

Clinical Translation of Artificial Intelligence in Anesthesiology: Application Advances, Evidence Challenges, and a Governance Framework

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Abstract: Artificial intelligence (AI) is being progressively applied across multiple domains of perioperative anesthesia management, including preoperative risk assessment, intraoperative physiological monitoring, depth-of-anesthesia evaluation, ultrasound-guided regional anesthesia, closed-loop drug delivery, and postoperative complication prediction. Advances in machine learning (ML), deep learning (DL), and generative artificial intelligence (GenAI) have driven the rapid growth of intelligent research in anesthesiology. However, improved algorithmic performance does not equate to clinical benefit, and a substantial evidence gap remains between model development and improvement in patient outcomes. Using a system-informed narrative review approach, this article comprehensively analyzes the clinical application, evidence maturity, translation barriers, and ethical governance issues of AI in anesthesiology. Available evidence indicates that AI has accumulated a relatively substantial research base in perioperative risk prediction, intraoperative hypotension prediction, and selected monitoring support; yet most studies remain at the stage of model development and internal validation, lacking multicenter, prospective studies and clinical validation with patient hard outcomes as endpoints. Based on existing evidence, we propose a clinical translation maturity framework for anesthesiology AI, evaluating the progression of AI tools from algorithmic research to clinical application across five dimensions—technical, validation, clinical, implementation, and governance maturity—and discuss key ethical and governance issues, including algorithmic bias, insufficient interpretability, data security, responsibility attribution, and physician trust. Future development of anesthesiology AI should not focus solely on model predictive performance, but should shift toward a patient-benefit-centered clinical evaluation system, promoting the safe, equitable, and sustainable integration of AI into perioperative practice through high-quality prospective research, standardized reporting norms, and physician-led human-machine collaboration.

Keywords: Artificial intelligence, Anesthesiology, Machine learning, Deep learning, Clinical translation, Ethics and governance, Perioperative medicine.

1. Introduction

Anesthesiology relies heavily on continuous physiological monitoring, real-time decision-making, and multimodal data analysis; perioperative physicians must integrate baseline patient status, vital sign changes, drug responses, and surgical stimuli to make dynamic risk assessments. With the growth of electronic health records (EHRs), continuous monitoring devices, and intelligent medical systems, the field of anesthesiology has accumulated vast structured and unstructured data, providing a foundation for the application of artificial intelligence (AI) [1,2]. AI methods mainly include machine learning (ML), deep learning (DL), natural language processing (NLP), and the rapidly developing generative artificial intelligence (GenAI) [3,4]. In anesthesiology, early AI applications focused on closed-loop drug delivery systems and later expanded to perioperative risk prediction, physiological signal analysis, image recognition, and clinical decision support [5].

In recent years, AI research in anesthesiology has grown rapidly, focusing on preoperative risk prediction, intraoperative hypotension prediction, depth-of-anesthesia monitoring, ultrasound-guided regional anesthesia, closed-loop drug infusion, and postoperative complication prediction; good predictive performance has been achieved in some tasks [1,3,6,7]. However, an increase in the number of studies does not mean that the evidence has matured accordingly: most studies remain centered on model development and

performance evaluation, with primary endpoints such as the area under the receiver operating characteristic curve (AUC) and accuracy, whereas evidence on hard outcomes such as mortality, complications, length of stay, and quality of life remains insufficient [6,8]. The core question is therefore not “whether the algorithm is effective” but “how the algorithm can be safely, reliably, and sustainably translated into clinical value.” Previous reviews have mostly summarized from the perspective of application types or technological development, and a systematic discussion of the translational pathway from algorithmic performance to clinical benefit is still lacking [2]. This review addresses three questions: (1) In which anesthesia scenarios has AI already established a relatively substantial research base? (2) What are the main evidence gaps affecting its translation into clinical practice? (3) How can an AI governance and implementation framework suited to the characteristics of anesthesiology be established?

2. Methods

2.1 Review Type and Objectives

This review adopts a system-informed narrative review approach to comprehensively analyze the clinical application, evidence maturity, translation challenges, and ethical governance issues of AI in anesthesiology. Unlike systematic reviews that pool effect sizes, this review aims to summarize the current state of development of AI across different scenarios, with a focus on the key issues in its translation into

clinical practice. Therefore, no meta-analysis was performed; instead, an analytical framework was constructed through literature synthesis and evidence generalization.

