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REVIEW ARTICLE

Artificial intelligence in anesthesiology: Clinical decision support, challenges, and future directions

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ABSTRACT

Artificial intelligence (AI) is increasingly incorporated into anesthesiology as clinicians seek tools that can enhance risk assessment, strengthen intraoperative monitoring, and support timely clinical decision-making. Recent studies describe its potential to assist with preoperative evaluation, predict physiological instability, and identify postoperative complications earlier than conventional methods. These applications highlight the capacity of AI to improve consistency and situational awareness across perioperative care. However, its broader clinical use remains limited by variability in data quality, the need for transparent algorithmic behavior, and uncertainties regarding clinical validation and integration into existing workflows. Understanding both the opportunities and constraints of AI is essential for guiding its safe and meaningful incorporation into anesthesiology practice.

Keywords: artificial intelligence, deep learning, clinical decision support, predictive analytics, perioperative management

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INTRODUCTION

Artificial intelligence (AI) is increasingly reshaping data-intensive areas of medicine, and anesthesiology is one of the clinical domains most suited to AI-driven decision support [1-3]. Perioperative care requires continuous interpretation of high-frequency physiologic signals, rapid risk assessment, and timely therapeutic adjustments—tasks that align closely with the capabilities of machine learning (ML), deep learning (DL), and reinforcement learning (RL) models. In recent years, the growing availability of electronic health records, physiologic waveform repositories, and perioperative data platforms has accelerated the integration of AI into anesthesia research and early clinical applications.

A wide range of AI methods have been explored for perioperative risk prediction. ML models using demographic, comorbidity, and intraoperative variables have demonstrated improved accuracy over traditional scoring systems for predicting hypotension, postoperative pulmonary complications, acute kidney injury (AKI), and unplanned intensive care unit (ICU) admission [3-7]. Deep-learning approaches further extend these capabilities by extracting features directly from raw physiologic signals such as arterial pressure waveforms, ECG, plethysmography, and EEG [8-10]. These models have shown promise in tasks including early detection of hemodynamic instability, identification of nociception-response patterns, and automated classification of anesthetic depth. Natural language processing (NLP) techniques have also enabled automated extraction of airway assessments, medication history, and intraoperative events from unstructured clinical notes, improving data completeness and supporting perioperative decision-making [11-13].

Beyond prediction, AI has begun to influence real-time intraoperative management. Closed-loop anesthesia delivery systems—using EEG-derived indices, BIS, or pharmacokinetic–pharmacodynamic models—have been tested in both observational studies and randomized trials, demonstrating more stable anesthetic depth, reduced drug consumption, and decreased provider variability [14-17]. RL has further been explored for automated titration of propofol or vasopressors, reflecting the trend toward adaptive, physiology-responsive anesthesia systems [5, 9]. At the same time, multimodal perioperative platforms integrating waveform streams, laboratory data, and documentation are emerging as critical infrastructure for safe AI implementation [15, 18, 19].

Despite these advances, significant challenges impede widespread clinical adoption [20-24]. Issues related to data quality, cross-institutional generalizability, algorithm interpretability, liability, and evolving regulatory frameworks remain central obstacles. Perioperative databases often contain missing values, inconsistent labeling, and heterogeneous documentation styles, while many high-performing algorithms function as “black boxes,” limiting clinician trust in high-stakes decision-making [15, 25, 26]. Regulatory bodies are also still developing pathways for adaptive, continuously learning AI systems.

Given these opportunities and constraints, a comprehensive synthesis of the current state of AI in anesthesiology is needed. This review summarizes the foundational computational methods relevant to anesthesia practice, examines current perioperative applications across preoperative, intraoperative, and postoperative settings, discusses key ethical, legal, and regulatory challenges, and highlights future directions for developing reliable, interpretable, and workflow-aligned AI systems [3, 4].

THE PRINCIPLES AND FOUNDATIONS OF AI TECHNOLOGY

AI in anesthesiology is supported by several core computational methods, each with its own way of processing data and addressing clinical problems. These approaches form the foundation of current AI systems. Understanding how each method works—and where it performs well or poorly—helps explain why some models are better suited for preoperative risk assessment, while others are more effective in real-time intraoperative monitoring. This perspective also clarifies why AI systems often show different levels of performance across institutions and why many tools require substantial data preparation before they can be reliably used in clinical practice [2, 3, 6].

Machine Learning

Machine learning (ML) works by learning statistical patterns from labeled clinical data [2, 14]. Instead of relying on fixed rules, ML models analyze large numbers of examples to identify relationships between input features and clinical outcomes. Once trained, these models can apply the learned patterns to new patients and generate predictions based on their individual characteristics.

Using this approach, ML relies on structured clinical variables—such as demographics, laboratory values, comorbidities, intraoperative vital signs, and surgical characteristics—to detect patterns linked to perioperative outcomes. In anesthesiology, ML models have been used to predict hypotension, postoperative respiratory complications, unplanned ICU admission, and delayed recovery [3, 5, 6]. Methods such as logistic regression, random forests, and gradient boosting often outperform traditional scoring systems because they capture nonlinear relationships and interactions among clinical variables [7, 14].

