Narrative Review

Scope of artificial intelligence in airway management

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ABSTRACT

The evolution of artificial intelligence (AI) systems in the field of anaesthesiology owes to notable advancements in data processing, databases, algorithmic programs, and computation power. Over the past decades, its accelerated progression has enhanced safety in anaesthesia by improving the efficiency of equipment, perioperative risk assessments, monitoring, and drug administration systems. AI in the field of anaesthesia aims to improve patient safety, optimise resources, and improve the quality of anaesthesia management in all phases of perioperative care. The use of AI is likely to impact difficult airway management and patient safety considerably. AI has been explored to predict difficult intubation to outperform conventional airway examinations by integrating subjective factors, such as facial appearance, speech features, habitus, and other poorly known features. This narrative review delves into the status of AI in airway management, the most recent developments in this field, and its future clinical applications.

Key words: Airway management, algorithmic programmes airway, anaesthesiology, artificial intelligence, intelligence, management, model

INTRODUCTION

Artificial intelligence (AI) is a multi-disciplinary branch of computer science that researches and develops technology, principles, techniques, and application systems for replicating and amplifying human knowledge, typically utilising algorithms for reasoning towards problems and performing analytical tasks.[1] The application of AI has grown significantly, mainly directed through technological improvements in statistics and computation power, by handling and processing enormous amounts of data to design analyses and predictions, even if not programmed to execute.[2]

This narrative review aims to summarise the recent advancements achieved in airway management concerning the application of AI. We also emphasise the associated problems in their implementation and future perspectives.

CONCEPT OF AI

AI includes machine learning (ML), deep learning (DL), language processing, speech and image identification, and expert systems.[3] ML includes algorithm training to determine paradigms and make predictions. Algorithm learning upgrades with experience, allowing process optimisation. DL is a sub-group of ML functions using neural networks, namely, convolutional neural network (CNN), artificial neural network (ANN), and recurrent neural network (RNN). It works through many processing layers to derive sophisticated information and infer characteristics that require high intelligence. DL is usually applicable for image detection and identifying abnormal patterns. A primary advantage of DL is that it instantly detects data patterns generally unnoticed by human intelligence.[4] An artificial neural network (ANN) is

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a computation model influenced by how biological neural networks of human minds handle information. For error reduction, ANNs adapt to the process and repeat the process until the desired output is attained. CNNs are differentiated from other neural networks by their superior performance with image, speech, or audio signal inputs.[5] They are more often utilised for classification and computer vision tasks. RNNs are a class of neural networks whose output from the previous step is fed as input to the current step. RNNs are mainly used for natural language processing, speech recognition, robot control, sequential prediction, and brain–computer interface.[6]

AI in the field of anaesthesia aims to improve patient safety, optimise resources, and improve the quality of anaesthesia management in all phases of perioperative care.[7] Despite clear guidelines and protocols, failed airway management, although rare, can still lead to life-threatening complications.[8,9] The remarkable progress in the application of AI may help to deal with perceived difficulties during airway management.[10] Thus, mastering AI for anticipation and planning in airway management has the potential to surpass the traditional methods of airway management.[11]

AI IN DIFFICULT AIRWAY ASSESSMENT AND MANAGEMENT

Facing a challenging airway in operation theatres and emergency areas is not unusual for anaesthesiologists. Preoperative assessment of a difficult airway is a vital component of anaesthesia for its potential to cause life-threatening complications.[12,13] Despite upgraded guidelines and advanced airway devices, unanticipated problems with difficult or failed airway management appear.[14] A careful preoperative airway assessment is the top priority for anaesthesiologists to improve understanding, prevention, and management of airway-related complications.[15] There are also certain patients where even a skilled anaesthesiologist struggles to predict intubation difficulty.[16] Among the methods currently used for assessing difficult airways, the upper lip bite test (ULBT) and modified 'LEMON' criterion have only poor to moderate discriminative power if used alone or in combination.[17,18] Other commonly used bedside airway examinations, the modified Mallampati test (MMT) and the thyromental distance, also have a sensitivity of 30% to 60% and a specificity of 60% to 80% with a low positive predictive value.[19] AI has been explored to predict difficult intubation to outperform conventional airway examinations by integrating subjective factors, such as facial appearance, speech features, habitus, and other poorly known features.[10]

Facial analysis techniques

A few investigators have analysed facial features to predict difficult intubation. Cuendet *et al*.[20] proposed the first non-invasive automatic face-analysis system to predict difficult intubation in a clinical setting. Specific statistical face models were selected from a database of 970 patients using the importance ranking specified by the random forest algorithm. With an area under the curve (AUC) of 0.779, this algorithmic AI model based on face scanning reported a precision level similar to the standard methods for predicting difficult airways.

