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Review Article

Artificial Intelligence in Rhinology: Current Applications, Clinical Utility, and Future Directions—A Systematic Review

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ABSTRACT

Background: Artificial intelligence (AI) has emerged as a powerful adjunct in rhinology, with expanding applications in diagnostic imaging, endoscopic assessment, disease classification, surgical planning, and clinical decision support. Recent advances in machine learning (ML), deep learning (DL), and convolutional neural networks (CNNs) have demonstrated promising diagnostic performance across a wide range of rhinologic disorders. However, the available evidence remains heterogeneous, and its readiness for routine clinical implementation requires critical evaluation.
Objective: To systematically review the current evidence on the applications of artificial intelligence in rhinology, with emphasis on its diagnostic performance, clinical utility, limitations, and future perspectives.
Methods: A systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. Electronic searches of PubMed/MEDLINE, Scopus, Embase, Web of Science, IEEE Xplore Digital Library, and the Cochrane Library were performed from database inception to May 31, 2025. Studies investigating AI-based techniques—including ML, DL, CNNs, natural language processing, and large language models—in rhinologic diseases were eligible for inclusion. Two reviewers independently screened studies, extracted data, and assessed methodological quality. Owing to substantial heterogeneity among studies, findings were synthesized narratively.
Results: Twenty-seven records were identified through database searching. Following duplicate removal and eligibility assessment, 12 studies published between 2019 and 2025 were included. AI applications encompassed computed tomography interpretation, endoscopic image analysis, chronic rhinosinusitis classification, nasal polyp detection, cytological assessment, radiomics, clinical decision support, surgical planning, and prediction of treatment outcomes. CNN- and DL-based models demonstrated high diagnostic performance in image-based applications, with reported diagnostic accuracies ranging from approximately 74% to 99% and area under the receiver operating characteristic curve (AUC) values of up to 0.93. AI-assisted systems improved diagnostic consistency, reduced interobserver variability, and supported clinical decision-making. Nevertheless, the available evidence was predominantly based on retrospective, single-center studies with relatively small datasets and limited external validation.
Conclusion: Artificial intelligence has significant potential to enhance rhinologic practice by improving diagnostic accuracy, optimizing image interpretation, facilitating surgical planning, and supporting personalized patient care. Despite encouraging results, current evidence is constrained by methodological heterogeneity and limited clinical validation. Large-scale multicenter prospective studies, standardized reporting frameworks, and externally validated, explainable AI models are essential before widespread integration of AI into routine rhinologic practice.

Keywords: Artificial Intelligence, Rhinology, Machine Learning, Deep Learning, Convolutional Neural Network, Chronic Rhinosinusitis, Nasal Polyps, Computed Tomography, Endoscopic Imaging, Systematic Review.

INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most influential technological advances in modern healthcare, revolutionizing disease diagnosis, medical imaging, clinical decision-making, and personalized patient care. By integrating computational techniques such as machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision, AI enables the analysis of large and complex clinical datasets that are often beyond the capacity of conventional analytical methods. Consequently, AI-assisted systems are increasingly being incorporated into various medical specialties to improve diagnostic accuracy, optimize clinical workflows, and support evidence-based decision-making (1,2).

Rhinology, a major subspecialty of otorhinolaryngology, encompasses the diagnosis and management of disorders affecting the nose and paranasal sinuses, including chronic rhinosinusitis (CRS), allergic rhinitis, nasal polyps, sinonasal neoplasms, and anatomical abnormalities. These conditions are frequently evaluated using clinical examination, nasal endoscopy, and radiological imaging, particularly computed tomography (CT) and magnetic resonance imaging (MRI). Accurate interpretation of these investigations is essential for diagnosis, disease staging, surgical planning, and postoperative follow-up. However, variability in image interpretation and disease assessment among clinicians may influence diagnostic consistency and treatment outcomes (3,4).

