The Evolution and Application of Artificial Intelligence in Rhinology: A State of the Art Review

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Abstract

Objective. To provide a comprehensive overview on the applications of artificial intelligence (AI) in rhinology, highlight its limitations, and propose strategies for its integration into surgical practice.

Data Sources. Medline, Embase, CENTRAL, Ei Compendex, IEEE, and Web of Science.

Review Methods. English studies from inception until January 2022 and those focusing on any application of AI in rhinology were included. Study selection was independently performed by 2 authors; discrepancies were resolved by the senior author. Studies were categorized by rhinology theme, and data collection comprised type of AI utilized, sample size, and outcomes, including accuracy and precision among others.

Conclusions. An overall 5435 articles were identified. Following abstract and title screening, 130 articles underwent full-text review, and 59 articles were selected for analysis. Eleven studies were from the gray literature. Articles were stratified into image processing, segmentation, and diagnostics (n = 27); rhinosinusitis classification (n = 14); treatment and disease outcome prediction (n = 8); optimizing surgical navigation and phase assessment (n = 3); robotic surgery (n = 2); olfactory dysfunction (n = 2); and diagnosis of allergic rhinitis (n = 3). Most AI studies were published from 2016 onward (n = 45).

Implications for Practice. This state of the art review aimed to highlight the increasing applications of AI in rhinology. Next steps will entail multidisciplinary collaboration to ensure data integrity, ongoing validation of AI algorithms, and integration into clinical practice. Future research should be tailored at the interplay of AI with robotics and surgical education.

Artificial intelligence (AI) has been quickly expanding within the health care domain, as it utilizes complex algorithms and sophisticated computation to perform human cognitive tasks at astronomical speed.[1-3] Given its promise for transforming medicine, it has seen increasing applications ranging from disease diagnosis to prognostication, treatment planning, and optimization of surgical efficiency.[3-5] Due to its rapid and ongoing development, it is vital for a clinician to be aware of recent advances and consider its application in surgical practice.

Machine learning (ML) and deep learning (DL) are subsets of AI, which have recently become more commonplace due to the increased availability of computational power (Supplemental Table S1, available online).[1] Additionally, the presence of big data has given ML the capability to make clinical predictions by identifying patterns within data, typically not identifiable by humans.[1] Furthermore, such algorithms utilize techniques that identify nonlinear relationships among data variables and in various settings, and they have demonstrated superior performance when compared with traditional statistics.[1] DL employs computations in multiple layers with methodologies that perform automated image segmentation or delineate phases within a surgical operation.[6] Within otolaryngology, DL's applications have ranged from image segmentation for diagnosis of maxillary sinusitis to differentiation of inverted papilloma (IP) from IP with malignant transformation.[7,8]

Due to the popularity of AI and its novel research outcomes, previous publications have introduced AI and its applications within otolaryngology.[9-11] Rhinology is a subspecialty that has seen a myriad of technological advances,

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such as image-guided surgical navigation.[12] Therefore, it is no surprise that there has been an increasing number of AI research within rhinology, given its promise to augment surgical practice and enhance patient-centered care.[13]

Although integration of technological advances such as ML, DL, and computer vision into current rhinologic practice is vital, it is still in its infancy, and the otolaryngologist must understand its fundamentals and potential surgical application. This state of the art review aims to review the current literature related to applications of AI in rhinology, discuss existing limitations, highlight areas of promise, identify gaps for future research, and provide otolaryngologists with an overview of the applications of AI in rhinology.

Methods

A preliminary search on AI in rhinology was done, which yielded a small number of articles. Therefore, a scoping review was conducted to capture a wider breadth of articles. The review protocol was published on the Open Science Framework (doi:10.17605/OSF.IO/5K2GB). The reporting of this scoping review was conducted in accordance with the PRISMA-ScR statement (Preferred Reporting Items for Systematic Reviews and Meta-analyses Extension for Scoping Reviews).[14] Risk of bias was not assessed in this review; however, the quality of literature was assessed via levels of evidence defined by the Oxford Centre for Evidence-Based Medicine.[15]

Data Sources and Search Strategy

To identify relevant articles, a search was performed with the following databases from the date of inception until January 2022: MEDLINE, Embase, Cochrane Central Register of Controlled Trials, Ei Compendex, IEEE, and Web of Science Core Collection. The ClinicalTrials.gov registry was also screened for related ongoing trials. Gray literature was included, specifically conference proceedings identified from database and registry searches. The search strategy was developed with the assistance of 2 institutional medical librarians and consisted of 2 concepts: AI (ML, DL, neural network, computer vision, and robotics) and rhinology. These concepts and their related terms and synonyms were combined through relevant Boolean operators (Supplemental Appendix A, available online). The search strategy was modified for syntax where required.

Study Selection

All publications obtained from the databases were exported to a systematic review management software (Covidence; Veritas Health Innovation Ltd). Duplicate studies were removed by this software. Articles were included if they focused on AI applications in rhinology. Exclusion criteria were as follows: AI in histopathology, nonautonomous robotic surgery, non-English studies, secondary literature, in vitro or animal studies, and lack of abstract or full-text access.

Search results were reviewed independently by title and abstract by 2 authors (A.A. and A.H.) with resolution of discrepancies by the senior author (A.T.). Short-listed articles were reviewed in full for eligibility by the 2 reviewers (A.A. and A.H.).

A final list of articles from each reviewer was compared and combined. A final list was presented to the supervising author for approval. Authors were not blinded to the journal, authors, or institution.

Main Outcomes and Data Extraction

The main outcomes extracted revolved around AI performance and included area under the curve, sensitivity, specificity, accuracy, Dice similarity coefficient, and F score. The Dice similarity coefficient is an accuracy metric used in medical image segmentation that measures degree of overlap between 2 volumes and ranges from 0 (no overlap) to 1 (perfect overlap).[16] F score, a measure of accuracy, attempts to combine the precision and recall within a model.[17] Overall, the measured outcomes allowed authors to comment on the accuracy of AI technologies in rhinology. Reviewers extracted relevant data from the articles in duplicate to reduce bias and error. Data were extracted with a predefined template that included study type, level of evidence, author, year, objective, AI type, sample size, methodology, and performance outcomes. No uncertainties arose during the data extraction process.

Synthesis of Results

Given the heterogeneity present in the studies within this review, a meta-analysis was not performed. Furthermore, the data were synthesized in a narrative fashion.

