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Review Article

RESPIRATION AND THE AIRWAY

Artificial intelligence in airway management: a narrative review

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Summary

This narrative review examines artificial intelligence (AI) applications in airway management through a structured literature search completed in July 2025. AI shows promise in predicting difficult airways through facial recognition, voice analysis, and multiparametric assessment. AI models demonstrate improved positive predictive values compared with conventional bedside tests, though prediction remains imperfect. The fundamental challenge of low positive predictive values persists, albeit at reduced levels. For videolaryngoscopy, AI-powered systems provide real-time structure identification, procedural guidance, tracheal tube placement verification, and potentially fewer complications. AI also offers cognitive support during critical scenarios by mitigating decision biases, providing intelligent alarms, and ensuring guideline adherence when human performance might be compromised by stress. In education, AI-enhanced virtual reality simulations create realistic practice environments with personalised feedback tailored to learners' needs. Experimental robotic intubation systems guided by AI algorithms demonstrate performance comparable with experts in controlled settings, though primarily for training and remote applications. Despite these advances, AI should complement rather than replace human expertise. Important challenges remain, including the risk of clinician deskilling, the 'black box' nature of some algorithms limiting transparency, and the need for robust validation before widespread implementation. The ideal approach involves human-machine collaboration where AI compensates for cognitive limitations while physicians contribute clinical judgement, context awareness, and empathy. As AI continues evolving, appropriate ethical frameworks and regulatory oversight must be developed in parallel to ensure these technologies enhance patient safety while preserving the essential human element of healthcare.

Keywords: airway management; artificial intelligence; intubation; machine learning; prediction; robotic airway systems; videolaryngoscopy; virtual reality training

Editor's key points

- AI shows promise in predicting difficult airways through facial recognition, voice analysis, and multiparametric assessment.
- For videolaryngoscopy, AI-powered systems provide real-time structure identification, procedural guidance, tracheal tube placement verification, and potentially fewer complications.
- AI offers cognitive support during critical scenarios by mitigating decision biases, providing intelligent alarms, and ensuring guideline adherence.
- In education, AI-enhanced virtual reality simulations create realistic practice environments with personalised feedback tailored to learners' needs.
- AI should complement rather than replace human expertise.

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AI will not replace humans, but those who use AI will replace those who don't.

Ginni Rometty, Former CEO of IBM

What is artificial intelligence?

There are many definitions of artificial intelligence (AI), but probably one of the most appropriate is provided on the official IBM website[1]: *Artificial intelligence is technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy*. This definition suggests that AI mimics natural intelligence but operates faster and without emotion, theoretically reducing emotional and cognitive biases.[2] However, Yudkowsky stated: '*by far, the greatest danger of artificial intelligence is that people conclude too early that they understand it*'.[3] Applications of AI in anaesthesia have been explored since the late 1980s,[4] with research expanding to include neural networks, depth of anaesthesia monitoring, event prediction, and operating room logistics.[5–7] The COVID-19 pandemic accelerated AI applications in healthcare,[8–10] with airway management emerging as an important application area. The main objective of this narrative review is to provide an overview of the available evidence related to the clinical uses of AI in airway management. We aim to assess the current status of investigations, classify AI models used for airway management, and identify gaps in existing literature to guide future research.

Methods

A literature search was performed on Medline and Scopus up to July 20, 2025 by three experienced researchers (LLV, AM and ECLG).[11] We combined Medical Subject Headings (MeSH) and free-text keywords. Boolean operators ('AND', 'OR') and truncation (*) were also used. The complete search strategy used is as follows: ('artificial intelligence' [MeSH Terms] OR 'machine learning' [MeSH Terms] OR 'deep learning' [MeSH Terms] OR 'neural networks (computer)' [MeSH Terms] OR 'computer vision' OR 'support vector machine' OR 'convolutional neural network' OR 'AI' OR 'ML') AND ('airway management' [MeSH Terms] OR 'intubation, intratracheal' [MeSH Terms] OR 'extubation' [MeSH Terms] OR 'difficult airway' OR 'video laryngoscopy' OR 'airway assessment' OR 'ventilation' OR 'laryngeal mask airway'). This strategy was adapted to the syntax of each database.