Recent advances in ML and DL have accelerated the development of AI models capable of automated image segmentation, lesion detection, disease classification, radiomic analysis, and prediction of clinical outcomes. Convolutional neural networks (CNNs), in particular, have demonstrated excellent performance in the analysis of sinonasal CT scans and endoscopic images, providing rapid and reproducible assessments while reducing observer variability. In addition to imaging applications, AI has shown promise in predicting disease severity, estimating postoperative outcomes, identifying patients at risk of recurrence, and supporting individualized treatment planning through data-driven clinical decision-support systems (5–8).

Despite these advances, the translation of AI into routine rhinologic practice remains limited. Most published studies are retrospective, involve relatively small datasets, and originate from single institutions, limiting their external validity and generalizability. Furthermore, considerable heterogeneity exists in study design, AI algorithms, imaging protocols, reference standards, and outcome measures, making direct comparisons between studies difficult. Challenges related to algorithm transparency, explainability, data privacy, ethical considerations, and regulatory approval further impede widespread clinical adoption (9–11).

Although numerous studies have investigated individual applications of AI in rhinology, the evidence remains dispersed across diverse clinical domains and methodological approaches. A comprehensive synthesis of the available literature is therefore required to evaluate current evidence, identify existing knowledge gaps, and determine the readiness of AI technologies for clinical implementation.

The objective of this systematic review was to critically evaluate the current applications of artificial intelligence in rhinology, with particular emphasis on diagnostic imaging, endoscopic assessment, disease classification, surgical planning, clinical decision support, and prediction of treatment outcomes. Additionally, this review examines the strengths, limitations, and future directions of AI technologies to provide an evidence-based perspective on their potential role in contemporary rhinologic practice.

MATERIALS AND METHODS

Study Design: This systematic review was conducted in accordance with the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020** guidelines. The review aimed to evaluate the current applications of artificial intelligence (AI) in rhinology, with particular emphasis on diagnostic imaging, endoscopic assessment, disease classification, surgical planning, clinical decision support, and prediction of treatment outcomes.

Literature Search Strategy: A comprehensive literature search was performed using **PubMed/MEDLINE, Scopus, Embase, Web of Science, IEEE Xplore Digital Library, and the Cochrane Library** from database inception to **May 31, 2025**. To maximize study identification, the reference lists of eligible articles and relevant review papers were manually screened for additional publications.

The search strategy combined Medical Subject Headings (MeSH) and free-text terms related to artificial intelligence and rhinology using Boolean operators. The principal search strategy was as follows:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Convolutional Neural Network" OR "Computer Vision" OR "Neural Network") AND ("Rhinology" OR "Nasal Disease" OR "Chronic Rhinosinusitis" OR "Sinonasal Disease" OR "Nasal Polyps" OR "Allergic Rhinitis" OR "Endoscopic Sinus Surgery" OR "Paranasal Sinuses") AND ("Diagnosis" OR "Imaging" OR "Computed Tomography" OR "Magnetic Resonance Imaging" OR "Endoscopy" OR "Prediction" OR "Classification" OR "Clinical Decision Support")

The search was restricted to **English-language studies involving human participants**.

Eligibility Criteria: Studies were selected according to predefined eligibility criteria.

Inclusion Criteria

* Original research articles.
* Narrative reviews.
* Systematic reviews.
* Scoping reviews.
* Guideline assessment studies.
* Studies evaluating AI-based techniques, including machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), natural language processing (NLP), large language models (LLMs), or related AI methodologies in rhinology.
* Human studies published in English.

Exclusion Criteria

* Editorials, letters, commentaries, conference abstracts, and expert opinions.
* Case reports and case series.
* Animal or in vitro studies.
* Studies unrelated to AI applications in rhinology.
* Duplicate publications.
* Articles without accessible full text or insufficient methodological data.

