Narrative Review

Role of artificial intelligence in perioperative monitoring in anaesthesia

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ABSTRACT

Artificial intelligence (AI) is making giant strides in the medical domain, and the field of anaesthesia is not untouched. Enhancement in technology, especially AI, in many fields, including medicine, has proven to be far superior, safer and less erratic than human decision-making. The intersection of anaesthesia and AI holds the potential for augmenting constructive advances in anaesthesia care. AI can improve anaesthesiologists' efficiency, reduce costs and improve patient outcomes. Anaesthesiologists are well placed to harness the advantages of AI in various areas like perioperative monitoring, anaesthesia care, drug delivery, post-anaesthesia care unit, pain management and intensive care unit. Perioperative monitoring of the depth of anaesthesia, clinical decision support systems and closed-loop anaesthesia delivery aid in efficient and safer anaesthesia delivery. The effect of various AI interventions in clinical practice will need further research and validation, as well as the ethical implications of privacy and data handling. This paper aims to provide an overview of AI in perioperative monitoring in anaesthesia.

Key words: Anaesthesia, artificial intelligence, close-loop anaesthesia, monitoring, perioperative

INTRODUCTION

Humans have always been in the quest to augment their intelligence. Artificial intelligence (AI) and machine learning (ML) can distil information from massive datasets, but only humans can understand the context of the information. AI is making a rapid foray into the medical field. It helps in making the most of the knowledge acquired by humans. It learns and reacts to the data and thus allows humans to redirect their efforts from mundane tasks to more high-priority areas.

One of the major reasons for morbidity and mortality in anaesthesia is human error.[1] The anaesthesiologist delivering anaesthesia has to tackle multiple tasks simultaneously, a patient with many clinical conditions, procedures, drugs, equipment and clinical uncertainty. This cognitive overload can become challenging for the anaesthesiologist, and AI can help choose the best plan for the patient and improve safety and outcome.[2] Anaesthesiologists are well placed to harness the advantages of AI in various areas like perioperative monitoring, anaesthesia care, drug delivery, post-anaesthesia care unit, pain management and intensive care unit. Multiple techniques in the field of AI find an application in the clinical practice of anaesthesiology and benefit workflow patterns, decision-making, event prediction and optimisation of operating room logistics.

METHODS

A search was done on the search engines (Google Scholar, Scopus and PubMed) for articles with the

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keywords: artificial intelligence, perioperative, monitoring, anaesthesia delivery and risk prediction. The information on monitoring technologies and the themes relating to applications of AI were extracted from the identified articles. Numerous algorithms used in AI studies and their applications are outside the scope of this review and were thus not included. Reviewing full-text articles helped identify studies relevant to the depth of anaesthesia monitoring, control of anaesthesia delivery and prediction of events and risks. Most studies investigated how AI benefits anaesthesia practice by helping the clinician's workflow, decision-making and drug delivery based on perioperative monitoring parameters. AI is an expansive field, and here we aim to present the role of the perioperative depth of anaesthesia monitoring, clinical decision support systems (CDSS) and closed-loop anaesthesia delivery (CLAD).

DISCUSSION

Though the outcomes of ML and AI are similar, ML forms a part of AI by dint of evolution. ML uses various learning algorithms like supervised learning, unsupervised learning and reinforcement learning to solve problems.[3]

An example of supervised learning is the study by Kendale *et al.* The authors studied patients' electronic health records (EHRs) to identify those who had hypotension after propofol administration. The 70% training dataset was then analysed for a 30% test case to assess the algorithm's accuracy in predicting hypotension after induction.[4]

Unsupervised learning can be described by identifying asthmatic patients who would benefit from glucocorticoid therapy.[5] Padmanabhan *et al.* developed an anaesthesia controller to target propofol infusion rates based on the bispectral index (BIS) and mean arterial pressure feedback. The reinforced learning algorithm fine-tunes the drug rate based on the response. This also helps the results to be in the range and prevents overdosing or underdosing.[6]

AI uses various models within the three ML algorithms, like fuzzy logic, classical ML, neural networks, deep learning and Bayesian methods.