Results

Characteristics of Included Studies

The search strategy yielded 5435 articles after duplications were removed. A total of 5305 articles were excluded during title and abstract screening due to the publications not meeting the inclusion criteria or successfully fulfilling the exclusion criteria. This resulted in 130 articles that were sought for retrieval and assessment for eligibility (**Figure 1**). Articles were excluded due to wrong intervention (n = 14), study design (n = 30), outcomes (n = 4), incorrect medical field (n = 12), lack of full-text access (n = 8), and non-English language (n = 3). After exclusion of these articles, 59 were included in this review, with 11 coming from gray literature, mainly conference proceedings. These were stratified into various categories (Supplemental Tables S2-S9, available online): image processing, segmentation, and diagnostics (n = 27); rhinosinusitis classification (n = 14); treatment and disease outcome prediction (n = 8); optimizing surgical navigation and phase assessment (n = 3); robotic surgery (n = 2); olfactory dysfunction (n = 2); and diagnosis of allergic rhinitis (n = 3). The frequency of publications increased with time, as 76% of publications occurred from 2016 to 2021, 16% from 2010 to 2015, and 8% from 2004 to 2009 (**Figure 2**). This reflects the increased relevance and popularity of AI applications within rhinology in recent years.

Level of Evidence

The level of evidence based on the Oxford Centre for Evidence-Based Medicine pertaining to the included studies can be referenced in the tables for each category.[15] As expected, there was
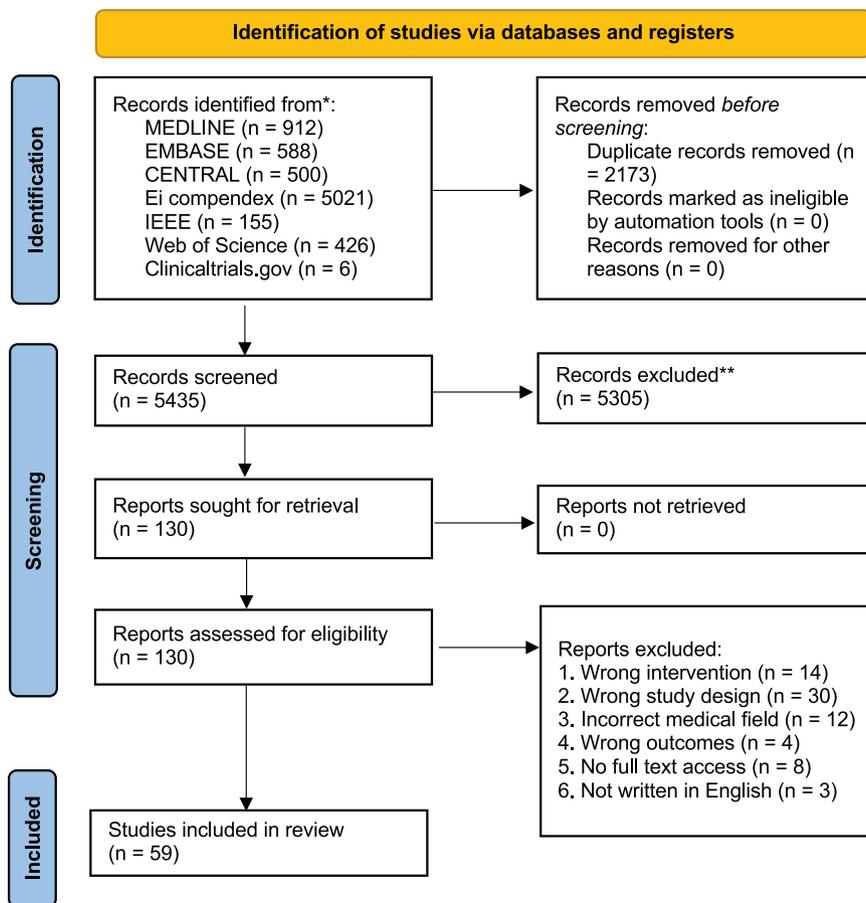
Figure 1. PRISMA flowchart of study identification.

significant heterogeneity in the study design, objective, and results. Overall, the level of evidence ranged from 2 to 5.

Discussion

Review of AI

In general, AI is broadly separated into ML and natural language processing.[9] The subsets of AI are briefly introduced to serve as a primer prior to summarizing the results of this review (Supplemental Table S1, available online). However, more in-depth information on the components of AI can be found in a review article written by Bur et al.[9] Within ML, subsets can be divided into supervised learning and unsupervised learning.[3] ML models are typically developed by splitting a data set into a training and testing set.[18] In supervised learning, each point within a data set has an associated label, and the model is then validated via assessment of the testing set.[18] Within otolaryngology, supervised learning has been used for classification of disease, including diagnosis of peritonsillar abscess,[19] prediction of hearing outcome following sudden sensorineural hearing loss,[20] and detection of oropharyngeal carcinoma,[21] among others. Unsupervised learning, however, aims to identify patterns from unlabeled data.[22] For example, clustering, a form of unsupervised learning, assesses an unlabeled data set to identify clusters to which a patient population may belong.[22] This can especially be useful when
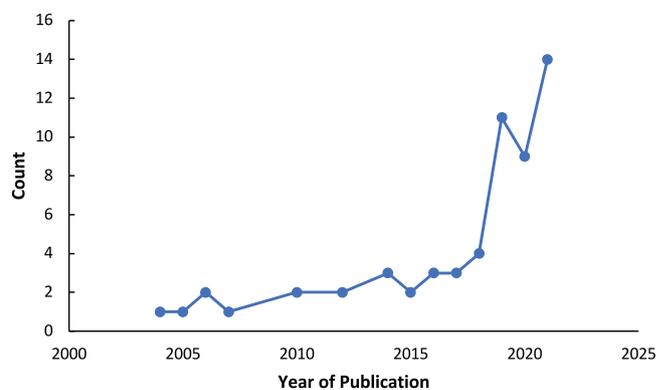

Figure 2. Trend of publications focusing on the application of artificial intelligence in rhinology.

there are subtle differences present within the study population typically difficult to directly discern.[22] Finally, DL has recently seen an uprise in use due to the advent of computational power and availability of large data sets.[23] DL algorithms can be used for classifying an image for diagnostics (eg, tumor vs no tumor) or segmentation (delineating a region of interest within an image such as a tumor).[23] In otolaryngology, DL has shown an ability to predict extranodal extension with high accuracy[24] and detect thyroid nodules on ultrasound images.[25] The advantage of DL is the ability to automate

image segmentation and classification and avoid the manual labor of image labeling; however, training of such algorithms requires a large data set, manual work up-front, and advanced computational throughput.[2]

Several themes were identified in this state of the art review. The studies have therefore been synthesized into categories in which otolaryngologists come across in their daily clinical practice (Supplemental Tables S2-S9, available online).