Study Selection

All retrieved records were imported into **EndNote X9**, and duplicate citations were removed. Two reviewers independently screened titles and abstracts for potential eligibility. Full-text articles were subsequently assessed against the predefined inclusion and exclusion criteria. Disagreements were resolved through discussion and consensus, with consultation from a third reviewer when necessary. The study selection process is summarized using the **PRISMA 2020 flow diagram**.

Data Extraction

Data extraction was independently performed by two reviewers using a standardized data extraction form. The following variables were collected:

* First author
* Year of publication
* Country
* Study design
* Sample size
* Rhinologic condition
* Clinical application
* AI methodology
* Machine learning model
* Imaging modality (CT, MRI, or endoscopy)
* Performance metrics (accuracy, sensitivity, specificity, and AUC)
* Principal findings
* Clinical implications
* Study limitations

Any discrepancies were resolved through consensus.

Quality Assessment

The methodological quality of the included studies was independently assessed by two reviewers. Diagnostic accuracy studies were evaluated using the **Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2)** tool, whereas observational studies were assessed using the **Newcastle–Ottawa Scale (NOS)**. Narrative reviews, systematic reviews, scoping reviews, and guideline assessment studies were appraised qualitatively because validated risk-of-bias instruments are not applicable to these study designs. Overall methodological quality was categorized as low, moderate, or high risk of bias where appropriate.

Outcome Measures

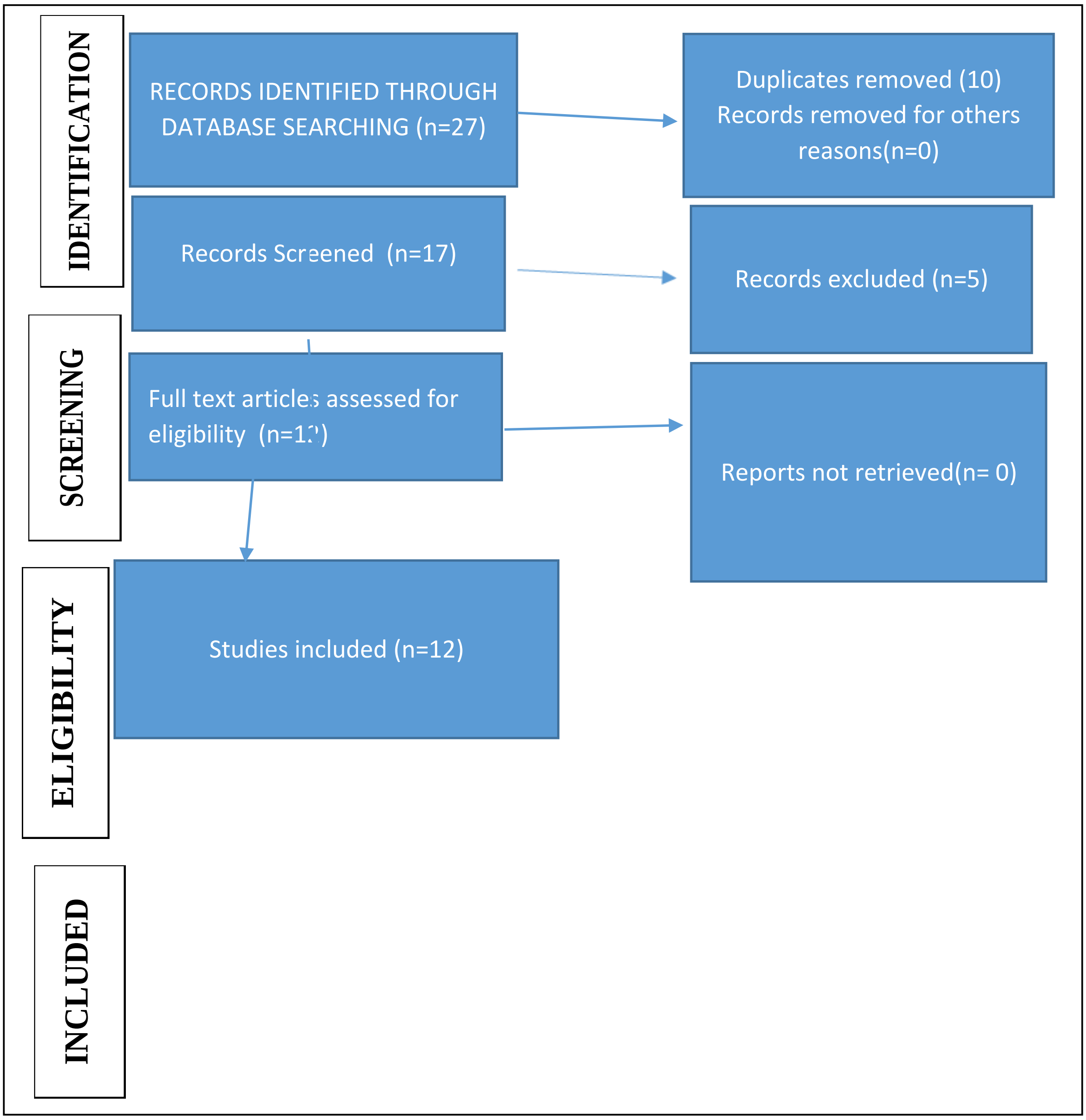
The primary outcome was the diagnostic performance of AI applications in rhinology.
Secondary outcomes included:

* Diagnostic accuracy
* Sensitivity
* Specificity
* Area under the receiver operating characteristic curve (AUC)
* Image classification performance
* Automated anatomical segmentation
* Disease prediction
* Clinical decision support
* Surgical planning
* Prediction of treatment outcomes
* Workflow efficiency
* Clinical applicability

Data Synthesis

Because of substantial heterogeneity in study design, patient populations, AI methodologies, imaging modalities, datasets, and reported outcome measures, quantitative meta-analysis was considered inappropriate. Therefore, findings were synthesized narratively. Studies were grouped according to their primary clinical application, including diagnostic imaging, endoscopic image analysis, disease classification, prognostic prediction, surgical planning, and clinical decision support.

Diagnostic performance measures—including accuracy, sensitivity, specificity, AUC, precision, F1-score, and Dice similarity coefficient—were summarized where available to facilitate comparison across studies.



RESULTS

Study Selection

The database search identified **27 records**. After removal of **10 duplicate records**, **17 studies** underwent title and abstract screening. Five studies were excluded during screening, leaving **12 full-text articles** for eligibility assessment. All 12 articles met the predefined inclusion criteria and were included in the final systematic review. The study selection process is summarized in the **PRISMA 2020 flow diagram** (Figure 1).

Characteristics of Included Studies

The 12 included studies were published between **2019 and 2025** and represented a broad range of study designs, including comparative, observational, experimental, cross-sectional, review, scoping review, and guideline assessment studies. The studies originated from several countries, including the United States, China, Canada, Italy, Turkey, Australia, and Israel.

The AI methodologies evaluated included machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF), XGBoost, U-Net, ResNet, transfer learning models, natural language processing (NLP), and large language models such as ChatGPT and Gemini.

The principal clinical applications of AI comprised automated interpretation of computed tomography (CT) images, endoscopic image analysis, chronic rhinosinusitis classification, nasal polyp detection, cytological image analysis, radiomics, prediction of treatment outcomes, clinical decision support, and assessment of guideline adherence. The characteristics of the included studies are summarized in **Table 1**.