A key strength of ML is its relative interpretability [3, 19]. Many ML methods can show which variables contribute most to a prediction through feature importance rankings or visualization tools such as partial dependence plots. This level of transparency is valuable in anesthesiology, where clinicians must justify decisions and understand the reasoning behind risk assessments. ML models also perform well in structured environments—such as preoperative clinics—where documentation is standardized and data quality is stable. However, real-world datasets often contain missing values, inconsistent labeling, and wide variation in documentation habits. Differences in electronic record systems, coding practices, and perioperative workflows further limit how well ML models generalize across institutions [4, 21, 23]. For these reasons, substantial data cleaning, harmonization, and feature engineering are usually required before ML systems can be reliably deployed in clinical practice.

Deep Learning

Deep learning (DL) works by using multi-layer neural networks to learn complex patterns directly from raw, high-dimensional data. Instead of relying on handcrafted features, DL models automatically extract useful information from signals such as EEG or physiologic waveforms as they are trained on large datasets [3, 8].

This ability makes DL particularly valuable in anesthesiology, where physiologic signals—including EEG, arterial pressure waveforms, ventilatory curves, and capnography—are continuous and difficult to interpret manually [9, 10, 18]. DL models can recognize important patterns within these signals, such as burst suppression on EEG or early changes in vascular tone or ventilation efficiency that may precede clinical instability. Convolutional and recurrent neural networks are commonly used for these tasks because they capture both spatial and temporal characteristics of physiologic data [3, 10].

The capacity to process complex signals in real time makes DL suitable for applications such as automated anesthesia depth assessment and prediction of hypotensive episodes [5, 17]. DL can detect subtle physiologic changes not easily visible on standard monitors, allowing earlier clinical intervention. However, DL requires large, well-labeled datasets and substantial computational resources [4, 22, 25]. Limited interpretability may reduce clinician trust in time-sensitive situations, and variability in waveform quality, sensor artifacts, and institutional monitoring practices makes routine deployment challenging.

NLP

NLP enables computers to interpret and structure information from clinical free-text [11, 13, 27]. By using algorithms that identify key terms, extract relevant concepts, and map them to structured fields, NLP can transform narrative documentation into data that can be searched, analyzed, or used by predictive models. This capability is particularly useful in anesthesiology, where important information—such as airway assessments, medication histories, prior anesthesia complications, and patient-specific concerns—is often recorded in unstructured notes rather than predefined fields [11, 12, 27, 28]. NLP systems can automatically extract these details, reduce the need for manual chart review, and populate missing or incomplete information. They also help standardize perioperative documentation by identifying omissions, such as incomplete airway grading or unclear drug histories [23, 25].

Despite its potential, NLP in anesthesiology faces several domain-specific challenges. Much of the perioperative documentation focuses on brief, task-oriented notes that often omit contextual details needed for accurate extraction. Airway descriptions, for example, may include informal wording, shorthand, or mixed scoring systems that make interpretation difficult. Important intraoperative events are frequently recorded as short time-stamped phrases without full narrative context, limiting the ability of NLP models to distinguish routine adjustments from clinically significant events. In addition, perioperative notes often combine anesthesia, surgical, and nursing inputs within a single record, creating ambiguity about which statements reflect anesthetic management versus other aspects of care. These characteristics reduce the reliability of information extracted by NLP models and illustrate the need for more structured documentation practices tailored to anesthesia workflows [23, 25].

RL and Closed-Loop Control

RL is a method in which a system learns through trial and error, using feedback on its actions to progressively refine its strategy. Instead of following fixed rules, RL adapts its behavior based on performance, making it suitable for tasks that require continuous adjustment, such as automated drug titration [5, 14]. In anesthesiology, RL-based systems use inputs such as BIS values, EEG-derived indices, or hemodynamic measurements to adjust propofol or opioid infusions in real time. These systems aim to maintain stable anesthesia depth, reduce overshoot, and smooth fluctuations associated with manual titration [9, 17]. Experimental studies have shown that RL-driven closed-loop systems can provide faster responses and more consistent control under controlled conditions [16, 17].

However, several anesthesia-specific factors limit their routine clinical use. Physiologic feedback signals are highly susceptible to artifacts from electrocautery, repositioning, airway manipulation, or surgical traction, which may lead to inappropriate dose adjustments. Anesthetic requirements also vary across surgical stages, making it difficult for a single control strategy to perform optimally during induction, incision, maintenance, and emergence. Patients with hemodynamic instability, multiple comorbidities, or atypical EEG patterns further challenge the robustness of RL systems. These issues highlight the need for reliable artifact detection, phase-specific control logic, and continuous clinician oversight before closed-loop systems can be used safely in real-world anesthesia care.

Integration Into Clinical Platforms

AI methods ultimately depend on clinical platforms to function reliably in anesthesiology. These platforms bring together physiologic waveforms, perioperative documentation, and laboratory data, providing the structured environment needed for model development and real-time inference [15, 18, 19]. Their design determines how well ML, DL, NLP, and RL can be translated into practice. At the same time, variability in data quality, device interfaces, and documentation habits introduces important constraints that influence model accuracy and generalizability [5, 9]. Overall, integrated platforms offer the necessary environment for translating computational techniques into clinical practice and support the system-level structures discussed later.

AI PLATFORMS AND DATA-INTEGRATION FRAMEWORKS

Building on the platform considerations outlined before, this section focuses on the system-level frameworks through which AI tools enter clinical anesthetic practice. Rather than describing individual algorithms, these platforms integrate physiologic monitoring, perioperative documentation, and model-driven analysis into unified interfaces that clinicians use in real time. Understanding how these platforms are organized—and how they differ in purpose—is essential for interpreting the practical value of current AI applications [15].