Image Processing, Segmentation, and Diagnostics

Our review identified 27 studies that were in the realm of image segmentation and classification (Supplemental Tables S2-S4, available online). Within the realm of computer vision, DL has demonstrated an ability to differentiate neoplasms such as IP from IP with malignant transformation,[7] segment nasopharyngeal carcinoma,[26] and classify IP vs nasal polyps on preoperative computed tomography (CT) scans.[27] Li et al developed a nasopharyngeal malignancy detection model from endoscopic images using a fully convolutional network.[28] The detection model was able to perform tumor detection in a much shorter time as compared with manual segmentation and outperform experts.[28] Therefore, in surgical oncology, DL can provide clinicians with further information in the preoperative setting for diagnosis[29,30] and the postoperative setting for monitoring of recurrence.[31] With ongoing advancements in AI, it remains to be seen whether the pre- and postoperative oncologic care that patients undergo will evolve with time.

Prior to sinonasal surgery, the team performs a thorough evaluation of patient imaging to identify anatomic variations, assess extent of sinonasal disease, and devise a surgical plan for addressing the sinonasal disease.[32] With the goal of reducing intraoperative complications, DL can serve as a tool in classification of anatomic variation, disease identification, and surgical planning.[23] For example, convolutional neural networks have been used in detecting osteomeatal complex occlusion for 2-dimensional coronal CT images,[33] predicting the location of the anterior ethmoid artery as within the mesentery or skull base,[34] and identifying a concha bullosa at the level of the osteomeatal complex.[35] However, such cohorts have included only 2-dimensional images, which makes the transferability difficult given that 3-dimensional scans are used within the clinical setting.[33] Nevertheless, DL tools demonstrate immense potential for enhancing preoperative evaluation and thereby reducing the risk of surgical complications.

DL algorithms have been used to diagnose sinusitis[36-38] or quantify sinus volumes[39-42] on radiographic imaging. In fact, algorithms have shown superior accuracy in the diagnosis of maxillary sinusitis when compared with the performance of radiologists[41] or dental residents.[43] In addition, studies have extended their scope to diagnose sinusitis in other sinuses (eg, frontal or ethmoid) with acceptable results.[44,45] As obtaining a large data set is not always feasible, one group was able to demonstrate high performance when diagnosing maxillary sinusitis within a smaller data set using a transfer learning approach.[46] Additionally, DL algorithms can be used for grading disease severity[47] to determine surgical candidacy or to detect anatomic structures within the nasal cavity[17,48-50] for surgical planning and medical education. Overall, this shows the promise of AI solutions in providing diagnostic and teaching support to clinicians and trainees.

Classification of Rhinosinusitis

The continued advancement in science has prioritized personalized medicine, which entails clustering patients into certain groups to streamline and determine the optimal treatment modality.[51] This is certainly evident in the evolution of chronic rhinosinusitis (CRS) diagnosis.[52] Recently, CRS subsets have migrated from the traditional CRS with and without polyps to the modern clustering of cases according to anatomic location and endotypes.[52] The observational nature that leads to disease clustering is the hallmark of unsupervised learning: a process that aims to identify patterns through observation of data as opposed to being provided a label for each data point.[53] Its utility has been demonstrated for cases such as predictions of patient phenotype or health status.[3,22,54]

This review highlights several studies of unsupervised learning to determine patient clusters within CRS (Supplemental Table S5, available online).[55-59] Parsel et al used 22 variables, such as demographics, quality of life domains (eg, SNOT-22), comorbidity scores, and disease diagnosis, to place patients in 7 distinct clusters.[55] Although most diagnoses were correlated with 1 cluster, some (eg, CRS without nasal polyposis) was associated with multiple patient clusters possibly due to differences in disease endotypes.[55] Divekar et al studied the use of the preoperative SNOT-22 survey for clustering CRS cases.[56] Interestingly, the last 2 clusters were associated with a lack of aspirin hypersensitivity, while the last cluster had minimal symptomatic improvement following surgery.[56]

Unsupervised learning has shown to successfully cluster patients with allergic rhinitis,[60] CRS with and without nasal polyposis,[58,61] and olfactory dysfunction.[62] Other forms of ML have been implemented to predict eosinophilic CRS[57] or distinguish controls from patients with bacterial sinusitis by using a collection of exhaled gas from the nasal airway.[63] Random forest models found IL-5 and IL-13 cytokines to be most predictive of olfactory dysfunction in patients with CRS who were undergoing surgery.[62] Nevertheless, studies that have aimed to classify and differentiate among forms of sinusitis[64-69] may have immense potential to improve surgical care.

Treatment and Disease Outcome Prediction

With the advent of electronic medical records and curation of medical databases, supervised ML algorithms have been increasingly applied within health care settings for providing disease predictions.[70] In the setting of CRS, factors such as preoperative SNOT-22 and disease phenotype have been used for predicting postoperative outcomes[71,72] (Supplemental Table S6, available online). Chowdhury et al used a random forest algorithm demonstrating preoperative SNOT-22 and

several cytokines, including IL-5 and TNF-α, to be important predictors of postoperative SNOT-22 scores.[73] As our understanding of CRS has evolved, its multifactorial nature has become evident.[52] Therefore, ML has a role to play in this realm given its ability to parse complex interrelationships among clinical variables.[74]

Using known clinical variables to provide predictions is an avenue to be explored with ML. ML algorithms have been trained and shown potential in distinguishing treatment responders vs nonresponders in acute rhinosinusitis,[75] differentiating postoperative quality of life following identification of patient clusters,[76] and predicting treatment outcomes in different patient cohorts.[77-79] Kim et al found that with Lund-Mackay score and age, the number of subepithelial human neutrophil elastase was predictive of surgical outcomes in patients who had CRS with nasal polyps.[80] ML models can also identify the importance of each variable within the prediction model and enhance its clinical interpretability.[81]

With health care's mission toward personalized medicine, ML algorithms identifying patients at risk of treatment failure can be used to strive for a preventative care model.[82] Fujima et al studied the use of quantitative magnetic resonance imaging variables in identifying local control vs failure in patients diagnosed with sinonasal squamous cell carcinoma and achieved high sensitivity and specificity.[83] Moreover, a neural network was superior in predicting risk of nasopharyngeal carcinoma recurrence as compared with traditional statistical methods such as logistic regression.[84] As ML predictive tools integrate into clinical practice, they can be used for disease prevention and prediction of recurrence.