We included original research articles involving human participants undergoing airway management in any clinical setting (operating theatre, intensive care, emergency department) where AI techniques (machine learning, deep learning, neural networks, computer vision, support vector machines, or related algorithms) were applied. Both observational (prospective and retrospective cohort studies, case-control studies) and interventional (randomised controlled trials) studies published up to July 20, 2025 were eligible, with no language restrictions applied.

Three reviewers (MS, DSP, and ML) independently screened titles and abstracts against the eligibility criteria. Disagreements at any stage were resolved through consensus. We consulted ChatGPT[12] to determine the review structure and identify key AI aspects requiring focus: AI for predicting (difficult) airway management, assistive AI for videolaryngoscopy and intubation, AI-based cognitive support, and role of AI and virtual reality in training. Table 1 provides a structured summary of current AI applications across these domains, highlighting key performance metrics, clinical benefits, and implementation challenges.

Artificial intelligence in prediction of airway management

Purely mathematical and statistical approaches for preprocedural airway assessment demonstrate poor positive and negative predictive values.[13] A recent editorial suggests that difficult airways represent a syndrome involving complex interactions among multiple factors, requiring individualised case-by-case assessment.[14] Modern airway assessment should use multiple tests, address all potential difficulties (ventilation, laryngoscopy, intubation, supraglottic airway rescue, and front-of-neck access), and incorporate context-sensitive evaluation,[15] considering anatomical measurements,[16] airway history, the patient's pathophysiological derangements,[17] clinical scenarios, the environment, and the clinical team.

AI represents a powerful tool for airway assessment by extracting knowledge from large datasets faster and more accurately than traditional methods.[18] Machine learning can analyse a large amount of information and generate an algorithm/model to recognise patterns and perform predictive tasks without the need for explicit instructions.[19] AI, using either supervised or unsupervised machine learning,[20] could understand the relationships among multiple variables to improve the accuracy of prediction.[21,22] AI models have been studied in thyroid,[23,24] head and neck procedures, and maxillofacial surgeries,[25] including obese patients,[26] paediatric patients,[27,28] and trauma patients.[29] Most of the analysed AI models outperform clinical evaluation in terms of precision and accuracy. Predictive performance improves as the number of variables included in the AI models increases, similar to learning from clinical experiences.[30] Models using only two or three parameters[31,32] perform worse than multiparametric models in both elective and emergency settings.[33–37] AI models could analyse radiological imaging data[38–40] to identify features associated with difficult airway,[41–43] provide airway segmentation and confirm tracheal tube position.[44] A landmark paper by Tavolara and colleagues[45] applied deep learning models for difficult airway identification using frontal face image analysis with a database of celebrities' portraits. Other studies analysed predictive airway assessment from facial images,[46–48] including difficult face mask ventilation,[49] difficult laryngoscopy,[50] difficult videolaryngoscopy,[51] and sleep apnoea[52] in both experienced and inexperienced medical personnel.[53] These AI models achieved positive predictive values of 45–76% when compared with 5–20% for conventional bedside evaluations, while maintaining comparable negative predictive values (92–98% *vs* 94–99%), representing a clinically meaningful improvement in correctly identifying patients with difficult airway while minimising false reassurance.[16,54,55] Xia and colleagues[54] report that AI outperforms conventional bedside evaluations in videolaryngoscopy because mouth, larynx, pharynx, and airway structures are readily visible during videolaryngoscopy.[56,57]

Table 1 Artificial intelligence applications in airway management: summary of current evidence. AGATI, automated glottic action tracking by artificial intelligence; AI, artificial intelligence; AR, augmented reality; CNN, convolutional neural network; TT, tracheal tube; NPV, negative predictive value; PPV, positive predictive value; VR, virtual reality.