Predictive and Monitoring Platforms

Hemodynamic instability—particularly intraoperative hypotension (IOH)—is a major determinant of postoperative myocardial injury, AKI, and mortality. AI-enabled predictive monitoring systems have therefore emerged as one of the earliest clinically deployed applications in anesthesiology [2, 3]. Among these, ML-based arterial waveform analysis tools, such as the hypotension prediction index (HPI), represent a widely studied example of how physiological signals can be transformed into forward-looking clinical alerts.

HPI algorithms analyze high-fidelity arterial pressure waveforms and generate a unitless index (0-100) reflecting

Table 1. Overview of representative AI platforms and models used in anesthesiology

Platform/model	Input data	Primary function	Evidence/limitations
HPI	Arterial waveform	Predict intraoperative hypotension	Validated; limited generalizability
SmartPilot view	Drug data, demographics	Predict anesthetic depth, drug interactions	Useful but model assumptions needed
Closed-loop anesthesia systems	EEG, BIS, hemodynamics	Automated drug titration	Effective in trials; limited real-world uptake
ML airway prediction tools	Facial images, airway scores	Predict difficult airway	Good accuracy; ethical issues
ICU early-warning ML models	Vitals, labs, trends	Detect deterioration/sepsis	High sensitivity; integration challenges

the probability of impending hypotension, typically defined as a mean arterial pressure (MAP) < 65 mmHg sustained for at least 1 minute [29-31]. Several observational and interventional studies provide evidence that these systems can reduce the burden of IOH [32-34]. In a single-center propensity-score–matched study of non-cardiac surgical patients (n = 136 per group), HPI-guided care was associated with a significantly lower time-weighted average (TWA) of MAP < 65 mmHg compared with standard arterial pressure monitoring (0.070 vs. 0.180 mmHg, $p < 0.001$) [35]. Similarly, a pilot randomized study in primary hip arthroplasty reported that HPI-triggered goal-directed hemodynamic therapy reduced both the number and duration of hypotensive episodes relative to usual practice [36]. Real-world multicenter data involving more than 700 non-cardiac surgical patients further suggest that HPI monitoring is associated with lower TWA hypotension values than historical cohorts [37].

These findings collectively indicate that predictive-monitoring platforms may enable clinicians to anticipate hemodynamic decline earlier than conventional threshold-based alarms. Their clinical value lies not merely in retrospective analytics but in providing actionable, physiologically informed alerts that allow timely intervention.

However, several limitations temper the generalizability of current evidence. First, the accuracy of predictive algorithms depends on high-quality arterial waveform acquisition; damping, catheter malfunction, or electrocautery artefacts may degrade performance. Second, most existing studies are observational, single-center, or pilot-scale, and large randomized trials linking predictive monitoring to reductions in organ injury or mortality remain limited. Third, physiologic perturbations resulting from abrupt surgical events—such as bleeding or major vascular clamping—may not be preceded by detectable waveform signatures, limiting predictive capability in certain contexts. For these reasons, AI-enabled predictive systems should be implemented as part of a broader hemodynamic management framework, supported by clinician oversight and complementary monitoring modalities.

Table 1 outlines several commonly referenced AI platforms and model types used in anesthesiology, highlighting their input data, primary functions, and current limitations.

Drug-Guidance and Decision-Support Tools

Closed-loop and model-based anesthetic delivery systems are emerging as an important area of AI translation in anesthesia [2]. Their aim is to provide more stable and consistent drug administration than manual titration. One of the earliest and best-studied platforms is the McSleepy system from McGill University. In a randomized trial of 186 patients, McSleepy maintained hypnosis closer to the BIS target than manual control, keeping patients within the desired range for a larger proportion of time [38]. Multicenter evaluations have reported similar patterns, showing that automated delivery can reduce provider-to-provider variability and stabilize anesthetic depth across different clinical settings [39].

Closed-loop concepts have also been applied to hemodynamic management. A norepinephrine closed-loop system used during abdominal surgery maintained systolic arterial pressure within the predefined range for close to 90% of anesthesia time, compared with substantially lower proportions under manual titration [40]. No automation-related adverse events were observed, suggesting that vasopressors—due to their rapid onset and clear physiologic targets—may be particularly suitable for closed-loop regulation.

Adjunctive drugs are another practical concern. Low-dose ketamine (0.3 mg/kg) is commonly used during anesthesia, and a randomized study found that its administration did not impair closed-loop TIVA controller performance or EEG signal quality [41]. This suggests that current systems remain stable even when multimodal anesthesia strategies are incorporated.

Overall, current evidence indicates that AI-supported drug-guidance and closed-loop systems can enhance anesthetic stability and reduce variability across practitioners. Their broader adoption, however, will depend on reliable monitoring inputs, robust safety mechanisms, and stronger evidence connecting improved control metrics with meaningful patient outcomes.

Documentation and Data-Extraction Systems

NLP and documentation-support platforms are becoming increasingly relevant as anesthetic records grow more complex and text-heavy [13, 27]. Much of the perioperative information essential for risk assessment—such as airway features, previous anesthetic complications, and comorbidities—is often embedded in free-text notes rather than structured fields. NLP tools therefore play an important role in improving data completeness and supporting clinical decision-making [16].

