ENT UK Undergraduate Essay Prize 2023

Artificial Intelligence: the future of innovation in medical practice related to Otolaryngology or are the risks too high?

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"It is customary to offer a grain of comfort, in the form of a statement that some peculiarly human characteristic could never be imitated by a machine. I cannot offer any such comfort, for I believe that no such bounds can be set."

-- Alan Turing, 1951

Introduction:

The term 'artificial intelligence' describes the ability of a computer to perform tasks typically thought to require human intelligence,[1] such as language processing, reasoning, problem solving and importantly the ability to learn. Since the 1950s there have been growing efforts to develop artificial intelligence, hampered largely by the ability to manage the large data sets required for artificial intelligence to materialise.[2] Thereafter, the speed and memory of computers has doubled every two years, roughly in line with Moore's law,[3] providing the required computational power to develop AI. Consequently, in the 21st century AI is slowly being implemented into daily life. Face ID, autocorrect, internet search bars and Netflix have all been utilising AI for years, representing only a fraction of its theoretical potential.[4]

Otolaryngological research using a subgroup of AI known as machine learning, has risen in popularity over the last decade, exhibited by a marked increase in the quantity of related publications (Figure 1). Implemented effectively, AI has the capacity to transform otolaryngology and healthcare at large, whether that be automating diagnosis, improving management decision making or improving the cost efficiency of the NHS.[5] There are boundless applications of the technology, beyond the extent of this essay, but discussed are a range of the exciting utilisations of AI in Ear Nose and Throat surgery (ENT).

