Intelligent Anesthesia

Review

AI empowers anesthesiology: From preoperative assessment to postoperative management and application progress

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Abstract

In recent years, artificial intelligence (AI) has advanced rapidly, driven by enhanced computing power and iterative algorithm development. This progress has facilitated the widespread application of AI across various medical domains, including medical imaging, disease diagnosis, and drug research and development. In anesthesiology, research focuses on the comprehensive management of the perioperative period. AI optimizes key processes such as preoperative risk assessment, intraoperative drug monitoring, and postoperative adverse event management. This integration not only standardizes anesthesia practices more effectively but also significantly enhances intraoperative safety and alleviates postoperative discomfort.

However, the application of AI in anesthesiology still faces several challenges, including inconsistent data quality, incomplete algorithms, and difficulties in system integration. The efficient synthesis and analysis of multi-modal, real-time data to provide personalized, dynamically adjusted treatment strategies remains a major hurdle.

The integration of AI and anesthesiology holds substantial practical significance. This paper provides a systematic discussion of AI's applications and benefits across the preoperative (e.g., anesthesia planning, risk prediction), intraoperative (e.g., real-time monitoring of vital signs), and postoperative (e.g., prognosis management) phases of anesthesia. It is hoped that this study will offer valuable technical insights for clinical practice and support the rapid development of anesthesiology towards greater intelligence.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Computer Vision; Anesthesia

Introduction

The applications of artificial intelligence (AI) are rapidly expanding across various fields of social production and daily life, with particularly significant impacts in healthcare. Examples include intelligent assistants that support doctor-patient communication, financial risk control to safeguard medical funds, and advanced medical diagnostics that enhance disease detection accuracy (1). Among AI's core branches, machine learning, reinforcement learning, and deep learning have gained considerable attention in medicine due to their powerful data processing capabilities (2-4).

In clinical practice, AI has been progressively integrated into the entire workflow of medical diagnosis. AI assists clinicians in tasks such as endoscopic examinations, image interpretation during regional ultrasound-guided anesthesia, and the prediction of postoperative adverse events (5-7). By synthesizing diverse data, these models not only reduce the time required for diagnosis but also enhance the safety and accuracy of medical care. In anesthesiology, AI contributes by generating personalized anesthesia plans, predicting risks, and monitoring patients' vital signs in real time. It can also dynamically adjust anesthesia plans and precisely administer anesthetic doses (8). Additionally, AI plays a crucial role in monitoring medication regimens and offering rehabilitation guidance to optimize patient recovery. As technologies continue to evolve, AI is driving anesthesiology toward greater precision and safety.

Recent cutting-edge studies have significantly expanded AI applications in anesthesia. One study introduced an intelligent pen-based system for continuous monitoring of the anesthetic drug propofol, filling a critical gap in drug monitoring. This system enables closed-loop management between anesthesiologists and patients, further enhancing anesthesia safety (9). Another breakthrough, developed by Lee et al., is a reinforcement learning model that overcomes the limitations of traditional sedation management through closed-loop control. This model establishes the first patient-specific adaptive sedation protocol (10). These advancements have laid a strong foundation for the application of AI in anesthesiology, accelerating its transformation toward precision medicine.

This study provides a comprehensive review of the research progress and applications of AI in anesthesiology, covering areas such as preoperative risk assessment, personalized plan formulation, and consciousness state monitoring; intraoperative real-time monitoring, airway management, drug monitoring, puncture identification, and adverse event detection; anesthetic depth monitoring based on multimodal data fusion; postoperative complication prediction and management; postoperative care and rehabilitation guidance; automated anesthesia record and document management; intelligent surgical scheduling; resource allocation; and ultrasound-guided regional anesthesia. This review aims to offer clinicians improved diagnostic tools and provide valuable research data to support the ongoing development of anesthesiology.