Table 1. Characteristics of Included Studies

Author	Year	Country	Study Design	AI Technique	Clinical Application
Ay et al.	2022	Turkey	Comparative study	CNN, SVM, RF	Nasal polyp classification
Wong et al.	2020	Canada	Observational study	CNN	CT image interpretation
Dimauro et al.	2019	Italy	Experimental study	CNN	Cytological diagnosis
Raghavan et al.	2025	USA	Comparative study	XGBoost, RF, DNN	Outcome prediction
Kaul et al.	2024	Australia	Review study	Machine Learning	Radiomics
Osie et al.	2023	USA	Scoping Review study	ML, DL, CNN	AI applications in rhinology
Wu et al.	2023	China	Review	DL, ResNet, SVM	Diagnostic imaging
Ye et al.	2024	China	Cross-sectional study	ChatGPT	Clinical question answering
Macmath et al.	2023	USA	Review	ML, DL, NLP	Allergy and rhinology
Tessler et al.	2024	Israel	Guideline Assessment	ChatGPT	Guideline adherence
Ramchandani et al.	2023	USA	Comparative study	Gemini, GPT-4	Medical education
Amanian et al.	2024	USA	Scoping Review	ML, CNN, NLP	AI in rhinology

Diagnostic Performance of Artificial Intelligence

Overall, AI demonstrated encouraging diagnostic performance across multiple rhinologic applications. CNN- and DL-based models consistently achieved high accuracy in image-based diagnostic tasks, particularly in CT image interpretation, nasal polyp detection, and cytological image classification.

Reported diagnostic accuracies ranged from approximately **74% to 99%**, depending on the clinical application and AI model. CNN-based systems achieved accuracies of up to **98.3%** for nasal polyp detection and **99%** for cytological image classification, while CT image interpretation yielded an area under the receiver operating characteristic curve (AUC) of **0.93**. Machine learning–based radiomic models demonstrated AUC values ranging from **0.73 to 0.92**, and outcome prediction models using XGBoost and random forest algorithms achieved diagnostic accuracies between **74.5% and 85.5%**. Large language models, including ChatGPT and GPT-4, reported overall accuracies exceeding **80%** in clinical decision-support applications. A summary of diagnostic performance is presented in **Table 2**.

Table 2. Diagnostic Performance of AI Models

AI Technique	Clinical Application	Reported Performance
CNN	Nasal polyp detection	Accuracy up to 98.3%
CNN	CT image interpretation	Accuracy 81%; AUC 0.93
CNN	Cytological diagnosis	Accuracy up to 99%
Machine Learning	Radiomics	AUC 0.73–0.92
XGBoost / RF	Outcome prediction	Accuracy 74.5–85.5%

ChatGPT / GPT-4	Clinical decision support	Overall accuracy >80%

Clinical Applications
Artificial intelligence was applied across several domains of rhinology. Diagnostic imaging constituted the most frequently investigated application, followed by disease classification, radiomic analysis, prognostic prediction, clinical decision support, and surgical planning.

AI-assisted systems were used to improve CT image interpretation, automate nasal polyp detection, classify chronic rhinosinusitis, analyze cytological specimens, evaluate allergic rhinitis, support treatment planning, and assess adherence to clinical practice guidelines. These applications are summarized in **Table 3**.

Table 3. Clinical Applications of Artificial Intelligence

Clinical Area	AI Application
Chronic rhinosinusitis	Disease diagnosis and classification
Nasal polyps	Automated image detection
Sinonasal CT	Image interpretation
Cytology	Automated cellular classification
Allergic rhinitis	Clinical assessment
Surgical decision support	Treatment planning
Guideline adherence	AI-assisted recommendations

Methodological Quality
The methodological quality of the included studies was generally **low to moderate risk of bias**. Diagnostic accuracy studies assessed using QUADAS-2 demonstrated acceptable methodological quality, whereas observational studies evaluated using the Newcastle–Ottawa Scale showed moderate risk of bias, primarily because of retrospective study designs and limited external validation.

Common methodological limitations included relatively small sample sizes, single-center datasets, heterogeneous AI algorithms, and lack of prospective multicenter validation. Studies evaluating large language models also highlighted concerns regarding generalizability and clinical applicability. A detailed summary of the risk-of-bias assessment is presented in **Table 4**.