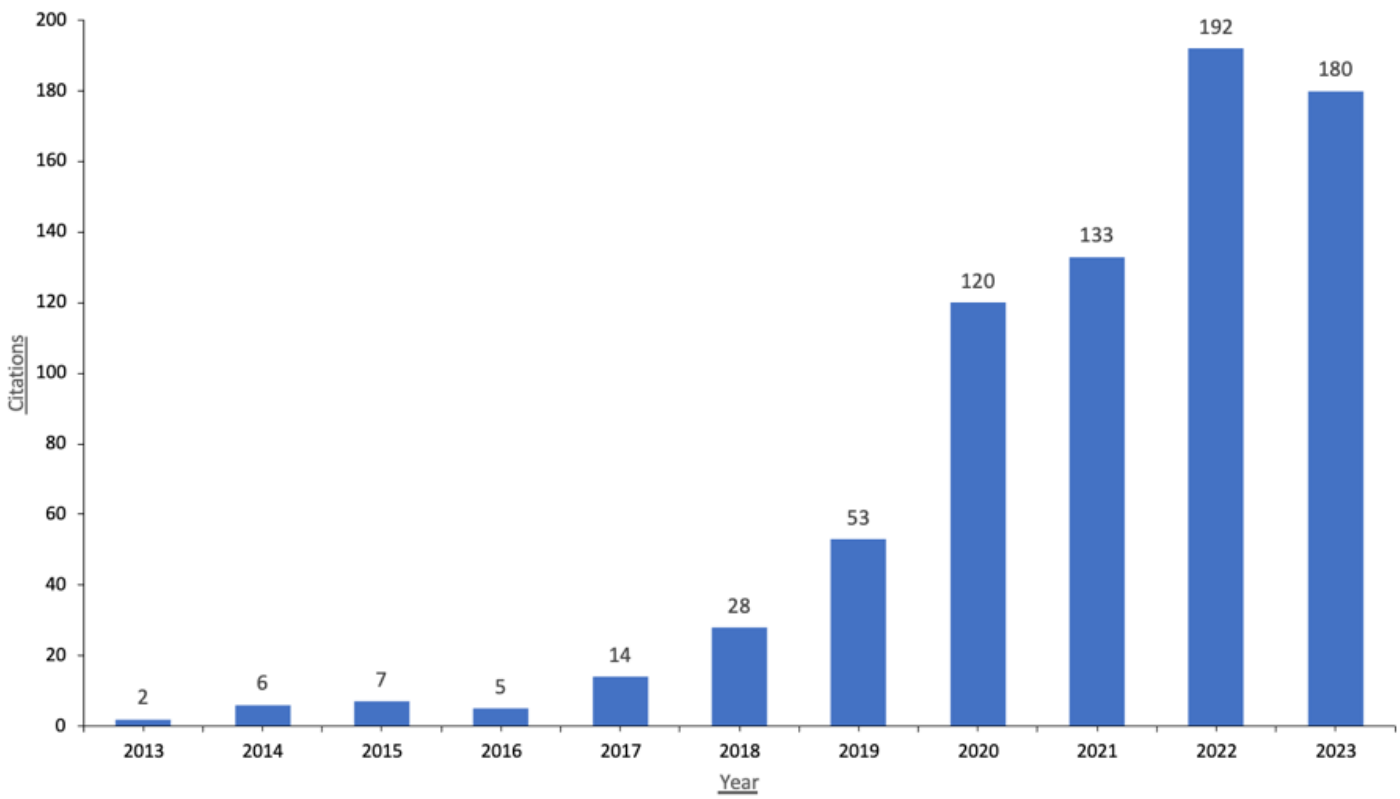

Figure 1: *Citations per year for machine learning articles published in otolaryngology literature from 2013 to November 2023. (Author's own).*

What is Artificial Intelligence?

Artificial intelligence is an umbrella term describing a range of computational techniques, with this essay largely concerning two models: machine learning (ML) and natural language processing (NLP) (see Figure 2 and 3).

Term	Description
Machine learning	A subset of AI, having evolved to allow computers to learn, without the need for direct programming.[6]
Deep learning	A multi-layered separation approach using neural networks to emulate the human approach to learning for algorithm development.[7]
Artificial neural networks	Computing systems inspired by, and that function similar to the human brain.[8]
Natural language processing	The branch of artificial intelligence encompasses the understanding and interpretation of human language by computers.[9]
Large language model	A type of language model notable for its ability to achieve general-purpose language understanding and generation.[10] ChatGPT is a pertinent example of a large language model, with integrated machine learning allowing it to adapt over time.[11]
Ground truth	The target outcome when training and validating a machine learning model.[12]

Figure 2: *Glossary of terms.*

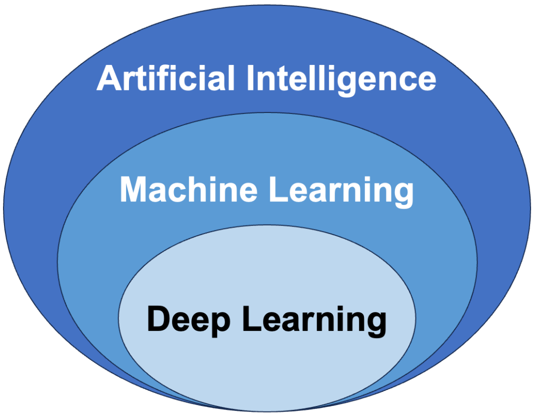

Figure 3: *Subgroups of artificial intelligence (Author's own).*

Supervised ML models are iteratively trained by comparing the actual output to the ideal output, adjusting the rules within its own algorithm with repetition until the outputs align.[13] ML uses prior experience to improve its associations, meaning the probability of correctly classifying data (the output) increases as the algorithm is trained with more data. Once trained, the model can be applied to a new data set, recognising patterns based upon its training. Figure 4 outlines a generic application of a neural network, to classify input histopathological samples.