Fuzzy logic builds on rule-based systems, where appropriate rule sets are determined using expert human inputs for the machine to follow. However, AI focuses more on the data and mathematical models. Research in fuzzy logic relevant to applications for drug delivery is advancing gradually.[7]

Classical ML uses data properties to formulate algorithms for complex data analysis with the help of experts who select the requisite features. In the study by Hu *et al.*, the authors used a decision tree to calibrate the patient-controlled analgesia (PCA) dosing regimen based on drug consumption, medical and surgical history, and patient demography.[8]

The most popular methods as of now are neural networks and deep learning. The pattern closely resembles the biological nervous system. The input layer is the data: electroencephalogram (EEG), entropy, mean arterial pressures and heart rate variability. A hidden layer analyses the data, and the output layer yields an interpretable result, such as whether the patient is awake or asleep. Between each layer are multiple neural networks, and different outputs can be achieved based on the designed algorithms.[9] Deep learning learns from various datasets and may provide more significant outputs. These features could be utilised to automate monitoring of the depth of anaesthesia and control anaesthesia delivery.

Natural language processing focuses on understanding human language through machines. It is applied to retrieve information from the free text fields and construct structured databases. This becomes useful for studying all the surgical cases, adverse events and other perioperative processes related to the cases.[10]

Computer vision is another subfield of AI. Here, the machine understands the visual inputs like images and videos by automated acquisition, processes and analyses to understand the result. Perioperative uses of AI include automated analyses of ultrasonographic images, identification during regional blocks for anaesthesia and analgesia, and diagnostic interventions.[11]

AI in anaesthesia can empower anaesthesiologists with decision-making and help them address clinical issues more efficiently. AI can be categorised into CDSS, pharmacological and mechanical robotic applications and depth of anaesthesia monitoring. CDSS plays a significant role in perioperative monitoring by aiding in optimal anaesthesia care. The patient data and procedure knowledge are analysed by computer-based tools, which determine the dose of anaesthesia drugs and fluid management. This also helps in perioperative care, like analgesia management, and prevents patient deterioration post-anaesthesia by analyses of patient parameters to detect early signs.[12]

The earliest efforts to develop an automated anaesthesia system began in 1950. Based on EEG signal, Bickford described a closed-loop feedback control system to monitor and maintain the depth of anaesthesia.[13] Researchers at McGill University in Montreal, Quebec and the McGill University Health Centre (MUHC) took a leaf out of Bickford's work. They developed a system of controllers based on response algorithms which attempted to maintain the target variable (depth of anaesthesia) around a set point [Figure 1]. This system was given the nomenclature of 'McSleepy'.[14] Dumont used a quantifiable input, such as a BIS, rather than an EEG, but the overall structure remained the same.[15]

AI finds application in pharmacological robotics, where the system engages with the alerts and recommendations based on perioperative monitoring data and delivers patient-specific anaesthesia.

The first-generation open loop–type pharmacological robots are target-controlled infusion (TCI) systems that can build pharmacokinetic models of different drugs. In these systems, specific plasma drug levels are achieved through software-assisted delivery of doses and continuous infusion. TCI works on estimated plasma and effect-site concentrations that could vary from the actual concentrations, especially in patients exhibiting extreme anthropomorphic features.[16]

CLAD works on the principle of continuous clinical and bio-signal data processing with a complex input–output process. The robot delivers appropriate pharmacological dosing of anaesthetic agents and helps manage fluid and analgesia. The algorithm of CLAD helps in appropriate drug dosing while also identifying potential drug interactions.[17,18]

When faced with clinical complexity, rule-based algorithms cannot match a skilled human's ability. Herein, AI algorithms can learn from a large set of inputs and be 'trained' to perform the task and deliver desired responses. In an anaesthesia machine, the controller gets trained by a plethora of sample cases as control inputs like BIS, albeit under the supervision of human anaesthesiologists. The neural network ensures that the system delivers requisite set point outputs. Thus, the system is 'trained' or 'grown' in a 'bottom-up' manner instead of a 'top-down' approach of handcrafting control rules.[19]

The only difference is that AI-trained delivery systems do not depend on human rationalisation and introspection. The desired set of responses is learnt by the system automatically by imitation. It could achieve the decision-making level equivalent to that of an anaesthesiologist, with the added advantage of speed and accuracy.

As early as the 1970s, CDSS was tested and used primarily for academic purposes as it was time-consuming and had poor system integration.[20] In its current format, CDSS interacts with EHR and can be administered by computers, tablets and smartphones.

