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Applications of Artificial Intelligence in Anesthesia and Perioperative Medicine: A Systematic Review of the Literature

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Abstract: **Review Article**

***Introduction*:** Artificial intelligence (AI) is rapidly expanding across many fields of medicine, including anesthesia and perioperative medicine. Through machine learning and deep learning techniques, it has become possible to analyze large amounts of physiological, hemodynamic, ventilatory, and electroencephalographic data in order to improve intraoperative monitoring, anticipate complications, and optimize clinical decision-making. ***Objective*:** To analyze the main applications of AI in anesthesia and perioperative medicine and to evaluate its potential contribution to clinical practice based on the available literature. ***Methods*:** A systematic review of the literature was conducted using PubMed, Scopus, and Embase for the period 2010–2025. The search strategy included the following keywords: “artificial intelligence,” “machine learning,” “deep learning,” “anesthesia,” “anesthesiology,” “perioperative,” “hypotension,” “EEG,” “ventilation,” and “postoperative complications.” Original studies focusing on clinical or perioperative applications of AI in anesthesia were included. ***Results*:** The main areas of application identified were prediction of intraoperative hypotension, monitoring of anesthetic depth, automated administration of anesthetic agents, ventilatory optimization, and prediction of postoperative complications. In the study by Hatib *et al.*, an algorithm developed from 1,334 patients, 545,959 minutes of recordings, and 25,461 hypotensive episodes achieved an **area under the curve (AUC)** of 0.95 at 15 minutes and 0.97 at 5 minutes before the event. The randomized HYPE trial demonstrated a reduction in the **time-weighted average (TWA)** of hypotension from 0.44 mmHg to 0.10 mmHg using a predictive alert system. For postoperative delirium, Bishara *et al.*, reported an AUC of 0.851 with XGBoost in a cohort of 24,885 patients. For postoperative pulmonary complications, Li *et al.*, reported an AUC ranging from 0.878 to 0.881, outperforming the ARISCAT score. Closed-loop propofol delivery systems also provided better maintenance of the target depth of anesthesia than manual control. ***Conclusion*:** AI represents a promising tool in anesthesia and perioperative medicine. It may improve early detection of adverse events, personalize patient management, and enhance anesthetic safety. However, most currently available studies remain retrospective or focused mainly on technical performance. Prospective multicenter validation studies are still needed before broad implementation in routine practice.

Keywords: Artificial Intelligence, Anesthesia, Perioperative Medicine, Machine Learning, Deep Learning, Intraoperative Hypotension, Postoperative Delirium, Mechanical Ventilation.

1. INTRODUCTION

Artificial intelligence is playing an increasingly important role in medicine, particularly in anesthesia and perioperative medicine, where large amounts of hemodynamic, ventilatory, biological, and EEG data are continuously generated in real time [1–4].

In this context, machine learning methods may help detect complex relationships among variables, predict adverse events, and improve clinical decision-making [1, 3, 8, 9].

The main applications of AI in perioperative medicine include preoperative risk stratification, prediction of intraoperative events, partial automation of anesthetic drug administration, and prediction of postoperative complications [8–12]. Among these, prediction of intraoperative hypotension is one of the most advanced fields. Hatib *et al.*, showed that an algorithm based on arterial waveform analysis could predict a hypotensive event with an AUC of 0.95 at 15 minutes and 0.97 at 5 minutes before onset [1]. The randomized HYPE trial subsequently demonstrated that a predictive warning system could significantly reduce exposure to intraoperative hypotension [2].

Other applications include monitoring of anesthetic depth, closed-loop anesthetic drug delivery systems, and prediction of postoperative delirium and postoperative pulmonary complications [3–7].

Despite these promising results, several limitations remain, including methodological heterogeneity, insufficient external validation, and the limited number of prospective studies demonstrating robust clinical benefit [2, 9–11].

The aim of this review is to identify the main applications of AI in anesthesia and perioperative medicine, present the reported performance of these systems in the literature, and discuss their limitations and future perspectives.

2. Materials and Methods

2.1 Study design

This study is a systematic review of the literature conducted using a structured approach inspired by PRISMA recommendations.

2.2 Data sources

The bibliographic search was performed using the following databases: PubMed, Scopus, and Embase.

2.3 Search period

The literature published between January 2010 and December 2025 was targeted in order to cover the recent period marked by the expansion of machine learning and deep learning applications in medicine.