Optimizing Surgical Navigation and Surgical Phase Assessment

Image-guided surgery was a major milestone in the evolution of rhinology. It allowed for improved dissection and surgical navigation while reducing risk of injury to nearby critical structures.[85] There has been ongoing investment of research in achieving submillimeter accuracy given the current registration accuracy of 2 mm.[86] As a result, computer vision methods have been explored to improve traditional registration methods.[87,88] Three studies were highlighted in this subcategory (Supplemental Table S7, available online). Reiter et al developed a learning-based video CT registration algorithm providing 3-dimensional reconstructions of the sinonasal cavity during endoscopy.[87] This work was improved with implementation of a self-supervised convolutional neural network method to register intraoperative videos with CT scans achieving submillimeter accuracy.[88] Finally, surgical phase assessment has been recently explored to help with predicting surgical steps, avoiding complications, and providing feedback to surgeons.[6] Bieck et al implemented a natural language processing technique predicting future surgical steps from the current endoscope location.[89] Further studies in this realm may focus on providing surgeons with the optimal surgical pathway and even predicting the ideal instrumentation depending on the anatomic region that is being operated on.

Robotic Surgery

Robotic surgery has made significant advances in other domains of otolaryngology, such as management of oropharyngeal tumors, while attaining reduction in complications and postoperative morbidity.[90] Due to the bony barriers and small nasal aperture, its current application in rhinology has been limited.[90] We included studies within robotics if they had a component of full or semiautomation relevant to the task (Supplemental Table S8, available online). Steinhart et al constructed a robot that was able to successfully follow a path and perform automated resection of the anterior wall of the sphenoid sinus.[91] To provide surgeons the ability to operate with 2 hands, Dai et al designed an automated endoscope holder utilizing a tracking algorithm.[92] With the development of flexible and miniature instruments, the use of complex ML algorithms, and the integration of image-guidance systems, the next evolution in rhinology may be with the advent of robotic sinonasal surgery with various automation features.[90]

Olfactory Dysfunction

ML algorithms were utilized among several studies to determine associations between sinonasal inflammation and olfactory dysfunction[62] (Supplemental Table S9, available online). Morse et al studied a CRS group, identifying 5 patient subgroups in which they characterized inflammatory patterns and studied their association with olfactory dysfunction.[62] Within the patient clusters, there were statistically significant differences in Smell Identification Test scores.[62] Thereafter, applied ML models found IL-5 and IL-13 cytokines to be most predictive of olfactory dysfunction in patients with CRS who were undergoing surgery.[62] Similarly, unsupervised analysis has been studied to classify specific clusters within viral rhinitis cases based on olfactory function scoring systems.[93] Clustering techniques are beneficial as specific patient clusters can be followed in a prospective setting to study whether other factors may contribute to olfactory dysfunction. This is especially relevant with the COVID-19 pandemic, as smell and taste loss has served as a predictor of COVID-19 infections.[94] As long-term data continue to be curated, ML may have a role in identifying patients at risk of long-term olfactory dysfunction,[95] establishing routine follow-up, and offering intervention should olfactory dysfunction develop.

Diagnosis of Allergic Rhinitis

Although allergic rhinitis is one of the most common allergic presentations, patients require an individualized treatment approach.[96] However, given the various allergens and other potential etiologies, the timely diagnosis and treatment of this common condition may be a challenge.[96] Therefore, clinical decision support tools aimed to aid clinicians with this diagnosis may be of benefit. For example, Jabez Christopher et al compared various supervised learning approaches and developed a tool for the diagnosis of allergic rhinitis via results of intradermal skin tests.[97] Interestingly, the tool had a diagnostic accuracy of 88% vs 58.2% when compared with junior clinicians.[97]

Given the increasing incidence of allergic rhinitis, especially in children, AI can identify risk factors to help with disease prevention.[98] Using a random forest approach, Huang et al found prenatal air quality to be an important predictor of developing childhood allergic rhinitis.[98] Unsupervised techniques can also be used to identify patients who may develop severe forms of allergic rhinitis.[60] Therefore, AI can identify risk factors for developing allergic rhinitis, and with public health measures, we can move toward a preventive medical approach for rhinologic conditions (Supplemental Table S9, available online).

Conclusions and Implications for Practice

AI is quickly gaining traction and becoming a popular area of research within otolaryngology.[9,99] Studies to date have mainly focused on rhinosinusitis classification and image processing and segmentation. This has been partly due to the enhanced computational power and ability to train and test on complex data sets.[1,2,23] Future areas of research will certainly be extended into robotic surgery within rhinology, especially with the goal of reducing surgical morbidity, lowering a surgeon's cognitive load, and enhancing surgical dissection and patient outcomes. Additionally, DL has a role in identifying phases within a surgical procedure, providing performance metrics, and serving as a tool for trainee education.[6,89]

AI studies within rhinology have shown promise to augment clinical practice by aiding clinical diagnosis and allowing clinicians to focus on delivering empathetic care to patients. Supervised learning may be incorporated into the clinical setting to help clinicians infer a provisional diagnosis.[55,100] As we move toward personalized medicine, clustering patients into disease endotypes or classifying disease from large data sets or various imaging modalities in an efficient manner is of utmost importance. However, as consideration is given to the integration of AI algorithms into the clinical domain, we must confirm data integrity, use large data sets to ensure generalizability, and validate the algorithm using external data sets.[101] Therefore, multi-institutional collaborations are needed given the requirements of big data while preserving patient confidentiality.[99] Importantly, it must be iterated to clinicians that AI will assist them and augment their practice instead of replacing human intelligence.[102]

Most publications to date have been within the research setting, and the question remains how to incorporate ML technologies into clinical practice.[103] This is especially challenging with the "black box" component of ML[101] and the lack of regulatory frameworks for evaluating AI algorithms.[103] Furthermore, ensuring that clinical judgment is not biased from an algorithm's suggestion is an ongoing area of discussion within the AI community.[99,101] Finally, it is vital to confirm lack of bias within the original data set for training algorithms to ensure that the results are robust and generalizable. For example, dermoscopic images with the presence of a ruler were more likely to be deemed malignant as at baseline, malignant images more frequently had a ruler in the image.[104] Nevertheless, ML can be a tool to complement health care practice and support clinical intuition.[1]

There are several limitations to the current study. First, histopathology studies were excluded given that otolaryngologists rarely interpret pathology and cytology slides. Second, studies that did not focus on the applications of AI in rhinology were excluded, which may have removed studies that had a minor AI component. However, our literature encompassed multiple clinical and engineering databases to be as comprehensive as possible for this review. Additionally, the references of systematic reviews and relevant studies were cross-checked for any other studies that may have fit the inclusion criteria. Finally, we included gray literature publications to ensure that studies in their early research phases were still afforded consideration in this review given the infancy of the applications of AI in rhinology.

We conducted a comprehensive state of the art review on the application of AI in rhinology. To date, this field has evolved with the introduction of image-guided surgery and advanced instrumentation.[85,86,90] There is no doubt that it will continue to evolve with the continued evolution and translation of AI. As additional AI-centered research is conducted, AI interest groups should be established at institutional levels to ensure data integrity, patient data confidentiality, and continued validation of algorithms.[101] Ongoing education in this area will ensure that otolaryngologists can parse through the technicalities of AI research and products, understand the clinical application of a proposed algorithm, and work toward integrating it into their clinical practice as a clinical decision support tool.