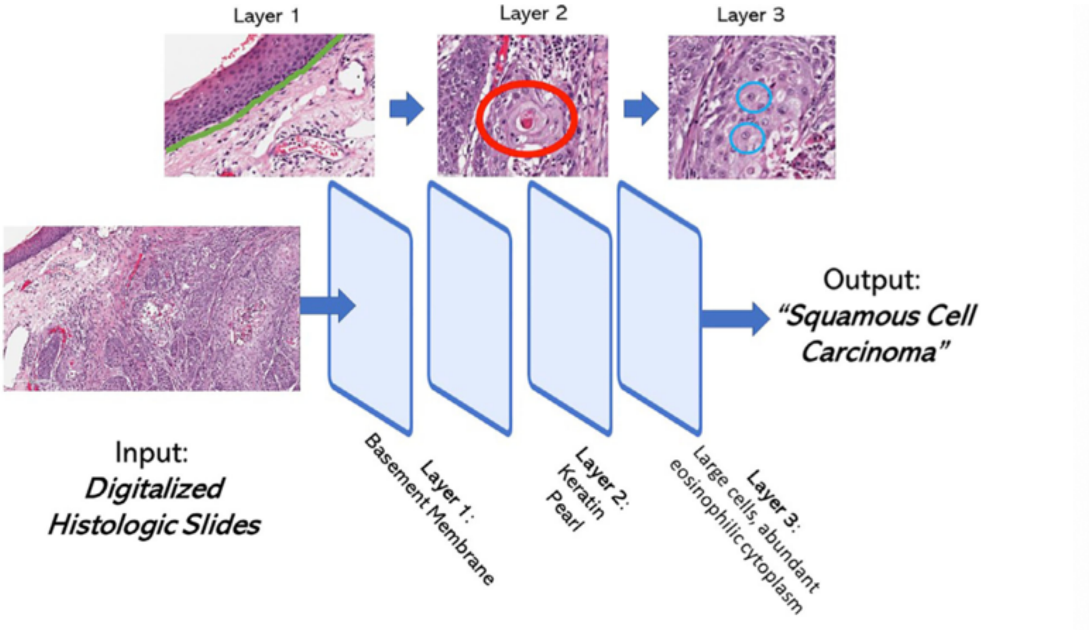

Figure 4: *Example technique of a trained neural network to classify histopathological samples (Crowson et a.).*[14]

ML can draw upon an array of heterogenous data inputs, including laboratory results, radiological imaging, and medical notes.[15] Sophisticated ML models such as deep learning can discern complex non-linear patterns that classical computers cannot.[16] Trained algorithms require external validation through testing data before they can be applied in the real-world to determine whether the same patterns are identified with a change of input.[17] Additional impact studies are needed before artificial intelligence can be successfully implemented into the clinical environment, and will require surveillance to monitor for any issues, including model drift, discussed later.[18]

In the following sections, this essay will draw upon existing literature to evaluate the potential for these AI models to be applied within otolaryngology.

Applying Artificial Intelligence to ENT:

Harnessing Big Data:

Due to the rapid digitalisation of medical records, health providers around the world now have easy access to electronic health record systems within extensive patient databases.[(19, 20)] Medical records, imaging results, pathological findings, genomic data, and other huge data sets are collectively referred to as 'big data' in healthcare.[15] The processing and management of big data poses three main challenges: the volume of data, variety of data sources, and the rate of processing.[21] Machine learning may have the capability to improve the challenges associated with each of these issues.

Yang et al., developed an NLP model (known as GatorTron) pretrained with over 82 billion anonymised words of clinical text.[22] GatorTron can excerpt patient information from massive volumes of unstructured electronic health records, an otherwise labour and time intense endeavour. Within otolaryngology, future iterations of GatorTron could be trained to identify patients at risk of postoperative complications prior to a tonsillectomy or tracheostomy, allowing prophylaxis to mitigate any risks.[23] Though uncommon, severe complications including haemorrhage and infection are considered important sources of morbidity and mortality postoperatively.[(24, 25)] Early identification of both individuals at high risk of complication and those where the consequence of a complication would be catastrophic is essential.[26] For example, prophylactic antibiotics are not always indicated so as not to promote drug-resistant bacteria,[27, 28] so careful selection of individuals who would benefit most is imperative. Ultimately, implementation of NLP systems could improve patient outcomes, reduce the length of hospital stays, and avoid substantial extra costs to the NHS.[29]

In ENT surgery, machine learning AI has already been applied to large genomic datasets, including the recognition of 40 gene profiles indicative of a greater propensity for HPV-related oropharyngeal cancers. [30] Integrated into all data dense branches of ENT, AI could transform the way patients are diagnosed and catalyse the transition to personalised treatments. [15]

Improving nystagmus diagnosis to aid referral to otolaryngology:

Vestibular dysfunction is a common otolaryngological presentation from primary to tertiary care,[31] with typical symptoms including vertigo, nausea, and postural instability.[32] Benign paroxysmal positional vertigo (BPPV) is the most common cause of vertigo, and the symptoms can be debilitating.[33] Since 1952, BPPV has been diagnosed by eliciting positional-dependent nystagmus via the Dix-Hallpike manoeuvre.[34] In clinical practice, spotting positional nystagmus can be difficult for unspecialised clinicians, and studies have suggested that BPPV is being underdiagnosed.[35] At the primary care level, misdiagnosis results in unnecessary referral to specialists, which contributes to the increasing ENT waiting list. As of June 2022, 510,000 people were awaiting ENT consultations, operations, and procedures.[36] Therefore, improving the diagnosis and treatment of conditions such as BPPV at the first point-of-care can help alleviate some of the pressure on ENT as a speciality. This is in addition to reducing the duration of symptoms, which subsequently reduces the risk of associated complications such as falls,[37] linked to great morbidity in the elderly.[38]