2.4 Search strategy

The following keywords, alone or combined with Boolean operators, were used: “artificial intelligence,” “machine learning,” “deep learning,” “anesthesia,” “anesthesiology,” “perioperative,” “hypotension,” “EEG,” “depth of anesthesia,” “closed-loop,” “ventilation,” “postoperative complications,” and “delirium.”

2.5 Inclusion Criteria

The following were included: original human studies, studies evaluating a clinical or perioperative application of AI in anesthesia, studies involving algorithm development, validation, or clinical assessment, and articles published in English or French.

2.6 Exclusion Criteria

Editorials, comments, letters to the editor, narrative reviews without methodological structure, animal studies, purely technical studies without identifiable clinical application, and studies outside the anesthetic or perioperative setting were excluded.

2.7 Study selection

Study selection was based on screening of titles and abstracts followed by full-text review of potentially relevant articles. Particular attention was paid to studies reporting robust quantitative performance measures such as AUC, sensitivity, specificity, calibration, time within target range, or measurable clinical impact.

2.8 Data extraction

Extracted variables included year of publication, study design, sample size, application domain, type of algorithm used, main performance indicators, and comparison with conventional approaches.

3. RESULTS

3.1 Overview of identified applications

Applications of AI in anesthesia and perioperative medicine can be broadly grouped into five main domains: prediction of intraoperative hypotension, monitoring of anesthetic depth, automated administration of anesthetic agents, ventilatory optimization and prediction of postoperative pulmonary complications, and prediction of postoperative complications, particularly delirium [1–12].

Most published studies were retrospective analyses, model development studies, or technical validation studies. Randomized clinical trials assessing clinical impact remain relatively limited [2, 6, 7, 10].

The main included studies, their application areas, the types of algorithms used, and their principal findings are summarized in **Table 1**.

Table 1: Main included studies on applications of artificial intelligence in anesthesia and perioperative medicine

Author, year	Domain	Study type	Population	Algorithm / system	Main findings	Ref.
Hatib *et al.*, 2018	Prediction of intraoperative hypotension	Development + external validation	1,334 patients for training, 204 for external validation	Machine learning based on arterial waveform	AUC 0.95 at 15 min, 0.95 at 10 min, 0.97 at 5 min; sensitivity 88–92%; specificity 87–92%	[1]
Wijnberge *et al.*, 2020	Prevention of intraoperative hypotension	Randomized controlled trial	68 randomized patients, 60 analyzed	Predictive HPI alert system	Reduction in TWA of hypotension from 0.44 to 0.10 mmHg	[2]
Bishara *et al.*, 2022	Postoperative delirium	Retrospective study	24,885 patients	XGBoost, neural network, regression	Best performance with XGBoost: AUC 0.851	[3]
Li *et al.*, 2024	Postoperative pulmonary complications	Development + validation	10,284 patients	Explainable XGBoost	AUC 0.878 to 0.881; superior to ARISCAT	[4]
Park *et al.*, 2020	Anesthetic depth monitoring	Development study	374 patients	Deep neural network applied to EEG	Mean squared error 0.048; mean absolute error 0.05	[5]
Hemmerling *et al.*, 2010	Automated propofol control	Randomized controlled trial	40 patients	Closed-loop propofol system	Excellent control 55% vs 33%; inadequate control 7% vs 19%; MDAPE 9.1% vs 15.7%	[6]
Puri *et al.*, 2016	Automated anesthesia delivery	Multicenter randomized trial	242 patients	CLADS	BIS within target 81.4 ± 8.9% vs 55.34 ± 25%	[7]

3.2 Prediction of intraoperative hypotension

Intraoperative hypotension is the most emblematic domain of AI application in anesthesia. The landmark study by Hatib *et al.*, developed a machine learning algorithm based on high-fidelity arterial waveform analysis [1]. The model was trained on 1,334 patients, corresponding to 545,959 minutes of recording and 25,461 hypotensive episodes, and was then externally validated in a prospective cohort of 204 patients [1].

Reported performance was high, with an AUC of 0.95 at 15 minutes before the hypotensive event, an AUC of 0.95 at 10 minutes, and an AUC of 0.97 at 5 minutes.

Sensitivity ranged from 88% to 92% and specificity from 87% to 92% depending on the prediction horizon [1]. These findings suggest that a critical hemodynamic event can be anticipated several minutes in advance through algorithmic analysis of the arterial waveform.