Several real-world implementations demonstrate this potential. Commercial electronic health record systems, such as Epic, now incorporate NLP modules that automatically extract key perioperative descriptors from preoperative assessments and intraoperative anesthesia records [42]. These tools can identify airway difficulty indicators, prior adverse anesthetic events, or medication history with performance metrics comparable to manual abstraction in institutional validation studies [34, 43]. In addition, research models trained on large critical care datasets—such as MIMIC—have shown that NLP can reliably identify postoperative complications, including respiratory events and AKI, from narrative notes [9]. Although these systems are not specific to anesthesia, their methodologies have been applied to perioperative datasets with similar performance [44].

NLP has also been used to improve the quality of documentation. Automated systems have been developed to detect missing fields in anesthesia records, flag inconsistencies, and convert narrative entries into structured variables for postoperative analytics [13]. These approaches reduce the burden of manual data entry and may enhance the accuracy of downstream AI models by ensuring more complete and consistent input data [18].

Despite these advances, NLP performance is influenced by documentation style, institutional templates, and variability in clinician writing [19]. Models trained in one center may not transfer seamlessly to another without substantial recalibration [21]. Moreover, the integration of NLP outputs into real-time clinical workflows remains limited; most platforms currently serve a retrospective or semi-automated quality-assurance role [4].

Overall, documentation and NLP-based information extraction systems provide a foundation for reliable perioperative data management. Their continued development will be critical for supporting AI deployment, enabling higher-quality datasets, and reducing documentation burden in anesthesia practice.

Summary of Platform Integration

Across prediction, drug-guidance, and documentation platforms, current AI-enabled systems illustrate how perioperative data can be transformed into clinically meaningful support. Predictive monitoring tools demonstrate that waveform-based ML models can identify hemodynamic instability before it becomes clinically apparent, offering clinicians an opportunity to intervene earlier. Closed-loop anesthetic and vasopressor systems show that automation can stabilize drug delivery and reduce variability across providers. Meanwhile, NLP-driven documentation platforms highlight the value of converting narrative notes into structured, analyzable information, improving both data completeness and the performance of downstream analytical models.

Although each category of platform addresses different stages of the anesthetic workflow, they share several common themes: the need for reliable, high-quality physiological and textual inputs; the importance of transparent safety and override mechanisms; and the challenge of integrating new technologies into existing clinical routines. These considerations will shape how AI systems evolve from research tools into dependable elements of routine anesthesia practice.

Building upon the system-level frameworks described above, AI technologies are increasingly being translated into direct clinical applications. Together, these platforms lay the technical foundation for the application-focused concepts discussed later, where AI tools move beyond data processing and begin to directly influence intraoperative decision-making and patient management.

AI APPLICATIONS IN PERIOPERATIVE CARE

As the technical foundations of predictive analytics, closed-loop drug delivery, and NLP-based documentation mature, the focus of AI in anesthesia is gradually shifting from system development to direct clinical application. While current platforms mainly support monitoring, titration, and information processing, emerging AI tools are beginning to influence real-time decision-making throughout the perioperative course. These applications extend from preoperative risk stratification and intraoperative management to postoperative recovery and complication surveillance. Understanding how these tools function in clinical settings—not only technically, but also within workflow, safety, and team dynamics—is essential for evaluating their potential impact on patient outcomes. This section summarizes the major application domains of AI in perioperative anesthesia and highlights both opportunities and remaining challenges for routine clinical adoption.

Preoperative Applications

To provide an overview of how AI supports perioperative care across different stages, **Table 2** summarizes representative applications spanning the preoperative, intraoperative, and postoperative periods. Preoperative evaluation is one of the most practical settings for AI support. Many tools assist anesthesiologists with risk identification, documentation review, and planning before entering the operating room [2].

Table 2. Applications of AI across perioperative anesthesia care

Stage of care	AI function/purpose	Representative evidence
Preoperative	Risk stratification for complications; patient phenotyping	ML models predicting hypotension, difficult airway, AKI
Intraoperative	Prediction of physiological instability; monitoring interpretation; drug titration support	Early warning for hypotension, EEG/BIS interpretation, closed-loop systems
Postoperative	Complication prediction; recovery trend assessment	Models predicting PONV, delirium, pulmonary complications

Airway assessment is a major focus of preoperative AI research

Important details from previous anesthetics—such as difficult intubation, limited cervical mobility, poor laryngeal view, or airway trauma—are often recorded in narrative notes [3]. NLP can extract these descriptions and combine them with structured features such as mouth opening, BMI, and symptoms of obstructive sleep apnea [38]. These combined models may improve prediction of difficult laryngoscopy and help clinicians plan video laryngoscopy or awake intubation. Documentation systems that incorporate NLP, as described before, provide the infrastructure for these applications [38, 42].

AI can also support prediction of hemodynamic instability before induction

ML models using baseline vital signs, comorbidities, and echocardiographic findings can estimate the risk of post-induction hypotension or exaggerated responses to surgical stimulation [32]. Predictive platforms similar to those used intraoperatively, such as waveform-based tools, can be adapted to preoperative data to guide decisions on arterial line placement, fluid preparation, and choice of induction agents [29, 33].

Risk estimation extends to postoperative outcomes

Models trained in demographic data, comorbidities, laboratory values, and surgical characteristics can estimate the likelihood of respiratory complications, delirium, prolonged PACU stay, or unplanned ICU admission [19]. These predictions may help determine postoperative monitoring needs. Integrated perioperative dashboards, like those introduced before, support these assessments by linking preoperative information with expected intraoperative and postoperative risk patterns [43].

AI also contributes to preoperative optimization

Algorithms analyzing laboratory trends and comorbidity profiles can identify patients who may benefit from improved glucose control, anemia correction, pulmonary conditioning, or additional cardiac testing [20, 43].

