule-based tools to models that learn from complex clinical data. In practice, AI-assisted systems are mainly used to support diagnosis, risk prediction, workflow prioritization, and treatment planning rather than replace physician judgment [8-10].

A major driver of this development is the growing availability of heterogeneous data. Imaging, electronic health records, laboratory results, pathology, and longitudinal follow-up can now be analyzed together, allowing AI to capture interactions that are difficult to model with conventional approaches [8,11]. This is particularly relevant to precision medicine, where decisions often depend on integrating several forms of information.

At the same time, technical accuracy alone is insufficient for adoption. AI systems still require transparent evaluation, prospective validation, and clear reporting of inputs, outputs, and intended use. The CONSORT-AI extension reflects the need for more rigorous standards in clinical assessment [10]. In practice, usefulness depends on reproducibility, interpretability, and clinical relevance as much as on performance [9-10].

Overall, AI-assisted decision support is moving from isolated prediction tools toward broader systems that integrate multimodal information and generate more context-sensitive recommendations [8,11]. This direction is especially relevant in thyroid disease, where management depends on combined interpretation of imaging, cytology, clinical factors, and follow-up context.

4 AI Applications in Thyroid Disease Diagnosis

4.1 AI-Assisted Ultrasound Image Analysis

Thyroid ultrasound is the first-line imaging method for evaluating nodules, but interpretation remains influenced by operator experience. This has made ultrasound one of the most active areas for AI application in thyroid disease. Peng et al. developed the deep-learning model ThyNet and showed that it could distinguish benign from malignant nodules while helping reduce unnecessary FNA in selected cases [6]. This study moved beyond image classification toward real diagnostic management.

Subsequent work has reinforced this direction. Wang et al. reported an integrated AI model that improved diagnostic accuracy in suspicious nodules while also outputting recognizable risk features [12]. Li et al. further showed in a prospective real-world study that AI achieved performance comparable to experienced radiologists, improved the performance of less-experienced readers, and reduced unnecessary biopsy in selected nodules [13]. These studies suggest that the most practical role of AI is assistive rather than autonomous.

4.2 AI-Based Risk Stratification Models

In thyroid imaging, risk stratification is often more relevant than simple binary classification because management

depends on estimated malignancy risk. Although ACR TI-RADS has improved consistency, intermediate-risk nodules still produce uncertainty and interobserver variation.

Wu et al. showed that a deep-learning model based on ACR TI-RADS could improve the differential diagnosis of TR4 and TR5 nodules [14]. Ha et al. developed a machine learning–based fine-grained stratification system using predefined clinicoradiological features and reported higher specificity and AUROC than several TI-RADS-based interpretations while maintaining similar sensitivity [15]. Clinically, this is important because reducing unnecessary biopsy and surgery depends heavily on improving specificity in borderline cases.

4.3 Decision Support in Real Clinical Practice

The key translational question is whether AI improves physician performance under realistic clinical conditions. Xu et al. conducted a multicenter prospective study and found that AI support significantly improved the diagnostic performance of junior radiologists, bringing their results closer to those of senior radiologists in a two-echelon framework [16]. Current evidence therefore supports a measured view: the most useful systems appear to support radiologists in ultrasound interpretation and risk assessment rather than function as fully independent readers [6,12-16].

5 Multimodal Data Integration in Precision Medicine

Precision medicine increasingly depends on integrating heterogeneous clinical information rather than interpreting a single test in isolation. Reviews of biomedical data fusion show that multimodal deep learning can model nonlinear relationships across imaging, laboratory findings, pathology, longitudinal data, and other information streams that single-source approaches may miss [17-18].

This is directly relevant to AI-assisted decision-making. The value of multimodal systems lies not in adding more variables, but in combining complementary evidence into a unified predictive framework. A major review in Nature Medicine emphasized that multimodal biomedical AI may support personalized medicine by integrating medical images, electronic records, biosignals, and molecular data into richer computational representations of patient status [19].

Methodological strategy also matters. Reviews suggest that intermediate and joint-representation fusion may be better suited than shallow or late fusion when the goal is to model complex biological interactions [17]. A scoping review further showed that multimodal deep learning has expanded into computer-aided diagnosis, segmentation, report generation, and cross-modal retrieval [18].

In thyroid disease, this perspective is clinically relevant because ultrasound alone often does not resolve uncertainty. Decisions also depend on age, thyroid function, cytology, symptoms, and follow-up context. A 2024 study developed an ultrasound-based radiomics-clinical machine learning model for TI-RADS 3 nodules and found that the combined model outperformed the clinical model alone in predicting papillary thyroid microcarcinoma [20].

A broader extension of this approach is the digital twin, a virtual patient representation integrating medical, physiological, and longitudinal data to support prediction of disease progression and treatment response [21]. However, implementation remains a major challenge. A scoping review of AI-based prediction models in healthcare found that guidance is stronger for model development and validation than for software development, impact assessment, and routine implementation [22]. For thyroid decision support, multimodal AI will be clinically useful only if it can be validated, interpreted, and integrated into real workflows.