Author Contributions

Ameen Amanian, project inception, preparation of research protocol, search strategy design, abstract and full-text screening for study selection, data collection and analysis, preparation of manuscript and revisions of final manuscript; **Austin Heffernan**, abstract and full-text screening for study selection, data collection and analysis, preparation of manuscript and revisions of final manuscript; **Masaru Ishii**, study conception and design, revision, and final approval of the manuscript; **Francis X. Creighton**, study conception and design, revision, and final approval of the manuscript; **Andrew Thamboo**, project inception, resolution of differences in abstract and full-text paper selection, manuscript editing critical for important intellectual content.

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Supplemental Material

Additional supporting information is available in the online version of the article.

References

1. Hashimoto DA, Rosman G, Rus D, Meireles OR. Artificial intelligence in surgery: promises and perils. *Ann Surg*. 2018;268(1): 70-76. doi:10.1097/SLA.0000000000002693

2. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present and future. *Stroke Vasc Neurol*. 2017;2(4):230-243. doi:10.1136/svn-2017-000101

3. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. *Nat Med*. 2019;25(1):30-36. doi:10.1038/s41591-018-0307-0

4. Kumar Y, Koul A, Singla R, Ijaz MF. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. *J Ambient Intell Humaniz Comput*. Published online January 13, 2022. doi:10.1007/s12652-021-03612-z

5. Huang S, Yang J, Fong S, Zhao Q. Artificial intelligence in cancer diagnosis and prognosis: opportunities and challenges. *Cancer Lett*. 2020;471:61-71. doi:10.1016/j.canlet.2019.12.007

6. Garrow CR, Kowalewski KF, Li L, et al. Machine learning for surgical phase recognition: a systematic review. *Ann Surg*. 2021;273(4):684-693. doi:10.1097/SLA.0000000000004425

7. Liu GS, Yang A, Kim D, et al. Deep learning classification of inverted papilloma malignant transformation using 3D convolutional neural networks and magnetic resonance imaging. *Int Forum Allergy Rhinol*. Published online January 6, 2022. doi:10.1002/alr.22958

8. Jung SK, Lim HK, Lee S, Cho Y, Song IS. Deep active learning for automatic segmentation of maxillary sinus lesions using a convolutional neural network. *Diagn Basel Switz*. 2021;11(4):688. doi:10.3390/diagnostics11040688

9. Bur AM, Shew M, New J. Artificial intelligence for the otolaryngologist: a state of the art review. *Otolaryngol Head Neck Surg*. 2019;160(4):603-611. doi:10.1177/0194599819827507

10. You E, Lin V, Mijovic T, Eskander A, Crowson MG. Artificial intelligence applications in otology: a state of the art review. *Otolaryngol Head Neck Surg*. 2020;163(6):1123-1133. doi:10.1177/0194599820931804

11. Crowson MG, Ranisau J, Eskander A, et al. A contemporary review of machine learning in otolaryngology–head and neck surgery. *Laryngoscope*. 2020;130(1):45-51. doi:10.1002/lary.27850

12. Tajudeen BA, Kennedy DW. Thirty years of endoscopic sinus surgery: what have we learned? *World J Otorhinolaryngol Head Neck Surg*. 2017;3(2):115-121. doi:10.1016/j.wjorl.2016.12.001

13. Norgeot B, Glicksberg BS, Butte AJ. A call for deep-learning healthcare. *Nat Med*. 2019;25(1):14-15. doi:10.1038/s41591-018-0320-3

14. Tricco AC, Lillie E, Zarin W, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): checklist and explanation. *Ann Intern Med*. 2018;169(7):467-473. doi:10.7326/M18-0850

15. Oxford Centre for Evidence-Based Medicine. Oxford Centre for Evidence-Based Medicine 2011 levels of evidence. Accessed March 21, 2022. https://www.cebm.net/wp-content/uploads/2014/06/CEBM-Levels-of-Evidence-2.1.pdf

16. Zou KH, Warfield SK, Bharatha A, et al. Statistical validation of image segmentation quality based on a spatial overlap index. *Acad Radiol*. 2004;11(2):178-189. doi:10.1016/s1076-6332(03)00671-8

17. Neelapu BC, Kharbanda OP, Sardana V, et al. A pilot study for segmentation of pharyngeal and sino-nasal airway subregions by automatic contour initialization. *Int J Comput Assist Radiol Surg*. 2017;12(11):1877-1893. doi:10.1007/s11548-017-1650-1

18. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. *Future Healthc J*. 2019;6(2):94-98. doi:10.7861/futurehosp.6-2-94

19. Wilson MB, Ali SA, Kovatch KJ, Smith JD, Hoff PT. Machine learning diagnosis of peritonsillar abscess. *Otolaryngol Head Neck Surg*. 2019;161(5):796-799. doi:10.1177/0194599819868178

20. Bing D, Ying J, Miao J, et al. Predicting the hearing outcome in sudden sensorineural hearing loss via machine learning models. *Clin Otolaryngol*. 2018;43(3):868-874. doi:10.1111/coa.13068

21. Mascharak S, Baird BJ, Holsinger FC. Detecting oropharyngeal carcinoma using multispectral, narrow-band imaging and machine learning. *Laryngoscope*. 2018;128(11):2514-2520. doi:10.1002/lary.27159

22. Deo RC. Machine learning in medicine. *Circulation*. 2015;132(20):1920-1930. doi:10.1161/CIRCULATIONAHA.115.001593

23. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24-29. doi:10.1038/s41591-018-0316-z

24. Kann BH, Aneja S, Loganadane GV, et al. Pretreatment identification of head and neck cancer nodal metastasis and extranodal extension using deep learning neural networks. *Sci Rep*. 2018;8(1):14036. doi:10.1038/s41598-018-32441-y

25. Chu C, Zheng J, Zhou Y. Ultrasonic thyroid nodule detection method based on U-Net network. *Comput Methods Programs Biomed*. 2021;199:105906. doi:10.1016/j.cmpb.2020.105906

26. Tang P, Zu C, Hong M, et al. DA-DSUnet: Dual Attention–based Dense SU-net for automatic head-and-neck tumor segmentation in MRI images. *Neurocomputing*. 2021;435:103-113. doi:10.1016/j.neucom.2020.12.085

27. Ren T, Li X, Tian Y, Li W. Deep learning framework for preoperative recognition of inverted papilloma and nasal polyp. *IEEE Access*. 2021;9:120502-120511. doi:10.1109/ACCESS.2021.3099687