Domain	AI method	Clinical use	Performance	Key benefits	Main limitations
Airway prediction	Deep learning, CNN, machine learning	Difficult intubation/ventilation prediction via facial images, voice analysis, imaging, multiparametric models	PPV 45–76% *vs* 5–20% conventional; NPV 92–98% *vs* 94–99% conventional	Noninvasive; smartphone-compatible; outperforms bedside tests; multiparametric integration	Prediction remains imperfect; population-dependent; low PPV persists (albeit improved)
Videolaryngoscopy assistance	CNN, deep learning (AGATI, Mask R-CNN, U-Net)	Real-time vocal cord/glottis/trachea identification; procedural guidance	Specificity 0.97–0.99; sensitivity 0.87–0.89	Real-time feedback; educational tool; supports inexperienced clinicians	Blade-specific training; variable performance across anatomy; dedicated hardware required
Emergency support	Neural networks, AI-enhanced ultrasound	TT position verification; oesophageal intubation detection; cognitive decision support; intelligent alarms	Variable (TT: sensitivity 95%, specificity 50%)	Rapid verification; reduces errors; mitigates cognitive bias; guideline adherence	Limited specificity for some applications; better for education than real-time decisions currently
Robotic systems	AI-guided robotics with haptic feedback	Semi-autonomous intubation in controlled/simulated settings	Comparable with experts in simulators	Potential for remote/hazardous settings; tele-mentoring	Prohibitive cost; simulator-to-clinic gap; liability unresolved; limited clinical validation
Training and education	VR/AR with AI feedback	Laryngoscopy, bronchoscopy, neonatal intubation simulation	Skills transfer demonstrated	Safe practice; rare scenarios; personalised learning; no patient risk	High cost; lacks standardised validation; long-term outcome benefit unproven
Overall challenges	All AI systems	Clinical implementation	N/A	Human-AI collaboration potential	'Black box' algorithms; deskilling risk; data bias; validation gaps; ethical/regulatory frameworks lagging

Voice patterns and acoustic features[58,59] have also been used to predict difficult mask ventilation, difficult laryngoscopy, and undiagnosed sleep apnoea syndrome.[60] Certain voice patterns were associated with difficult laryngoscopy with 76.1% accuracy.[61] Similarly, the area under the curve (AUC) for the prediction of difficult mask ventilation with voice patterns was 74%.[62]

Many AI models have been tested using smartphones, which are readily accessible to anaesthesiologists for difficult airway recognition based on a patient's subjective facial assessment. To date, systematic and narrative reviews indicate that AI models exhibit average-to-good discriminative ability to recognise difficult airways.[55,63] Based on these findings, we envision a future with handheld devices to video/audio record the patient for airway evaluation and management.[64,65] A recent study testing Chat-GPT-4's ability to develop perioperative anaesthetic plans revealed important AI limitations, with the system occasionally failing to meet minimum standards.[66] Best practice remains combining AI predictive models and physician experiences to take care of the patient.[67,68]

Artificial intelligence in videolaryngoscopy and intubation

Once an airway management plan is established, videolaryngoscopy and intubation can be enhanced by assistive AI.[69] AI models can support laryngoscopy and intubation through anatomical structure recognition (upper airway, larynx, trachea, bronchi), tracheal tube position verification, and robotic intubation system guidance.[70]

The first AI models designed for anatomy recognition were applied in bronchoscopy[71] to identify normal and pathological structures, with a performance comparable with that of the most experienced experts.[72] When applied to