Another AI model based on CNN was created by Hayasaka *et al*.[21] to classify tracheal intubation difficulties. This model had an AUC of 0.864 and was appropriate for untrained personnel performing endotracheal intubation in emergency scenarios. The model recognises facial contour and predicts difficult endotracheal intubation, with a sensitivity and specificity of 81.8% and 83.3%, respectively. Likewise, Tavolara *et al*.[22] designed a method to assess difficult airways using images from the front face by ensembling CNN-based feature extractors in conjunction with attention-based multiple-instance learning. Facial images for the DL model were extracted from an extensive database to train CNNs on 11 corresponding facial portions to improve the model's overall performance.

More recently, Wang and colleagues, for the first time, applied a semi-supervised DL method to improve an AI model for predicting difficult airways.[4] Facial images were taken from nine specific and different angles from patients scheduled for elective surgery. The assembled image compilation was further subdivided into sub-sets to train and test based on the ratio of 8:2. This system achieved a good balance between performance and cost. This AI-based image analysis system looks promising to identify patients with difficult airway conditions.

Zhou and colleagues used multiple ML and DL algorithms to identify challenging airways in patients with thyroid disorders scheduled for thyroid surgery.[23] Among the algorithms, gradient boosting was accurate with 100% precision and an AUC of more than 0.8. This model also incorporated parameters such as age, sex, weight, height, and body mass index for developing the ML algorithm.

Regarding mask ventilation, Pei Bei *et al*.[24] designed 3D geometric morphometrics for predicting difficult mask ventilation. They used 3D facial scans of 669 adult patients scheduled for general anaesthesia. The performance of ten different ML algorithms was compared with the 'DIFFMASK' score. The model demonstrated better predictive performance with an AUC of 0.785 and a sensitivity of 0.686 (95% CI, 0.578–0.847) with ML algorithms.

The AI tools to predict difficult intubation in perioperative settings are likely to play a more crucial role than conventional approaches in emergency departments for predicting difficult airways and first-pass success.[25] However, automatic face recognition for AI modelling may pose challenges for future research on predicting difficult airways. First, the diverse clinical scenarios can undermine the algorithm's prediction. Second, a good-quality database is required for the real-time applicability of the model.

Speech features analysis

Acoustic parameters analysed during speech can reflect the anatomy of the upper airway, such as the mandible's opening, the mandible, the length of the mandible, the maxilla or laryngeal tube's volume, the oropharyngeal cavity's volume, and other internal structures.[26] Any structural alterations in these anatomical features can also change pronunciation, making speech a comprehensive indicator for predicting difficult airways. Recently, a few studies have reported some evidence supporting this novel association.

An assessment model designed using five phonetic features of vowels and formants reliably guided difficult airway prediction. Among the Chinese population, phonetic characteristics incorporating formant frequencies (f1–f4) and bandwidths (bw1–bw4) effectively predicted difficult intubation and mask ventilation with an AUC of 0.709 and 0.779, respectively.[27,28] A step further would be to combine acoustic analysis with multi-lingual machine translation (MMT) techniques, which is thought to improve the model's accuracy.[29,30]

In the future, AI-based acoustic systems have the potential to identify patients with difficult airways based on speech from remote locations. However, multi-centric studies involving diverse populations are necessary to confirm the promising role of voice technology in predicting difficult airways.

Role of AI in video-assisted laryngoscopes and flexible bronchoscopes

Video laryngoscopes (VLs) have helped to improve the view of the glottic opening and shortened the tracheal intubation time. They are often preferred for airway management due to their highest first-pass success rate across clinical settings.[31] However, there are two potential areas for improvement in the VL technique. Firstly, the 2-dimensional (2D) visualisation on a screen deprives depth perception, sometimes leading to delayed or failed intubations. Secondly, the personnel performing the endotracheal intubation is required to execute simultaneous manipulation of multiple tools.

A few researchers tried to overcome these drawbacks by incorporating AI-based algorithms in existing VL to better visualise the upper airway structures with real-time feedback. In a recent study, the authors tried to develop an AI model for segmenting structures in the oral cavity using VL images acquired while performing emergency intubations.[32] Their Configured Mask R system based on the CNN had excellent precision with high specificity for vocal cords, epiglottis, and cricoid cartilage. However, this study was limited by inadequate model validation. In another similar attempt, Carlson and colleagues evaluated the efficacy of augmented reality video laryngoscopy by video recording the intubation attempts performed on mannequins.[33] Four different ML algorithms analysed the videos of endotracheal intubation attempts and time intervals. The algorithms were further trained and tested to improve the accuracy. They reported 80% accuracy in computer algorithms in identifying the glottic opening and suggested further refinements.

Considering the variety of blade designs available to perform VL, it is also crucial to pay attention to the design of VL devices and the corresponding deep-learning innovations. This necessitates future research on VL, focusing on improving design with three-dimensional visualisation of airway structures with a real-time feedback system using an AI interface. No current studies are exploring AI to aid and guide flexible fibreoptic intubations. The authors perceive that this would be an exciting area worth exploring.

