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Artificial Intelligence-Supported Systems in Anesthesiology and Its Standpoint to Date—A Review

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Abstract

Artificial intelligence (AI) is the technique that enables computers to solve problems and perform tasks that traditionally require human intelligence. The availability of large amounts of medical data from electronic medical records and powerful modern microcomputers enables the development of AI in medicine. AI has proven its applicability in many different medical areas, such as drug discovery, diagnostic radiology and pathology, as well as interventional applications in cardiology and surgery. However, until today, AI is scarcely used in the clinical practice of anesthesiology. Although there has been a significant body of research published on AI applications for anesthesiology in the literature, the number of developed robot systems for commercial use or those ready for clinical trials remains limited. The limitations of AI systems are identified and discussed, which include incorrect medical data formatting, individual patient variability, the lack of ability of current AI systems, anesthesiologist inexperience in AI usage, system unreliability, unexplainable AI conclusions and strict regulations. In order to ensure anesthesiologists' trust in AI systems and improve their implementation in daily practice, strict quality control of the systems and algorithms should be undertaken. Further, anesthesiology personnel should play an integral role in the development of AI systems before we are able to see more AI integration in clinical anesthesiology.

Keywords

Artificial Intelligence, Anesthesiology, Machine Learning, Pharmacological Robot, Mechanical Robot, ChatGPT

1. Introduction

Since the first mortality incident in anesthesiology was reported in 1848 [1], many further deaths in anesthesiology have occurred [2]-[7] and have been reported up until today [8] [9]. Human error has been identified as the main cause of morbidity and mortality in anesthesiology [2] [3] [7] [10]-[15]. The anesthetist has to work simultaneously with many different aspects, such as multiple manual actions, equipment, choice of procedures, choice of drugs, hospital policies and clinical uncertainty. It is challenging under such conditions due to cognitive overload for anesthesiologists to weigh the outcome probabilities and choose the best management plan for each case [15]. For these circumstances, artificial intelligence (AI) may be a powerful computer technique to improve patient safety in anesthesiology.

Over the past decade, computer technology has improved significantly. Today, computer hardware is more cost-effective and powerful than ever before and is able to support high-functioning software. Furthermore, a large number of AI software have been developed with proven effectiveness in multiple different daily applications, such as Google Maps, search engines, banking, image recognition, natural speech processing, language translation, textual analysis and self-learning [16]. An example of the effective use of computer software is the Anesthesiology Information Management System (AIMS), which allows for the automatic and reliable collection, storage, and presentation of patient data during the perioperative period [17]. Computers have overcome the simple tasks of data recording and calculation following mathematic formulae to now being able to learn, think and work in a human-like fashion. For example, computer AI is able to interpret X-ray investigations and generate a report or another example is a computer large language model (LLM), such as ChatGPT is able to read, think, understand and answer questions [18]-[23].

Forty years ago, applications of computer technology in anesthesiology were reviewed in the literature [24]. Twenty-five years later, automatic intravenous anesthesiology was discussed [25]. Ten years after that, robotic anesthesiology topic was often discussed in the literature about how it affects daily practice in anesthesiology [26] [27] [28]. Recently, Thomas M. Hemmerling published the article "Robots Will Perform Anesthesiology in the Near Future" in anesthesiology [29]. Currently, artificial intelligence-supported tools in anesthesiology are being investigated, evaluated and developed intensively by medical practitioners, engineers and academics in the literature [30]-[39]. The earlier iterations of AI-assisted systems in anesthesiology were simplistic, using single closed-loop control and single control parameters, such as electroencephalogram indices [40]. Later developments of AI systems use multiple closed-loop controls incorporating multiple control parameters, as well as real-time data for machine learning to improve response [41] [42].

Nowadays, AI in anesthesiology is a very common topic discussed not only in the literature, but also in the media. Many medical technology companies showcase AI-supported anesthesiology equipment on their website [43] [44] [45]. AI uses the advantages of the availability of large amounts of medical data from electronic medical records and powerful modern microcomputers [46] [47]. AI is the technique that enables computers to mimic human intelligence to provide a solution for a problem [21]. AI has proven its applicability in many different areas of medicine, improving patient outcomes such as drug discovery, diagnostic applications in radiology and pathology, as well as therapeutic and interventional applications in cardiology and surgery [46] [47] [48] [49] [50].

Until today, although AI technology has proven its ability to help different areas, such as drug development, medical data recording, and pathology identification, AI is scarcely used in the current practice of anesthesiology [21] [46] [48] [49]. In the current literature, AI-based studies are focused on theory development and proposals of AI systems [51]. Further to this, it can be noted that few of these have demonstrated themselves practical in the daily use of anesthesiology [51].

This fact opens the question of what is the availability of commercial AI-supported systems and what are the barriers to the implementation of AI technology in anesthesiology, as well as how the application of AI-supported systems in anesthesiology can be improved in the near future.

2. Aims and Objectives

The aim of this article is to give readers a quick up to date picture of the abilities of AI technology and its potential implementation in anesthesiology, the availability of commercial AI-supported systems for anesthesiology and those in the late stages of development. There will also be a discussion about the barriers to AI use in practice and the potential future AI applications to improve patient safety in anesthesiology.

3. Method

The databases of PubMed, ScienceDirect, Library of Western Australian Health Service, and arXiv—Artificial Intelligence databases were searched using combinations of the following keywords: artificial intelligence, anesthesiology, machine learning, pharmacological robot, mechanical robot, mortality, and morbidity. Worldwide Web search through Google, Bing and Yahoo search engines using commercial names of AI-supported systems. Included in this review are publications with a focus on AI algorithm learning techniques, and the application of AI algorithms in anesthesiology in the perioperative period. Peer-reviewed published articles, and official commercial worldwide websites, published between 2006 and 2023 were eligible for inclusion, including older papers referenced in historical review. Excluded from the review are studies of AI algorithms for use in anesthesiology in theoretical or early stages of development and AI application in non-anaesthetic areas of medicine as they are outside the scope of the aims and objectives of this article. As a literature review article using published information, ethics approval is not required.

4. What Is Artificial Intelligence Technology?

In order to help the reader to answer the question: "should an anaesthetic be AI robot assisted or entirely human controlled?" AI technology should be briefly summarized.

Artificial intelligence is a complex concept as AI which enables computers to mimic human intelligence to provide a solution for a problem is the transformation of mathematic performance to medical application [21] [52]. AI is used to make a robot perform different tasks such as learning, understanding, reasoning, problem solving, word recognition and decision making like humans. Traditionally, a robot is a device which is able to perform physical actions including walking or arm movement. However, nowadays, the meaning of the word "robot" has become wider and is often thought as a system, which can perform physical and/or non-physical activities like reading documents, answering questions, data recalling and summarizing, and object recognition. Artificial intelligence has been defined as the study of algorithms that give machines the ability to reason and perform functions [47].

4.1. Key Parts in AI Technology

4.1.1. Big Data

Following the widespread use of electronic medical records (EMRs) and increasing modern medical investigations, huge amounts of health and medical data are available [53]. Big data can be used as inputs for training AI algorithms, in this case, it is called "training data" [46]. The data can be numerical, text, image, audio, and video. In order for an AI tool to work accurately and reliably, the used data must be reliable with correct information and in the correct format [40] [47] [53]. The computer rule "garbage in-garbage out" is valid in AI technology [31] [46].

4.1.2. Machine Learning (ML)

Machine learning is a practical field of AI with the aim to develop software that enables a computer to learn from training data, gain experience and gradually improve its ability to make predictions [54]. ML can be applied to identify patterns and make decisions with minimal human intervention. It is important for automatic anesthesiology delivery as it is necessary for the predictive analytics required for clinical decision-making [55].

Traditional computer programs are programmed with explicit instructions to elicit certain behaviors from a machine based on specific inputs. Machine learning, on the other hand, allows for programs to learn from and react to data without explicit programming. Most applications of AI for anesthesiology are still in research and development [47]. The current focus of artificial intelligence within anesthesiology is not on replacing clinician judgment or skills but on investigating ways to assist them [47]. Machine learning is driven by an algorithm.

4.1.3. Algorithm

Algorithm is a computer program, which sets the data analysis rules for machine learning to follow [21] [56]. In other words, an algorithm is a mathematical model responsible for machine learning and performing the requested activities. For machine learning, big data is used as inputs for data analysis following an algorithm. The algorithm is trained by training data to improve its performance [21] [56]. The U.S. Food and Drug Administration (FDA) approved the first AI algorithm for use in medicine in April 2018 which analysed the images of the fundus to diagnose diabetic retinopathy [47]. Until today, 70 algorithms have been approved by the FDA for different areas of medicine such as, radiology, cardiology, internal medicine and general practice, 22 of which have perioperative utility [56]. Recently the transparency of these algorithms are discussed and reviewed. Unfortunately, there is no FDA approved algorithm with anesthesiology utility found [57].

4.2. Types of Machine Learning

4.2.1. Supervised Learning

An algorithm is trained following the rules, which are set by a human expert to predict a pre-specified output. Supervised learning is recognized as "knowledge based" or "expert systems based" machine learning. Supervised learning requires training data and their associated outcomes to be inputted by a human expert in the algorithm's learning process. For example, a radiologist is required to input many chest X-ray images and its corresponding findings into the AI algorithm to "teach" it, so that when asked to evaluate a new X-ray, the AI is able draw from previous learning to suggest the findings. The data used to assess the performance of the algorithm's accuracy and reliability is named "test data". After supervised learning process, the trained algorithm is able to provide the asked output for new data inputs [47] [51].

4.2.2. Unsupervised Learning

Unsupervised learning is where algorithms identify patterns within an inputted clinical dataset (big data) which is then applied to analyze new data inputs [47]. Unsupervised learning is recognized as a "non-knowledge based" system [58].

