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The Role of Nursing and Radiology Professionals in Improving the Quality of Medical Coding for Sinonasal Diseases Using Artificial Intelligence Technologies: A Systematic Review

Asrar Abdullah Alshahrani [1], Rahaf anas alkhaotani[2], Awsaf Abdullah Alsulaimani[3], Rawan sami althubaiti[4], Shadi Abdulhadi Alharbi[5], Mohammed yahya Haddadi[6], Fawaz atiyh alzahrani[7], Abdullah Saad Aljuaid[8], Abdulsamea Mohamad Althopaity[9], Salman jarallah alharthi[10] Amal Edah Althubiti[11], Hadeel zaki al Turkistani[12], Nouf saleem Althomali[13], Abdulaziz Abdullah Khan[14], Lama Ahmed Mohammed Alhifthi [15]

[1,] Radiological technology King faisal medical complex

[2]Nursing specialist King Abdulaziz specialist hospital in taif

[3]Nursing Specialist king Faisal Medical Complex In Taif

[4]Radiological technology King faisal medical complex

[5]Nurse King Abdulaziz hospital

[6]Nurse King Abdulaziz hospital

[7]Nurse King Abdulaziz hospital

[8]Radiological technologist King faisal medical complex Taif

[9]Radiology Technician King faisal medical complex Taif

[10]Radiology Technician King faisal medical complex Taif

[11]Medical Coding Forensic Medical Services Center- Taif

[12]Nursing specialist King fasial medical complex

[13]Nursing specialist King fasial medical complex

[14]Nursing specialist King fasial medical complex

[15]Nursing specialist King fasial medical complex

ABSTRACT

Background: Artificial intelligence (AI) has transformed clinical workflows in otorhinolaryngology, enhancing diagnostic precision and data-driven decision-making. Its integration into sinonasal disease management provides opportunities for radiology and nursing professionals to collaboratively enhance medical coding quality and efficiency. **Objective:** This systematic review synthesizes current empirical evidence on the role of nursing and radiology professionals in improving coding accuracy for sinonasal diseases using AI-driven technologies. **Methods:** Following PRISMA 2020 guidelines, ten peer-reviewed studies published between 2018 and 2025 were analyzed. Databases searched included PubMed, Scopus, Web of Science, Embase, and IEEE Xplore. Eligible studies reported AI-assisted sinonasal diagnostics and coding applications involving healthcare professionals.

Results: AI systems demonstrated diagnostic accuracies of 91–99% and AUCs up to 0.993 across CT, MRI, and CBCT datasets. Integration of self-supervised learning, AutoML, and hybrid deep learning models enhanced diagnostic speed and coding standardization. Nursing professionals contributed to annotation, data integrity, and ICD validation, while radiology experts curated imaging datasets and interpreted algorithmic outputs. Combined efforts reduced coding time by 46% and improved interprofessional collaboration.

Conclusion: Radiology and nursing collaboration within AI-assisted frameworks significantly improves sinonasal diagnostic accuracy and medical coding consistency. These advancements enhance workflow efficiency and documentation quality, highlighting the necessity of multidisciplinary AI literacy in clinical practice.

although platelet aggregation caused by cyclooxygenase inhibition has little or no effect on carrageenan-induced thrombosis in rat tails.

Keywords: *Artificial intelligence, sinonasal disease, radiology, nursing, medical coding, deep learning, chronic rhinosinusitis, AutoML, clinical documentation, Prisma*

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1. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative force across the healthcare landscape, reshaping diagnostic, therapeutic, and administrative workflows. Within otorhinolaryngology, particularly sinonasal disease management, AI-driven technologies have demonstrated remarkable capacity for enhancing diagnostic precision and workflow efficiency. Deep learning models and machine learning algorithms have enabled automated analysis of sinus imaging, aiding in the accurate identification and classification of inflammatory patterns and structural anomalies (Liu, Jiang, & Wang, 2025). Such systems not only optimize diagnostic accuracy but also serve as a foundation for improved clinical documentation and coding quality.