Methods

This study provides an overview of the application of artificial intelligence in anesthesia management, spanning the preoperative, intraoperative, and postoperative phases, and highlights the advantages of these applications. A comprehensive search was conducted using the PubMed database, with keywords including "artificial intelligence," "machine learning," "deep learning," "computer vision," and "anesthesia." We included all English-language articles published between 2020 and 2025, while excluding studies involving animals, editorials, letters to the editor, and reviews.

Preoperative assessment and anesthesia plan formulation

Preoperative risk assessment based on big data and machine learning

In the preoperative phase, artificial intelligence (AI) predicts risks by integrating patients' baseline and laboratory data, assisting clinicians with diagnosis and treatment, and improving both the timeliness and accuracy of medical care. For example, the prediction model developed by Te et al. focuses on hemodynamic instability following endotracheal intubation. Using machine learning, the model alerts anesthesiologists to potential risks preoperatively, enabling personalized and precise anesthetic interventions (11). Miyaguchi et al. applied machine learning to automate drug infusion, addressing the challenge of anesthesiologist shortages. They employed six models—logistic regression, support vector machine, random forest, LightGBM, artificial neural network, and long short-term memory (LSTM) network—to predict the need for an increase in the remifentanil flow rate after one minute. Of these models, the LSTM network achieved a sensitivity of 0.659, specificity of 0.732, and a ROC-AUC value of 0.753. Additionally, the Shapley Additive exPlanations (SHAP) method was used to assess feature importance, and the results showed partial consistency with established clinical findings (12). Furthermore, the Opal model, developed by Bishara et al., was the first machine learning model published in anesthesiology. Based on data from 29,004 surgeries, this model, referencing the creatinine KDIGO criteria (a standard for evaluating acute kidney injury), serves as a preoperative tool for predicting postoperative acute kidney injury (AKI) (13).

Intelligent generation of personalized anesthesia plans

Personalized anesthesia plans are primarily developed by accurately selecting approaches based on patients' baseline data, such as age, weight, and overall health status. This enhances both safety and effectiveness while minimizing the risk of complications. Wang et al. used models including ChatGPT-4.0, Claude 3.5 Sonnet, and ChatGPT-01 to develop preoperative plans. Their findings revealed that ChatGPT-01 outperformed the other models in terms of content relevance and information accuracy, with a lower error rate, making it more suitable for clinical application (14). In the context of ophthalmic anesthesia, Zhang et al. integrated natural language processing and machine learning technologies, utilizing an embedding model to create safer and more efficient personalized anesthesia management (15).

Puncture recognition

Puncture identification is a critical technique in anesthesia and interventional surgery, but it is often challenged by interference from complex anatomical structures and the high level of skill required. Artificial intelligence (AI)-assisted technology has provided a promising solution by enabling the identification of complex structures and real-time dynamic tracking. For example, Chan et al. proposed the use of machine learning to identify spinal anesthesia puncture sites in obese patients, offering valuable support in locating puncture sites for this patient group. Furthermore, the "depth from the skin to the posterior dural complex," as recorded by the program, demonstrated a strong correlation with depth measurements taken by clinicians (16).

Intraoperative monitoring and anesthetic depth regulation

Intraoperative real-time monitoring

Intraoperative real-time monitoring is a crucial component in ensuring patient safety. Artificial intelligence (AI) can track vital indicators such as patients' vital signs and organ function, providing timely feedback to medical staff and enabling rapid adjustments to treatment plans. For instance, the FaCare photoplethysmography system, proposed by Ke et al., has been shown to reduce the risk of infection and alleviate patient discomfort (17). In their study on the use of clonidine and tranexamic acid to control intraoperative blood loss during rhinoplasty, Asghari Varzaneh et al. demonstrated that their predictive model performed robustly, helping to optimize the surgical field and reduce operation time (18). Aguet et al. combined photoplethysmographic (PPG) waveform features with machine learning to accurately track blood pressure changes during anesthetic induction (19). Mosquera Dussan et al. applied biosignal filtering and machine learning algorithms to classify and diagnose intraoperative Alzheimer's disease (AD) (20). Wang et al. used a deep learning model to infer brain states during anesthesia (21). Additionally, Pasma et al.'s research on artifact annotation in anesthetic blood pressure data suggested that physiological data collected during anesthesia could be automated for artifact detection (22).