The randomized HYPE trial then evaluated the clinical impact of a predictive alert system based on this concept. In patients undergoing non-cardiac surgery with invasive arterial monitoring, this system reduced the **TWA** of hypotension from 0.44 mmHg in the control group to 0.10 mmHg in the intervention group. Median hypotension time per patient also decreased from 32.7 to 8.0 minutes [2].

A recent meta-analysis of machine learning-augmented interventions confirmed that HPI-type systems reduce the duration of intraoperative hypotension, while also emphasizing the current lack of demonstrated benefit on several secondary clinical outcomes [10].

3.3 Monitoring of anesthetic depth

Monitoring of anesthetic depth has traditionally relied on analysis of the electroencephalographic signal through derived indices such as the **BIS.** AI, and particularly deep learning techniques, has introduced new approaches allowing richer and more dynamic analysis of brain signals. Park *et al*., developed a real-time system based on a deep neural network applied to EEG. This model was evaluated on data from 374 subjects under inhalational anesthesia. Reported performance included a mean squared error of 0.048 and a mean absolute error of 0.05, with an estimation time of approximately 20 milliseconds, making real-time implementation feasible [5].

These results suggest that deep learning models may improve assessment of hypnotic state, better detect fluctuations in anesthetic depth, and potentially reduce the risks of overdose or intraoperative awareness [11].

3.4 Automated administration of anesthetic agents

Automated administration of anesthetic agents, especially propofol, represents another important application of AI and intelligent systems [6, 7]. Closed-loop systems automatically adjust hypnotic drug infusion based on an output variable such as BIS or another depth-of-anesthesia index.

In a randomized trial, Hemmerling *et al.*, compared an automated propofol administration system with manual management. The closed-loop group showed excellent hypnosis control during 55% of anesthesia time compared with 33% in the manual group. Inadequate control was observed during only 7% of time in the automated group versus 19% in the control group [6].

In a multicenter randomized trial, Puri *et al.*, reported that BIS remained within the target range during 81.4 ± 8.9% of anesthesia time in the automated group compared with 55.34 ± 25% in the manual group. These findings highlight the ability of intelligent systems to maintain greater hypnotic stability and reduce inter-practitioner variability [6, 7].

3.5 Ventilatory optimization and postoperative pulmonary complications

Perioperative ventilatory optimization is another increasingly important field. By analyzing dynamic respiratory parameters and complex perioperative variables, AI may help identify patients at risk of postoperative pulmonary complications and possibly guide individualized ventilatory strategies. Li *et al.*, studied 10,284 elderly patients undergoing 10,484 procedures and developed an explainable XGBoost model integrating preoperative variables and dynamic intraoperative ventilatory parameters. The model achieved an AUC of 0.878 in the validation cohort and 0.881 in the prospective cohort, markedly outperforming the ARISCAT score, whose AUC ranged from 0.496 to 0.533 [4].

The most influential variables included dynamic compliance, driving pressure, and mechanical power. These findings are clinically relevant because such parameters are potentially modifiable by the anesthesiologist during surgery.

3.6 Prediction of postoperative delirium

Postoperative delirium is one of the most extensively studied complications in predictive AI models applied to the perioperative setting [3, 8, 9]. Bishara *et al.*, analyzed a cohort of 24,885 patients using preoperative electronic health record data. The incidence of postoperative delirium was 5.3%. Among the tested models, XGBoost achieved the best performance with an AUC of 0.851, outperforming the neural network and conventional logistic regression [3]. These results indicate that the use of routine clinical data processed by advanced algorithms may significantly improve risk stratification for postoperative delirium.

3.7 Overall synthesis of results

Overall, the available studies show encouraging performance of AI in anesthesia. The most robust findings concern prediction of intraoperative hypotension, with AUC values ranging from 0.95 to 0.97 [1], prediction of postoperative pulmonary complications with AUC values around 0.88 [4], and prediction of postoperative delirium with an AUC of 0.851 in a large cohort [3].

Automated systems for hypnotic control have also demonstrated better maintenance within the anesthetic target range than manual adjustment [6, 7]. These findings support the growing interest in AI as a tool to enhance anesthetic practice, although the level of clinical validation remains uneven across different domains [8–10].