28. Li C, Jing B, Ke L, et al. Development and validation of an endoscopic images-based deep learning model for detection with nasopharyngeal malignancies. *Cancer Commun (Lond)*. 2018;38(1):59. doi:10.1186/s40880-018-0325-9

29. Ogawa M, Osaga S, Shiraki N, et al. Utility of CT texture analysis to differentiate olfactory neuroblastoma from sinonasal squamous cell carcinoma. *Sci Rep*. 2021;11(1):4679. doi:10.1038/s41598-021-84048-5

30. Ramkumar S, Ranjbar S, Ning S, et al. MRI-based texture analysis to differentiate sinonasal squamous cell carcinoma from inverted papilloma. *AJNR Am J Neuroradiol*. 2017;38(5):1019-1025. doi:10.3174/ajnr.A5106

31. Chang CY. Spatiotemporal Hopfield neural cube for diagnosing recurrent nasal papilloma. *Med Biol Eng Comput*. 2005;43(1):16-22. doi:10.1007/BF02345118

32. O'Brien WT, Hamelin S, Weitzel EK. The preoperative sinus CT: avoiding a "CLOSE" call with surgical complications. *Radiology*. 2016;281(1):10-21. doi:10.1148/radiol.2016152230

33. Chowdhury NI, Smith TL, Chandra RK, Turner JH. Automated classification of osteomeatal complex inflammation on

computed tomography using convolutional neural networks. *Int Forum Allergy Rhinol*. 2019;9(1):46-52. doi:10.1002/alr.22196

34. Huang J, Habib AR, Mendis D, et al. An artificial intelligence algorithm that differentiates anterior ethmoidal artery location on sinus computed tomography scans. *J Laryngol Otol*. 2020; 134(1):52-55. doi:10.1017/S0022215119002536

35. Parmar P, Habib AR, Mendis D, et al. An artificial intelligence algorithm that identifies middle turbinate pneumatisation (concha bullosa) on sinus computed tomography scans. *J Laryngol Otol*. 2020;134(4):328-331. doi:10.1017/S0022215120 000 444

36. Kuwana R, Ariji Y, Fukuda M, et al. Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs. *Dentomaxillofac Radiol*. 2021;50(1):20200171. doi:10.1259/dmfr.2020 0171

37. Oh JH, Kim HG, Lee KM, et al. Effective end-to-end deep learning process in medical imaging using independent task learning: application for diagnosis of maxillary sinusitis. *Yonsei Med J*. 2021;62(12):1125-1135. doi:10.3349/ymj.2021.62.12.1125

38. Kim Y, Lee KJ, Sunwoo L, et al. Deep learning in diagnosis of maxillary sinusitis using conventional radiography. *Invest Radiol*. 2019;54(1):7-15. doi:10.1097/RLI.0000000000000503

39. Giacomini G, Pavan ALM, Altemani JMC, et al. Computed tomography-based volumetric tool for standardized measurement of the maxillary sinus. *PloS One*. 2018;13(1):e0190770. doi:10.1371/journal.pone.0190770

40. Passera K, Potepan P, Setti E, et al. A fuzzy-C-means clustering algorithm for a volumetric analysis of paranasal sinus and nasal cavity cancers. *Conf Proc IEEE Eng Med Biol Soc*. 2006;2006: 3078-3081. doi:10.1109/IEMBS.2006.260334

41. Humphries SM, Centeno JP, Notary AM, et al. Volumetric assessment of paranasal sinus opacification on computed tomography can be automated using a convolutional neural network. *Int Forum Allergy Rhinol*. 2020;10(11):1218-1225. doi:10.1002/ alr.22588

42. Huang R, Nedanoski A, Fletcher DF, et al. An automated segmentation framework for nasal computational fluid dynamics analysis in computed tomography. *Comput Biol Med*. 2019;115: 103505. doi:10.1016/j.compbiomed.2019.103505

43. Murata M, Ariji Y, Ohashi Y, et al. Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. *Oral Radiol*. 2019;35(3): 301-307. doi:10.1007/s11282-018-0363-7

44. Jeon Y, Lee K, Sunwoo L, et al. Deep learning for diagnosis of paranasal sinusitis using multi-view radiographs. *Diagnostics (Basel)*. 2021;11(2):250. doi:10.3390/diagnostics11020250

45. Natsheh AR, Ponnapalli PV, Anani N, Benchebra D, El-kholy A. Neural networks-based tool for diagnosis of paranasal sinuses conditions. In: *2010 7th International Symposium on Communication Systems, Networks Digital Signal Processing (CSNDSP 2010)*. IEEE Explore; 2010:780-784. doi:10.1109/CSNDSP 16145.2010.5580314

46. Mori M, Ariji Y, Katsumata A, et al. A deep transfer learning approach for the detection and diagnosis of maxillary sinusitis on panoramic radiographs. *Odontology*. 2021;109(4):941-948. doi:10.1007/s10266-021-00615-2

47. Sensakovic WF, Pinto JM, Baroody FM, Starkey A, Armato SG III. Automated segmentation of mucosal change in rhinosinusitis patients. *Proc SPIE*. 2010;7624:76243N. doi:10.1117/12.844 282

48. Kuo CFJ, Leu YS, Hu DJ, Huang CC, Siao JJ, Leon KBP. Application of intelligent automatic segmentation and 3D reconstruction of inferior turbinate and maxillary sinus from computed tomography and analyze the relationship between volume and nasal lesion. *Biomed Signal Process Control*. 2020;57:101660. doi:10.1016/j.bspc.2019.101660

49. Laura CO, Hofmann P, Drechsler K, Wesarg S. Automatic detection of the nasal cavities and paranasal sinuses using deep neural networks. In: *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE Explore; 2019:1154-1157. doi:10.1109/ISBI.2019.8759481

50. Tingelhoff K, Moral AI, Kunkel ME, et al. Comparison between manual and semi-automatic segmentation of nasal cavity and paranasal sinuses from CT images. *Annu Int Conf IEEE Eng Med Biol Soc*. 2007;2007:5505-5508. doi:10.1109/IEMBS. 2007.4353592

51. Deng J, Hartung T, Capobianco E, Chen JY, Emmert-Streib F. Editorial: artificial intelligence for precision medicine. *Front Artif Intell*. 2021;4:834645. doi:10.3389/frai.2021.834645

52. Grayson JW, Hopkins C, Mori E, Senior B, Harvey RJ. Contemporary classification of chronic rhinosinusitis beyond polyps vs no polyps: a review. *JAMA Otolaryngol Head Neck Surg*. 2020; 146(9):831-838. doi:10.1001/jamaoto.2020.1453

53. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015; 521(7553):436-444. doi:10.1038/nature14539