4.2.3. Reinforcement Learning

Reinforcement learning refers to the process, by which an algorithm is used to attempt a certain task via a device, and the result of the task (success or failure) is reported and the algorithm learns from trial and error and improves its next action [47]. This training method is based on rewarding desired outcomes and/or punishing undesired ones [59].

4.3. Techniques in Machine Learning

There are different techniques for ML, such as, fuzzy logic, standard logic, neural networks, classical learning, deep learning, and Bayesian methods.

4.3.1. Classical Machine Learning

In the classical machine learning process, the training data is selected from big data by experts to guide the algorithms in the learning process [47].

4.3.2. Neural Networks and Deep Learning

Neural networks, like biological nervous systems, process signals in layers of computational units (neurons) and is the most important technique for machine learning [40] [52]. A neural network consists of an input layer that describes the input data and an output layer that describes the result, with a hidden layer in between which is a data processing step using at least one algorithm [52]. That means many machine learning algorithms can run in a neural network simultaneously to give the outcome. For very big data sets and complicated task requests, many layers of neural networks are required and thus expands to become "deep neural networks" or "deep learning techniques" [47]. Most commonly, supervised learning type is used to train deep neural networks [54].

4.3.3. Fuzzy Logic

Unlike standard logic or digital logic using binary numbering for positive and negative outcomes, fuzzy logic allows for probability, *i.e.* processing numerical values between 0.0 and 1.0 [60]. Fuzzy logic allows the algorithm to guess a result then later prove it in the next step. The rule-based systems (*i.e.* if… then systems) are used in Fuzzy logic [60]. Usually, fuzzy logic technique is used for supervised machine learning type [58].

4.3.4. Bayesian Method

Bayesian method use algorithms which can model uncertainty and update probability from new data. From the previous results or factors that may influence an event, Bayesian method can provide a description of probability of the event [47].

4.3.5. Natural Language Processing Model

Natural language processing models are the algorithms which focus on machine understanding of human language [47]. Natural language processing can achieve understanding of syntax and semantics to approximate meaning from phrases, sentences, or paragraphs [47]. The natural language processing model can be used to automatically analyze EMR [40].

4.3.6. Computer Vision Model

Computer vision model are the algorithms which enable the AI to understand images and videos. In medicine, computer vision has proven its ability to help clinicians in interpreting radiological investigations [47]. For example, computer vision can be applied in anesthesiology to analyze ultrasound images to identify anatomical structures during ultrasound guided procedures [40] [47].

5. AI-Supported Systems in Anesthesiology

Nowadays, it is easy to find ever increasing daily applications of AI technology such as in the car industry for example, Tesla's autopilot or voice recognition devices such as Amazon's Alexa [61] [62]. Further to this, AI has proven its human-like processing abilities in the case of the IBM created system Deep Blue's victory in chess over grandmaster Garry Kasparov in 1998 [47].

More topically, in November 2022 the AI robot "ChatGPT" was launched by Open AI. The early testing shows that Chat GPT can read and understand text correctly, write text summaries, reason, answer questions and provide suggestions [19] [63] [64] [65]. This commercial device has performed imperfectly but with acceptable accuracy and reliability for its practical purpose [18]. Fortunately, in these cases errors can be tolerated as they do not directly cause mortality or morbidity.

The application of AI in anesthesiology is different as it requires absolute accuracy and reliability due to its direct effect on patient outcomes [16]. Hence, the AI tools and algorithms used for medical purposes must be rigorously tested, trialed and approved by a governing health body before they can be used in the clinical setting.

For applications of Artificial Intelligence in Anesthesiology, a number of early-stage research and tests have been reported in the literature and many suggestions for AI system evaluation guidelines have been proposed but there are no current internationally accepted guidelines for AI tool performance benchmarking and evaluation [66].

In the earlier stages of AI in anesthesiology, Liu *et al.* introduced a dual closed-loop anesthesiology control system which used electroencephalograms (EEGs) as a single monitoring data as the input to control propofol and remifentanil infusion [67]. Today, more complex big data such as electrocardiogram, variability of heart rate, blood pressure, pulse oximetry, EEG based monitoring (e.g. bispectral index (BIS)), mean arterial pressure (MAP) are proposed as control parameters to maintain stable anesthesiology [30] [32] [40] [47]. The anesthesiology control systems usually use sophisticated machine learning types such as reinforcement learning and learning techniques such as deep learning or fuzzy logic to achieve the desired standard [47].

The current proposed AI robots can perform a number of activities in anesthesiology, such as: clinical decision support, control of anesthetic medication delivery, adverse event prediction, ultrasound interpretation for regional anesthesiology, pain response monitoring and prediction, depth of anesthesiology monitoring and management of operating theatre logistics [47]. Robots in anesthesiology are proposed to reduce the repetitive actions of the workload [68]. This review focuses on the recently proposed robots at the late stages of their development as early developments are far from implementation in clinical anesthesiology and many remain in theoretical stages, which is outside of the scope of our review.

5.1. Clinical Decision Support Systems

Artificial intelligence can provide guidance or suggestions from data it has analyzed to support clinical decision making such as alerting the clinician to possible drug-drug interactions for patient safety [52]. Anesthetists can use the abilities of AI-supported tools to provide safe care and improve patient outcomes from surgery [15] [31] [47] [66] [69].

Topically, ChatGPT (Generative Pre-trained Transformers) is a natural language model that was launched in November 2022 and trained by OpenAI. ChatGPT has been tested in different areas including medicine, research, education and software engineering [20]. There is a concern of accuracy, as ChatGPT does not provide citations used to generate information for its answer, and when references are asked to be provided, ChatGPT in some cases provided unrelated or non-existent citations [65] [70]. The algorithms in ChatGPT use reinforcement type learning to improve their function by continuous feedback from complex real-world situations [71]. The drawback of this learning type is that it is high cost and time consuming. ChatGPT has the potential to revolutionize the healthcare industry by improving patient outcomes, reducing costs, and facilitating more efficient and accurate diagnosis and treatment [18].

ChatGPT can use the natural language processing model to automate analysis of electronic medical record data. ChatGPT is currently being tested to extract information from free text such as EMR data or journal articles to build databases and learn [19]. It can then use inputted patient information to identify surgical candidates, assess for risk of adverse events, or facilitate billing [19]. Although ChatGPT provides promising outcomes in areas such as writing software codes and answering general questions, the gap between ChatGPT and applications in anesthesiology remains wide. Recently, ChatGPT was tested on different medical exams such as The United States Medical Licensing Exam (USMLE) and a Korean parasitology examination [72] [73]. ChatGPT performed poorly in the USMLE at a just pass level despite many correct answers to the questions currently published on the internet [70] [72]. Furthermore, ChatGPT's performance on the parasitology examination was worse than that of medical students who sat the same exam in Korea [73]. ChatGPT has not been trained for medicine specifically, because of this, there are a number of limitations that still remain such as not being able to access medical research articles and an inability to provide a critique on a presented medical article [20].

AlertWatch-OR by AlertWatch™ is a commercial clinical decision support (CDS) system, which is run by AI technology and designed specifically for use in anesthesiology [44]. It can provide case-specific advice after training using the available big data in combination with physiologic and laboratory data [58] [74]. This CDS system can detect adverse respiratory and haemodynamic events during anesthesiology and provide guidance for management of these intraoperative events to maintain stable anesthesiology and increase compliance to anesthesiology guidelines [74] [75]. Furthermore, the algorithm can be trained by supervised or non-supervised learning types and its ability is improved over time based on the availability of new data sets and user feedback [58]. The AIMS can be used to develop the CDS system to provide real-time advice to deliver safe patient care in anesthesiology as a requested corrective measure can be made immediately [31] [58].

AlertWatch has a notable strength in its user-friendly visual display utilizing pictured organ systems, colour codes and text descriptions of alerts [76].

SEDLINE® by Masimo (USA) monitors are commercial AI-supported tool in current clinical use [77]. They assess of depth of sedation using algorithms to process electroencephalogram waveforms to generate a Patient State Index between 0 (no activity) and 100 (alert) [78]. These devices can be unreliable as they heavily depend on the patient age, anesthetic agents used and interference from motion or electrocautery [47].

5.2. Pharmacological Robots

The most important application of AI and machine learning in anesthetic practice is intraoperative management using closed-loop control algorithms. The typical feedback closed-loop control of intraoperative management is illustrated in **Figure 1**.

The closed-loop control algorithm of the AI robot collects and analyses a large amount of physiological data from many patients and draws patterns to actuate and maintain patient parameters at setpoints [51]. A closed-loop anesthesiology delivery system which intervenes only on the hypnotic component has successfully been used in the past for total intravenous anesthesiology induction and maintenance [79]. This is important for machine learning to enable prediction of the changes in control parameters (vital signs) of the patient during the operation [79]. During the anaesthetic, the algorithm is asked to detect if the patient parameters start to drift out the desired ranges, which are set by the anesthetist [79]. The algorithm will make the actuator adjust the drug injection rates to maintain a stable anaesthetic and alarm should the parameters move out of the expected control conditions [16] [79]. The difference between the conventional closed-loop control and AI-supported control is that the AI-supported tools take into account more control parameters and are able to learn from new training datasets to improve its performance with experience [51].