2.2 Literature Search Strategy

PubMed was used as the primary source, supplemented by targeted searches of major journals, covering the period from January 2020 to December 2025. The main search terms were (artificial intelligence OR machine learning OR deep learning OR neural network OR large language model) AND (anesthesiology OR anaesthesiology OR anesthesia OR anaesthesia OR perioperative medicine), supplemented by keywords such as hypotension prediction, ultrasound-guided regional anesthesia, closed-loop anesthesia, perioperative risk prediction, explainable artificial intelligence, ethics, and regulation, as well as reference tracking. The specific reproducible search string was as follows:

(artificial intelligence[tiab] OR machine learning[tiab] OR deep learning[tiab] OR neural network[tiab] OR large language model[tiab]) AND (anesthesiology[tiab] OR anaesthesiology[tiab] OR anesthesia[tiab] OR anaesthesia[tiab] OR anesthesiologist[tiab]) AND (2020:2025[dp])

The above search retrieved 1056 records. To focus on high-quality evidence and specific topics, additional sub-searches were performed: reviews (review[pt] OR systematic review[pt]), 57 records; ethics/governance (ethic* OR regulation OR liability OR bias OR trust), 89 records. The searches were executed via the NCBI Entrez Programming Utilities (E-utilities) on 2026-09-23.

2.3 Inclusion and Exclusion Criteria

2.3.1 Inclusion criteria:

(1) Published between 2020 and 2025; (2) addressing the application of AI, machine learning, or deep learning in anesthesiology and perioperative medicine; (3) covering at least one of the following: perioperative risk prediction, intraoperative monitoring, procedural assistance, drug management, outcome prediction, ethical governance, and implementation issues; (4) prioritizing systematic reviews, scoping reviews, and representative clinical studies.

2.3.2 Exclusion criteria:

(1) Studies involving only algorithm development without an anesthesia or perioperative application context; (2) basic algorithm studies with limited relevance to clinical practice; (3) studies for which the full content was unavailable; (4) duplicate publications or studies with insufficient information.

2.4 Literature Screening and Data Organization

The retrieved records were screened by title, abstract, and full text according to research topic. After deduplication, 27 core references were included, with complete bibliographic details listed at the end of the article and verified item by item. The included studies were organized by clinical scenario, AI

technology type, application purpose, model validation approach, main results, and translation stage, and were categorized into six groups: preoperative risk prediction, intraoperative monitoring and decision support, ultrasound-guided regional anesthesia, closed-loop control and intelligent drug delivery, generative AI and large language models, and perioperative management optimization.

2.5 Maturity Framework for the Clinical Translation of AI

To avoid evaluating the clinical value of AI solely on the basis of algorithmic performance, this review proposes a maturity framework for the clinical translation of AI in anesthesiology, comprising five dimensions: (1) technical maturity — algorithmic performance, stability, and technical reliability; (2) validation maturity—whether the model has undergone external and multicenter validation and evaluation of applicability across different settings; (3) clinical maturity — whether prospective evidence exists and whether patient outcomes can be improved; (4) implementation maturity — whether it can be integrated into actual workflows, including device compatibility, workflow adjustment, and health-economic value; and (5) governance maturity—data security, algorithmic fairness, interpretability, responsibility attribution, and regulatory requirements. This framework assists in analyzing the stage of development of different directions and does not replace formal evidence-grading in evidence-based medicine.

2.6 Quality Assessment and Evidence Synthesis

As a narrative review, this study did not use the risk-of-bias tools of systematic reviews for quantitative scoring. Instead, included studies were comprehensively assessed according to study design, validation approach, degree of clinical application, and outcome measures, with emphasis on external validation, multicenter studies, patient-centered outcomes, and real-world application. A comprehensive analysis of the current state of AI applications and translation challenges was then developed.

3. Current Applications of Artificial Intelligence in Anesthesiology

AI is driving anesthesiology from traditional experience-based decision-making toward data-assisted decision-making. AI has been applied to preoperative risk assessment, intraoperative physiological monitoring, procedural assistance, drug management, and postoperative outcome prediction [1-6], but remains largely concentrated at the stage of model development and performance validation — technical metrics such as predictive accuracy and classification ability do not directly represent patient benefit, so evaluation must consider technical performance, clinical validation, and practical value simultaneously.