Analgesic and opioid-related risk assessment is another emerging area

Models incorporating prior opioid exposure, sleep apnea status, and medication history can identify patients at higher risk of postoperative respiratory depression or opioid sensitivity [42]. These insights may inform selection of multimodal analgesia and early regional techniques.

AI performs best when documentation is clear and data streams are well structured. When supported by integrated platforms, preoperative AI can make evaluations more consistent and help clinicians identify risk factors earlier [23].

Intraoperative Applications

The intraoperative period produces continuous physiologic signals that change rapidly with anesthesia, surgical stimulation, and patient condition. AI systems aim to assist anesthesiologists by identifying early instability, interpreting complex waveforms, guiding drug titration, and organizing information from multiple monitors [6].

Hemodynamic monitoring is a major focus of intraoperative AI

ML and DL models analyze arterial pressure waveforms, heart rate variability, and plethysmography to detect early patterns that precede hypotension [29, 33]. Systems such as the HPI provide a commercial example of this approach [34]. Research models use similar waveform-derived features and can alert clinicians several minutes before blood pressure declines. These signals may prompt checks of preload status, adjustments in anesthetic depth, or earlier preparation of vasopressors [36].

AI also supports interpretation of EEG during general anesthesia

DL models can classify EEG patterns, detect burst suppression, and track transitions in anesthetic depth more consistently than visual inspection alone [9]. These tools are especially helpful when EEG signals are complex, such as in elderly patients or cases with variable baselines. Platforms like SmartPilot View, which already display expected drug effects, can incorporate such models to refine depth-of-anesthesia guidance [6].

Ventilation and airway management can also benefit from waveform-based analysis

AI tools have been developed to evaluate ventilatory waveforms, capnography, and plethysmography. These models may identify early signs of airway obstruction, reduced compliance, or ineffective ventilation [43].

Table 3. Key challenges in implementing AI in anesthesiology

Challenge category	Description
Data quality and variability	Inconsistent perioperative data, missing values, device heterogeneity
Transparency and interpretability	Black-box behavior limits clinician trust
External validation	Single-center models lack population generalizability
Workflow integration	AI outputs not seamlessly aligned with clinical decision pathways
Ethical and legal concerns	Privacy, bias, data governance, unclear liability
Resource and cost barriers	High computational and IT demands; staff training needs

Closed-loop drug delivery is another emerging application

RL and adaptive control systems adjust propofol or opioid infusions based on EEG or hemodynamic feedback. These systems have shown stable performance in controlled studies and can reduce overshoot while maintaining a more consistent anesthetic depth [33, 41]. Although still investigational, they build directly on the architectures of existing drug-guidance platforms [39].

AI can also improve integration of multiple intraoperative signals

Dashboards that merge waveform data, ventilator settings, gas analysis, and real-time documentation can reduce the burden of switching between monitors. ML helps consolidate physiologic trends, while NLP extracts key events entered during the procedure [20]. These integrated displays may enhance situational awareness during rapid physiologic changes [26].

Postoperative Applications

Respiratory complications are a major target for postoperative AI

ML models can analyze vital signs, ventilatory trends, opioid dosing, and comorbidity profiles to estimate the risk of respiratory depression or airway obstruction [17, 37]. These systems may help identify patients who require closer observation or more conservative opioid strategies [16].

AI also assists with hemodynamic and neurologic surveillance

Models using postoperative vital signs, fluid balance, and laboratory values can estimate the likelihood of hypotension, delayed emergence, or early neurologic deterioration [9].

Pain management is another area where AI has been explored

Models trained in pain scores, opioid requirements, and physiologic responses can identify patients at risk for inadequate analgesia or opioid sensitivity [45].

NLP supports postoperative documentation and data extraction

NLP systems can scan recovery notes, nursing assessments, and early progress entries to extract key problems such as nausea, desaturation episodes, or agitation [42].

Wearable devices provide additional postoperative data sources

Heart rate variability, activity levels, sleep patterns, and mobility can be analyzed using ML to identify deviations from expected recovery [6].

AI can also support early identification of patients who may require readmission or extended follow-up

Models combining preoperative risk factors, intraoperative trends, and early postoperative indicators can help target postoperative phone calls, clinic visits, or remote monitoring [7].

Summary of Applications

Across the perioperative period, AI applications share several common features. They improve risk recognition before surgery, enhance real-time interpretation of physiologic signals during anesthesia, and support early detection of adverse trends in recovery. Although the specific tools differ in focus—from prediction models to waveform analysis and documentation extraction—they all function by organizing complex information and providing timely cues that complement clinical judgment. Collectively, these systems demonstrate that AI is most effective when embedded within existing workflows and directed toward specific, actionable tasks. These characteristics also highlight the technical and practical limitations that shape the challenges discussed in the next section.

CHALLENGES IN USING AI IN ANESTHESIOLOGY

As anesthesiology moves toward broader clinical adoption of AI technologies, several categories of challenges have become increasingly evident. **Table 3** provides a structured summary of these barriers to implementation. As AI systems move closer to real-time perioperative use, their deployment inevitably raises ethical, legal, and regulatory questions that extend beyond technical performance. These concerns will shape how anesthesiology integrates automation and data-driven decision support into routine clinical care.