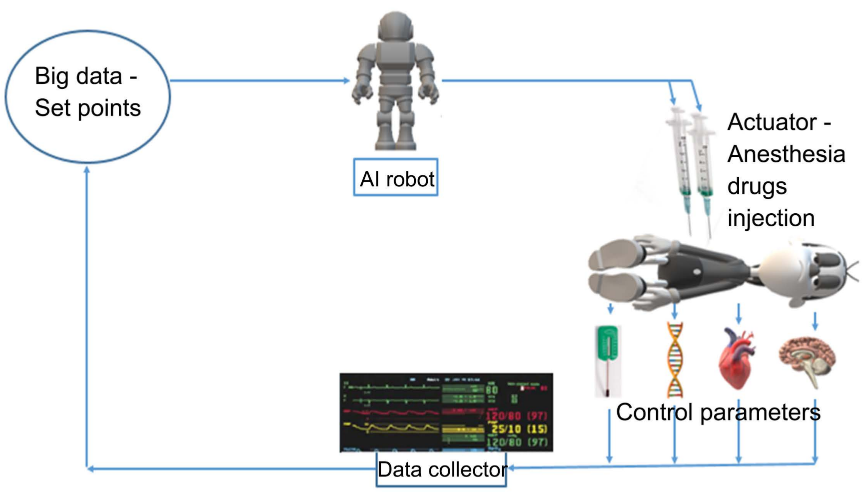

Figure 1. AI-supported feedback closed-loop control in intraoperative management.

Pharmacological robots are AI-supported systems which operated using a closed-loop control algorithm. These robots can inject the required doses of anaesthetic drugs into the patient to reach preset values to maintain a stable anesthetic [74] [79]. The possible advantage of pharmacological robots lies in rural and remote medicine to make anesthesiology accessible at anytime and anywhere without the need of the presence of a trained anesthetist [76].

An AI-supported robot McSleepy was introduced by Hemmerling *et al.* in 2013 as a pharmacological robot which can autonomously control sedation, analgesia and neuromuscular blockade simultaneously during induction, maintenance and emergence [41] [74]. McSleepy is an automated closed-loop system delivering a hypnotic agent, analgesic agent and muscle relaxant, remifentanil and rocuronium targeting the parameters of BIS, analgoscore (nociception score based on blood pressure and heart rate) and muscle relaxation using train of four ratio [41]. Hemmerling *et al.* reported pilot studies of the efficacy of this system have shown good performance indices in a randomized control trial of 186 patients twenty patients undergoing elective thyroidectomies in Pisa, with their anesthesiology remotely controlled in Montreal, as well as its application in complex cardiac surgery [41] [80] [81].

In an earlier iteration of McSleepy in 2008 as reviewed by Naaz *et al.*, a closed-loop feedback control system maintaining anesthesiology depth using a hand-crafted rule and response algorithm was unsuccessful in management of complex cases [40]. To overcome this weakness, a neural network learning technique was applied [40].

Recently, a closed-loop system for intravenous anesthesiology delivery has been developed named iControl-RP. This robot is able to make decisions and control the administration of the intravenous agents Propofol and Remifentanil [47]. iControl-RP takes into account neuromonitoring using NeuroSENSE (EEG based quantification of cortical activity including burst suppression ratio) monitoring as well as haemodynamic monitoring data into its decision making [42]. West *et al.* has found iControl-RP to perform at an acceptable level in clinical practice and is a feasible solution for propofol and remifentanil anesthesiology closed-loop control [42].

Sedasys® by Ethicon (USA) was an AI-supported robot which can be managed by non-anaesthetic medical staff [82] [83]. However, this device has been withdrawn from the market in 2016, three years after its FDA approval in 2013 along with approval for use in Australia the European Union and Canada for gastrointestinal endoscopy [74] [84]. This robot performed a propofol sedation in healthy adults (patients of ASA 1 and 2). This robot records patient blood pressure, oxygen saturation, respiratory rate and automatically adjusted propofol infusion rate, oxygen flow and gave the operator cues to optimize patient care.

CLADS™ is a manual or automatic closed-loop system for propofol intravenous anesthesiology delivery. This system was developed at the Postgraduate Institute of Medical Education and Research, Chandigarh, India [85]. It uses BIS as the control variable and electroencephalographic indices as the input variable

[85]. The CLADS™ system is able to use 5-secondly BIS feedback, taking into account BIS error, to adjust propofol infusion rates following a pharmacokinetic model to maintain preset BIS values [86].

A clinical trial using CLADS™ was carried out in different groups of patients using the automatic mode of propofol infusion (non-cardiac surgery, cardiac surgery, postoperative sedation, and high-altitude surgery). The trial results showed CLADS™ was effective and efficient as compared to manual control and can be a useful tool to decrease cognitive load for anesthesiologists during anesthesiology [85] [86].

RUGLOOP-IITM (Department of Anesthesiology, University Medical Center, Groningen, Netherlands) is a robust, patient-individualized closed-loop control system for propofol administration using BIS as control variable. This system uses Bayesian methodology for machine learning [87]. This system uses Bayesian variances to distinguish the specific patient model from the population model [87]. It was found that the RUGLOOP™ system could achieve induction within set time limits and less overshooting of BIS above pre-set values than human control [87]. The closed-loop control of anesthesiology maintenance had similar quality and movement scores to human controlled anesthesiology and was feasible in terms of hemodynamic and respiratory stability [87].

The CONCERT-CL™ (VERYARK Technology Co., Ltd. (Guangxi, China)) is a closed-loop propofol and remifentanil infusion system to control intravenous anesthesiology [88]. This system, similar to others, is a target-controlled infusion (TCI) system and uses BIS as a control variable [88]. A clinical trial was performed in 2013 on 89 patients, who were between 18- and 65-years-old and have ASA classifications I or II and required general anesthesiology [88]. The CONCERT-CL was used to automatically regulate the TCI of propofol to maintain the BIS value in preset range [88]. The trial results show the CONCERT-CL system can regulate the TCI of propofol successfully as the BIS value is maintained in an adequate range [88]. While using this system reduces the workload of anesthetists' significantly, it was only a valuable assistant which required the constant supervision of an anesthesiologist [88].

Many other closed-loop control systems have been tested in the practice of anesthesiology, unfortunately their performances were not feasible and have not been further improved or tested to date [67] [89] [90]. The main challenges faced by these systems were patient safety and efficacy [83].

Closed-loop anesthesiology delivery systems control the depth of anesthesiology with greater accuracy and using less sedative agents than human controlled anesthesiology as the automated systems change the medication rate more often than human anesthesiologists [29] [79]. This has a sedative agent sparing effect and may improve patient outcomes in the post operative period by reducing the incidence of delirium [42].

5.3. Mechanical Robots

Mechanical robots are AI-supported tools that also operate by a closed-loop control algorithm. These robots perform the manual tasks of an anesthesiologist automatically. The use of mechanical robots in anesthesiology can reduce some of the anesthesiologists' repetitive actions. This gives the anesthetist more time to focus on patients and related perioperative issues, hence improving patient safety and service quality [51] [74].

Endotracheal intubation and regional anesthesiology are the main proposed fields of application of mechanical robots.

5.3.1. Endotracheal Intubation

For the robotic endotracheal intubation development, the AI-supported multi-purpose Da Vinci® Surgical System (Intuitive Surgical, Inc., Sunnyvale, CA, USA) was tested successfully in the performance of two anesthesiologist controlled semi-automated simulated fibreoptic intubations [74] [91]. The Da Vinci robot design has multiple robotic arms so it can handle complicated cases with different technical difficulty levels [91]. There have been successful simulated oral and nasal fiberoptic intubations on an airway simulation manikin, while direct laryngoscope intubations are challenging and not feasible [91]. It can be noted that these intubations were technically difficult due in part to the multiple arms and the robotic interface [91].

The Kepler Intubation System (KIS) is designed to perform intubation automatically or semi automatically [92]. The system consists of a remote control centre and control joystick linked to a robotic arm with a standard videolaryngoscope [92]. In the semi-automatic mode, the robotic arm is controlled by the joystick, which is operated using a specific software and interface [92]. Hemmerling *et al.* concluded that using the KIS, a human expert is able to achieve remote intubations between 40 - 60 seconds after a trial of 90 simulated manikin intubations [92].

5.3.2. Regional Anesthesiology

In terms of development of robotic regional anesthesiology, tracking nerves is an ideal task for the computer vision artificial intelligence technique. However, it should be noted that due to the variation in ultrasound images and the similar acoustic impedance between nerves and their surroundings, makes it a more difficult task than AI's usual daily application in facial recognition technology [33].

The DaVinci system has been used to perform trials of nerve block and placement of a perineural catheter on a non-human model using ultrasound-guided technique [40].

The Magellan system (Oceanic Medical Products, Inc., Atchison, KS, USA) is designed to perform semi-automatic regional anesthesiology using ultrasound guided technique for peripheral nerve blocks [40]. The robot has an arm with a nerve block needle at the end and can be controlled by a joystick [33] [74].

A recent training study of five anesthesiologists used the Magellan robotic arm to assess learning curves on a nerve phantom [93]. The study found steep improvements on learning curves over 10 needle insertions using the robot compared with manual insertion [93]. Notably, this study was limited by its small sample size, lack of performance criteria and low repetitions [93]. Given that earlier attempts had considerably longer performance times than later attempts, the steep learning curves are likely due to the novelty of the technology [93]. The Magellan system uses a custom algorithm which assists in recognition of nerves in ultrasound images [93]. Notably, the robotic assistance system allowed operators to learn needle positioning faster compared to manually and there is a reduction in the variability in time to position needle between subjects [93].

In the US, AI-supported mechanical robots remain in the development stage, no truly automated closed-loop anesthesiology delivery systems have been approved for commercial clinical use [74].

5.4. Event Prediction

Various types and techniques of machine learning have been tested for application of perioperative care risk prediction such as supervised learning, reinforcement learning, neural networks, deep learning and fuzzy logic. Preoperatively, risk assessment is an invaluable tool for both elective and emergency surgical cases where prediction of mortality and/or morbidity has the potential to change perioperative management [94]. An intraoperative example is neural networks that can be applied for prediction of the hypnotic effect of an induction bolus dose of propofol with greater accuracy than the average estimate of anesthesiologists in practice [95].