6 AI-Assisted Personalized Treatment and Medication Decisions

The role of AI extends beyond diagnosis to treatment recommendation and longitudinal management. Personalized care is inherently sequential: clinicians choose an intervention, observe response, and adjust subsequent management. This explains growing interest in reinforcement learning, which is designed to learn strategies across repeated decision points and is therefore conceptually relevant to adaptive therapy and long-term disease management [23-24].

Recent reviews describe reinforcement learning as a potentially useful framework for personalized treatment decisions while also emphasizing challenges in safety, evaluation, and interpretability [23-24]. Although thyroid-specific reinforcement learning studies remain limited, the logic is relevant because thyroid management often involves repeated follow-up, adjustment of surveillance intervals, biopsy decisions, and post-diagnostic monitoring.

More immediate support for individualized management comes from imaging-derived models. A 2024 study reported that a deep-learning radiomics model based on ultrasound could objectively evaluate thyroid nodules and improve physicians' diagnostic performance [25]. A 2023 study comparing ultrasonography-based radiomics and computer-aided diagnosis also found good diagnostic performance and suggested potential to optimize ACR TI-RADS recommendations and reduce unnecessary biopsy, particularly with the radiomics approach [26]. Although these studies focus mainly on risk assessment, they point toward a broader role for AI in guiding intervention intensity and follow-up strategy.

Future progress is unlikely to depend on a single algorithm. More plausibly, individualized thyroid management will require layered systems that combine multimodal characterization, validated prediction tools, and adaptive decision

support that updates recommendations as new information becomes available [21-24].

7 Emerging Intelligent Platforms for Disease Management

Recent progress in medical AI has encouraged a shift from single-task algorithms to integrated digital platforms that support multiple stages of care. Unlike isolated diagnostic models, these systems aim to connect data acquisition, predictive analysis, workflow support, and longitudinal monitoring within broader clinical environments [27-28].

This shift is especially relevant in thyroid disease, where care often involves repeated interactions among ultrasound assessment, radiologic interpretation, biopsy decision-making, and follow-up. AI is therefore increasingly discussed not only as an image-analysis tool but also as part of a broader management platform supporting stratification, documentation, and standardized decisions [28-29].

Evidence from multicenter thyroid studies supports this integrated view. AI-assisted systems have improved diagnostic performance and reduced variability, particularly when used to support less-experienced readers in real ultrasonography settings [28-29]. This suggests that platform-based deployment is most useful when AI augments workflows rather than operates separately from them.

Beyond diagnosis, intelligent platforms are increasingly linked to remote care, digital follow-up, and workflow redesign. Recent discussions in digital medicine emphasize that sustainable adoption depends on how well these systems are incorporated into broader care models and coordinated clinical operations [27,30]. In thyroid disease, this means AI may gradually extend from diagnostic support to more continuous patient management.

8 Challenges and Future Perspectives

Despite substantial technical progress, several barriers still limit broader adoption of AI-assisted decision systems. One of the most persistent is explainability. In high-stakes settings, clinicians remain cautious about models whose reasoning is difficult to interpret. Reviews of explainable AI in healthcare emphasize that interpretability is closely related to trust, safety assessment, and detection of hidden bias or model failure [31-32].

Regulation is another major challenge. As AI tools move closer to routine use, validation, reporting standards, intended use, and post-market oversight become increasingly important. Analyses of FDA-authorized AI-based medical devices show expanding regulatory approval while also highlighting the need for clearer characterization of algorithm function and stronger evidence of generalizability across clinical settings [33]. This is especially relevant in thyroid applications, where variation in imaging practice and patient populations may influence real-world performance.

Data governance and privacy will also shape future progress. Federated learning has attracted increasing attention because it allows collaborative model training without direct sharing of sensitive patient data. A recent systematic review showed that federated approaches are being applied across a growing range of healthcare settings, although major technical and operational challenges remain [34].

For thyroid disease, the field appears to be entering a more translational phase. The key questions are no longer only whether AI can detect or classify nodules, but whether these tools can be externally validated, clinically interpreted, and integrated into routine care [28,35]. Future progress will likely depend on moving from stand-alone diagnostic models toward clinically embedded systems that support risk stratification, follow-up planning, and individualized management.

9 Conclusion

Artificial intelligence is reshaping clinical decision-making by supporting more structured analysis of complex medical data and the broader move toward precision-oriented care. In thyroid disease, the most important advances have been seen in ultrasound interpretation, risk stratification, and the early development of integrated decision-support tools [28-30].

At the same time, successful translation will depend on more than model accuracy. Explainability, external validation, workflow integration, regulation, and privacy-preserving collaboration will determine whether AI systems become dependable clinical tools rather than remain research-stage technologies [32-35]. With continued progress in multimodal learning, federated modeling, and integrated digital platforms, AI is likely to play an increasing role in thyroid disease management and in personalized medicine more broadly [27,34-35].

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