54. Wang Y, Zhao Y, Therneau TM, et al. Unsupervised machine learning for the discovery of latent disease clusters and patient subgroups using electronic health records. *J Biomed Inform*. 2020;102:103364. doi:10.1016/j.jbi.2019.103364

55. Parsel SM, Riley CA, Todd CA, Thomas AJ, McCoul ED. Differentiation of clinical patterns associated with rhinologic disease. *Am J Rhinol Allergy*. 2021;35(2):179-186. doi:10.1177/ 1945892420941706

56. Divekar R, Patel N, Jin J, et al. Symptom-based clustering in chronic rhinosinusitis relates to history of aspirin sensitivity and postsurgical outcomes. *J Allergy Clin Immunol Pract*. 2015; 3(6):934-940.e3. doi:10.1016/j.jaip.2015.06.018

57. Thorwarth RM, Scott DW, Lal D, Marino MJ. Machine learning of biomarkers and clinical observation to predict eosinophilic chronic rhinosinusitis: a pilot study. *Int Forum Allergy Rhinol*. 2021;11(1):8-15. doi:10.1002/alr.22632

58. Lal D, Hopkins C, Divekar RD. SNOT-22-based clusters in chronic rhinosinusitis without nasal polyposis exhibit distinct endotypic and prognostic differences. *Int Forum Allergy Rhinol*. 2018;8(7):797-805. doi:10.1002/alr.22101

59. Soler ZM, Hyer JM, Ramakrishnan V, et al. Identification of chronic rhinosinusitis phenotypes using cluster analysis. *Int Forum Allergy Rhinol*. 2015;5(5):399-407. doi:10.1002/alr .21496

60. Caimmi D, Baiz N, Sanyal S, Banerjee S, Demoly P, Annesi-Maesano I. Discriminating severe seasonal allergic rhinitis: results from a large nation-wide database. *PloS One*. 2018; 13(11):e0207290. doi:10.1371/journal.pone.0207290

61. Divekar RD, Samant S, Rank MA, et al. Immunological profiling in chronic rhinosinusitis with nasal polyps reveals distinct VEGF and GM-CSF signatures during symptomatic exacerbations. *Clin Exp Allergy*. 2015;45(4):767-778. doi:10.1111/cea.12463

62. Morse JC, Shilts MH, Ely KA, et al. Patterns of olfactory dysfunction in chronic rhinosinusitis identified by hierarchical cluster analysis and machine learning algorithms. *Int Forum Allergy Rhinol*. 2019;9(3):255-264. doi:10.1002/alr.22249

63. Thaler ER, Hanson CW. Use of an electronic nose to diagnose bacterial sinusitis. *Am J Rhinol*. 2006;20(2):170-172. doi:10.1177/194589240602000209

64. Soloviev N, Khilov A, Shakhova M, et al. Machine learning aided automated differential diagnostics of chronic rhinitis based on optical coherence tomography. *Laser Phys Lett*. 2020;17(11):115608. doi:10.1088/1612-202X/abbf48

65. Rustam Z, Shandri N, Siswantining T, Pandelaki J. Kernel entropy based fuzzy C-means (KEFCM) for acute sinusitis. *J Phys Conf Ser*. 2021;1752:012040. doi:10.1088/1742-6596/1752/1/012040

66. Rustam Z, Hartini S, Pandelaki J. Kernel perceptron algorithm for sinusitis classification: 5th International Conference on Mathematics: Pure, Applied and Computation, ICoMPAC 2019. *J Phys Conf Ser*. 2020;1490(1):012025. doi:10.1088/1742-6596/1490/1/012025

67. Arfiani, Rustam Z, Pandelaki J, Siahaan A. Kernel spherical K-means and support vector machine for acute sinusitis classification: 9th Annual Basic Science International Conference 2019, BaSIC 2019. *IOP Conf Ser Mater Sci Eng*. 2019;546(5):052011. doi:10.1088/1757-899X/546/5/052011

68. Nuseir A, Nuseir A, Alsmirat M, Al-Ayyoub M, Mahdi M, AL-Balas H. Performance of different machine learning methods for sinus diseases classification. In: *2021 12th International Conference on Information and Communication Systems (ICICS)*. IEEE Explore; 2021:77-82. doi:10.1109/ICICS52457.2021.9464624

69. Yeh MH, Luo HF, Lin NW, Chen ZY, Yeh CC. A study on electrical properties of acupuncture points in allergic rhinitis. In: *2012 IEEE 14th International Conference on E-Health Networking, Applications and Services (Healthcom)*. IEEE Explore; 2012:82-87. doi:10.1109/HealthCom.2012.6380071

70. Uddin S, Khan A, Hossain ME, Moni MA. Comparing different supervised machine learning algorithms for disease prediction. *BMC Med Inform Decis Mak*. 2019;19(1):281. doi:10.1186/s12911-019-1004-8

71. Soler ZM, Jones R, Le P, et al. Sino-Nasal Outcome Test–22 outcomes after sinus surgery: a systematic review and meta-analysis. *Laryngoscope*. 2018;128(3):581-592. doi:10.1002/lary.27008

72. Smith TL, Litvack JR, Hwang PH, et al. Determinants of outcomes of sinus surgery: a multi-institutional prospective cohort study. *Otolaryngol Head Neck Surg*. 2010;142(1):55-63. doi:10.1016/j.otohns.2009.10.009

73. Chowdhury NI, Li P, Chandra RK, Turner JH. Baseline mucus cytokines predict 22-item Sino-Nasal Outcome Test results after endoscopic sinus surgery. *Int Forum Allergy Rhinol*. 2020;10(1):15-22. doi:10.1002/alr.22449

74. Sidey-Gibbons JAM, Sidey-Gibbons CJ. Machine learning in medicine: a practical introduction. *BMC Med Res Methodol*. 2019;19(1):64. doi:10.1186/s12874-019-0681-4

75. Qi W, Abu-Hanna A, van Esch TEM, et al. Explaining heterogeneity of individual treatment causal effects by subgroup discovery: an observational case study in antibiotics treatment of acute rhino-sinusitis. *Artif Intell Med*. 2021;116:102080. doi:10.1016/j.artmed.2021.102080

76. Adnane C, Adouly T, Khallouk A, et al. Using preoperative unsupervised cluster analysis of chronic rhinosinusitis to inform patient decision and endoscopic sinus surgery outcome. *Eur Arch Otorhinolaryngol*. 2017;274(2):879-885. doi:10.1007/s00405-016-4315-8

77. Kim JW, Huh G, Rhee CS, et al. Unsupervised cluster analysis of chronic rhinosinusitis with nasal polyp using routinely available clinical markers and its implication in treatment outcomes. *Int Forum Allergy Rhinol*. 2019;9(1):79-86. doi:10.1002/alr.22221