5.5. Ultrasound Guidance

Ultrasound guided technique is commonly used in mechanical robots as described above such as the Magellan system used to perform regional anesthesiology [96]. The most common machine learning technique employed to achieve ultrasound image classification is neural networks and deep learning [47]. Smistad and Løvstakken used 15 ultrasound images of patient's groins to train a convolutional neural network in identifying femoral artery and vein, distinguishing it from other femoral anatomical structures such as muscle, bone or acoustic shadow with an accuracy of 94.5% ± 2.9% on average [97].

5.6. Pain Management

There are currently no commercial AI products available for widespread use in the area of pain management in the perioperative setting. Attempted AI application in pain management has a wide range from the processing of brain imaging for identifying pain to prediction of opioid dose response using biomarkers [47].

Images were collected from human volunteers who had functional magnetic resonance imaging while exposed to painful and non-painful thermal stimulation and used machine learning to analyse their differences and similarities. They found that machine learning analysis the brain images as a whole more accurately identifies pain than the analysis of individual brain regions associated with nociception [47].

PainChek™ is an AI tool used to identify pain in patients with dementia and is designed for use in Geriatric medicine and therefore is outside the scope of this review on AI-supported systems in anesthesiology [98].

Gram *et al.* analysed electroencephalopathy signals from 81 patients using machine learning techniques and predicted with 65% accuracy which patients would respond to post-operative opioid therapy [99].

5.7. Depth of Anesthesiology Monitoring

Algorithms have been developed to analyze complex EEG waveforms using machine learning techniques to create an index directly related to measurement of depth of anesthesiology [47]. The strength of using sophisticated neural networks and deep learning techniques is the ability of the algorithm to engage in unsupervised learning to identify patterns that will best predict target values such as awareness based on EEG as well as haemodynamic data [100]. The AI algorithm is able to predict this more reliably than a human expert [47].

5.8. Operating Room Logistics

Combes *et al.* trained a neural network using data from an EMR database containing information of staffing, operating room flow and time in post anesthesiology care unit to predict duration of one episode of surgical care [101]. The prediction is based on operating team, type of operation and relevant patient medical history. It is notable that the accuracy of their models never exceeded 60% [101].

Another example of combined fuzzy logic and neural network techniques to optimize bed use is by Devi *et al.* who modelled type of surgery, surgical team experience, type of anesthesiology, experience of the anaesthetic team and relevant patient factors in ophthalmologic surgery [102]. They achieved accuracy between 81% - 86% in prediction of duration of surgical care episode depending on case type [102].

In these models, the potential of AI technology is not to replace the anesthesiologist, but to augment and improve the workflow and decision making of the surgical and anesthesiology teams [47].

Summarized below (**Table 1**) are the AI-supported tools in anesthesiology at late stages of development reviewed in this article.

6. Limitations and Discussion of AI-Supported Systems in Anesthesiology

AI algorithms have many times proven their capability in complex human-like thinking for example the chess algorithm "Deep Blue" winning against grandmaster Garry Kasparov twenty-six years ago [47]. Although a number of research on AI application for anesthesiology are published in the literature, but fully developed systems or those ready for clinical trials remain limited [31] [54] [94] [95] [97] [100] [101] [102] [104]. This gap in the literature represents an

Table 1. AI-supported systems for anesthesiology.

Tool	Description	Application area	Ref.
ChatGPT	• Natural language processing model • Poor performance	Clinical decision support providing of information and guidance	[20]
AlertWatch-OR	• Provide case-specific advice • Can be trained by supervised learning or non-supervised learning types • Uses a novel visual display of organ systems with a combination of color codes • Textual description to present alerts	Clinical decision support	[75]
SEDLINE	• These devices can be unreliable as they heavily depend on the patient age, anesthetic agents used and interference from motion or electrocautery.	Clinical decision support	[77]
Mc Sleepy	• Closed-loop feedback control system • Targeting BIS parameter, analgoscore, muscle relaxation • Suitable for complex case and telemedicine • Can autonomously control sedation, analgesia and neuromuscular blockade simultaneously during induction, maintenance and emergence	Propofol, remifentanil, rocuronium infusion	[41]
Sedasys	• Can be managed by non-anaesthetic medical staff • Withdrawn from the market in 2016	Propofol sedation	[103]
iControl-RP	• Closed-loop system for intravenous anesthesiology delivery • Make decisions and control the administration of IV agents such as Propofol and Remifentanil • iControl-RP takes into account neuromonitoring using BIS as well as haemodynamic monitoring data into its decision making	Propofol sedation	[42]
CLADS	• Electroencephalographic indices as the input variable • BIS as the control variable • Can be operated in manual or automatic mode • Achieve good trial results	Propofol sedation	[85]
RUGLOOP	• Patient-individualized closed-loop control system • Uses Bayesian technique for machine learning algorithm • Accurate propofol injection • Acceptable robustness	Propofol sedation	[87]
CONCERT-CL	• Target controlled infusion (TCI) system • Successful clinical trial was carried out in 2013	Propofol, remifentanil, infusion	[88]
DaVinci® Surgical System	• Has multiple robotic arms so it can handle complicated cases • Simulated fiber-optic-assisted oral and nasal intubations of a manikin were successful	Endotracheal intubation and regional anesthesiology	[91]

Continued

Kepler Intubation System (KIS)	• Perform intubation automatically or semi automatically • Consists of a single robotic arm controlled by a joystick to guide endotracheal intubation remotely • Robotic arm linked to a videolaryngoscope	Intubation	[92]
Magellan system	• Used for peripheral nerve block • Semi-automatic • Using ultrasound guided technique • Has an arm with a nerve block needle at the end • Arm can be controlled by a joystick • Ultrasound-guided nerve recognition.	Regional anesthesiology	[96]

opportunity for the development and progression of clinical anesthesiology in line with multiple other industries and areas of medicine successfully implementing AI technology.

Therefore, despite the advancements and strengths of AI in anesthesiology and the promise it offers, the limitations of the application of AI technology in anesthesiology are important to consider. This will enable the capitalization of AI technology to improve patient outcomes by reducing cognitive load for anesthesiologists, improve efficiency, and open the possibility of remote anesthesiology.

6.1. Big Data Processing

AI machine performs prediction or answers a question by using medical training data, which must be reliable and connected to a specific case in a strict format. Unfortunately, a standard data format for ML is not available at present and there exists much incompatibility between data formats from different EMR systems [3] [46] [51]. Furthermore, the quantity and quality of the training data is very important as if small datasets or irrelevant data is used for the algorithm training process, then the output will be similarly unreliable when used to aid decision making [105].

Current AI developments are based on differing data formats that is not conducive to international adoption. To accelerate and encourage the development and subsequent application of AI technology in anesthesiology, the author believes a common data format between international EMRs is a vital first step to the further development of AI systems for use in anesthesiology. The aforementioned AIMS is a good example of a widely adopted software enabling perioperative patient data collection [17].

In order for the AI-supported systems to work effectively, they should process big data and give accurate outputs in real time. Currently, acquiring and processing high velocity and large data volumes in an operating room setting is a challenge due to the multiple and complex algorithms used in AI-supported robots for use in anesthesiology [58]. The author believes due to the limited resources in healthcare, the plausibility of upgrading expensive computer systems to support each new generation of algorithms is unrealistic. Therefore, the algorithms should be designed to be simplified and efficient.

6.2. Individual Case Variability

AI robots answer questions based on the information from many factors, but are unable to take into account the variability of significance of each factor for individual patients as there may be wide variation. For example, ML works based on general models such as the pharmacokinetic model, which adequately calculates plasma concentration of drugs, but is unable to predict the effect of such plasma concentration on patient sedation [88]. Furthermore, the monitoring on which measurement of adequate sedation and unawareness is based, predominantly EEG, remains notoriously unreliable [106]. Due to this inadequacy, AI algorithms are still not competent enough in practice to surpass human performance [40].

The beginnings of development to overcome the wide variability between individual patients can be seen in the novel robots using Bayesian method for machine learning. The continuous updating of data from experience theoretically enables the robots to adapt its decision making from real time data updates during anesthesiology. The author suggests that improvement of user-friendly graphic interfaces and algorithms to enable increased individual patient data inputs is important for the personalization of AI anesthesiology and hence improve patient outcomes.

6.3. Lack of Knowledge and Ability of the Current AI-Supported Systems

Anesthetists make complex considerations for each case involving collecting patient information, review of medical data, designing anaesthetic plans, and performing individualized clinical procedures. The anesthetist works in a multidisciplinary team including the surgeon, pharmacists, medical specialties, pre- habilitation allied health staff etc. to negotiate the surgical plan and perform the optimal anesthesiology. Human intelligence is used to deal with many complex medical and interpersonal situations simultaneously, which mathematical algorithms are unable to replicate [54]. Further to this, as summarized in **Table 1**, the current pharmacological robots use electroencephalographic indices as a main or only control parameter as a measure of sedation. However, these values are notoriously unreliable and are affected by much interference [21]. Current developed ML algorithms are neither sophisticated enough nor have adequate ability to integrate all aspects of an anesthesiologist's work; thus, it is impossible for AI technology to replace an anesthesiologist in the near future [40].

Human intelligence can be used to deal with abnormal cases; thus skill, experience and knowledge of an anesthetist are combined to make life saving decisions. The AI machine actions or gives predictions following mathematical rules, the predicting algorithms used in AI systems do not support human intervention in a clinical setting. It is difficult for the AI user to know the appropriate actions to take when the robot gives a warning or makes an unexpected decision during anesthesiology [54]. Because of this potential need for rescuing interventions, it is unlikely that anesthetic delivery systems would ever function fully autonomously without clinician supervision [55].