4. DISCUSSION

This review highlights the growing role of AI in anesthesia and perioperative medicine. The most advanced applications currently involve hemodynamic prediction, postoperative risk stratification, partial automation of anesthetic drug delivery, and more recently, certain dimensions of perioperative organizational management [1].

Prediction of intraoperative hypotension is probably the most mature example to date. The high performance observed in the Hatib study and in the HYPE trial illustrates the transition from reactive anesthesia to more predictive anesthesia. This shift is particularly relevant because intraoperative hypotension is associated with renal, myocardial, and neurological complications, thereby reinforcing the value of tools capable of anticipating it [2]. Nevertheless, the meta-analysis by Mehta *et al.*, reminds us that reducing hypotension does not yet systematically translate into demonstrated improvement in all major postoperative outcomes [10].

In the field of postoperative delirium, AI models also appear promising. Their capacity to automatically integrate large amounts of preoperative clinical data could improve identification of at-risk patients and support targeted preventive measures [8,9]. Similarly, prediction of postoperative pulmonary complications from dynamic ventilatory variables is especially interesting because it introduces the possibility of real-time intervention on modifiable factors.

Automated administration of anesthetic agents represents another important perspective. Results observed with closed-loop systems show that it is possible to improve the precision of hypnotic control and reduce inter-practitioner variability [6, 7]. In the long term, these tools may contribute to more stable, more reproducible anesthesia that is less dependent on individual practice patterns.

Beyond direct patient management, AI is also expanding into operating room management and perioperative workflow optimization. A recent systematic review showed its potential usefulness for predicting surgical duration, optimizing post-anesthesia care unit resources, and detecting schedule cancellations [12]. Although these organizational applications differ from the anesthetic act itself, they may influence the overall efficiency of perioperative care.

However, despite these encouraging findings, several limitations must be emphasized. A large proportion of studies remain retrospective or primarily focused on technical performance. Results obtained from historical datasets do not necessarily guarantee identical effectiveness under real-world conditions. In addition, methodological heterogeneity remains substantial with regard to event definitions, input variables, algorithms used, and comparison criteria [8, 10].

Methodological robustness is a central issue. Arina *et al*., showed that most published models still rely on single-center validation, with multicenter external validation remaining uncommon and risk of bias often being high according to PROBAST [9]. Likewise, Bellini *et al*., highlighted reporting limitations according to TRIPOD in the current literature [8]. These weaknesses reduce the generalizability of results and should be taken into account before broad clinical implementation.

Explainability is also a key issue. Clinicians are more likely to adopt a model when they understand the variables underlying the prediction. Explainable approaches, such as those incorporating interpretable ventilatory parameters, may therefore facilitate faster adoption than purely “black-box” models [11].

Finally, several practical and ethical questions remain, including responsibility in case of error, data protection, the risk of algorithmic bias, and the role of human supervision [9]. AI should not be viewed as a substitute for the anesthesiologist, but rather as a decision-support tool intended to strengthen clinical expertise.

5. CONCLUSION

AI is progressively emerging as a major innovation in anesthesia and perioperative medicine. Current evidence shows high performance in several key domains, particularly prediction of intraoperative hypotension, prediction of postoperative pulmonary complications, identification of delirium risk, and automated control of anesthetic depth.

These advances suggest that AI may contribute to improving anesthetic safety, anticipating adverse events, and further personalizing perioperative care. However, available evidence is still dominated by retrospective studies or technical validation studies, and the demonstration of broad clinical benefit in routine practice remains incomplete.

The future of AI in anesthesia will therefore depend on rigorous prospective validation, improved model explainability and ergonomic integration into monitoring systems. In all cases, its role should remain that of a clinical decision-support tool under the continuous supervision of the anesthesiologist.

List of Abbreviations

Abbreviation	Full term
AI	Artificial Intelligence
EEG	Electroencephalography
AUC	Area Under the Curve
HPI	Hypotension Prediction Index
HYPE	Hypotension Prediction trial
TWA	Time-Weighted Average
XGBoost	Extreme Gradient Boosting
ARISCAT	Assess Respiratory Risk in Surgical Patients in Catalonia
BIS	Bispectral Index

MDAPE	Median Absolute Performance Error
CLADS	Closed-Loop Anaesthesia Delivery System
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROBAST	Prediction model Risk Of Bias ASsessment Tool
TRIPOD	Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis
PACU	Post-Anesthesia Care Unit

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