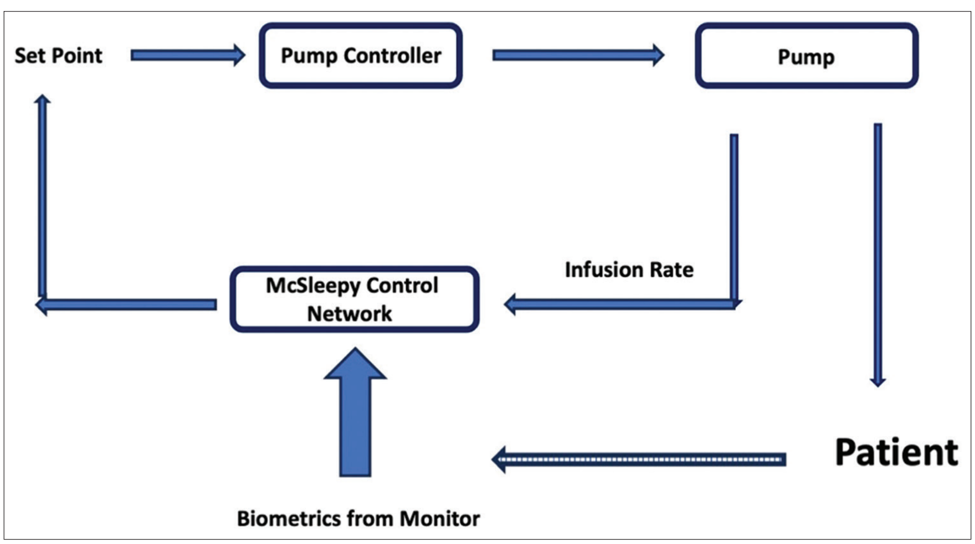

Figure 1: Closed-loop anaesthesia delivery – McSleepy model

It can be knowledge-based, where relevant data is retrieved and analysed to generate a suitable output. The non-knowledge-based system relies on AI and ML to access complete patient data to extract relevant clinical knowledge.[21] During perioperative care, this helps set ventilation parameters, use low-flow anaesthesia, and monitor and manage blood pressure, postoperative nausea and vomiting. CDSS helps assess intraoperative blood loss by monitoring intravascular volume and other haemodynamic parameters. Accepted clinical guidelines could be converted through CDSS into dynamic and usable tools for managing specific patients in real-time while facilitating the efficient collection of patient care information to monitor outcomes. This enables CDSS to help improve care by selecting the best patient treatment. It can offer automated recommendations on various areas like administering anaesthetic agents, analgesia dosage and fluid management as part of perioperative care and help reduce medication errors and adverse events.

Perioperative monitoring is a tedious task, and alarm fatigue experienced by the anaesthesiologist during anaesthesia administration can be a serious safety concern for the patients. Cognitive robots driven by AI could be integrated into alarm systems to analyse multiple parameters simultaneously, thus helping to lower false alarm rates and operator fatigue.[22] Monitoring the depth of anaesthesia forms the backbone of AI applications in anaesthesia practice.[23]

The main organ targeted by anaesthesia is the brain. Hence, the anaesthetic effect could be monitored via EEG. Different anaesthetic drugs produce various EEG changes; notwithstanding, any newly developed processed EEG monitor for monitoring the depth of anaesthesia would require further research and validation. Deep learning models in AI could assist in eliminating the need to perform clinical trials on hypnosis-level monitors.[24]

A non-invasive modality like EEG could be an effective tool for studying brain activity since the central nervous system is the main organ targeted by anaesthesia. Shalbaf *et al*. worked on EEG to analyse entropy, spectral and fractal signals, which were then applied to an algorithm that had the characteristics of all the groups. The best characteristics (sample entropy, Shannon permutation entropy, beta-index and detrended fluctuation) were then applied to a neuro-fuzzy classification algorithm, an adaptive neuro-fuzzy inference system with linguistic hedges (ANFIS-LH). ANFIS-LH distils out the unimportant features in the input and suitably changes the output. This method was studied in 17 patients who received sevoflurane anaesthesia, and it classified their EEG data based on the various states of depth of anaesthesia with an accuracy of 92%. This included a range from awake to light to general and deep states of anaesthesia. Similarly, 50 patients who were administered propofol and volatile anaesthesia also demonstrated an accuracy of 93% when their EEG signals were classified into awake or general anaesthesia. This new real-time monitoring system will help the anaesthesiologist assess the depth of anaesthesia (DoA) quickly and accurately.[25]