For anesthesiologists to confidently use AI robots, clear visualization features rich in information and explanation needs to be an integral part of the machines. The author suggests that these graphic interfaces should be designed by anesthesiologists to appropriately rationalize information displayed. Computational or engineering related errors which are out of the scope of practicing anesthesiologists should be minimized to avoid unnecessary apprehension.

The author believes, to improve safety and reliability, AI needs time to prove its ability and improvements implemented before it is applied in daily practice safely as patients cannot be treated as test subjects for novel technology with little evidence base. This is a lesson learned from the development of McSleepy, which in its early version used a hand-crafted rule and response algorithm and did not work well to handle complex cases. Later improvements were made by applying neural network machine learning [40].

6.4. Deskilling of Anesthesiologists

The deskilling phenomenon could be seen when the regional block needle tracking system was utilized [21]. This potential dependence during the training process on AI technology may decrease overall competence among trainees despite reduction in variation [21]. Skills are maintained and improved through experience. The fear then becomes if anesthesiologists come to rely heavily on automated systems, it would lead to the decrease in skills such as intubation or titration of sedatives [33]. Anesthesiologists need to maintain their specialized skill through practice in the cases of technological failures or emergency situations. The author firmly believes the development of AI systems for use in anesthesiology therefore should be designed with the aim of assisting, not replacing anaesthesists.

Further to clinical skills, anaesthesists have a very involved role in teaching trainees through sharing of hands-on experience and valuable insights during cases which cannot be replaced by AI technology such as natural language models [20].

6.5. AI Technology Error

As we are all familiar with, sophisticated modern computers are still subject to error or failures without warning which can result from software defects, data artifact, hardware failures or logic errors [58]. Potentially significant morbidity or mortality can occur to a patient if such errors transpire in anesthesiology to trigger inappropriate decision making or administering incorrect drugs [58].

While error in technology remains an inevitable occurrence, there are some improvements which can decrease the rate of error and failure [107]. For this, we can learn and consider strategies from the aviation industry, one with established low failure and error rates despite the complex engineering of AI-supported aircrafts [107]. The first thing to consider is the balance between quality of build and cost-effectiveness of the systems [107]. While the author is aware a compromise will always need to be made, rationalization of the areas of cost-cutting is important as to not compromise patient safety. There should be strict and clear maintenance services if the widespread use of AI-supported systems were to become widely used with clear documentation in logbooks. The machines should be made from high quality components by specialized manufacturers. There should also be an automatic and neutral recording system of errors which cannot be tampered with similar to the black boxes (flight recorders) on aircrafts.

6.6. AI Systems Can Be Black Boxes

Due to the complexities of processing by AI algorithms applying deep learning, how the decisions are made can be difficult to understand, even by the engineers that understand the used mathematical algorithms [46] [47] [54]. Furthermore, commercialized AI systems often have proprietary algorithms which usually remain confidential, much like the method of BIS calculation [108]. This opacity means AI systems operate by "black box" functioning model which understandably creates apprehension among anesthesiologists, discouraging them to rely on AI systems in practice.

Explainability of the decisions made is vital to increase the transparency of AI systems and encourage its trust and integration in anaesthetic practice [109]. This is particularly important in cases where there is a differing opinion between anesthesiologists and AI systems as knowing how the respective decisions are made will enable comparison, rationalization and thus enactment of the optimal decision.

The author proposes, to improve the transparency, the algorithms should include algorithm explanation windows for how decisions are reached as well as for reasoning of error messages that are written in plain language. This would increase the trust anesthesiologists have for AI technology in anesthesiology and therefore increase its' implementation and acceptance in daily practice.

6.7. Regulation

There exist many obstacles in the strict guidelines and regulations for the implementation of AI technology in clinical practice, and for good reason due to the high stakes nature of anesthesiology [56]. However, this causes a delay in the development and adoption of AI technology in hospitals around the world as only limited AI technologies have been approved for use. For example, only static or locked algorithms that return expected and predictable outcomes have been approved by the FDA [47].

This is well illustrated in the case of the pharmacological robot Sedasys™. Its failure on the market was in part due to the highly restrictive and conservative function that was programmed by the developers in order to satisfy the criteria for FDA approval [84]. This particular robot was restricted to only being able to titrate propofol infusions down, and required an anesthesiologist to manually increase the dose if the patient's sedation lightened [84]. Therefore, not only was this device have limited usefulness in clinical practice, it may also have decreased the interest of using AI systems in anesthesiology.

Another challenge exists in patient privacy and confidentiality when accessing patient big data for inputs in AI systems [31]. For this reason, there needs to be regulatory changes to enable assumed consent and an opt-out system to access patient data [94].

Health regulators need to make strict laws to regulate AI application to prevent harm to patients. It is difficult for regulators to approve complex, "black box" AI-supported robots, as they need a long time to prove their safety and reliability, therefore delaying their development and implementation. The author suggests a potential solution lays in a modular design strategy where simple AI algorithms should be designed and tested first, then slow integration of more algorithm units to build a more complex system.

6.8. Lack of Knowledge and Experience of Practicing Anesthesiologists in Using AI

At present, few anesthesiologists are familiar with the way AI robots work or are involved in the development of these machines [40]. As a consequence of this opacity, there will be less confidence and acceptance in using AI robots in practice hence slowing the development and implementation of AI robots in the routine practice of anesthesiology [54].

Furthermore, given the current general lack of knowledge and experience of AI in anesthesiology, the anesthesiologist will be met with difficult situations when AI robots make unexpected decisions, thus creating a barrier to using these machines in regular practice.

The author thinks the key to the success of AI applications in anesthesiology is to begin at the beginning. Anesthetists should be heavily involved in the design of AI-supported systems for use in anesthesiology as this enables the rationalization of important features in clinical use. Furthermore, there exists an ongoing need for further clinical studies evaluating the relevance of AI-supported systems and their effectiveness in real-world applications through rigorous outcome assessments.

All anesthesiology personnel should be trained to understand AI technology as without knowledge and experience, and the user will likely achieve poor outcomes using AI-supported systems and feel mistrust for these systems [40]. The author suggests training should include medical staff at all levels, from medical students to senior clinicians, if the introduction of these systems in anesthesiology is to succeed. To achieve this, AI training courses for medical students, junior doctors and anesthetists should be provided frequently to normalize the presence of AI in medicine.

Earlier in this article, there has been a discussion of multiple areas of anesthesiology where AI has potential applications, including pain medicine, event prediction and operating room logistics. However, most robots at later developmental stages are focused on pharmacological and mechanical robots with a very direct potential impact on patient morbidity and mortality. To improve the reception and trust of AI systems in anesthesiology, development of AI could begin with diagnostic and logistical supports first, which can improve patient outcomes without direct potential for harm.

7. Conclusion

In conclusion, artificial intelligence technologies have the potential to reduce the cognitive load on anesthesiologists to enable concentration on other tasks, which improves patient safety and outcomes. The identified limitations above should be addressed to accelerate the development of artificial intelligence for application in anesthesiology. Strict quality control of the systems and algorithms should be undertaken before application on patients, as adverse events have the potential to decrease trust and become a barrier to future endeavours. The cooperation of anesthesiologists and engineers in the development of AI is required in system design to improve usability. Lastly, the design of AI systems should use a modular design concept to simplify regulatory approval processes. If we begin at the beginning and develop simple and explainable AI algorithms, we may be able to see AI integrated into daily anaesthetic practice in the near future.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Beecher, H.K. (1941) The First Anesthesia Death with Some Remarks Suggested by It on the Fields of the Laboratory and the Clinic in the Appraisal of New Anesthetic Agents. *Anesthesiology*, **2**, 443-449. https://doi.org/10.1097/00000542-194107000-00008

[2] Clifton, B. and Hotten, W. (1963) Deaths Associated with Anaesthesia. *BJA*: *British Journal of Anaesthesia*, **35**, 250-259. https://doi.org/10.1093/bja/35.4.250

[3] Dinnick, O. and Patterson, R.L. (1966) Deaths Associated with Anaesthesia: Observations on 600 Cases. *Survey of Anesthesiology*, **10**, 155-156. https://doi.org/10.1097/00132586-196604000-00037

[4] Edwards, G., Morton, H., Pask, E. and Wylie, W. (1956) Deaths Associated with Anaesthesia: A Report on 1,000 Cases. *Anaesthesia*, **11**, 194-220. https://doi.org/10.1111/j.1365-2044.1956.tb07975.x

[5] Jenkins, S. (2021) Anaesthesia-Related Deaths Analysed. *ANZCA Bulletin*, **30**, 30-31.

[6] Kothari, D., Gupta, S., Sharma, C. and Kothari, S. (2010) Medication Error in Anaesthesia and Critical Care: A Cause for Concern. *Indian Journal of Anaesthesia*, **54**, 187-192. https://doi.org/10.4103/0019-5049.65351

[7] Schulz, C.M., Krautheim, V., Hackemann, A., Kreuzer, M., Kochs, E.F. and Wagner,

K.J. (2015) Situation Awareness Errors in Anesthesia and Critical Care in 200 Cases of a Critical Incident Reporting System. *BMC Anesthesiology*, **16**, Article No. 4. https://doi.org/10.1186/s12871-016-0172-7

[8] Costin, L. (2022) Young Man Dies after Appendix Surgery. https://www.perthnow.com.au/news/crime/young-man-dies-after-appendix-surgery-c-8360420

[9] Oglesby, F., Ray, A., Shurlock, T., Mitra, T. and Cook, T. (2022) Litigation Related to Anaesthesia: Analysis of Claims against the NHS in England 2008-2018 and Comparison against Previous Claim Patterns. *Anaesthesia*, **77**, 527-537. https://doi.org/10.1111/anae.15685

[10] Arnstein, F. (1997) Catalogue of Human Error. *British Journal of Anaesthesia*, **79**, 645-656. https://doi.org/10.1093/bja/79.5.645

[11] Rayan, A.A., Hemdan, S.E. and Shetaia, A.M. (2019) Root Cause Analysis of Blunders in Anesthesia. Anesthesia. *Essays and Researches*, **13**, 193-198. https://doi.org/10.4103/aer.AER_47_19

[12] Donaldson, M.S., Corrigan, J.M. and Kohn, L.T. (2000) To Err Is Human: Building a Safer Health System. National Academies Press, Washington DC.