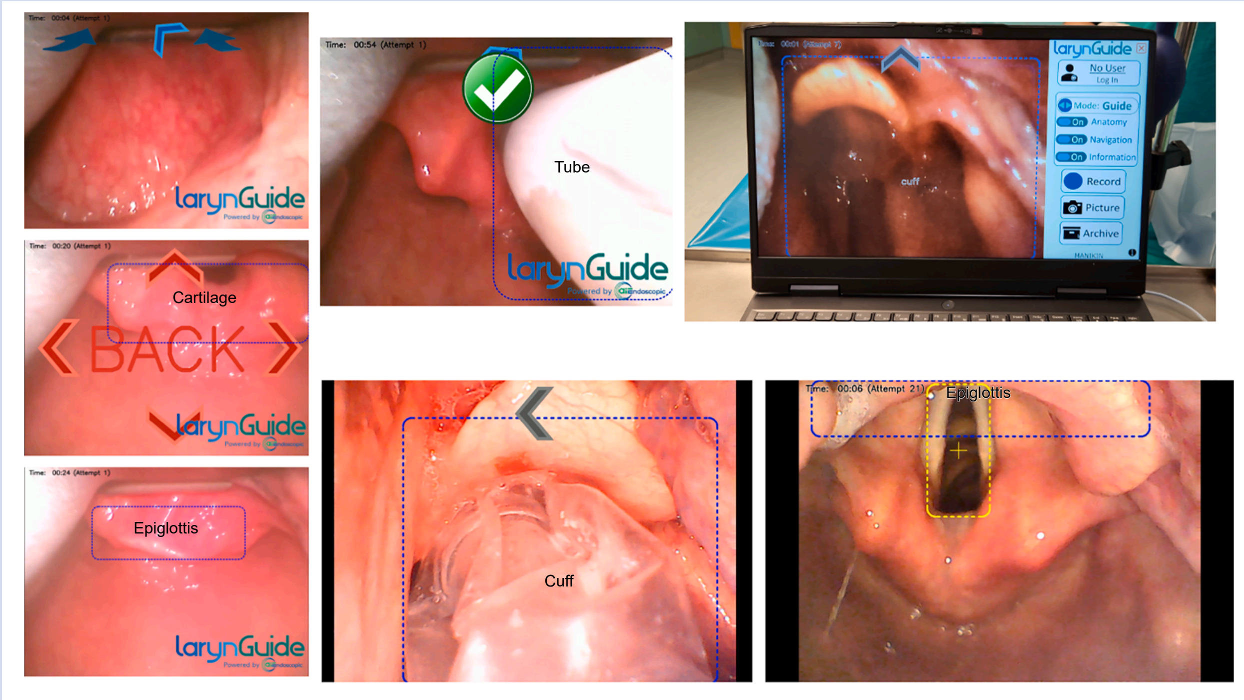

Fig 1. Airway images obtained from a videolaryngoscope connected to a laptop equipped with an advanced AI model for structure recognition and assistive information (see text for details). The system can provide real-time anatomy labelling, movement suggestions and adjustments, confirmation of correct positioning, and offline performance data analysis. AI, artificial intelligence.

videolaryngoscopy, AI models must be tested specifically for different types of videolaryngoscopy blades (shape, curvature, design).[73] Bronchoscopy and laryngoscopy images were incorporated into AI convolutional neural network models to provide real-time classification and identification of vocal cords and trachea. The best performing models showed specificity of 0.971–0.985 and sensitivity of 0.865–0.892[74] with real-time feedback. Similar results were described with an open-source model 'AGATI - automated glottic action tracking by artificial intelligence',[75] convolute neural network models,[76] and various other AI algorithms.[77–86] These algorithms offer virtual assistance during laryngoscopy, and improve intubation success rates, particularly for less experienced clinicians. However, the clinical value of improved positive predictive values must be weighed against potential overconfidence in AI outputs, which might paradoxically increase risks or reduce vigilance.

Figure 1 shows videolaryngoscopy views with integrated AI support (LarynGuideTM software, aiEndoscopic, Zurich, Switzerland; https://www.aiendoscopic.com/projects/larynguide) from an ongoing study in our institution. The ability of AI to identify airway structures and provide real-time information is valuable and carries significant implications. AI may provide support in teaching and training, managing difficult airways, integrating multiple datasets (CT scans, MRI, preoperative endoscopy), and cognitive supports.

Models for neonatal videolaryngoscopy and intubation have also been developed,[87,88] but with lower performance in identify structures when compared with adult models. However, opportunities for adequate training are rare, and neonatal airways are fragile.[89] The need for AI assistance in the neonatal field is tremendous.