Mid-latency auditory evoked potential is another monitoring tool which can be used to judge the depth of anaesthesia in patients. Zhang *et al*. reported the accuracy of these signals as 96.8% (awake patients), 86% (adequate anaesthesia) and 86.6% (emergence from anaesthesia).[26]

Nagaraj *et al*. studied heart rate variability to assess sedation in critical care settings.[27] Ranta *et al*. found in their analysis of statistics of almost 550 patients who underwent general anaesthesia that 6% reported intraoperative awareness. However, the predictability of awareness for these networks increased to 66% when additional features like blood pressure, heart rate and end-tidal carbon dioxide were investigated, but the specificity was 98%. These approaches have a high utility because the neural network can auto-update itself with the attributes in the dataset and utilise the chief attributes which predict the endpoint (e.g. awareness) instead of being taught the features suggested by the clinicians to be the most prognostic.[28]

The advantages of AI are also being exploited to achieve control of mechanical ventilation. Various studies have described automated weaning from mechanical ventilation. Schäublin *et al*. studied fuzzy logic during routine general anaesthesia in 30 patients whose mechanical ventilation was controlled using closed-loop feedback. The aim of accomplishing and maintaining end-tidal carbon dioxide fraction ($FETCO_2$) was achieved by automatically regulating the respiratory frequency (f) and tidal volume (VT). Regarding reliability and safety, these studies demonstrated comparable outcomes between fuzzy control and human control.[29]

Schädler *et al*. gave the first illustration of an automated weaning system called the Evita Weaning System (EWS) (Evita 4; Dräger Medical, Lübeck, Germany). The novel EWS reduced the patient's respiratory workload by controlling the ventilatory settings in an automated manner. This is applied to the settings in a pressure-controlled and pressure-support mode. EWS has made it feasible to control the mechanical ventilator remotely, thus weaning the patients from the controlled mode of mechanical ventilation to assisted spontaneous breathing.[30]

Perioperative monitoring towards event prediction has also been identified in the database of about 53 papers. Following the induction dose of propofol, hypnosis was compared between neural networks and practising anaesthesiologists, as evaluated by BIS measurement. There was a sensitivity of 82.35% and a specificity of 64.38% with the former, compared to a sensitivity of 20.64% and a specificity of 92.51% with the latter.[31]

To predict the return of consciousness after general anaesthesia (propofol with remifentanil), Nunes *et al.* studied 20 patients. In comparison, neural networks and fuzzy models showed mixed results.[32]

The artificial neural network (ANN) has also been tested to predict the recovery of a neuromuscular block during general anaesthesia. The network was trained with parameters such as electromyographic train-of-four response, end-tidal carbon dioxide concentration, multiple minimum alveolar concentration, and peripheral and central temperature. Santanen *et al.*[33] hypothesised that a neural net could predict the recovery time significantly better and more accurately than a clinician.

One of the most important consequences of spinal anaesthesia is hypotension, which is multifactorial. Lin *et al.* used ANNs with available data to detect complex patterns. One thousand five hundred and one patients receiving spinal anaesthesia were studied. The predictive model was developed using their anaesthesia records; 75% of the data was used for training ANN and 25% for the test. This test set helped in validating the performance of the neural predictive model. Human review of this data was also done by involving senior anaesthesiologists. They predicted hypotensive events during spinal anaesthesia by clinical experience, with a sensitivity ranging from about 16% to 36.1% and a specificity ranging from 64% to 87.0%. The ANN model fared much better, with a sensitivity of 75.9% and a specificity of 76%. Thus, using a computer-based predictive model in the perioperative period would increase vigilance, allow for patient-specific therapeutic intervention and suggest an alternative method of anaesthesia.[34]

CONCLUSIONS

Enhancement in technology, especially AI, in many fields, including medicine, has proven to be far superior, safer and less erratic than human decision-making. Humanity aspires to utilise technology to improve decision-making by developing tools like CDSS for anaesthesia monitoring and delivery without replacing the physician's judgement. The strengths and flaws of AI-driven healthcare technology will ensure good patient outcomes if understood well. Thus, careful consideration in adopting AI is needed in perioperative care, where incorrect deductions can be disastrous.

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Conflicts of interest

There are no conflicts of interest.

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