Ethical Considerations

AI models trained on historical data may inherit or amplify existing inequities in perioperative care [19]. If the underlying data underrepresent certain demographic or clinical subgroups, predictive performance may differ across patient populations, raising concerns about fairness and clinical safety [3]. Transparency is another central ethical issue. Many high-performing models operate as "black boxes," making it difficult for clinicians to understand why a given recommendation is generated [24]. When decisions affect airway management, hemodynamic control, or anesthetic depth, the inability to trace model reasoning can undermine trust and complicate shared decision-making [26]. Ensuring explainability, equitable performance, and clear communication of model limitations is essential for ethical adoption [16].

Legal and Professional Responsibility

Introducing AI into intraoperative management blurs traditional boundaries of responsibility. If a closed-loop system administers a drug adjustment that contributes to an adverse event, accountability may be unclear: does liability rest with the clinician, the institution, or the developer [26]? Current malpractice frameworks assume human-controlled actions and do not yet fully accommodate collaborative human–machine decision-making [16]. Moreover, institutions implementing AI tools must consider new obligations related to model oversight, performance auditing, and documenting how decisions were influenced by automated systems [21]. Clarifying roles, responsibilities, and expectations will be crucial as AI becomes more embedded in anesthetic workflows [19].

Regulatory Challenges

Existing regulatory pathways were not designed for AI systems that may update, adapt, or incorporate new data over time [24]. Most jurisdictions treat AI tools as static software, requiring re-approval for significant modifications [26]. This limits the ability of models to evolve with changing clinical environments. Regulators are also developing guidance for performance monitoring, cybersecurity, data governance, and transparency—areas particularly relevant for perioperative systems that rely on high-frequency physiologic data [21]. Institutions must pair regulatory compliance with adequate infrastructure, including secure data pipelines and personnel trained to maintain and audit AI-enabled devices [7].

FUTURE DIRECTIONS

AI in anesthesiology is positioned to move from isolated tools toward integrated systems that support real-time decision-making. Several developments will shape this transition. First, efforts to build large, well-curated, and multi-center perioperative datasets will improve the generalizability of AI models and reduce institutional bias [23]. More consistent documentation and standardized waveform storage will further enhance model reliability.

Second, future systems will likely integrate multiple data streams—physiologic signals, laboratory results, imaging, and clinical text—into unified platforms capable of tracking patient trajectories across the perioperative period [21]. This shift from single-task models to multimodal intelligence may provide more holistic assessments and more actionable clinical guidance.

Third, usability will become increasingly important. AI tools must fit naturally into the fast-paced anesthetic workflow, offering clear, concise output rather than frequent alerts. Interfaces developed with direct clinician input will be essential for minimizing cognitive load and building trust.

Finally, interpretability and safety will remain central. Methods that convey uncertainty, highlight influential signals, and support transparent human oversight will be critical for deploying AI in high-stakes intraoperative decisions. As systems evolve, continuous auditing and well-defined override mechanisms will help ensure stable performance over time.

Together, these directions point toward a future where AI augments anesthesiology through reliable, interpretable, and workflow-aligned support—provided that development remains centered on real clinical needs.

CONCLUSION

AI offers promising support for perioperative risk prediction, monitoring, and decision assistance, but its current role remains primarily adjunctive. Key limitations in data quality, interpretability, and implementation highlight the need for cautious integration and further validation. With sustained methodological and regulatory progress, AI has the potential to complement clinical judgment and contribute to safer, more consistent anesthetic care.