Artificial intelligence in videolaryngoscopy during emergency

AI assistance offers significant potential during intubation by providing real-time, dynamic cognitive support. This capability is particularly valuable in difficult or emergency airway management, where stress could increase the risk of cognitive biases.[90] AI assistance can also rapidly provide reliable information about tube depth and position. Multiple studies demonstrate excellent performance analysing chest radiographs and CT scans to identify airway issues.[44,91]

Detection of oesophageal intubation[92] could be improved by neural network models capable of providing automated tube position check[93] and oesophageal intubation recognition[94] to reduce errors. However, a recent study evaluating AI's ability to differentiate correct from incorrect tube placement showed a sensitivity of 95% but specificity of only 50%.[95] The accompanying editorial notes that current AI systems may be more valuable for education and cognitive support (providing alerts, guidelines, and intelligent summaries) rather than for real-time clinical decision-making during airway management.[96] For oesophageal intubation detection, AI models interpreting lung sliding may be more reliable than analysis of laryngoscopic imaging.[97]

AI-assisted drug delivery and closed-loop systems may reduce peri-intubation cardiovascular complications in high-risk patients by adjusting induction agents based on monitoring of physiological parameters.[98,99] Finally, intelligent alarms may be enhanced through AI application in laryngoscopy and intubation, resulting in increased patient safety.[100]

Artificial intelligence in robotic intubation

Parallel advances in micromotors, electronics, and servo-assisted mechanisms have enabled robotic prototypes with potential applications in airway management. Various robotic intubation systems have been developed and tested in simulated airway scenarios. Initial tests were performed using the DaVinci surgical robot equipped with a flexible bronchoscope,[101] followed by intubation robots.[102,103] Most robotic systems, particularly newer versions,[82,104–106] showed intubation times and success rates comparable with expert physicians' performance. Inclusion of haptic feedback, pressure, and localisation sensors may create robotic systems capable of performing swift intubation while reducing potential airway trauma.

Despite technological sophistication, robotic intubation faces formidable barriers to clinical adoption: prohibitive costs, space requirements, interface complexity, and unresolved liability issues regarding AI-driven decisions in critical situations. These systems currently demonstrate value primarily in training and remote or hazardous settings[107–110] (such as tele-mentoring or airborne contagion scenarios), not in routine clinical practice. Claims of expert-level performance require critical scrutiny—controlled simulator studies poorly predict performance in emergency scenarios with anatomical variations, physiological instability, and time pressure. The gap between laboratory success and clinical utility remains substantial.

Artificial intelligence in airway management training

AI has become a valuable tool in training healthcare professionals in airway management, providing innovative methods to enhance skill acquisition and decision-making. Through advanced simulations, virtual reality, and personalised feedback systems, AI enables trainees to practice complex procedures in a safe and controlled environment, improving their confidence and competence. Additionally, AI-driven training platforms can adapt to individual learning needs, identify areas for improvement, and offer targeted guidance, thereby accelerating the learning curve. As technology continues to advance, AI-based training programs are poised to transform airway management education by offering more realistic, accessible, and effective training experiences for clinicians at all levels.[4]

Studies have demonstrated associations between video game use and improved laryngoscopy/intubation skills, suggesting that neural and behavioural priming facilitates motor skill development.[111] Application of virtual reality for laryngoscopy and airway management training has been examined in several studies,[112–116] including bronchoscopy[117–119] and simulation.[13,120–122] AI-assisted cognitive support improves both technical and non-technical airway management skills without patient risk, while simultaneously enhancing task-specific neural pathways.[123] Virtual reality has also been used, although with less demonstrated benefit, for cardiopulmonary resuscitation training of lay people and healthcare professionals.[124,125] High-fidelity virtual reality systems may transform airway management education by enabling extended training, simulating rare scenarios, and reducing patient-associated training risks.

The future of artificial intelligence in airway management

Technological evolution has provided new airway management tools, devices, and techniques; changed the definition of 'difficult' airway; and improved patient safety. Substantial evidence indicates that human factors, cognitive biases, and non-technical issues remain the leading causes of airway management-related complications.