Table 4. Summary of Risk of Bias

Study	Study Design	Assessment Tool	Overall Risk of Bias	Main Concerns
Ay et al., 2022	Comparative	QUADAS-2	Low	Small sample size; single-center study
Wong et al., 2020	Observational	QUADAS-2	Moderate	Retrospective design; limited external validation
Dimauro et al., 2019	Experimental	QUADAS-2	Low	Limited dataset; lack of multicenter validation
Raghavan et al., 2025	Comparative	Newcastle–Ottawa Scale (NOS)	Moderate	Retrospective data; potential selection bias
Ye et al., 2024	Cross-sectional	Newcastle–Ottawa Scale (NOS)	Moderate	Single-center study; limited generalizability
Ramchandani et al.	Comparative	Newcastle–Ottawa Scale (NOS)	Moderate	AI model comparison without external validation
Tessler et al., 2024	Guideline Assessment	Not applicable*	Moderate	Evaluation based on large language model responses

Future Perspectives
Across the included studies, future research priorities consistently included multicenter prospective validation, development of standardized and diverse datasets, enhancement of explainable AI models, improved interoperability with existing clinical systems, and establishment of regulatory frameworks for safe clinical implementation.

Overall Findings

Collectively, the available evidence indicates that AI has considerable potential to improve rhinologic practice through enhanced diagnostic accuracy, automated image interpretation, disease classification, prognostic prediction, and clinical decision support. Nevertheless, widespread clinical implementation remains constrained by methodological heterogeneity, limited external validation, and the predominance of retrospective studies involving relatively small patient cohorts.

DISCUSSION

This systematic review provides a comprehensive overview of the current applications of artificial intelligence (AI) in rhinology and highlights its growing role in diagnostic imaging, endoscopic assessment, disease classification, surgical planning, clinical decision support, and prediction of treatment outcomes. Across the included studies, AI-based approaches consistently demonstrated promising diagnostic performance, particularly for image-based applications, supporting their potential as valuable adjuncts to conventional clinical practice. Nevertheless, the available evidence remains methodologically heterogeneous, emphasizing that AI technologies are still evolving and require further validation before routine clinical implementation.[12]

One of the principal findings of this review is the rapid expansion of AI-assisted image analysis in rhinology. Convolutional neural network (CNN)-based algorithms achieved high diagnostic accuracy in the interpretation of computed tomography (CT) images, automated detection of nasal polyps, and cytological image classification. These findings are consistent with the broader literature demonstrating the superiority of deep learning models in medical image analysis, where automated feature extraction enables accurate and reproducible classification while minimizing observer-dependent variability. In rhinology, such technologies have the potential to improve diagnostic consistency, facilitate earlier disease detection, and assist clinicians in the evaluation of complex sinonasal disorders.[13]

Beyond diagnostic imaging, AI has demonstrated increasing utility in disease classification and prognostic prediction. Machine learning algorithms, including random forest and XGBoost models, were successfully applied to predict treatment outcomes, estimate disease severity, and support individualized clinical decision-making. These predictive models represent an important step toward precision medicine by integrating clinical, radiological, and pathological information to generate personalized risk estimates. Although these applications remain largely investigational, they illustrate the expanding scope of AI beyond image interpretation alone.[14]

Recent advances in large language models (LLMs), including ChatGPT and Gemini, have further broadened the potential applications of AI in rhinology. The included studies explored their role in clinical decision support, medical education, and evaluation of guideline adherence. While these models demonstrated encouraging performance in knowledge-based tasks, concerns remain regarding factual accuracy, reproducibility, hallucination, and the absence of domain-specific clinical validation. Consequently, LLMs should currently be regarded as supportive educational and decision-assistance tools rather than autonomous clinical systems.[15]

Despite encouraging results, several important limitations were consistently identified across the included studies. Most investigations were retrospective, conducted at single institutions, and based on relatively small datasets, thereby limiting external validity and generalizability. Considerable heterogeneity was observed in AI architectures, imaging protocols, reference standards, annotation strategies, and outcome measures, precluding direct comparison of results across studies. Furthermore, only a limited number of studies reported external validation using independent datasets, an essential prerequisite for reliable clinical deployment.[16]