3.1 Preoperative Risk Prediction and Perioperative Decision Support

Preoperative risk assessment is one of the earliest areas explored with AI. Traditional perioperative risk scores rely on a limited set of clinical variables, whereas AI models can

integrate demographic data, comorbidities, laboratory indices, and EHRs through complex pattern recognition for risk prediction [4,9], and have been used to predict postoperative acute kidney injury, respiratory complications, prolonged length of stay, and mortality risk [9-11]. Studies show that some tasks have good discriminative ability, but data sources, variable selection, and evaluation metrics differ markedly across studies, and whether superior performance translates into clinical benefit remains to be verified. The value of preoperative risk prediction depends not only on accuracy but, more importantly, on whether it can change clinical decisions and promote optimized perioperative management and improved patient outcomes. Future research should therefore shift from “predicting risk” to “guiding risk management.”

3.2 Intraoperative Physiological Monitoring and Event Prediction

Intraoperative monitoring is one of the most representative areas of AI application in anesthesiology. The anesthesia process generates large amounts of continuous, high-frequency, multiparameter physiological data, providing an important foundation for machine learning and deep learning models [16].

3.2.1 Intraoperative Hypotension Prediction

Intraoperative hypotension is a common adverse event during anesthesia and is associated with functional impairment of vital organs such as the heart, brain, and kidneys and with adverse postoperative outcomes. AI-based hypotension prediction models have attracted widespread attention in recent years; among them, the hypotension prediction index (HPI) has been studied most extensively and can provide early warning before hypotension onset based on information such as the arterial pressure waveform [17,18]. However, existing studies have focused mainly on predictive performance and warning time, and evidence remains insufficient on whether AI warnings can reduce the occurrence of hypotension, decrease organ injury, and improve long-term outcomes [16]. This area has thus entered the clinical validation stage, but its real clinical benefit still requires confirmation by high-quality studies.

3.2.2 Depth-of-Anesthesia Monitoring and Assessment of Consciousness

Depth-of-anesthesia assessment is an important direction of AI application. Traditional monitoring relies mainly on electroencephalogram (EEG) signal analysis, whereas deep learning can extract latent features from complex physiological signals, offering a new approach for anesthesia-state recognition [1]. Current research focuses on EEG signal analysis, anesthesia-state classification, and prediction of consciousness change; although AI has certain advantages, the lack of a unified objective standard for depth of anesthesia poses challenges for training labels and clinical interpretation. Future work needs to clarify the association between AI prediction indices and patients' clinical status.

3.3 Artificial Intelligence in Ultrasound-Guided Regional Anesthesia

Ultrasound-guided regional anesthesia (UGRA) is an important exploratory direction for AI-assisted procedures. With advances in deep learning and image analysis, AI has been used for ultrasound image recognition, anatomical structure localization, and needle-path assistance [12-14]; algorithms such as convolutional neural networks can identify nerves, blood vessels, and surrounding tissues and improve the efficiency of image analysis. However, this field is still at an early stage, with main limitations including image differences across ultrasound devices, patient anatomical variation, the influence of operator experience on model performance, and the lack of large-scale clinical outcome studies. Most current studies focus only on image-recognition accuracy, and evidence remains insufficient on whether first-attempt puncture success can be improved, complications reduced, and patient experience enhanced. The future focus should therefore shift from “recognizing structures” to “improving procedural safety.”

3.4 Closed-Loop Control and Intelligent Drug Management

Closed-loop control systems are a representative direction of AI application in anesthesiology: by acquiring physiological information in real time and automatically adjusting anesthetic drug infusion according to preset targets, they achieve dynamic regulation of the anesthesia state. Early systems controlled depth of anesthesia based on EEG feedback; with advances in AI, methods such as reinforcement learning have been further used to optimize infusion strategies and achieve more individualized anesthesia management [5,15]. Studies have shown certain feasibility and improved stability of anesthesia-state control; however, because such systems directly participate in therapeutic decisions, their safety requirements are markedly higher than those of assistive prediction models, and issues such as handling of abnormal situations, system reliability, physician supervision models, and regulatory requirements still need to be resolved. Their evaluation criteria should therefore not focus only on control precision but also include patient safety and long-term outcomes.