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REFERENCES

1. Bignami E, Cavaliere F. A panoramic flight through artificial intelligence in anesthesiology and critical care medicine: The present of an intelligent future. Minerva Anestesiol. 2022;88:757-9. doi:10.23736/S0375-9393.22.16988-9
2. Connor CW. Artificial intelligence and machine learning in anesthesiology. Anesthesiology. 2019;131:1346-59. doi:10.1097/ALN.0000000000002694 PMid:30973516 PMCid:PMC6778496
3. Hashimoto DA, Witkowski E, Gao L, Meireles O, Rosman G. Artificial intelligence in anesthesiology: Current techniques, clinical applications, and limitations. Anesthesiology. 2020;132:379-94. doi:10.1097/ALN.0000000000002960 PMid:31939856 PMCid:PMC7643051
4. Cascella M, Innamorato MA, Simonini A. Recent advances and perspectives in anesthesiology: Towards artificial intelligence-based applications. J Clin Med. 2024;13(15):4316. doi:10.3390/jcm13154316 PMid: 39124584 PMCid:PMC11312484
5. Davoud SC, Kovacheva VP. On the horizon: Specific applications of automation and artificial intelligence in anesthesiology. Curr Anesthesiol Rep. 2023;13:31-40. doi:10.1007/s40140-023-00558-0 PMid:38106626 PMCid:PMC10722862
6. Lopes S, Rocha G, Guimaraes-Pereira L. Artificial intelligence and its clinical application in Anesthesiology: A systematic review. J Clin Monit Comput. 2024;38:247-59. doi:10.1007/s10877-023-01088-0 PMid:37864754 PMCid:PMC10995017
7. Romito BT, Alexander JC. The role of artificial intelligence in preoperative assessment, surgical risk stratification, and predictive analytics in anesthesiology and critical care. Anesthesiol Clin. 2025;43:419-29. doi:10.1016/j.anclin.2025.05.001 PMid:40752945
8. Bellini V, Russo M, Lanza R, et al. Artificial intelligence and "the art of Kintsugi" in Anesthesiology: Ten influential papers for clinical users. Minerva Anestesiol. 2023;89:804-11. doi:10.23736/S0375-9393.23.17279-8
9. Mathis M, Steffner KR, Subramanian H, et al. Overview and clinical applications of artificial intelligence and machine learning in cardiac anesthesiology. J Cardiothorac Vasc Anesth. 2024;38:1211-20. doi:10.1053/j.jvca.2024.02.004 PMid:38453558 PMCid: PMC10999327
10. Mika S, Gola W, Gil-Mika M, Wilk M, Misiolek H. Artificial intelligence-supported ultrasonography in anesthesiology: Evaluation of a patient in the operating theatre. J Pers Med. 2024;14(3):310. doi:10.3390/jpm 14030310 PMid:38541052 PMCid:PMC10970942
11. Almeida VFA, Dantas M, Phuyal D, Shen F. Enhancing perioperative documentation with artificial intelligence scribes in anesthesiology. Anesth Analg. 2026;142(2):e31-3. doi:10.1213/ANE.0000000000007863 PMid:41237408
12. Doyal A, Vander Ploeg M, Wnek R, et al. Leveraging artificial intelligence in anesthesiology research and article writing: Opportunities, challenges, and best practices. A A Pract. 2025;19(7):e02009. doi:10.1213/XAA.0000000000002009 PMid:40657800
13. Humbsch P, Horn E, Bohm K, Gintrowicz R. [ChatGPT for use in technology-enhanced learning in anesthesiology and emergency medicine and potential clinical application of AI language models: Between hype and reality around artificial intelligence in medical use]. Anaesthesiologie. 2024;73:324-35. doi:10.1007/s00101-024-01403-7 PMid:38691128 PMCid: PMC11076380
14. Alexander JC, Joshi GP. Anesthesiology, automation, and artificial intelligence. Proc (Bayl Univ Med Cent). 2018;31:117-9. doi:10.1080/08998280.2017.1391036 PMid:29686578 PMCid:PMC5903534
15. Lonsdale H, Burns ML, Epstein RH, et al. Strengthening discovery and application of artificial intelligence in anesthesiology: A report from the Anesthesia Research Council. Anesth Analg. 2025;140:920-30. doi:10.1213/ANE.0000000000007474 PMid:40305700
16. Minehart RD, Stefanski SE. Artificial intelligence supporting anesthesiology clinical decision-making. Anesth Analg. 2025;141:536-9. doi:10.1213/ANE.0000000000007473 PMid:40080433
17. Ye J, Bronstein S. Artificial intelligence in anesthesiology drug administration. Anesthesiol Clin. 2025;43:431-51. doi:10.1016/j.anclin.2025.05.002 PMid:40752946
18. Byrne ML, Cozowicz C, Memtsoudis SG, Mariano ER, Elkassabany NM. Unlocking the potential of big data and artificial intelligence in regional anesthesiology and acute pain medicine. Anesthesiol Clin. 2025;43:785-97. doi:10.1016/j.anclin.2025.08.003 PMid:41233108
19. Paiste HJ, Godwin RC, Smith AD, Berkowitz DE, Melvin RL. Strengths-weaknesses-opportunities-threats analysis of artificial intelligence in anesthesiology and perioperative medicine. Front Digit Health. 2024;6:1316931. doi:10.3389/fdgth.2024.1316931 PMid: 38444721 PMCid:PMC10912557
20. Abad-Gurumeta A, Gomez-Rios MA. Artificial intelligence in anesthesiology and critical care: Transformative potential and unresolved ethical challenges. Not all that glitters is gold. Minerva Anestesiol. 2025;91:254-6. doi:10.23736/S0375-9393.25.18911-6