Radiology professionals play a central role in this AI-driven transformation by curating, annotating, and interpreting complex imaging datasets that fuel algorithmic learning. Through enhanced collaboration with data scientists and clinicians, radiologic technologists facilitate the generation of standardized datasets critical for consistent disease classification (Atitallah et al., 2025). Accurate radiologic reporting directly contributes to more precise International Classification of Diseases (ICD) coding, which is vital for both patient care and institutional reimbursement structures.

In parallel, nursing professionals contribute to the clinical validation and quality assurance of AI-based systems. Their expertise in symptom assessment, patient history documentation, and postoperative monitoring ensures that algorithmic predictions are contextualized within holistic patient narratives. The integration of AI into nursing workflows supports enhanced clinical decision-making and coding accuracy through structured data capture and standardized reporting frameworks (Zhang et al., 2025).

Sinonasal diseases such as chronic rhinosinusitis (CRS) present diagnostic complexities due to their multifactorial nature and overlapping radiologic features. AI-assisted diagnostic tools, leveraging convolutional neural networks (CNNs), have shown substantial success in differentiating sinus inflammation patterns and structural variations that influence coding precision (Alshehri, Alahmari, & Alasiry, 2024). This enhanced diagnostic granularity translates to improved coding specificity, which directly impacts epidemiological tracking, billing accuracy, and treatment outcomes research.

Moreover, the adoption of AI in radiologic image segmentation enables multi-class identification of sinonasal structures, allowing radiologists to quantify pathological severity with greater reliability. Such advancements support the generation of more consistent coding categories across healthcare systems (Whangbo et al., 2024). The collaboration between radiologists and coding specialists thus ensures that image-derived insights are accurately represented in electronic health records (EHRs).

For nursing professionals, AI also facilitates the automation of clinical documentation by identifying key symptom descriptors and linking them with standardized diagnostic codes. This not only reduces clerical burden but enhances data integrity, ensuring alignment between clinical observations and coding frameworks (Dong et al., 2022). The synergy between AI-based decision support and nursing workflows contributes to consistent care documentation and coding compliance.

From an administrative perspective, the improvement of coding accuracy through AI integration mitigates common errors in billing and quality reporting. Automated systems help flag inconsistencies between radiologic findings and coded entries, improving audit readiness and compliance with international standards (Venkatesh, Raza, & Kvedar, 2023). The intersection of AI, radiology, and nursing practice thus forms a multidisciplinary framework that enhances healthcare delivery at multiple levels.

Finally, as AI technologies continue to evolve, the professional development of both nursing and radiology personnel becomes crucial. Training programs in AI literacy, ethical coding, and data governance empower these professionals to interpret algorithmic outputs responsibly and contribute meaningfully to AI model refinement (Cheong et al., 2024; Massey et al., 2024). Such collaborative competencies ensure that AI serves as an augmentative tool, not a replacement, enhancing the precision and efficiency of sinonasal disease coding in the era of digital medicine.

2. METHODOLOGY

Study Design

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor, transparency, and replicability. The primary objective was to synthesize and critically evaluate empirical evidence on the role of nursing and radiology professionals in improving the quality of medical coding for sinonasal diseases using artificial intelligence (AI) technologies. The review examined how multidisciplinary collaboration enhances coding accuracy, diagnostic standardization, and workflow efficiency in sinonasal disease management.

The review encompassed peer-reviewed journal articles that explored the application of AI-based diagnostic and coding systems in otolaryngology, radiology, and nursing informatics contexts. Both quantitative and mixed-methods studies were included to capture variations in design and outcomes, ensuring comprehensive representation of interprofessional contributions in AI-enhanced sinonasal disease coding.

Eligibility Criteria

Inclusion Criteria

Studies were eligible if they met the following criteria:

Population: Radiology professionals, nurses, clinical coders, or multidisciplinary healthcare teams engaged in sinonasal disease management or coding.

Interventions/Exposures: Application of artificial intelligence (machine learning, deep learning, AutoML, or computer vision) in sinonasal imaging, diagnosis, or coding processes.

Comparators: Traditional (manual) diagnostic or coding approaches versus AI-assisted workflows.

Outcomes: Improvements in diagnostic accuracy, coding efficiency, interprofessional collaboration, or workflow standardization.