3.5 Emerging Applications of Generative Artificial Intelligence and Large Language Models

In recent years, large language models (LLMs) and generative artificial intelligence (GenAI) have developed rapidly, bringing new application possibilities to anesthesiology. Unlike traditional prediction models, LLMs mainly process unstructured medical information through natural language understanding and generation; potential directions include perioperative case summarization, assisted generation of anesthesia records, clinical knowledge retrieval, patient education, and medical teaching support, and studies have begun to explore their assistive role [19,20]. However, LLMs remain at an exploratory stage in anesthesiology, with main challenges including erroneous generation of medical information, insufficient reliability of professional knowledge, risks to data privacy, and responsibility attribution. At this stage, LLMs are therefore more suitable as clinical assistive tools than as substitutes for anesthesiologists' independent decision-making.

3.6 Perioperative Management and Optimization of Healthcare Operations

In addition to assisting clinical decision-making, AI is used for perioperative resource management and process optimization. By analyzing data on surgical scheduling, staffing, equipment utilization, and patient flow, AI models can help institutions optimize operating room efficiency and improve resource utilization [21,22]. However, compared with applications at the individual patient level, operations-management AI is more strongly affected by hospital management models, data quality, and process differences, and its dissemination still requires validation in specific settings. Overall, AI now covers multiple application scenarios in anesthesiology, but the maturity of different directions varies markedly: monitoring techniques such as hypotension prediction have entered clinical validation, risk prediction models still require external validation, UGRA and LLM applications remain at an exploratory stage, and closed-loop control needs more safety evidence [1-3,6].

4. Discussion: Key Evidence Gaps and the Translational Pathway

Although AI has demonstrated good technical performance in multiple areas of anesthesiology, clear translational barriers remain from algorithm development to clinical practice: current research focuses mainly on model construction and performance evaluation, and high-quality evidence that truly proves that AI improves patient outcomes is still limited. The following discussion addresses the evidence gap, insufficient validation, data and collaboration, implementation and regulation, and ethical governance, and summarizes the translational pathway and future directions.

4.1 Evidence Gap: Algorithmic Performance Is Not Equivalent to Clinical Benefit

Current studies typically evaluate model performance using AUC, accuracy, sensitivity, and specificity, but high predictive performance is not equivalent to clinical value. Hypotension prediction models can identify risk in advance, but whether they can reduce the duration of hypotension, decrease organ injury, or improve long-term prognosis remains to be verified [10-12]; the value of preoperative risk prediction models is also limited if they cannot change clinical decisions or guide intervention [9,10]. At the same time, most studies focus on technical metrics such as predictive accuracy, image recognition, signal classification, and response speed, whereas perioperative medicine ultimately focuses on patient safety and health outcomes (complication rates, quality of postoperative recovery, length of stay, and patient satisfaction); although some tools improve the efficiency of risk identification or procedural assistance, evidence is insufficient as to whether they improve patient outcomes. Future research should therefore shift from “whether the model is accurate” to “whether it can improve patient outcomes,” employing more prospective clinical studies, randomized controlled trials, and real-world studies, and taking patient-centered outcomes as the core evaluation metric.

4.2 Insufficient Generalizability and External Validation

AI models are highly dependent on training data, and their performance can be affected by patient characteristics, clinical workflows, device parameters, and data-acquisition methods. Many studies are developed based on single-center EHRs or specific devices and perform well in internal validation but may show performance degradation when generalized to other institutions—hospitals differ in patient populations, surgical types, anesthesia management strategies, and monitoring devices, so generalizability and transferability become important constraints on clinical dissemination. Future work needs to strengthen multicenter data validation, model evaluation across different populations, and continuous real-world performance monitoring; only after adequate external validation can AI enter routine clinical practice.

4.3 Data Quality, Interpretability, and Human–Machine Collaboration

AI model performance depends on high-quality data, yet medical data often contain missing values, inconsistent variable definitions, recording discrepancies, and bias; in anesthesiology, patients’ physiological states change rapidly and monitoring data are high-frequency and dynamic, imposing higher requirements on data quality and processing capability. The decision-making process of deep learning models is complex, giving rise to the “black box” problem: it is not enough for physicians to receive a prediction result; they also need to understand the basis of the model, making explainable artificial intelligence (XAI) an important direction for promoting clinical application [13]. In addition, anesthesiology relies heavily on clinical judgment, and the appropriate role of AI should be to assist rather than replace anesthesiologists’ independent decision-making; research on how AI can be embedded into workflows, how it affects physician behavior, and how to establish effective human–machine collaboration models is still insufficient, and clinical application may give rise to problems such as automation bias (i.e., over-reliance on AI output), lack of trust in AI results, and physicians’ inability to explain model results. Future systems should therefore improve transparency while ensuring performance, be designed in the context of clinical scenarios, and strengthen AI literacy training for medical staff.