[13] Merhavy, Z., Merhavy, C. and Varkey, T. (2021) Anesthetic Drugs: A Comprehensive Overview for Anesthesiologists. *Journal of Clinical Anesthesia and Intensive Care*, **2**, 42-53. https://doi.org/10.46439/anesthesia.2.012

[14] Choy, C.Y. (2008) Critical Incident Monitoring in Anaesthesia. *Current Opinion in Anesthesiology*, **21**, 183-186. https://doi.org/10.1097/ACO.0b013e3282f33592

[15] Choy, Y. (2006) Critical Incident Monitoring in Anaesthesia. *The Medical Journal of Malaysia*, **61**, 577-585.

[16] Connor, C.W. (2019) Artificial Intelligence and Machine Learning in Anesthesiology. *Anesthesiology*, **131**, 1346-1359. https://doi.org/10.1097/ALN.0000000000002694

[17] Ehrenfeld, J.M. and Rehman, M.A. (2011) Anesthesia Information Management Systems: A Review of Functionality and Installation Considerations. *Journal of Clinical Monitoring and Computing*, **25**, 71-79. https://doi.org/10.1007/s10877-010-9256-y

[18] Koubaa, A., Boulila, W., Ghouti, L., Alzahem, A. and Latif, S. (2023) Exploring ChatGPT Capabilities and Limitations: A Critical Review of the NLP Game Changer. (Preprint) https://doi.org/10.20944/preprints202303.0438.v1

[19] Cascella, M., Montomoli, J., Bellini, V. and Bignami, E. (2023) Evaluating the Feasibility of ChatGPT in Healthcare: An Analysis of Multiple Clinical and Research Scenarios. *Journal of Medical Systems*, **47**, Article No. 33. https://doi.org/10.1007/s10916-023-01925-4

[20] Eysenbach, G. (2023) The Role of ChatGPT, Generative Language Models and Artificial Intelligence in Medical Education: A Conversation with ChatGPT and a Call for Papers. *JMIR Medical Education*, **9**, e46885. https://doi.org/10.2196/46885

[21] Bellini, V., Carna, E.R., Russo, M., Di Vincenzo, F., Berghenti, M., Baciarello, M. and Bignami, E. (2022) Artificial Intelligence and Anesthesia: A Narrative Review. *Annals of Translational Medicine*, **10**, Article No. 528. https://doi.org/10.21037/atm-21-7031

[22] Arora, A. (2020) Artificial Intelligence: A New Frontier for Anaesthesiology Training. *British Journal of Anaesthesia*, **125**, e407-e408. https://doi.org/10.1016/j.bja.2020.06.049

[23] Liévin, V., Hother, C.E. and Winther, O. (2022) Can Large Language Models Reason about Medical Questions? (Preprint)

[24] Zissos, A. and Strunin, L. (1985) Computers in Anaesthesia. *Canadian Anaesthetists Society Journal*, **32**, 374-384. https://doi.org/10.1007/BF03011342

[25] Russell, D. (1998) Intravenous Anaesthesia: Manual Infusion Schemes versus TCI Systems. *Anaesthesia*, **53**, 42-45. https://doi.org/10.1111/j.1365-2044.1998.53s113.x

[26] Atchabahian, A. and Hemmerling, T.M. (2014) Robotic Anesthesia: How Is It Going to Change Our Practice? *Anesthesiology and Pain Medicine*, **4**, e16468. https://doi.org/10.5812/aapm.16468

[27] Hemmerling, T.M., Taddei, R., Wehbe, M., Morse, J., Cyr, S. and Zaouter, C. (2011) Robotic Anesthesia—A Vision For the Future of Anesthesia. *Translational Medicine@ UniSa*, **1**, 1-20.

[28] Wehbe, M., Arbeid, E., Cyr, S., Mathieu, P.A., Taddei, R., Morse, J. and Hemmerling, T.M. (2014) A Technical Description of a Novel Pharmacological Anesthesia Robot. *Journal of Clinical Monitoring and Computing*, **28**, 27-34. https://doi.org/10.1007/s10877-013-9451-8

[29] Hemmerling, T.M. (2020) Robots Will Perform Anesthesia in the Near Future. *Anesthesiology*, **132**, 219-220. https://doi.org/10.1097/ALN.0000000000003088

[30] Gambus, P.L. and Jaramillo, S. (2019) Machine Learning in Anaesthesia: Reactive, proactive… Predictive! *British Journal of Anaesthesia*, **123**, 401-403. https://doi.org/10.1016/j.bja.2019.07.009

[31] Seger, C. and Cannesson, M. (2020) Recent Advances in the Technology of Anesthesia. *F*1000*Research*, **9**, Article No. 375. https://doi.org/10.12688/f1000research.24059.1

[32] Dutta, A., Sethi, N., Puri, G.D., Sood, J., Choudhary, P.K., Jain, A.K., Panday, B.C. and Gupta, M. (2022) Automated Closed-Loop Propofol Anesthesia versus Desflurane Inhalation Anesthesia in Obese Patients Undergoing Bariatric Surgery: A Comparative Randomized Analysis of Recovery Profile. (Preprint) https://doi.org/10.21203/rs.3.rs-1668189/v1

[33] McKendrick, M., Yang, S. and McLeod, G. (2021) The Use of Artificial Intelligence and Robotics in Regional Anaesthesia. *Anaesthesia*, **76**, 171-181. https://doi.org/10.1111/anae.15274

[34] Montomoli, J., Hilty, M.P. and Ince, C. (2022) Artificial Intelligence in Intensive Care: Moving Towards Clinical Decision Support Systems. *Minerva Anestesiologica*, **88**, 1066-1072.

[35] Pirracchio, R. (2022) The Past, the Present and the Future of Machine Learning and Artificial Intelligence in Anesthesia and Post Anesthesia Care Units (PACU). *Minerva Anestesiologica*, **88**, 961-969.

[36] Dumitru, M., Berghi, O.N., Taciuc, I.-A., Vrinceanu, D., Manole, F. and Costache, A. (2022) Could Artificial Intelligence Prevent Intraoperative Anaphylaxis? Reference Review and Proof of Concept. *Medicina*, **58**, Article 1530. https://doi.org/10.3390/medicina58111530

[37] Zaouter, C., Joosten, A., Rinehart, J., Struys, M.M. and Hemmerling, T.M. (2020) Autonomous Systems in Anesthesia: Where Do We Stand in 2020? A Narrative Review. *Anesthesia & Analgesia*, **130**, 1120-1132. https://doi.org/10.1213/ANE.0000000000004646

[38] Xu, C., Zhu, Y., Wu, L., Yu, H., Liu, J., Zhou, F., Xiong, Q., Wang, S., Cui, S. and

Huang, X. (2022) Evaluating the Effect of an Artificial Intelligence System on the Anesthesia Quality Control during Gastrointestinal Endoscopy with Sedation: A Randomized Controlled Trial. *BMC Anesthesiology*, **22**, Article No. 313. https://doi.org/10.1186/s12871-022-01796-1

[39] Wingert, T., Lee, C. and Cannesson, M. (2021) Machine Learning, Deep Learning, and Closed Loop Devices—Anesthesia Delivery. *Anesthesiology Clinics*, **39**, 565-581. https://doi.org/10.1016/j.anclin.2021.03.012

[40] Naaz, S. and Asghar, A. (2022) Artificial Intelligence, Nano-Technology and Genomic Medicine: The Future of Anaesthesia. *Journal of Anaesthesiology Clinical Pharmacology*, **38**, 11-17. https://doi.org/10.4103/joacp.JOACP_139_20

[41] Hemmerling, T., Arbeid, E., Wehbe, M., Cyr, S., Taddei, R. and Zaouter, C. (2013) Evaluation of a Novel Closed-Loop Total Intravenous Anaesthesia Drug Delivery System: A Randomized Controlled Trial. *British Journal of Anaesthesia*, **110**, 1031-1039. https://doi.org/10.1093/bja/aet001

[42] West, N., Van Heusden, K., Görges, M., Brodie, S., Rollinson, A., Petersen, C.L., Dumont, G.A., Ansermino, J.M. and Merchant, R.N. (2018) Design and Evaluation of a Closed-Loop Anesthesia System with Robust Control and Safety System. *Anesthesia & Analgesia*, **127**, 883-894. https://doi.org/10.1213/ANE.0000000000002663

[43] Goverdhan Dutt Puri, P.M., Jayant, A. and Singh, G. (2023) CLADS Closed Loop Anaesthesia Delivery System. http://www.clads-iaads.com/index.php?PageID=1058

[44] AlertWatch™ (2023) The Intelligent Monitoring Platform. https://www.alertwatch.com/

[45] Intuitive (2023) Da Vinci Surgical Systems. https://www.intuitive.com/en-us/products-and-services/da-vinci/systems

[46] Kelly, C.J., Karthikesalingam, A., Suleyman, M., Corrado, G. and King, D. (2019) Key Challenges for Delivering Clinical Impact with Artificial Intelligence. *BMC Medicine*, **17**, Article No. 195. https://doi.org/10.1186/s12916-019-1426-2

[47] Hashimoto, D.A., Witkowski, E., Gao, L., Meireles, O. and Rosman, G. (2020) Artificial Intelligence in Anesthesiology: Current Techniques, Clinical Applications and Limitations. *Anesthesiology*, **132**, 379-394. https://doi.org/10.1097/ALN.0000000000002960