The successful integration of AI into routine rhinologic practice will require careful consideration of ethical, regulatory, and practical challenges. Algorithm transparency, explainability, patient privacy, data security, and mitigation of algorithmic bias remain fundamental requirements for trustworthy AI systems. Clinicians should retain ultimate responsibility for patient management, with AI serving as an adjunctive tool that complements rather than replaces clinical expertise. Collaborative efforts among clinicians, data scientists, engineers, and regulatory authorities will be essential to ensure the development of safe, transparent, and clinically applicable AI technologies.[17,18]

The findings of this review have several important clinical implications. AI-assisted systems may improve the accuracy and consistency of image interpretation, reduce diagnostic variability, enhance workflow efficiency, and support individualized treatment planning. These benefits may be particularly valuable in high-volume clinical settings and in regions where access to experienced rhinologists is limited. Nevertheless, widespread adoption should await rigorous prospective validation demonstrating improved patient outcomes, cost-effectiveness, and integration into existing healthcare systems.[19,]

This review possesses several strengths. It provides a comprehensive synthesis of the contemporary literature encompassing multiple AI methodologies and diverse rhinologic applications. In addition, methodological quality was systematically evaluated, and the review highlights both the opportunities and current limitations of AI in rhinology. However, the findings should be interpreted in light of several limitations. The evidence base remains relatively small and heterogeneous, precluding quantitative meta-analysis. Furthermore, publication bias and the predominance of retrospective studies may have influenced the reported diagnostic performance of AI models.[20]

Future research should prioritize large-scale multicenter prospective studies incorporating standardized datasets, externally validated algorithms, and transparent reporting according to established AI-specific guidelines. Particular emphasis should be placed on explainable AI, interoperability with electronic health record systems, and assessment of real-world clinical effectiveness. Comparative studies evaluating AI-assisted and clinician-only diagnostic performance, together with cost-effectiveness analyses, will be essential to determine the practical value of AI in routine rhinologic care.[1]

Overall, the current evidence indicates that artificial intelligence has substantial potential to transform rhinologic practice by enhancing diagnostic accuracy, supporting clinical decision-making, and facilitating precision medicine. Although considerable progress has been achieved, further methodological refinement and high-quality clinical validation are necessary before AI can be safely and reliably incorporated into everyday rhinologic practice.

CONCLUSION

Artificial intelligence (AI) is rapidly reshaping the field of rhinology, with expanding applications in diagnostic imaging, endoscopic assessment, disease classification, surgical planning, clinical decision support, and prediction of treatment outcomes. The evidence synthesized in this systematic review indicates that AI-based technologies, particularly machine learning and deep learning algorithms, demonstrate promising diagnostic performance and have the potential to improve diagnostic accuracy, enhance workflow efficiency, reduce interobserver variability, and support personalized patient management.

Despite these encouraging developments, the current evidence remains limited by methodological heterogeneity, retrospective study designs, relatively small datasets, and insufficient external validation. These limitations underscore the need for rigorous multicenter prospective studies, standardized datasets, transparent reporting standards, and robust external validation before AI can be widely implemented in routine rhinologic practice.

Future research should focus on the development of explainable, trustworthy, and clinically validated AI systems that can be seamlessly integrated into existing healthcare workflows while maintaining patient safety, data privacy, and ethical standards. Collaborative efforts among clinicians, engineers, data scientists, and regulatory authorities will be essential to facilitate the responsible translation of AI technologies into everyday clinical practice.

In conclusion, artificial intelligence represents a transformative adjunct rather than a replacement for clinician expertise. With continued technological innovation, rigorous clinical validation, and appropriate regulatory oversight, AI has the potential to become an integral component of precision rhinology, ultimately improving diagnostic accuracy, therapeutic decision-making, and patient outcomes.

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