Video-nystagmography is one non-invasive diagnostic method for observing nystagmus, in which a patient wears a set of goggles that can trace eye movements during positional changes.[39] It is effective in diagnosing BPPV, but a major drawback is that it requires an expert to manually evaluate the data to ascertain that outcome. Several diagnostic support systems have been developed in recent years using machine learning to automate the diagnosis of BPPV.[40] Lee et al (2023), trained a validated convolutional neural network to be capable of removing motion artifacts and detecting nystagmus with an accuracy of over 91%.[41] Theoretically, any camera could be used in conjunction with the eye-tracking algorithm, and further improvements in the sensitivity and specificity of future models, could ease diagnostic uncertainty in primary care.[42] An accessible handheld version could reduce ENT referrals, improve diagnosis in remote areas with low access to specialists,[43] as well as identify more serious types of nystagmus (E.g., Brun's nystagmus, associated with cerebellopontine angle tumours and stroke which require immediate referral).[44]

This potential for AI to facilitate first-point-of-care identification and differentiation of nystagmus using a cost-effective data input reflects a broader trend in ENT diagnostics. Indeed, using comparable machine learning technologies, AI has showed promise in the diagnosis of cholesteatoma from routine otoscopy,[45] vocal cord pathology from voice recordings,[46] and tumours from endoscopic imaging, as will be explored.

Diagnostic artificial intelligence in otolaryngology:

In rhinology, deep learning has already illustrated its capability as a diagnostic tool. There are models which pledge to improve detection of nasopharyngeal malignancy, using endoscopic imaging inputs.[47] Li et al (2018), developed a model able to automatically segment nasopharyngeal images, detecting areas of malignancy from background tissue. It was demonstrated to outperformed radiological experts in detection of nasopharyngeal malignancies, whilst operating faster and thus more efficiently. As well as detecting tumours, the output of the model could be applied to guide biopsy and even resection of nasopharyngeal and laryngeal tumours. Using fresh, unprocessed surgical specimens that were not fixed, stained, or sectioned, Zhang et al used stimulated Raman scattering (SRS) microscopy, combined with a deep-learning algorithm to accurately diagnose laryngeal squamous cell carcinoma.[48] The rapid evaluation of tissue was able to identify residual neoplasm in simulated surgery margins, implying that the AI assisted SRS microscopy could provide intraoperative assessment of the surgical margins. The benefits include full removal of the tumour, meaning better outcomes and reduced recurrence rates for patients. The predictive capability of ML also confers the ability to stratify disease by severity and thus gauge the relative probability of different outcome variables such as recurrence or mortality likelihood.[49] Such a tool could be implemented preoperatively to guide patient centred care discussions about management options, enabling patients to be more informed about risk, improving autonomy and their ability to consent.

Similar studies have used AI to automate the segmentation of magnetic resonance images, with ML technologies able to delineate the gross volume of a nasopharyngeal carcinoma from normal adjacent tissues.[50] Without the assistance of an AI tool, this is a time-consuming and expensive process for specialists.[51] Figure 5 exhibits the visual segmentation of the deep-learning model, compared with the delineation of the nasopharyngeal carcinoma ground truth, which when quantitively compared show a small relative gain (5.17-13.8%), meaning the algorithm is effective in detecting the entire tumour. The algorithm is comparably accurate yet considerably faster at calculating the tumour volume and its boundaries, allowing the patient's condition to be staged and radiotherapy planning to commence sooner. Clinically, this means a quicker turnaround from diagnosis to management for patients,[52] without sacrificing accuracy or precision.