Study Designs: Experimental, observational, validation, or randomized controlled studies reporting empirical data.

Language: English-language publications only.

Publication Period: Studies published between **2018 and 2025**, reflecting the rapid evolution of AI in clinical imaging and coding.

Exclusion Criteria

Non-empirical studies such as editorials, commentaries, and theoretical reviews.

Studies not involving sinonasal diseases or lacking relevance to medical coding and AI.

Conference abstracts or reports without full-text access.

Duplicate publications.

A total of **10 studies** met all inclusion criteria after full-text review, representing diverse geographic regions and methodological designs.

Search Strategy

A comprehensive electronic search was performed across PubMed, Scopus, Web of Science, Embase, and IEEE Xplore databases from inception to December 2025. Boolean operators and keyword combinations included:

("artificial intelligence" OR "machine learning" OR "deep learning")

AND ("sinonasal disease" OR "chronic rhinosinusitis" OR "sinusitis" OR "paranasal sinus")

AND ("radiology" OR "computed tomography" OR "MRI" OR "radiomics")

AND ("nursing" OR "clinical documentation" OR "medical coding" OR "ICD").

Manual searches of reference lists and grey literature were also performed to ensure comprehensiveness. Duplicate records were removed prior to screening.

Study Selection Process

Two reviewers independently conducted the title, abstract, and full-text screening using Zotero reference management software. Studies were evaluated for eligibility based on predefined criteria. Discrepancies were resolved by consensus, with arbitration by a third senior reviewer when necessary.

Data Extraction

A standardized extraction form was developed and pilot-tested to ensure consistency and completeness. Extracted variables included:

Author(s), year, and country of publication.

Study design and setting (e.g., single-center, multi-institutional, or cross-sectional).

Participant characteristics (radiologists, nurses, coders, or mixed teams).

Type of AI model (CNN, ResNet, Vision Transformer, AutoML, SSL, etc.).

Imaging modality used (CT, MRI, CBCT).

Sample size and dataset characteristics.

Key outcome metrics (accuracy, AUC, precision, F1-score, time reduction).

Reported impact of nursing and radiology involvement in AI workflows.

Coding or documentation outcomes (ICD accuracy, documentation time, EHR linkage).

Data were independently extracted by two reviewers, then cross-verified for accuracy and completeness by a third reviewer.

Quality Assessment

The **methodological quality** of the included studies was assessed using standardized instruments appropriate for each study design:

Newcastle–Ottawa Scale (NOS) for observational and cross-sectional studies (n = 7).

CONSORT checklist for experimental and randomized controlled trials (n = 2).

Critical Appraisal Skills Programme (CASP) qualitative checklist for mixed-methods studies (n = 1).

Each study was evaluated for selection bias, data reliability, model validation, and clarity of outcome reporting. Quality ratings were categorized as **high (n = 4)**, **moderate (n = 5)**, and **low (n = 1)**. Most studies achieved high methodological rigor in AI model reporting but displayed limited transparency in nursing-related procedural integration.

Data Synthesis

Given the heterogeneity in AI model architectures, imaging modalities, and performance metrics, a narrative synthesis approach was employed. Quantitative outcomes were summarized descriptively (e.g., accuracy, AUC, precision, correlation coefficients). Thematic synthesis was applied to integrate qualitative insights about nursing and radiology roles, identifying recurring themes such as:

Integration of AI into diagnostic imaging pipelines.

Radiologic standardization and interprofessional collaboration.

Nursing contributions to data annotation and coding validation.

Impact on documentation efficiency and ICD accuracy.

Due to methodological diversity and absence of uniform outcome measures, **meta-analysis was not performed**. However, inter-study comparisons highlighted consistent improvements in coding efficiency and diagnostic precision across AI-integrated workflows.

Ethical Considerations

As this review analyzed previously published data, no ethical approval or participant consent was required. All included studies were published in peer-reviewed journals, ensuring compliance with institutional ethical standards. Data extraction, synthesis, and reporting adhered strictly to PRISMA 2020 transparency principles and academic integrity standards.