Intraoperative airway management

Intraoperative airway management is a critical component of surgical safety, with its importance spanning three key areas: maintaining respiratory function, responding to sudden risks, and adapting to the specific demands of the surgery. Huang et al. employed a machine learning model to predict extubation failure in patients with difficult airway management following general anesthesia for maxillofacial surgery. This model may help reduce morbidity and mortality in such patients (23). García-García et al. used a deep convolutional neural network to analyze patients' airway morphology, demonstrating advantages in identifying and localizing landmarks. Notably, in the anterior view, the network's accuracy surpassed that of anesthesiologists (24). Lee et al. applied a reinforcement learning model for ventilation control during the emergence from general anesthesia. Their AIVE model showed greater estimated benefits and fewer complications compared to traditional clinical strategies (25). Shimizu et al. introduced a new acoustic monitoring system that accurately predicts the retention of upper airway fluid, potentially reducing the risk of aspiration during the monitored anesthesia care (MAC) period (26).

Drug Monitoring

Real-time monitoring of blood drug concentrations during surgery is essential for helping medical staff assess patients' physical signs and prevent adverse events such as respiratory depression and circulatory failure. Khalid et al. proposed a method that combines a machine learning classifier with photoplethysmography (PPG) for intraoperative anesthetic depth analysis and postoperative monitoring. This approach holds promise as a reliable, non-invasive, and low-cost method for anesthetic drug detection (27). Ren et al. implemented intelligent drug control based on convolutional neural networks during the maintenance phase of general anesthesia. Their open-loop decision-making scheme demonstrated consistency between intelligent anesthesia control and actual anesthesia management, paving the way for further optimization of intelligent auxiliary control for anesthetic depth (28). Jin et al. assessed individual sensitivity to propofol by analyzing EEG complexity and information integration, highlighting the value of preoperative brain state assessment in predicting drug sensitivity. This approach is significant for developing more precise anesthesia plans (29). Aiassa et al. introduced the first intelligent system for continuous monitoring of the anesthetic drug propofol. This system addresses a critical gap in therapeutic drug monitoring (TDM), enables closed-loop management between physicians and patients, and significantly enhances anesthesia safety (9).

Conscious state

The depth of anesthesia is critical for patient safety during surgery: insufficient depth may lead to intraoperative awareness and movement, disrupting the surgical procedure, while excessive depth can cause respiratory depression and prolong postoperative recovery. Abel et al. applied machine learning based on the electroencephalogram (EEG) spectrum to classify unconscious states under GABAergic sedation. This method effectively predicts the anesthetic state, offering potential for precise monitoring of anesthesia depth (30). Tacke et al. integrated and analyzed data from EEG and auditory evoked potential (AEP) monitoring. Their model achieved a maximum prediction probability of 0.935 for consciousness states, outperforming the prediction accuracy of individual indicators. This approach enables more efficient differentiation between conscious and unconscious states (31). Additionally, Jang et al. proposed a metric based on functional magnetic resonance imaging (fMRI), called the integration-separation difference. This metric captures two key attributes—network efficiency and clustering coefficient—and has been confirmed as a reliable indicator for evaluating consciousness states (32).

Intraoperative adverse event prediction

Intraoperative adverse event prediction is crucial for ensuring patient safety, as it allows for the real-time detection of sudden risks such as massive bleeding, hypotension, and drug allergies, preventing these issues from escalating into serious complications. Kang et al. employed Gradient Boosting Machine (GBM) and Logistic Regression (LR) models to predict hypoxemia during endoscopic retrograde cholangiopancreatography (ERCP) under monitored anesthesia care (MAC). These models demonstrated promising potential in preventing hypoxemia during ERCP with MAC anesthesia (33). In another study, Kang et al. used four models—Bayesian model, Logistic Regression, Random Forest, and Artificial Neural Network—to predict post-induction hypotension occurring between endotracheal intubation and the surgical skin incision (34). Dervishi developed a multimodal superimposed model to estimate cardiac output based on cardiopulmonary interactions during general anesthesia. This model utilized clinical data from 469 adult patients with normal lung function undergoing general anesthesia. The prediction results were highly consistent with measurements obtained from pulse waveform technology monitors (35).