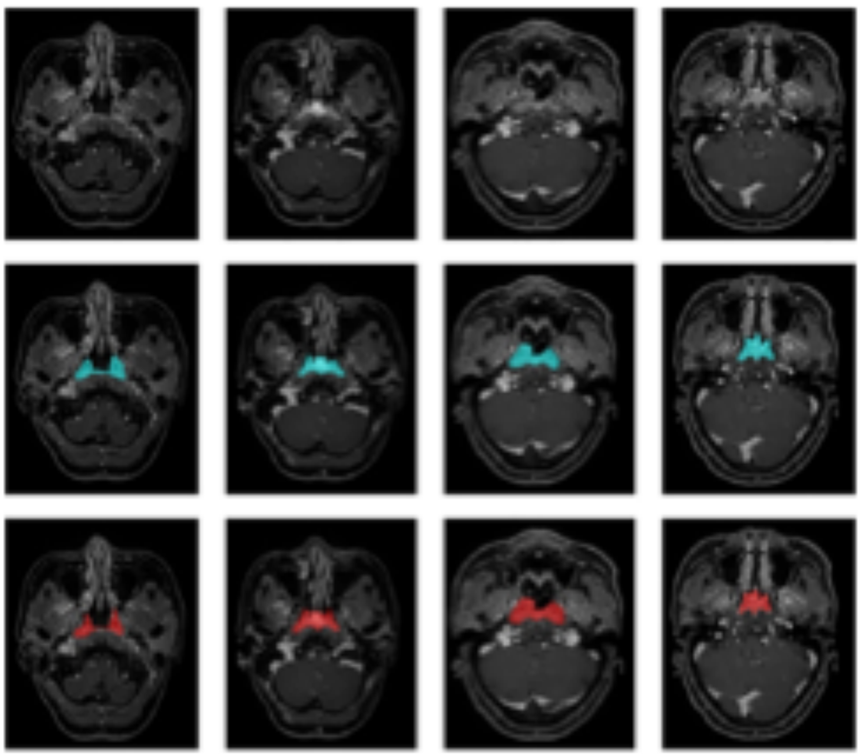

Figure 5: *Axial MRI head scans, demonstrating visual segmentation. Row 1, input slices. Row 2 segmentation by the deep-learning algorithm. Row 3, ground truth. (Tang et al).*[50]

Reducing surgical margins with Artificial Intelligence:

The prospect of fully autonomous robotic surgery may not be as close to science fiction as some may believe. As early as 2004, fully autonomous robotic sphenoidotomy has been performed on cadaveric specimens,[53] able to penetrate the anterior wall without damaging nearby structures, (directed in relation to CT imaging). Though rudimentary, and lacking any artificial intelligence, this serves as a compelling proof of concept of the accuracy robotics can deliver.[54] Nearly 20 years on, some medical robots can be calibrated to an accuracy of 0.1-0.5mm.[55] The margins obtained in parotidectomy of parotid gland cancers can be limited by the facial nerve, often resulting in positive margins.[56] Paired with a probe capable of detecting and precisely defining surgical margins via hyperspectral spacing, or microscopy as discussed earlier, future surgery guided by AI would have unparalleled precision and accuracy.[(57, 48, 58)] Eliminating the margin of error would reduce complication rates, reduce the need for revision surgery, whilst maintaining positive outcomes.[59] Further integration of neural networking software, guided by input from radiological imaging and videography, could revolutionise the way surgery is conducted in ENT.

Inherent risks of Artificial Intelligence use within otolaryngology:

Input and validation issues:

Machine learning algorithms rely heavily on the input training data to develop their pattern recognition. Errors introduced in input data (e.g., the margin for error in biochemical serum readings) could be propagated and adversely skew the algorithm and cause judgement errors. In the context of diagnostic algorithms, such errors could risk harming patients, whether through false negatives (and thus missed diagnoses) or false positives (and thus unnecessary procedures).[60] Due to the potential of harming patients, this diagnostic deployment of AI thus risks violating the core medical ethical principle of non-maleficence. Discrepancies between training data and real-world data could cause a similar result, as the limit on available training data may impact the quality of the algorithm.[61]

Model drift is the decay of a machine-learnings tool's predictive capabilities, resulting from a change in real-world input.[62] This was seen in an AI tool used to assist breast screening mammography, which when implemented on a different mammography machine could no longer consistently identify screen-detected cancers.[63] Such a drop was even seen simply following the installation of a software update.[63] Regular validation and calibration of AI tools will be essential to preventing model drift, and it would be pertinent to integrate AI model monitoring to help detect any divergence.

There is also the fear that doctors may become overly reliant upon these diagnostic aids, pertaining to the machine exceeding its guiding role of our intuition and judgement.[64] Doctors need to consider a patient's best interests beyond AI's specific recommendations, to elicit the most beneficial outcome for each patient even if not the most curative.