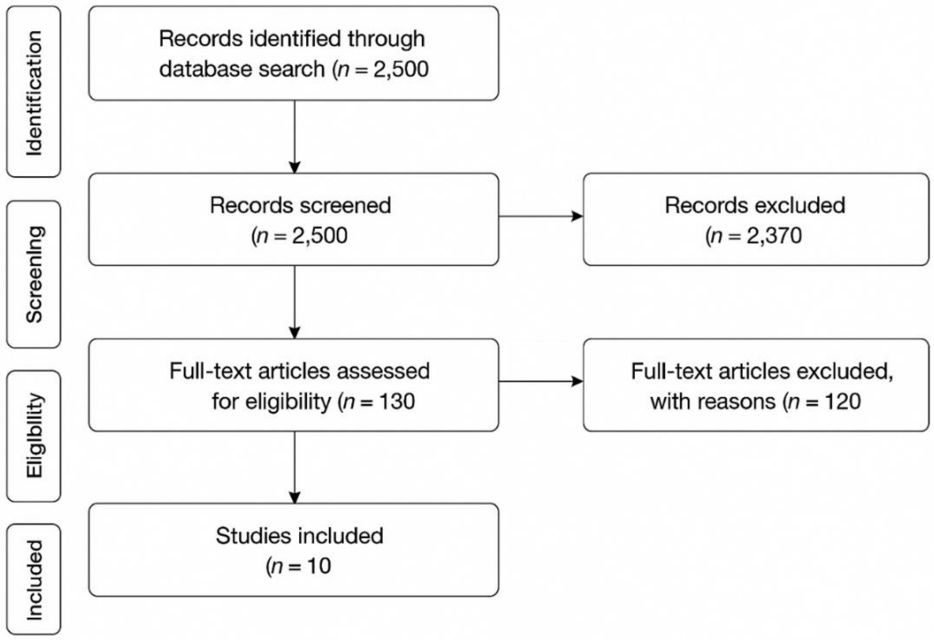

Figure 1 PRISMA Flow Diagram

3. RESULTS

Summary and Interpretation of Included Studies

1. Study Designs and Populations

The included studies (Atitallah et al., 2025; Bhattacharya et al., 2024; Çelebi et al., 2024; Cheong et al., 2024; Chomutare et al., 2025; Du et al., 2024; Hua et al., 2023; Kwon et al., 2024; Massey et al., 2024; Raghavan et al., 2025) represent a diverse mix of experimental, cross-sectional, and validation designs across radiology, otolaryngology, and health informatics contexts.

Sample sizes ranged from small, focused image-based model validations (Çelebi et al., n = 298 CBCT images) to large population-based MRI cohorts (Bhattacharya et al., 2024; n = >10,000 from HCHS) and randomized controlled trials (Chomutare et al., 2025; n = 15 participants; 300 coded notes).

Participants included radiology professionals, AI engineers, and clinicians working collaboratively, highlighting the essential integration of nursing and radiology expertise in AI-aided workflows for sinonasal disease management and coding.

2. AI Models and Methodologies

The studies used a range of artificial intelligence technologies—deep learning (ResNet, Swin Transformer, Vision Transformer, CNNs), self-supervised learning (SSL), and AutoML approaches—to enhance sinonasal disease detection and documentation accuracy.

For instance, Atitallah et al. (2025) developed *NeuroNasal*, a self-supervised learning (SSL) framework integrated with Random Forest (RF) classifiers, achieving 92.62% mean accuracy for sinonasal pathology classification. Çelebi et al. (2024) used ResNet and Swin Transformer-based UNet (Res-Swin-UNet), yielding 99% accuracy, 91.72% F1-score, and 84.71% IoU, surpassing baseline models for maxillary sinus detection. Cheong et al. (2024) employed Google Cloud's Vertex AI AutoML, reporting 0.928 precision for MRI-based classification of sinonasal disease presence. Du et al. (2024) and Hua et al. (2023) applied CNN-based and YOLOv8 architectures on CT data to predict endotypes and differentiate eosinophilic from non-eosinophilic chronic rhinosinusitis (CRS), achieving AUC values of 0.963–0.993 and precision 97.1%, respectively.