AI applications can support both technical skill development (through virtual/augmented reality and 3D-printed simulators) and non-technical skills (through improved communication, guideline access, data interpretation, and clinical decision support).[126–129] However, substantial concerns temper this optimism and warrant careful consideration. Excessive reliance on AI risks clinician deskilling—a phenomenon whereby automation-induced erosion of manual and cognitive skills leaves practitioners unprepared when technology fails.[130] This concern extends beyond individual competence: widespread AI adoption may diminish professional roles, reduce clinical experience opportunities, and undermine the experiential learning foundation necessary for effective clinical teaching. AI and robotic intubation systems may particularly accelerate these effects by reducing hands-on practice opportunities. The 'black box' nature of many deep learning algorithms presents a critical transparency problem because outputs emerge from processes neither clinicians nor developers fully understand, raising accountability questions when errors occur. Data privacy, algorithmic bias, and informed consent protocols remain unresolved.[131]

Furthermore, most AI models discussed remain experimental or have been tested only in controlled environments. Few demonstrate definitive improvements in clinical outcomes or real-world safety metrics. The gap between laboratory performance and bedside implementation is substantial and poorly characterised.[132] Commercial systems often lack standardised validation metrics, and their superiority over traditional methods remains unproven in rigorous comparative studies measuring actual patient outcomes or long-term skill retention. In airway management, an excellent editorial by Heidegger and colleagues[133] raised several points that depict the current role of AI in airway management.

Although AI models outperform clinical examination in predicting difficult airways,[16,54,55] these improvements must be contextualised against fundamental prediction limitations. Yentis[134] demonstrated conventional approaches yield poor positive predictive values, and the Cochrane review by Roth and colleagues[135] confirmed the limited discriminative ability of bedside tests. AI does not fundamentally solve the low positive predictive value problem; it improves these values modestly while maintaining high negative predictive values. The practical implication is that AI shifts the risk–benefit balance: accepting more false-positive predictions (requiring unnecessary advanced preparation) to reduce false-negative predictions (unprepared difficult airways). This trade-off aligns with modern safety culture emphasising preparedness over precision.

Moreover, even perfect prediction cannot, by itself, prevent poor airway management or adverse outcomes. The value of AI lies not solely in predictive accuracy, but in its potential to support the entire airway management ecosystem: predictive preparation, procedural guidance, cognitive support during execution, and post-event analysis for system improvement. AI models can incorporate and interpret vast datasets, provided the data are available and properly structured. Contextual factors in clinical scenarios, including emotional and relational elements, may not translate into data that AI can interpret, resulting in inadequate system outputs.

Implementation of AI requires prudence, responsibility, and new ethical frameworks. For example, 'Algorithmic Clinical Accountability' could define shared responsibility between AI systems and healthcare providers in clinical decision-making. Regulatory and legal safeguards must evolve in parallel with AI's accelerating integration into clinical practice.[127] Moreover, healthcare providers should be educated about how AI models are created, their limitations, and how clinicians can leverage them to our patients' advantage.

The optimal goal is cautious, evidence-based human-machine collaboration where AI complements, not replaces, clinician expertise. However, AI may reduce demand for human clinicians, erode experiential learning opportunities essential for teaching, and introduce new failure modes when algorithms malfunction or misinterpret clinical context. Patients benefit from both accurate predictions and empathetic human connection[136]—AI provides only the former. Recognising these challenges, the Anesthesia Research Council steering committee recently formed an expert workgroup to define current and future AI incorporation in anaesthesia while exploring implementation needs, limitations, and barriers. This workgroup emphasises that AI developers must remain focused on patient-centred solutions that support healthcare providers and improve healthcare systems.[137]

Authors' contributions

Idea and writing: MS
Literature search, draft of the manuscript and revision: DSP, ECLG, LLV, AM, ST
Critical review: ML, FP
Approved the final version of the manuscript: all authors

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT-4 in order to determine the review structure and identify key AI aspects requiring focus. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declarations of interest

MS has received paid consultancy from Teleflex Medical, Verathon Medical, and DEAS Italia; he is a patent co-owner (no royalties) of DEAS Italia and has received lecture grants and travel reimbursements from MSD Italia and Boston Scientific France. MS has an NDA with Flexicare (UK) and aiEndoscopic (Switzerland); MS is a member of the PUMA writing group and immediate past President of the European Airway Management Society (EAMS). LLV has an NDA with Flexicare (UK) and AIEndoscopic (Switzerland). DSP, AM, ECLG,ST, ML, and FP declare that they have no conflicts of interest.

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