78. Szaleniec J, Szaleniec M, Stręk P, et al. Outcome prediction in endoscopic surgery for chronic rhinosinusitis—a multidimensional model. *Adv Med Sci*. 2014;59(1):13-18. doi:10.1016/j.advms.2013.06.003

79. Szaleniec J, Szaleniec M, Stręk P. A stepwise protocol for neural network modeling of persistent postoperative facial pain in chronic rhinosinusitis. *Bio-Algorithms and Med-Systems*. 2016;12(2):81-88. doi:10.1515/bams-2016-0008

80. Kim DK, Lim HS, Eun KM, et al. Subepithelial neutrophil infiltration as a predictor of the surgical outcome of chronic rhinosinusitis with nasal polyps. *Rhinology*. 2021;59(2):173-180. doi:10.4193/Rhin20.373

81. Qi Y. Random forest for bioinformatics. In: Zhang C, Ma Y, eds. *Ensemble Machine Learning: Methods and Applications*. Springer; 2012:307-323. doi:10.1007/978-1-4419-9326-7_11

82. Greenland P, Hassan S. Precision preventive medicine—ready for prime time? *JAMA Intern Med*. 2019;179(5):605-606. doi:10.1001/jamainternmed.2019.0142

83. Fujima N, Shimizu Y, Yoshida D, et al. Machine-learning-based prediction of treatment outcomes using MR imaging–derived quantitative tumor information in patients with sinonasal squamous cell carcinomas: a preliminary study. *Cancers*. 2019;11(6):E800. doi:10.3390/cancers11060800

84. Kumdee O, Bhongmakapat T, Ritthipravat P. Prediction of nasopharyngeal carcinoma recurrence by neuro-fuzzy techniques. *Fuzzy Sets Syst*. 2012;203:95-111. doi:10.1016/j.fss.2012.03.004

85. Beswick DM, Ramakrishnan VR. The utility of image guidance in endoscopic sinus surgery: a narrative review. *JAMA Otolaryngol Head Neck Surg*. 2020;146(3):286-290. doi:10.1001/jamaoto.2019.4161

86. Knott PD, Batra PS, Citardi MJ. Computer aided surgery: concepts and applications in rhinology. *Otolaryngol Clin North Am*. 2006;39(3):503-522. doi:10.1016/j.otc.2006.01.007

87. Reiter A, Leonard S, Sinha A, Ishii M, Taylor RH, Hager GD. Endoscopic-CT: learning-based photometric reconstruction for endoscopic sinus surgery. In: *Medical Imaging 2016: Image Processing*. Vol 9784. SPIE; 2016:331-336. doi:10.1117/12.2216296

88. Liu X, Sinha A, Ishii M, et al. Dense depth estimation in monocular endoscopy with self-supervised learning methods. *IEEE Trans Med Imaging*. 2020;39(5):1438-1447. doi:10.1109/TMI.2019.2950936

89. Bieck R, Heuermann K, Pirlich M, Neumann J, Neumuth T. Language-based translation and prediction of surgical navigation steps for endoscopic wayfinding assistance in minimally invasive surgery. *Int J Comput Assist Radiol Surg*. 2020;15(12):2089-2100. doi:10.1007/s11548-020-02264-2

90. Campbell RG, Harvey RJ. How close are we to anterior robotic skull base surgery? *Curr Opin Otolaryngol Head Neck Surg*. 2021;29(1):44-52. doi:10.1097/MOO.0000000000000683

91. Steinhart H, Bumm K, Wurm J, Vogele M, Iro H. Surgical application of a new robotic system for paranasal sinus surgery. *Ann Otol Rhinol Laryngol*. 2004;113(4):303-309. doi:10.1177/000348940411300409

92. Dai X, Zhao B, Zhao S, et al. An endoscope holder with automatic tracking feature for nasal surgery. In: *2016 IEEE International Conference on Information and Automation (ICIA)*. IEEE Explore; 2016:1-6. doi:10.1109/ICInfA.2016.7831788

93. Lötsch J, Hummel T. Data science-based analysis of patient subgroup structures suggest effects of rhinitis on all chemosensory perceptions in the upper airways. *Chem Senses*. 2021;46:bjab001. doi:10.1093/chemse/bjab001

94. Callejon-Leblic MA, Moreno-Luna R, Del Cuvillo A, et al. Loss of smell and taste can accurately predict COVID-19 infection: a machine-learning approach. *J Clin Med*. 2021;10(4):570. doi:10.3390/jcm10040570

95. Babaei A, Iravani K, Malekpour B, Golkhar B, Soltaniesmaeili A, Hosseinialhashemi M. Factors associated with anosmia recovery rate in COVID-19 patients. *Laryngoscope Investig Otolaryngol*. Published online November 2, 2021. doi:10.1002/lio2.690

96. Testera-Montes A, Jurado R, Salas M, Eguiluz-Gracia I, Mayorga C. Diagnostic tools in allergic rhinitis. *Front Allergy*. 2021;2:721851. doi:10.3389/falgy.2021.721851

97. Jabez Christopher J, Khanna Nehemiah H, Kannan A. A clinical decision support system for diagnosis of allergic rhinitis based on intradermal skin tests. *Comput Biol Med*. 2015;65:76-84. doi:10.1016/j.compbiomed.2015.07.019

98. Huang Y, Wen HJ, Guo YLL, et al. Prenatal exposure to air pollutants and childhood atopic dermatitis and allergic rhinitis adopting machine learning approaches: 14-year follow-up birth cohort study. *Sci Total Environ*. 2021;777:145982. doi:10.1016/j.scitotenv.2021.145982

99. Arambula AM, Bur AM. Ethical considerations in the advent of artificial intelligence in otolaryngology. *Otolaryngol Head Neck Surg*. 2020;162(1):38-39. doi:10.1177/0194599819889686

100. Hsueh WD, Conley DB, Kim H, et al. Identifying clinical symptoms for improving the symptomatic diagnosis of chronic rhinosinusitis. *Int Forum Allergy Rhinol*. 2013;3(4):307-314. doi:10.1002/alr.21106

101. Anderson M, Anderson SL. How should AI be developed, validated, and implemented in patient care? *AMA J Ethics*. 2019;21(2):E125-E130. doi:10.1001/amajethics.2019.125

102. Crigger E, Khoury C. Making policy on augmented intelligence in health care. *AMA J Ethics*. 2019;21(2):E188-E191. doi:10.1001/amajethics.2019.188

103. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med*. 2019;17(1):195. doi:10.1186/s12916-019-1426-2

104. Narla A, Kuprel B, Sarin K, Novoa R, Ko J. Automated classification of skin lesions: from pixels to practice. *J Invest Dermatol*. 2018;138(10):2108-2110. doi:10.1016/j.jid.2018.06.175