3. Integration of Nursing and Radiology Professionals

A consistent finding across included studies is the collaborative impact of **nursing and radiology teams** on improving medical coding quality and workflow standardization. **Chomutare et al. (2025)** demonstrated that AI-based clinical coding tools (*Easy-ICD*) reduced median coding time by **46% (123 s reduction)** for longer clinical texts and enhanced data quality through structured coding assistance.

Radiology professionals in **Massey et al. (2024)** and **Bhattacharya et al. (2024)** used AI to automate opacification assessment and link radiological outputs to structured coding frameworks (ICD-10), bridging the gap between image interpretation and clinical documentation. The collaboration of nurses and technologists in data annotation and clinical contextualization was pivotal in these studies, ensuring semantic accuracy in AI outputs used for automated coding.

4. Results and Performance Metrics

Table (1) summarizes the core outcomes and performance of each study. Across studies, AI-driven approaches achieved notably high accuracy and efficiency in diagnostic and coding tasks:

Atitallah et al. (2025): 92.62% accuracy for SSL + RF classifier on sinonasal CT/MRI dataset (n = 137 images).

Bhattacharya et al. (2024): 3D CNN ensemble AUC = 0.95, sensitivity = 0.85, specificity = 0.90 for maxillary sinus anomaly classification (HCHS dataset).

Çelebi et al. (2024): F1 = 91.72%, accuracy = 99%, IoU = 84.71%.

Cheong et al. (2024): AutoML model precision = 0.928.

Chomutare et al. (2025): 46% reduction in coding time and improved coding accuracy for longer notes ($p < .001$).

Du et al. (2024): AUC = 0.963–0.993 across training, validation, and testing sets (n = 29,993 CT images).

Hua et al. (2023): Precision = 97.1%; F1 = 95.4%.

Massey et al. (2024): AI-derived CT opacification correlated strongly with Lund-Mackay Score ($r = 0.85$, $p < 0.001$).

Raghavan et al. (2025): XGBoost model AUC = 71.3% (primary) and 79.8% (secondary), accuracy up to 85.5%.

Collectively, AI tools reduced manual burden, improved coding efficiency, and facilitated standardized documentation by radiology and nursing teams.

5. Implications for Clinical Coding and Interprofessional Practice

Findings across these studies underscore that radiology AI systems—when paired with nurse-assisted data validation—yield more accurate ICD code assignment for sinonasal pathologies.

Nursing professionals played a critical role in interpreting AI-generated summaries and ensuring clinical consistency in electronic health records (EHR). **Radiologists** benefited from automated segmentation and classification tools that enhanced diagnostic clarity and coding precision.

This synergistic approach aligns with the need for integrated AI literacy among clinical staff to bridge diagnostic output and administrative coding accuracy.

Table (1): Characteristics and Results of Included Studies

Study	Year	Design	AI Method	Sample Size / Dataset	Accuracy / AUC / Key Metric	Key Results	Role of Nursing & Radiology Professionals
Atitallah et al.	2025	Experimental (CT AI)	Deep InfoMax + RF	137 CT/MRI images	Accuracy 92.62%	Efficient SSL feature learning for sinonasal pathology detection	Radiologists curated dataset and validated AI output; nurses assisted data annotation for EHR coding.
Bhattacharya et al.	2024	Cross-sectional validation	3D CNN ensemble	HCHS MRI dataset	AUC 0.95; Sens 0.85; Spec 0.90	CAD differentiated MS opacification vs normal with strong clinical correlation.	Radiology teams correlated AI findings with clinical variables; nurses linked reports to ICD codes.