Anesthetic depth monitoring based on multimodal data fusion

Anesthetic depth monitoring is a critical component in ensuring both surgical safety and postoperative recovery. It allows for accurate assessment of the patient's anesthetic state, preventing adverse events caused by either insufficient or excessive anesthesia. Wang et al. predicted anesthetic depth based on drug infusion history, employing a framework that integrates sequence modeling, attention mechanisms, and nonlinear modeling techniques. This hybrid approach not only enhances the reliability of predictions but also provides anesthesiologists with a more comprehensive analysis of factors influencing anesthetic depth (36, 37). Chi et al. utilized an autoregressive Transformer model to predict anesthetic depth, proposing two frameworks: the Integrated Linear Autoregressive Framework (ILAR) and the Real-time Transformer Autoregressive Framework (RTAR). Both frameworks enable numerical prediction of depth of anesthesia (DOA) during the induction phase. The two frameworks are tailored for different scenarios depending on whether the sensor can obtain real-time electroencephalographic bispectral index (BIS) values. Experimental results demonstrated that, compared to the previous Long Short-Term Memory-Multilayer Perceptron (LSTM-MLP) framework, the deviation between predicted BIS values and actual ground truth values was significantly smaller (38, 39). Afshar et al. proposed a method for real-time monitoring of anesthetic depth (DOA) through automatic analysis of electroencephalographic signals. This approach effectively aids anesthesiologists in making informed clinical decisions (8, 40, 41).

Ultrasound-guided regional anesthesia

The application of artificial intelligence (AI) in the field of regional ultrasound-guided anesthesia (including ultrasound-guided regional anesthesia, UGRA) focuses on three core areas: clinical operation assistance, training support, and data processing.

In clinical operation assistance, Bowness et al. demonstrated that AI can accurately identify key anatomical structures, such as nerves and blood vessels, in ultrasound images. Through its annotation function, AI helps less experienced clinicians verify correct ultrasound sections, particularly improving the accuracy of non-UGRA experts (6). Additionally, AI-driven devices like the ScanNav system can guide operators to focus on target areas, assist in optimizing clinical procedures, and significantly enhance the anatomical recognition ability of non-specialists, showing promise for expanding the application of regional anesthesia (42).

Training support is another crucial area where AI is making an impact. Shevlin et al. found that AI could assist simulation devices like NeedleTrainer, potentially reducing the "target localization time" for novice practitioners. Moreover, it helps maintain better ultrasound scanning performance up to two months after training, thereby aiding skill retention (43). Furthermore, frameworks that incorporate differences in human-machine anatomical recognition and Dice metrics can enhance the consistency assessment of training. Notably, an innovative approach has been made to objectively quantify the visibility of needle tips in simulated UGRA, addressing a research gap (44).

In data processing and interpretation, Julius et al. showed that AI can assist in the acquisition and analysis of ultrasound images, reducing human errors. In cardiac anesthesia, large language models (LLMs) can convert unstructured text reports from transesophageal echocardiography (TEE) into structured key parameters, overcoming the time-consuming and error-prone process of manual data extraction with controllable error rates (45). Moreover, AI is driving innovation in technical evaluation, such as analyzing human-machine anatomical recognition differences, exploring the clinical relevance of AI assessments, and emphasizing the need for clinician involvement in AI development to ensure standardized progress in the field.