Robotics in airway management

The application of robotic technology for airway management has been tested primarily on mannequins. Tighe and colleagues[34] performed the first robotic-aided endotracheal intubation in a mannequin using the DaVinci System, an expensive and bulky device. In 2012, Hemmerling designed a Kepler intubation robot system (KIS) for intubation in mannequins.[35] KIS was managed with a joystick connected to a robot arm with an affixed video laryngoscope. Later, the authors conducted a pilot study with KIS in 12 patients undergoing elective surgeries.[36] The real-time visual assistance and the robot arms' accuracy allowed for intubations without complications. Likewise, Cheng *et al*.[37] developed an IntuBot with a real-time, audio-visual-based navigation system to automate intubation. This robotic prototype incorporates an algorithm with two servo motors for steering the stylet and its tip towards the vocal cords.

Recently, Wang X and colleagues[38] developed a small, flexible, and portable robotic-assisted remote intubation system (RRAIS) to enhance the success rates of out-of-hospital intubations. This wireless long-distance intubation robot system was tested in 20 Bama miniature pigs. Although the total intubation time with RRAIS was longer, relatively less time was required in the "front" compared to direct laryngoscopy ($p < 0.01$). Recently, Biro and colleagues[39] conducted a proof-of-concept study in mannequin to analyse the performance of the Robotic Endoscope Automated Via Laryngeal Imaging for Tracheal Intubation (REALITI) system. This system incorporates a video endoscope with a joystick and has both manual and automatic control modes for directing the endoscope tip into the glottis, resembling a fibreoptic bronchoscope. The automated mode with image-recognising technology helped automatically place the endotracheal tube quicker than the manual mode.

Previously, researchers have also attempted to design devices that can open the airway and support the jaw in patients under general anaesthesia or deep sedation requiring non-invasive ventilation.[40,41] However, these devices were typically rigid in structure and lacked mask-fastening function to maintain airway patency. To overcome these drawbacks, a robot-assisted system equipped with a couple of snake arms and a mask-fastening mechanism was developed by Ma and colleagues.[42] The proposed airway management robot was verified to be valid in simulation testing. Future studies validating the scope of this clinical application need to be investigated.

AI application in drug administration control

Closed-loop anaesthesia delivery systems mark a transformative shift in the administration of anaesthesia by regulating drug delivery in real-time based on a bispectral index.[43,44] They operate by continuously monitoring the patient's physiological responses, autonomously controlling the depth of anaesthesia and optimising drug dosages more accurately than manually controlled systems. The incorporation of AI-driven closed-loop control algorithms has the potential to refine the precision of anaesthesia delivery by including more control parameters from large datasets of patients.[45] Such closed-loop drug delivery systems are beneficial during induction and early maintenance of anaesthesia when anaesthesiologists perform the task of securing endotracheal intubation. A closed-loop delivery system delivering either intravenous or inhalational anaesthetics helps to establish stable anaesthetic depth during attempts of difficult intubation. Given higher costs and sub-standard safety checks, few closed-loop systems have been developed. We believe the synergy between AI technology and closed-loop systems can transform towards a more automated and responsive approach to administering anaesthesia, promising improved outcomes.

FUTURE PERSPECTIVES AND RESEARCH RECOMMENDATIONS

Integrating AI with ultrasound-based or CT-guided navigation systems may offer real-time assistance with airway anatomy during endotracheal intubation. Further, it can help in precisely placing endotracheal tubes. By integrating automation and AI algorithms, real-time clinical data can aid in predicting airway challenges and may avoid unforeseen problems such as oesophageal intubation or airway-related injuries.

Robotic systems have the potential to facilitate tele-mentoring and real-time video conferencing at remote locations by providing real-time feedback on the procedures performed. This approach is particularly promising in resource-constrained settings where access to skilled anaesthesiologists may be limited. Further research on multi-centric robust clinical trials and comparative studies are warranted to evaluate the efficiency of AI-based systems in airway management.

CHALLENGES AND LIMITATIONS

Despite promising breakthroughs with AI-based airway management research, it has yet to be a real-world application. The substantial cost is a significant challenge for large-scale implementation. AI systems can exacerbate the bias if the selected data are inaccurate. There is a potential threat to data privacy and security if robust policies and regulations for data management are not in place. There has been an endless discussion over AI systems' ethical and legal liabilities in case of a faulty clinical application.[46] To overcome this, the following factors must be considered: (1) fully informed consent to apply data, (2) data privacy and security, (3) fair algorithm and bias, and (4) a user-friendly AI interface. Although the path for the extensive application of AI in airway management may be challenging, the final output can be innovative and unprecedented. This necessitates strengthening data size, quality, validation, etc., a comprehensive understanding of AI systems, establishing robust regulations and guidelines to resolve ethical and legal obligations.

CONCLUSIONS

AI is a transformative technology, evolving from nowhere to the newest state-of-the-art technologies, showing the potential of AI to reshape airway management entirely. Although AI techniques outperform traditional systems in airway management, uncertainty remains in their deployment in day-to-day clinical practice. Regardless of risks and challenges, adopting improvements in AI technology as an opportunity to make advancements is crucial. Future high-quality research in different population groups is essential to embrace AI's benefits in improving airway management's clinical outcomes.

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Conflicts of interest

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