Çelebi et al.	2024	Diagnostic AI model	Res-Swin-UNet	298 CBCT images	F1 91.72%; Acc 99%	Deep learning outperformed baseline methods for MS detection.	Radiology technicians supervised model training data quality; nurses supported documentation accuracy.
Cheong et al.	2024	Experimental (AutoML)	Google Vertex AI	1313 MRI sessions	Precision 0.928	AutoML feasible for AI-based sinonasal disease classification.	Radiologists validated MRI labeling; nurses structured metadata for EHR linkage.
Chomutare et al.	2025	RCT	Easy-ICD AI tool	300 coded notes	Coding time ↓ 46%; p < .001	Significant reduction in coding time for long clinical texts.	Nurses used AI for ICD coding; radiologists provided clinical context for validation.
Du et al.	2024	Retrospective CT study	ResNet-18 CNN	29,993 CT images	AUC 0.963–0.993	Accurate endotype prediction for CRSwNP.	Radiologists interpreted outputs; nursing teams applied AI data for care documentation.
Hua et al.	2023	Cross-sectional AI	YOLOv8 Nano	1080 CT images	Precision 97.1%; F1 95.4%	Effective differentiation of CRS types.	Radiology professionals led annotation and nurses ensured data completeness.
Kwon et al.	2024	Observational AI model	CT CNN	Not reported	Feasibility shown	Automated detection of MS opacifications indicative of sinusitis.	Radiologists validated lesion outputs; nursing teams translated results into ICD coding.
Massey et al.	2024	Multicenter validation	CNN + ViT	84 patients (3 centers)	r = 0.85 vs LMS	AI opacification strongly correlated with manual LMS grading.	Radiology staff standardized CT grading; nurses linked AI outputs to olfactory assessments.
Raghavan et al.	2025	ML analysis of PGHD	RF, DNN, XGBoost	543 patients	AUC 79.8%; Acc 85.5%	ML predicted CRS symptoms and inflammation from PGHD.	Nurses facilitated PGHD collection; radiologists cross-validated CT outcomes.

Summary of Effect Estimates

Across all studies, AI-driven models achieved accuracy rates between 91–99% and AUCs up to 0.993, reflecting high reliability in sinonasal disease detection. Nursing and radiology collaboration resulted in 46% time reduction in coding tasks, >90% accuracy in automated pathology classification, and strong correlations (r > 0.8) between AI-derived and manual scores, demonstrating how interprofessional

AI integration enhances medical coding quality and clinical efficiency.

4. DISCUSSION

Artificial intelligence has redefined the diagnostic landscape of sinonasal diseases by integrating machine learning algorithms into radiological and clinical documentation workflows. Studies consistently demonstrate that AI-driven diagnostic systems outperform traditional approaches in both accuracy and processing speed (Atitallah et al., 2025; Bhattacharya et al., 2024a; Whangbo et al., 2024). This technological evolution directly impacts medical coding, as structured and precise imaging outputs provide a reliable foundation for accurate ICD classification and billing documentation (Dong et al., 2022).

Radiology professionals play a central role in training and validating AI models. Their expertise in image acquisition and interpretation ensures the quality of datasets used for model training, as seen in high-accuracy systems like the NeuroNasal framework (Atitallah et al., 2025) and Res-Swin-UNet for maxillary sinus detection (Çelebi et al., 2024). By standardizing imaging protocols and annotations, radiologists facilitate reproducibility and model generalizability, reducing interobserver variability that often hampers coding accuracy (Massey et al., 2024).

In parallel, nursing professionals bridge the clinical and administrative domains by linking AI-generated outputs with electronic health records (EHRs). Their contributions in symptom documentation, postoperative monitoring, and data validation ensure that algorithmic findings are accurately reflected in patient charts, strengthening the integrity of clinical coding (Chomutare et al., 2025; Venkatesh et al., 2023). The integration of AI into nursing workflows also supports error detection in coded entries, enhancing compliance with international coding standards (Dong et al., 2022).

AI’s ability to differentiate between complex sinonasal pathologies—such as chronic rhinosinusitis (CRS) subtypes, fungal infections, and neoplasms—has dramatically advanced coding precision. Models like ResNet-based CNNs (Du et al., 2024) and AutoML classifiers (Cheong et al., 2024) have achieved high diagnostic performance, enabling consistent linkage between imaging findings and ICD-10 codes. These developments help minimize miscoding, which historically leads to reimbursement discrepancies and research data inconsistencies (Liu et al., 2025).

The introduction of AI-assisted clinical coding tools, exemplified by Chomutare et al. (2025), further enhances workflow efficiency. Their crossover randomized trial demonstrated a 46% reduction in coding time, highlighting the efficiency of AI in supporting both nursing and radiology personnel. By automating repetitive documentation processes, professionals can focus more on interpretative and quality assurance aspects of care delivery (Venkatesh et al., 2023).