The Black-box conundrum:

A black-box model describes machine learning algorithms that have an opaque hidden layer, meaning the decision-making processes that underly the output of the model are not easily interpreted by humans.[65] Integration of AI into clinical settings will rely on the trust of clinicians and patients, a difficult ask when the reasoning for life-changing decisions remain a mystery.[66] A cornerstone of ethical healthcare is a patient's right to make informed decisions about their health.[67] Without transparency as to the justification of clinical decision made by AI (e.g., the prognosis of a nasopharyngeal malignancy), patients may make clinical decisions that aren't in their best interest. Advancements are being made to achieve an AI that is explainable,[68] but until then there will be issues regarding maintaining patient-centred care and gaining trust for any healthcare AI system.[69]

Bias and data use:

As with all research, the introduction of bias whether by systematic error or the encouragement of certain outcomes, can have negative effects.[70] Some ML models have been shown to extensively manifest dangerous stereotyping, regarding gender, race, and disability,[71] a latent harm which needs to be addressed in these systems whether it be a systemic or selection bias.[72, 73] This also reflects a key limitation of AI: the need for large, high-quality, and representative datasets to accurately train algorithms. Such datasets are surprisingly scarce, with vulnerable groups consistently underrepresented across healthcare datasets.[74] Access to datasets poses added concerns, with private multi-national corporations responsible for most existing AI systems.[75] Patients have a right to privacy, and ensuring data remains anonymous is essential to preventing discrimination such as denial of health insurance due to an individual's gene profile.[76]

Mitigating the risks of Artificial Intelligence:

Establishing governance is paramount in the mitigation of the risks of artificial intelligence, especially in otolaryngology and healthcare in general.[77] Efforts have been made in recent years to develop foundational principles for the use of AI in medicine.[78] There are some key steps otolaryngologists hoping to authorise the use of AI within ENT should advocate for. Firstly, fairness must be safeguarded by verifying that any AI model being deployed has no bias and was trained on data specific to and representative of the target population. Secondly, it is crucial to ensure transparency and accuracy by using AI that is explainable and that has been externally validated. Equally, advocates should promote measures to enable all stakeholders to interpret the AI, such as education initiatives (whether that be a training course for otolaryngologists or leaflets for patients). Additionally, it is essential that any AI commissioned takes proactive measures to preserve the privacy of the individual's data it enlists. Finally, any model implemented would require continuous auditing and monitoring to ensure the AI operates as intended and is not at risk of causing harm to patients. Successfully conducted, these measures could ensure safe integration of AI into otolaryngology, reducing the risks and promoting the potential benefits.

Conclusion:

Rising pressures within ENT, whether because of staff shortages or growing demand, need to be tackled. AI won't be able to single-handedly resolve these issues, but it certainly has the facility to be a valuable tool in curbing struggles. AI is continually evolving, and at its current trajectory it would not be a surprise to see systems aiding otolaryngologists to routinely diagnose a range of conditions in the near future, perhaps even within the next decade. Indeed, the raw processing power AI can harness, is something humans will never be able to match, so embracing this technology can allow us to do things never previously thought to be possible.

Transferring AI's potential, into real-world innovation requires future iterations that comply to the important abovementioned principles of AI governance. Rigorous testing, study and monitoring at all levels of development and implementation is imperative to mitigate the sizeable risks that accompany artificial intelligence are diminished. To ensure AI positively transforms the speciality rather than opening a catastrophic Pandora's box, it is crucial that otolaryngologists advocate for appropriate governance.

Speculation that ENT surgeons will be replaced by a contingent of AI powered systems and machines is an improbable outcome, certainly in the immediate future. AI will likely change the landscape of otolaryngology, as an extension of the existing otolaryngological tool kit rather than a substitute. Admittedly, however, when discussing the potential of AI, Alan Turing was correct to say, "no such bounds can be set".

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Appendix:

Figure 1: *Citations per year for machine learning articles published in otolaryngology literature from 2013 to November 2023*

Database searched: Graph derived from data obtained from National Library of Medicine [Available from: https://pubmed.ncbi.nlm.nih.gov]
Search was run on December 2nd 2023
Articles included were from January 2013 – November 2023
Search criteria: [Machine learning AND otolaryngology]