[48] Vatansever, S., Schlessinger, A., Wacker, D., Kaniskan, H.Ü., Jin, J., Zhou, M.M. and Zhang, B. (2021) Artificial Intelligence and Machine Learning-Aided Drug Discovery in Central Nervous System Diseases: State-of-the-Arts and Future Directions. *Medicinal Research Reviews*, **41**, 1427-1473. https://doi.org/10.1002/med.21764

[49] Farghali, H., Canová, N.K. and Arora, M. (2021) The Potential Applications of Artificial Intelligence in Drug Discovery and Development. *Physiological Research*, **70**, S715-S722. https://doi.org/10.33549//physiolres.934765

[50] Parikh, R.B. and Helmchen, L.A. (2022) Paying for Artificial Intelligence in Medicine. *NPJ Digital Medicine*, **5**, Article No. 63. https://doi.org/10.1038/s41746-022-00609-6

[51] Singh, M. and Nath, G. (2022) Artificial Intelligence and Anesthesia: A Narrative Review. *Saudi Journal of Anaesthesia*, **16**, 86-93. https://doi.org/10.4103/sja.sja_669_21

[52] Gambus, P. and Shafer, S.L. (2018) Artificial Intelligence for Everyone. *Anesthesiology*, **128**, 431-433. https://doi.org/10.1097/ALN.0000000000001984

[53] Bellini, V., Valente, M., Gaddi, A.V., Pelosi, P. and Bignami E. (2022) Artificial In-

telligence and Telemedicine in Anesthesia: Potential and Problems. *Minerva Anestesiologica*, **88**, 729-734.

[54] Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H. (2019) Causability and Explainability of Artificial Intelligence in Medicine. Wiley Interdisciplinary Reviews: *Data Mining and Knowledge Discovery*, **9**, e1312. https://doi.org/10.1002/widm.1312

[55] Char, D.S. and Burgart, A. (2020) Machine Learning Implementation in Clinical Anesthesia: Opportunities and Challenges. *Anesthesia and Analgesia*, **130**, 1709-1712. https://doi.org/10.1213/ANE.0000000000004656

[56] Benjamens, S., Dhunnoo, P. and Meskó, B. (2020) The State of Artificial Intelligence-Based FDA-Approved Medical Devices and Algorithms: An Online Database. *NPJ Digital Medicine*, **3**, Article No. 118. https://doi.org/10.1038/s41746-020-00324-0

[57] Melvin, R.L., Broyles, M.G., Duggan, E.W., John, S., Smith, A.D. and Berkowitz, D.E. (2022) Artificial Intelligence in Perioperative Medicine: A Proposed Common Language with Applications to FDA-Approved Devices. *Frontiers in Digital Health*, **4**, Article 872675. https://doi.org/10.3389/fdgth.2022.872675

[58] Nair, B.G., Gabel, E., Hofer, I., Schwid, H.A. and Cannesson, M. (2017) Intraoperative Clinical Decision Support for Anesthesia: A Narrative Review of Available Systems. *Anesthesia & Analgesia*, **124**, 603-617. https://doi.org/10.1213/ANE.0000000000001636

[59] Barto, A.G. and Sutton, R.S. (1997) Reinforcement Learning in Artificial Intelligence. *Advances in Psychology*, **121**, 358-386. https://doi.org/10.1016/S0166-4115(97)80105-7

[60] Vlamou, E. and Papadopoulos, B. (2019) Fuzzy Logic Systems and Medical Applications. *AIMS Neuroscience*, **6**, 266-272. https://doi.org/10.3934/Neuroscience.2019.4.266

[61] Ingle, S. and Phute, M. (2016) Tesla Autopilot: Semi Autonomous Driving, an Uptick for Future Autonomy. *International Research Journal of Engineering and Technology*, **3**, 369-372.

[62] Zwakman, D.S., Pal, D. and Arpnikanondt, C. (2021) Usability Evaluation of Artificial Intelligence-Based Voice Assistants: The Case of Amazon Alexa. *SN Computer Science*, **2**, Article No. 28. https://doi.org/10.1007/s42979-020-00424-4

[63] Lee, J.Y. (2023) Can an Artificial Intelligence Chatbot Be the Author of a Scholarly Article? *Journal of Educational Evaluation for Health Professions*, **20**, Article No. 6.

[64] Transformer, C.G.P.-T. and Zhavoronkov, A. (2022) Rapamycin in the Context of Pascal's Wager: Generative Pre-Trained Transformer Perspective. *Oncoscience*, **9**, 82-84. https://doi.org/10.18632/oncoscience.571

[65] Bhattacharya, K., Bhattacharya, A.S., Bhattacharya, N., Yagnik, V.D., Garg, P. and Kumar, S. (2023) ChatGPT in Surgical Practice—A New Kid on the Block. *Indian Journal of Surgery*. https://doi.org/10.1007/s12262-023-03727-x

[66] Vasey, B., Nagendran, M., Campbell, B., Clifton, D.A., Collins, G.S., Denaxas, S., Denniston, A.K., Faes, L., Geerts, B., Ibrahim, M., *et al.* (2022) Reporting Guideline for the Early-Stage Clinical Evaluation of Decision Support Systems Driven by Artificial Intelligence: DECIDE-AI. *Nature Medicine*, **28**, 924-933. https://doi.org/10.1038/s41591-022-01772-9

[67] Liu, N., Chazot, T., Hamada, S., Landais, A., Boichut, N., Dussaussoy, C., Trillat, B., Beydon, L., Samain, E., Sessler, D.I. and Marc, F. (2011) Closed-Loop Coadmini-

stration of Propofol and Remifentanil Guided by Bispectral Index: A Randomized Multicenter Study. *Anesthesia & Analgesia*, **112**, 546-557. https://doi.org/10.1213/ANE.0b013e318205680b

[68] Haro-Mendoza, D., Pérez-Escamirosa, F., Pineda-Martínez, D. and Gonzalez-Villela, V.J. (2022) Needle Path Planning in Semiautonomous and Teleoperated Robot-Assisted Epidural Anaesthesia Procedure: A Proof of Concept. *The International Journal of Medical Robotics and Computer Assisted Surgery*, **18**, e2434. https://doi.org/10.1002/rcs.2434

[69] Moon, J.S. and Cannesson, M. (2022) A Century of Technology in Anesthesia & Analgesia. *Anesthesia & Analgesia*, **135**, S48-S61. https://doi.org/10.1213/ANE.0000000000005986

[70] Alser, M. and Waisberg, E. (2023) Concerns with the Usage of ChatGPT in Academia and Medicine: A Viewpoint. *American Journal of Medicine Open*, **9**, Article ID: 100036. https://doi.org/10.1016/j.ajmo.2023.100036

[71] Johnson, D., Goodman, R., Patrinely, J., Stone, C., Zimmerman, E., Donald, R., Chang, S., Berkowitz, S., Finn, A. and Jahangir, E. (2023) Assessing the Accuracy and Reliability of AI-Generated Medical Responses: An Evaluation of the Chat-GPT Model. (Preprint) https://doi.org/10.21203/rs.3.rs-2566942/v1

[72] Kung, T.H., Cheatham, M., Medenilla, A., Sillos, C., De Leon, L., Elepaño, C., Madriaga, M., Aggabao, R., Diaz-Candido, G. and Maningo, J. (2023) Performance of ChatGPT on USMLE: Potential for AI-Assisted Medical Education Using Large Language Models. *PLOS Digital Health*, **2**, e0000198. https://doi.org/10.1371/journal.pdig.0000198

[73] Huh, S. (2023) Are ChatGPT's Knowledge and Interpretation Ability Comparable to Those of Medical Students in Korea for Taking a Parasitology Examination?: A Descriptive Study. *Journal of Educational Evaluation for Health Professions*, **20**, Article No. 1.

[74] Hemmerling, T. and Giacalone, M. (2016) An Introduction to Robots in Anaesthesia. *ICU Management & Practice*, **16**, 96-100.

[75] Tremper, K.K., Mace, J.J., Gombert, J.M., Tremper, T.T., Adams, J.F. and Bagian, J.P. (2018) Design of a Novel Multifunction Decision Support Display for Anesthesia Care: AlertWatch® OR. *BMC Anesthesiology*, **18**, Article No. 16. https://doi.org/10.1186/s12871-018-0478-8

[76] Sathishkumar, S., Lai, M., Picton, P., Kheterpal, S., Morris, M., Shanks, A. and Ramachandran, S.K. (2015) Behavioral Modification of Intraoperative Hyperglycemia Management with a Novel Real-Time Audiovisual Monitor. *Anesthesiology*, **123**, 29-37. https://doi.org/10.1097/ALN.0000000000000699

[77] Jones, J.H., Nittur, V.R., Fleming, N. and Applegate, R.L. (2021) Simultaneous Comparison of Depth of Sedation Performance between SedLine and BIS during General Anesthesia Using Custom Passive Interface Hardware: Study Protocol for a Prospective, Non-Blinded, Non-Randomized Trial. *BMC Anesthesiology*, **21**, Article No. 105. https://doi.org/10.1186/s12871-021-01326-5

[78] Masimo® (2023) Next Generation SedLine(R) Brain Function Monitoring. https://www.masimo.com/products/continuous/root/root-sedline/

[79] Pasin, L., Nardelli, P., Pintaudi, M., Greco, M., Zambon, M., Cabrini, L. and Zangrillo, A. (2017) Closed-Loop Delivery Systems Versus Manually Controlled Administration of Total IV Anesthesia: A Meta-Analysis of Randomized Clinical Trials. *Anesthesia & Analgesia*, **124**, 456-464. https://doi.org/10.1213/ANE.0000000000001394