21. Erel S, Kilic AG. The use of artificial intelligence in anesthesiology: Attitudes and ethical concerns of anesthesiologists. Saudi J Anaesth. 2025;19:498-504. doi:10.4103/sja.sja_164_25 PMid:40994514 PMCid: PMC12456631
22. Gisselbaek M, Minsart L, Koselerli E, et al. Beyond the stereotypes: Artificial intelligence image generation and diversity in anesthesiology. Front Artif Intell. 2024;7:1462819. doi:10.3389/frai.2024.1462819 PMid: 39444664 PMCid:PMC11497631
23. Kloka JA, Holtmann SC, Nurenberg-Goloub E, Piekarski F, Zacharowski K, Friedrichson B. Expectations of anesthesiology and intensive care professionals toward artificial intelligence: Observational study. JMIR Form Res. 2023;7:e43896. doi:10.2196/43896 PMid:37307038 PMCid: PMC10337415
24. Salwei ME, Weinger MB. Artificial intelligence in anesthesiology: Field of dreams or fire swamp? Preemptive strategies for optimizing our inevitable future. Anesthesiology. 2024;141:217-21. doi:10.1097/ALN.0000000000005046 PMid:38980165 PMCid: PMC11831969
25. Erel S, Erkocak Arabaci O, Pampal HK. Examining the frequency of artificial intelligence generated content in anesthesiology and intensive care journal publications: A cross sectional study. Medicine (Baltimore). 2025;104:e41594. doi:10.1097/MD.0000000000041594 PMid:39993120 PMCid:PMC11857004
26. Raheja A, Belani KG. The practical and ethical implications of artificial intelligence in anesthesiology, pain medicine, and intensive care: Safeguards. Anesthesiol Clin. 2025;43:613-23. doi:10.1016/j.anclin.2025.05.011 PMid:40752957
27. Almeida VFA, Dantas M, Shen F, Ozmen BB. Toward transparent and standardized reporting of artificial intelligence models in anesthesiology. Anesth Analg. 2025;141:e69-e71. doi:10.1213/ANE.0000000000007712 PMid:40828684
28. Jin Z, Abola R, Bargnes V, 3rd et al. The utility of generative artificial intelligence chatbot (ChatGPT) in generating teaching and learning material for anesthesiology residents. Front Artif Intell. 2025;8:1582096. doi:10.3389/frai.2025.1582096 PMid: 40469072 PMCid:PMC12133725
29. Maheshwari K, Suddi S, Jian Z, et al. Performance of the hypotension prediction index with non-invasive arterial pressure waveforms in non-cardiac surgical patients. J Clin Monit Comput. 2021;35(1):71-8. doi:10.1007/s10877-020-00463-5 PMid:31989416 PMCid: PMC7889685
30. Tsoumpa M, Kyttari A, Matiatou S, et al. The use of the hypotension prediction index integrated in an algorithm of goal directed hemodynamic treatment during moderate and high-ris surgery. J Clin Med. 2021;10(24):5884. doi:10.3390/jcm10245884 PMid: 34945177 PMCid:PMC8707257
31. de Kaijzer IN, Vos JJ, Scheeren TWL. Hypotension prediction index: From proof-of-concept to proof-of-feasibility. J Clin Monit Comput. 2020;34(6):1135-8. doi:10.1007/s10877-020-00465-3 PMid:31974829
32. Abelha F. Hypotension prediction index and incidence of perioperative hypotension: A single-center propensity-score-matched analysis. J Clin Med. 2023;12:5479. doi:10.3390/jcm12175479 PMid: 37685546 PMCid:PMC10488065
33. Maheshwari K. Effect of the hypotension prediction index on intraoperative hypotension in noncardiac surgery: A randomized controlled trial. Anesthesia & Analgesia. 2020;131:122. doi:10.1213/ANE.0000000000004925
34. Wijnberge M. Intraoperative hypotension and the hypotension prediction index: A multicenter randomized controlled trial. Anesthesiology. 2020;133:1239. doi:10.1097/ALN.0000000000003577 PMid:32997732
35. Runge J, Graw J, Grundmann CD, Komanek T, Wischermann JM, Frey UH. Hypotension prediction index and incidence of perioperative hypotension: A single-center propensity-score-matched analysis. J Clin Med. 2023;12:5479. doi:10.3390/jcm12175479 PMid: 37685546 PMCid:PMC10488065
36. Schneck E, Schulte D, Habig L, et al. Hypotension prediction index–based protocolised haemodynamic management reduces the incidence and duration of intraoperative hypotension in primary total hip arthroplasty: A feasibility randomised blinded prospective interventional trial. J Clin Monit Comput. 2020;34(6):1149-58. doi:10.1007/s10877-019-00433-6 PMid:31784852
37. Kouz K, Garcia MIM, Cerutti E, et al. Intraoperative hypotension when using hypotension prediction index software during major noncardiac surgery: a European multicentre prospective observational registry (EU HYPROTECT). BJA Open. 2023;6:100140. doi:10.1016/j.bjao.2023.100140 PMid:37588176 PMCid: PMC10430826
38. Mongardon N, Zraier S, Haouache H, et al. Postoperative visual loss due to complicated mediastinal dissection and haemorrhagic shock treatment during cardiac surgery. Br J Anaesth. 2014;112(5):832-4. doi:10.1093/bja/aet472 PMid:24464612

39. Puri GD, Mathew PJ, Biswas I, et al. A multicenter evaluation of a closed-loop anesthesia delivery system: A randomized controlled trial. Anesth Analg. 2016;122:106-14. doi:10.1213/ANE.0000000000000769 PMid:25902324
40. Rinehart J, Desebbe O, Berna A, et al. Systolic arterial pressure control using an automated closed-loop system for vasopressor infusion during intermediate-to-high-risk surgery: A feasibility study. J Pers Med. 2022;12(10):1554. doi:10.3390/jpm12101554 PMid: 36294696 PMCid:PMC9604572
41. Li X, Li S, Xu C, et al. Feasibility of closed-loop TCI based on new EEG baseline in the presence of low dose of esketamine: A randomized controlled equivalence trial. Drug Des Devel Ther. 2025;19:3237-52. doi:10.2147/DDDT.S508264 PMid:40303915 PMCid: PMC12039841
42. Afshar M, Adelaine S, Resnik F, et al. Deployment of real-time natural language processing and deep learning clinical decision support in the electronic health record: Pipeline implementation for an opioid misuse screener in hospitalized adults. JMIR Med Inform. 2023;11:e44977. doi:10.2196/44977 PMid:37079367 PMCid:PMC10160938
43. Xie BH, Li TT, Ma FT, et al. Artificial intelligence in anesthesiology: A bibliometric analysis. Perioper Med (Lond). 2024;13:121. doi:10.1186/s13741-024-00480-x PMid:39716340 PMCid:PMC11668081
44. Liu K, Qiu W, Yang X. Exploring the growth and impact of artificial intelligence in anesthesiology: A bibliometric study from 2004 to 2024. Front Med (Lausanne). 2025;12:1595060. doi:10.3389/fmed.2025.1595060 PMid:40529130 PMCid:PMC12171226
45. Nanda M, Grant SA. Leveraging artificial intelligence for regional anesthesiology curriculum development. Reg Anesth Pain Med. 2024. doi:10.1136/rapm-2024-105906 PMid:39153838