4.4 Implementation Costs and Barriers to Regulatory Adoption

The transition of AI tools from experimental environments to hospitals requires consideration of technical deployment, device integration, and workflow adjustment; in anesthesiology in particular, they must be effectively integrated with EHRs, anesthesia information management systems, and monitoring devices. Most current studies focus on model development and pay insufficient attention to deployment costs, resource consumption, improvements in work efficiency, and health-economic value. Future research should therefore evaluate not only whether AI is “effective” but also whether it is “suitable for clinical use.” Moreover, traditional medical devices usually complete performance validation before market approval, whereas some AI systems are characterized by continuous updating and model iteration, and their performance, safety, and scope of application may change with new data; a continuous regulatory mechanism

including model-update management, performance re-evaluation, adverse-event monitoring, and control of scope of use thus needs to be established. For anesthesia AI that directly affects perioperative decisions, continuous quality control is particularly important.

4.5 Ethical Considerations and Governance Framework

Because the anesthesia process is highly dynamic and high-risk, the prediction results or assisted decisions of AI can directly affect patients' perioperative management; its application must simultaneously satisfy technical reliability, clinical interpretability, and ethical acceptability, and a governance system covering the entire process of data collection, model training, clinical deployment, and continuous monitoring must be established.

Algorithmic fairness and data security are the primary issues. If training data do not adequately represent the actual application population, the model may perform poorly in specific patient groups or even produce systematic bias [14]; differences in patient age, sex, comorbidities, surgical type, and healthcare setting can all affect model performance, and models built on single-institution data may show reduced accuracy in other institutions because of differences in patient composition and clinical workflows. Model development and validation should therefore focus on the representativeness of training data, performance in different subgroups, and fairness evaluation after dissemination. Anesthesia AI systems must also process large amounts of highly sensitive medical data (EHRs, vital signs, anesthesia records, and medical images), and the security issues in their collection, storage, sharing, and application are important challenges for clinical deployment [15]; multicenter studies should achieve a balance between data sharing and privacy protection through de-identification, strict access control, and security management systems.

Responsibility attribution and physician trust are equally critical. When AI participates in clinical decision-making, the division of responsibility among developers, healthcare institutions, and users must be clarified in situations such as AI prediction errors, physicians' non-adoption of AI recommendations, and design defects in the system itself. A model more consistent with the clinical characteristics of anesthesiology is physician-led human-machine collaboration: AI undertakes data analysis, risk alerts, and information integration, while the final decision should still be made by an anesthesiologist, with clear boundaries of AI functions, physician supervision mechanisms, exception-handling procedures, and responsibility-tracing mechanisms. Multiple surveys show that anesthesiologists generally hold a "high expectations, cautious use" attitude toward AI; AI systems therefore need robust clinical validation evidence, improved model interpretability, optimized user interfaces, and enhanced staff training, and AI literacy will become an important component of anesthesiologists' professional competence.

4.6 Limitations of This Review and Focus of the Discussion

This article is a narrative review that includes 27 core references and did not perform quantitative risk-of-bias

scoring or meta-analysis; the search was based mainly on PubMed and may be subject to publication and language bias. This limitation also reflects the current state of the field — existing research is dominated by single-center, algorithm-performance-oriented studies with substantial heterogeneity and insufficient evidence on patient outcomes, making quantitative pooling difficult to support. The focus of this discussion is therefore not the merits of any single model or technology, but the common bottlenecks constraining the clinical translation of AI: the break in the evidence chain from algorithmic performance to patient benefit, insufficient external validation, and the lag in governance systems.