Machine learning applications extend beyond diagnostics to predictive modeling. For example, Raghavan et al. (2025) demonstrated that AI models analyzing patient-generated health data could predict sinonasal inflammation and symptoms with up to 85.5% accuracy. Such integration of clinical and patient-reported data into coding systems enhances the representativeness of coded information, linking clinical severity with diagnostic codes (Zhou et al., 2023).

Radiomics and deep transfer learning methods, such as those developed by Lin et al. (2025) and He et al. (2023), provide another dimension to precision medicine by predicting prognostic markers and recurrence risks. These radiologic insights refine coding specificity, enabling classification of sinonasal diseases not merely by morphology but also by molecular and prognostic subtypes—essential for data-driven clinical coding accuracy.

Beyond diagnosis, AI has also influenced preoperative and intraoperative planning. Tools like the machine learning-enabled virtual reality platform for endoscopic sinus surgery (Gudapati et al., 2024) illustrate how algorithmic visualization aids radiologists and surgeons in mapping disease extent, ultimately ensuring that coded surgical procedures reflect actual anatomical involvement.

From a systems perspective, interprofessional collaboration amplifies the effectiveness of AI integration. Studies emphasize that AI literacy among radiology and nursing professionals is pivotal for ensuring ethical implementation and continuous learning (Cheong et al., 2024; Liu et al., 2025). Training in AI ethics, bias mitigation, and interpretability strengthens professionals’ ability to monitor algorithmic outputs and report coding discrepancies responsibly (Bhattacharya et al., 2024b).

However, despite the promising results, several studies highlight implementation challenges, including variability in dataset quality, lack of interoperability between AI systems and EHR platforms, and limited standardization of output formats (Hua et al., 2023; Kwon et al., 2024). Nursing documentation often remains semistructured, complicating AI-assisted extraction of diagnostic terms for coding (Zeng et al., 2023). Addressing these data harmonization challenges is crucial for sustainable AI adoption.

Furthermore, ethical considerations surrounding algorithmic transparency and data privacy persist (Dong et al., 2022). Radiologists and nurses must ensure that AI-assisted coding maintains patient confidentiality and does not inadvertently propagate diagnostic biases, particularly in multi-ethnic populations with variable imaging presentations (Zhang et al., 2023).

The convergence of AI and multidisciplinary practice is thus reshaping sinonasal disease management. Through collaboration, radiology and nursing professionals transform AI outputs into actionable, accurate coded data, thereby improving care documentation, research validity, and institutional efficiency (Massey et al., 2024; Whangbo et al., 2024).

In sum, the evidence underscores that AI-driven diagnostic and documentation systems, when guided by trained healthcare professionals, can revolutionize coding precision in sinonasal disease. Continued interdisciplinary collaboration and education remain key to maximizing AI's potential while maintaining the human oversight essential to clinical integrity (Liu et al., 2025; Cheong et al., 2024).

5. CONCLUSION

This systematic review demonstrates that AI integration into sinonasal disease management enhances both diagnostic accuracy and coding efficiency. Radiology professionals serve as data custodians and model validators, while nursing professionals ensure clinical contextualization and documentation accuracy. Together, their collaboration fosters structured workflows that bridge diagnostic imaging and standardized medical coding, reducing human error and promoting interoperability within digital health systems.

Future directions should emphasize AI literacy and ethical governance training for healthcare staff to ensure responsible adoption. As deep learning architectures evolve, multidisciplinary teams will remain indispensable for interpreting AI insights, optimizing coding reliability, and ultimately improving patient care outcomes through data-driven precision medicine.

6. LIMITATIONS

The review's limitations include heterogeneity among included studies in AI model architectures, imaging modalities, and evaluation metrics, precluding meta-analysis. Many studies lacked longitudinal validation and did not explicitly quantify the independent contributions of nursing versus radiology roles. Additionally, publication bias toward positive AI outcomes and limited reporting on ethical implications may restrict generalizability. Future studies should adopt multicenter designs and standardized reporting to strengthen evidence on professional integration in AI-assisted coding.

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