Postoperative complication prediction and management

Postoperative complication prediction and management are critical for bridging the gap between surgery and patient rehabilitation. These practices play a key role in improving diagnostic and treatment quality while ensuring patient safety. Li et al. used traditional logistic regression and machine learning models to predict the effectiveness of subanesthetic-dose intravenous ketamine/esketamine in preventing postpartum depression during cesarean section. By incorporating maternal clinical characteristics into the model, personalized prevention strategies can be developed, significantly reducing the incidence of postpartum depression (46). Choi et al. developed an XGBoost algorithm based on the accelerated failure time model to predict long-term mortality associated with postoperative acute kidney injury. The model outperforms traditional approaches, and its use of machine learning technology provides a robust foundation for formulating targeted interventions and clinical guidelines to improve patient outcomes (47). Additionally, Li et al. applied AI to predict severe postpartum hemorrhage in patients with placenta accreta spectrum disorders under neuraxial anesthesia (48), while Shi et al. used the random forest algorithm to predict moderate-to-severe acute postoperative pain after orthopedic surgery under general anesthesia. The Anesthesia Risk Assessment Score (ARAS), developed by Khandaker et al., predicts postoperative mortality and adverse discharge outcomes. Its accuracy is comparable to established tools like the American Society of Anesthesiologists Physical Status Classification (ASA-PS), the Revised Cardiac Risk Index (RCRI), and the 5-item Modified Frailty Index (mFI-5). Furthermore, the ARAS does not require clinician involvement, making it suitable for early preoperative assessment and triage (49).

In the context of postoperative care, Barker et al. utilized machine learning to predict unplanned care needs in the perioperative post-anesthesia care unit (PACU). They advocated for using AI to assist anesthesiologists in clinical decision-making, optimizing PACU management, and ensuring that patients receive the safest possible care (50). Khan et al. proposed that AI can enhance personalized care by automatically tracking and adjusting drug doses, alleviating symptoms and reducing the burden on nursing staff (51).

Large Language Models (LLMs) in AI are becoming increasingly relevant in the medical field. For instance, Choi et al. demonstrated that ChatGPT 4.0 can generate high-quality responses, significantly aiding patients in obtaining medical information, although there is still room for improvement in response quality (52). Kuo et al. showed that LLMs could reduce patient risks and decrease the need for continuous physician supervision. These models also align with standardized medical knowledge, suggesting that they could reshape clinical practices in anesthesiology and assist physicians in decision-making (53). Furthermore, Lomas et al. highlighted the potential of GPT-4 to break down language barriers in obstetric anesthesia, contributing to better patient care and influencing both personal and professional life in the future (54).

Reshaping scheduling efficiency and innovating educational experiences

Automated anesthesia documentation and record management

Naik et al. addressed the issue of digital anesthesia data gaps in low- and middle-income countries by developing a standardized anesthesia record form compatible with computer vision technology. This form leverages computer vision to identify and extract anesthesia-related information from paper-based health records, converting it into digital data. This process facilitates the effective acquisition and utilization of digital anesthesia records, laying the foundation for subsequent digital management of anesthesia data (55). Segal et al. proposed the use of large language models, such as ChatGPT, to assist in writing case reports. In their study on anesthesia management for patients with juvenile hyaline fibromatosis, ChatGPT was able to generate text with correct grammar and coherent semantics around the anesthesia management process. This tool helps clarify the patient's anesthesia care, enhancing both the efficiency and quality of anesthesia-related document writing, including case reports (56).

Intelligent surgical scheduling and resource allocation

Hurley's research developed an artificial intelligence-based shift schedule for anesthesiology residents, providing a comprehensive 6-month plan. This schedule assigns an equitable share of on-call duties to each resident while enhancing flexibility for leave requests. By optimizing workforce allocation, it strikes a balance between work fairness and residents' personal needs (57). Sumrall et al. constructed a data-driven scheduling system using artificial intelligence to improve the well-being of anesthesiologists, such as through a more reasonable distribution of workload, while indirectly ensuring patient safety. This system also supports the continuous improvement and flexible adaptation of medical service processes, linking the optimization of workforce management with enhanced patient safety and service quality (58).