[80] Hemmerling, T., Arbeid, E., Wehbe, M., Cyr, S., Giunta, F. and Zaouter, C. (2013) Transcontinental Anaesthesia: A Pilot Study. *British Journal of Anaesthesia*, **110**, 758-763. https://doi.org/10.1093/bja/aes498

[81] Zaouter, C., Hemmerling, T.M., Lanchon, R., Valoti, E., Remy, A., Leuillet, S. and Ouattara, A. (2016) The Feasibility of a Completely Automated Total IV Anesthesia Drug Delivery System for Cardiac Surgery. *Anesthesia & Analgesia*, **123**, 885-893. https://doi.org/10.1213/ANE.0000000000001152

[82] Goudra, B., Singh, P.M. and Lichtenstein, G.R. (2020) Medical, Political and Economic Considerations for the Use of MAC for Endoscopic Sedation: Big Price, Little Justification? *Digestive Diseases and Sciences*, **65**, 2466-2472. https://doi.org/10.1007/s10620-020-06464-3

[83] Alexander, J.C. and Joshi, G.P. (2018) Anesthesiology, Automation and Artificial Intelligence. *Baylor University Medical Center Proceedings*, **31**, 117-119. https://doi.org/10.1080/08998280.2017.1391036

[84] Goudra, B. and Singh, P.M. (2017) Failure of Sedasys: Destiny or Poor Design? *Anesthesia & Analgesia*, **124**, 686-688. https://doi.org/10.1213/ANE.0000000000001643

[85] Puri, G., Kumar, B. and Aveek, J. (2007) Closed-Loop Anaesthesia Delivery System (CLADS™) Using Bispectral Index: A Performance Assessment Study. *Anaesthesia and Intensive Care*, **35**, 357-362. https://doi.org/10.1177/0310057X0703500306

[86] Puri, G.D., Mathew, P.J., Biswas, I., Dutta, A., Sood, J., Gombar, S., Palta, S., Tsering, M., Gautam, P. and Jayant, A. (2016) A Multicenter Evaluation of a Closed-Loop Anesthesia Delivery System: A Randomized Controlled Trial. *Anesthesia & Analgesia*, **122**, 106-114. https://doi.org/10.1213/ANE.0000000000000769

[87] De Smet, T., Struys, M.M., Neckebroek, M.M., Van den Hauwe, K., Bonte, S. and Mortier, E.P. (2008) The Accuracy and Clinical Feasibility of a New Bayesian-Based Closed-Loop Control System for Propofol Administration Using the Bispectral Index as a Controlled Variable. *Anesthesia & Analgesia*, **107**, 1200-1210. https://doi.org/10.1213/ane.0b013e31817bd1a6

[88] Liu, Y., Li, M., Yang, D., Zhang, X., Wu, A., Yao, S., Xue, Z. and Yue, Y. (2015) Closed-Loop Control Better than Open-Loop Control of Profofol TCI Guided by BIS: A Randomized, Controlled, Multicenter Clinical Trial to Evaluate the CONCERT-CL Closed-Loop System. *PLOS ONE*, **10**, e0123862. https://doi.org/10.1371/journal.pone.0123862

[89] Liu, N., Chazot, T., Genty, A., Landais, A., Restoux, A., McGee, K., Laloë, P.-A., Trillat, B., Barvais, L. and Fischler, M. (2006) Titration of Propofol for Anesthetic Induction and Maintenance Guided by the Bispectral Index: Closed-Loop versus Manual Control: A Prospective, Randomized, Multicenter Study. *The Journal of the American Society of Anesthesiologists*, **104**, 686-695. https://doi.org/10.1097/00000542-200604000-00012

[90] Morley, A., Derrick, J., Mainland, P., Lee, B. and Short, T. (2000) Closed Loop Control of Anaesthesia: An Assessment of the Bispectral Index as the Target of Control. *Anaesthesia*, **55**, 953-959. https://doi.org/10.1046/j.1365-2044.2000.01527.x

[91] Tighe, P.J., Badiyan, S., Luria, I., Lampotang, S. and Parekattil, S. (2010) Robot-Assisted Airway Support: A Simulated Case. *Anesthesia and Analgesia*, **111**, 929-931. https://doi.org/10.1213/ANE.0b013e3181ef73ec

[92] Hemmerling, T.M., Wehbe, M., Zaouter, C., Taddei, R. and Morse, J. (2012) The Kepler Intubation System. *Anesthesia & Analgesia*, **114**, 590-594. https://doi.org/10.1213/ANE.0b013e3182410cbf

[93] Morse, J., Terrasini, N., Wehbe, M., Philippona, C., Zaouter, C., Cyr, S. and Hem-

merling, T. (2014) Comparison of Success Rates, Learning Curves, and Inter-Subject Performance Variability of Robot-Assisted and Manual Ultrasound-Guided Nerve Block Needle Guidance in Simulation. *British Journal of Anaesthesia*, **112**, 1092-1097. https://doi.org/10.1093/bja/aet440

[94] Ng, Z.Q., Jung, J.K. and Theophilus, M. (2021) Artificial Intelligence in Pre-Operative Assessment of Patients in Colorectal Surgery. *Turkish Journal of Colorectal Disease*, **31**, 99-104. https://doi.org/10.4274/tjcd.galenos.2021.2021-2-6

[95] Lin, C.-S., Li, Y.-C., Mok, M.S., Wu, C.-C., Chiu, H.-W. and Lin, Y.-H. (2002) Neural Network Modeling to Predict the Hypnotic Effect of Propofol Bolus Induction. *Proceedings of the AMIA Symposium*, San Antonio, TX, 9-13 November 2002, 450-453.

[96] Hemmerling, T.M., Taddei, R., Wehbe, M., Cyr, S., Zaouter, C. and Morse, J. (2013) First Robotic Ultrasound-Guided Nerve Blocks in Humans Using the Magellan System. *Anesthesia & Analgesia*, **116**, 491-494. https://doi.org/10.1213/ANE.0b013e3182713b49

[97] Smistad, E. and Løvstakken, L. (2016) Vessel Detection in Ultrasound Images Using Deep Convolutional Neural Networks. In: Carneiro, G., *et al.*, Eds., *DLMIA* 2016, *LABELS* 2016: *Deep Learning and Data Labeling for Medical Applications*, *Lecture Notes in Computer Science*, Vol. 10008, Springer, Cham, 30-38. https://doi.org/10.1007/978-3-319-46976-8_4

[98] Atee, M., Hoti, K. and Hughes, J.D. (2018) A Technical Note on the PainChek™ System: A Web Portal and Mobile Medical Device for Assessing Pain in People with Dementia. *Frontiers in Aging Neuroscience*, **10**, Article 117. https://doi.org/10.3389/fnagi.2018.00117

[99] Gram, M., Erlenwein, J., Petzke, F., Falla, D., Przemeck, M., Emons, M.I., Reuster, M., Olesen, S. and Drewes, A.M. (2017) Prediction of Postoperative Opioid Analgesia Using Clinical-Experimental Parameters and Electroencephalography. *European Journal of Pain*, **21**, 264-277. https://doi.org/10.1002/ejp.921

[100] Benzy, V. and Jasmin, E. (2015) A Combined Wavelet and Neural Network Based Model for Classifying Depth of Anaesthesia. *Procedia Computer Science*, **46**, 1610-1617. https://doi.org/10.1016/j.procs.2015.02.093

[101] Combes, C., Meskens, N., Rivat, C. and Vandamme, J.-P. (2008) Using a KDD Process to Forecast the Duration of Surgery. *International Journal of Production Economics*, **112**, 279-293. https://doi.org/10.1016/j.ijpe.2006.12.068

[102] Devi, S.P., Rao, K.S. and Sangeetha, S.S. (2012) Prediction of Surgery Times and Scheduling of Operation Theaters in Ophtholmology Department. *Journal of Medical Systems*, **36**, 415-430. https://doi.org/10.1007/s10916-010-9486-z

[103] Sahai, A., Wong, J.C., Gould, M. and Byrne, M.F. (2013) Tu1380 Multicenter Preliminary Experience with the SEDASYS Propofol Infusion Pump for Colonoscopy in Routine Clinical Practice: Safety and Endoscopist Satisfaction. *Gastrointestinal Endoscopy*, **77**, AB520. https://doi.org/10.1016/j.gie.2013.03.861

[104] Abel, J.H., Badgeley, M.A., Meschede-Krasa, B., Schamberg, G., Garwood, I.C., Lecamwasam, K., Chakravarty, S., Zhou, D.W., Keating, M. and Purdon, P.L. (2021) Machine Learning of EEG Spectra Classifies Unconsciousness during GABAergic Anesthesia. *PLOS ONE*, **16**, e0246165. https://doi.org/10.1371/journal.pone.0246165

[105] Birch, J., Creel, K.A., Jha, A.K. and Plutynski, A. (2022) Clinical Decisions Using AI must Consider Patient Values. *Nature Medicine*, **28**, 229-232. https://doi.org/10.1038/s41591-021-01624-y

[106] Mathur, S., Patel, J., Goldstein, S. and Jain, A. (2021) Bispectral Index. StatPearls Publishing LLC, Tampa, FL.

[107] Helmreich, R.L. (2000) On Error Management: Lessons from Aviation. *BMJ*, **320**, 781-785. https://doi.org/10.1136/bmj.320.7237.781

[108] Lee, H.-C., Ryu, H.-G., Park, Y., Yoon, S.B., Yang, S.M., Oh, H.-W. and Jung, C.-W. (2019) Data Driven Investigation of Bispectral Index Algorithm. *Scientific Reports*, **9**, Article No. 13769. https://doi.org/10.1038/s41598-019-50391-x

[109] Shen, M.W. (2022) Trust in AI: Interpretability Is Not Necessary or Sufficient, While Black-Box Interaction Is Necessary and Sufficient. (Preprint)