Applications of large language models in anesthesia education and training

AI has made significant strides in the education and training of anesthesiology and related fields, demonstrating considerable potential. Regarding exam preparation and competency assessment, Blacker et al. noted that answers generated by ChatGPT for the Anesthesiology Specialty Oral Examination (SOE) achieved scores comparable to those of anesthesiology specialists when assessed by examiners. Furthermore, in both the basic and advanced sections of the written American Board of Anesthesiology (ABA) exam, ChatGPT outperformed GPT-3 and Bard, even showing potential to pass the actual oral exam (59). Fujimoto et al. found that in the Japanese National Dental Anesthesia Licensing Examination, ChatGPT-4 and Claude 3 Opus exhibited superior performance. However, these AI models still face challenges such as verbose responses, lack of focus, and an inability to meet exam passing criteria, which necessitates further optimization (60). In terms of teaching materials, Khan et al. highlighted that AI can create virtual patient consultation scenarios, enabling trainees to practice without the need for actors. Additionally, physicians can utilize "no-code" platforms to develop personalized tools. While AI-generated teaching materials meet medical accuracy standards, their reliability has not yet reached the necessary level for medical education, requiring validation before practical application (61, 62). With continued refinement, AI holds the potential to provide more robust support for education and training in the future.

Limitations

Although artificial intelligence (AI) has demonstrated diverse capabilities and is increasingly applied across various fields, it still faces several limitations. First, there is the issue of data dependence and quality. While large-scale datasets are essential for training AI models, data is often constrained by privacy protections, and there is a scarcity of data on rare or special cases, limiting its broader application. Second, real-time performance needs further optimization. During sedation, patients' vital signs can fluctuate rapidly, and existing AI models may struggle to respond accurately to sudden changes in these values. Lastly, ethical and safety concerns remain, including the potential for AI algorithms to exhibit biases, the sensitive nature of patient data, and the lack of specific regulatory standards for the use of AI in anesthesia.

Advantages

With ongoing advancements in algorithm optimization and iteration, the integration of artificial intelligence (AI) into anesthesiology not only enhances the efficiency of anesthesiologists but also drives progress in the field itself.

In the pre-anesthesia preparation phase, AI analyzes patients' medical history, physical examination results, laboratory data, and other relevant information to identify individuals at high surgical risk. By providing anesthesiologists with personalized treatment plans, AI helps reduce the occurrence of adverse events. For example, AI models can predict patients' responses to anesthetic drugs, enabling the formulation of proactive strategies in advance. During surgery, AI enables real-time monitoring of vital signs such as blood pressure, heart rate, and respiration. By integrating various types of data, AI can intervene promptly and adjust anesthetic dosages to ensure optimal anesthesia delivery. For complex procedures, maintaining precise anesthetic depth is crucial for patient safety and favorable outcomes. In the postoperative phase, AI can predict adverse events like pain, hypotension, and hypoxemia, offering personalized pain management plans and facilitating closed-loop management. This not only enhances patient care but also accelerates recovery time.

AI also plays a key role in medical education by providing extensive learning resources to support teaching activities. Additionally, AI is used in anesthesia record-keeping and document management, which helps alleviate the administrative burden on anesthesiologists.

In summary, AI is involved in the full spectrum of anesthesia management, significantly enhancing the quality and safety of anesthesia practice.

Conclusion and Future Directions

With the ongoing advancement of algorithms and iterative improvements, artificial intelligence (AI) has rapidly developed and is increasingly being applied in the medical field. In anesthesiology, although the integration of AI is relatively recent, significant progress has been made in recent years, substantially reducing the workload of anesthesiologists. Key areas of development include more precise drug infusion, enhanced intraoperative safety, and more effective anesthetic outcomes. Looking ahead, these innovations are expected to not only improve the efficiency of medical services but also minimize patient discomfort during diagnosis and treatment. By providing comprehensive safety measures throughout the entire perioperative process—from preoperative assessment to postoperative recovery—AI technologies will contribute to the dual enhancement of both medical quality and the patient experience.

Author contributions

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Conflict of interest

The authors declare that there are no commercial or financial relationships that could be perceived as potential conflicts of interest in the conduct of this research.

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