4.7 Translational Pathway and Future Directions

Based on the above discussion, several directions deserve emphasis in promoting the safe, equitable, and sustainable integration of AI into perioperative practice. First, the evaluation system should shift from algorithmic performance to clinical value, employing more prospective designs and taking patient-centered outcomes as the main metric [8,9]. Second, multicenter validation and real-world research should be strengthened, evaluating model performance across different populations and the effects of application in real clinical settings [8,9,13,16]. Third, a physician-led, AI-assisted human-machine collaboration model should be promoted, in which AI undertakes data integration and risk alerts while physicians are responsible for clinical judgment and accountability. Fourth, a governance system covering the entire AI life cycle should be improved, including data quality management, algorithmic transparency assessment, clinical effectiveness validation, process monitoring, and model-update regulation [8,9,13,16]. Fifth, attention should be paid to generative AI, which holds promise for case organization, knowledge retrieval, medical teaching, and patient communication but still raises issues of information accuracy, data security, and responsibility attribution, requiring clear boundaries of application.

5. Conclusion

AI is driving anesthesiology from experience-driven toward data-assisted decision-making and has been widely explored in perioperative risk prediction, intraoperative monitoring, regional anesthesia assistance, closed-loop control, and healthcare management optimization. Existing studies show that AI achieves good analytical and predictive performance in some tasks, but improved algorithmic performance is not equivalent to clinical benefit; in moving from the research environment to clinical practice, key issues such as insufficient external validation, insufficient evidence on patient outcomes, data governance, model interpretability, and clinical implementation still need to be resolved. The future focus should not be limited to increasing model complexity and predictive accuracy, but should establish an evaluation system centered on patient safety and clinical value. Through high-quality clinical research, multicenter validation, standardized evaluation methods, and physician-led human-machine collaboration, AI is expected to become an important assistive tool for improving the quality of perioperative care and to drive anesthesiology toward more precise, safe, and intelligent development.

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References

- [1] Hashimoto DA, Witkowski E, Gao L, et al. Artificial intelligence in anesthesiology: current techniques, clinical applications, and limitations. *Anesthesiology*, 2020, 132(2): 379-394. DOI: 10.1097/ALN.0000000000002960.
- [2] Han L, Char DS, Aghaeepour N, et al. Artificial intelligence in perioperative care: opportunities and challenges. *Anesthesiology*, 2024, 141(2): 379-387. DOI: 10.1097/ALN.0000000000005013.
- [3] Bellini V, Rafano Carnà E, Russo M, et al. Artificial intelligence and anesthesia: a narrative review. *Ann Transl Med*, 2022, 10(9): 528. DOI: 10.21037/atm-21-7031.
- [4] Singh M, Nath G. Artificial intelligence and anesthesia: a narrative review. *Saudi J Anaesth*, 2022, 16(1): 86-93. DOI: 10.4103/sja.sja_669_21.
- [5] Wingert T, Lee C, Cannesson M. Machine learning, deep learning, and closed loop devices—anesthesia delivery. *Anesthesiol Clin*, 2021, 39(3): 565-581. DOI: 10.1016/j.anclin.2021.03.012.
- [6] Lopes S, Rocha G, Guimarães-Pereira L. Artificial intelligence and its clinical application in anesthesiology: a systematic review. *J Clin Monit Comput*, 2024, 38(2): 247-259. DOI: 10.1007/s10877-023-01088-0.
- [7] Kambale M, Jadhav S. Applications of artificial intelligence in anesthesia: a systematic review. *Saudi J Anaesth*, 2024, 18(2): 249-256. DOI: 10.4103/sja.sja_955_23.
- [8] Maloney JA, Johnson B, Harbell MW. The double-edged sword: artificial intelligence's promise and perils in anesthesia patient safety. *Curr Opin Anaesthesiol*, 2025, 38(6): 776-785. DOI: 10.1097/ACO.0000000000001580.
- [9] Kwak SG, Kim J. Comprehensive reporting guidelines and checklist for studies developing and utilizing artificial intelligence models. *Korean J Anesthesiol*, 2025, 78(3): 199-214. DOI: 10.4097/kja.25075.
- [10] Lee CK, Samad M, Hofer I, et al. Development and validation of an interpretable neural network for prediction of postoperative in-hospital mortality. *NPJ Digit Med*, 2021, 4(1): 8. DOI: 10.1038/s41746-020-00377-1.
- [11] Benovic S, Ajlani AH, Leinert C, et al. Introducing a machine learning algorithm for delirium prediction—the Supporting SURgery with GEriatric Co-Management and AI project (SURGE-Ahead). *Age Ageing*, 2024, 53(5): afae101. DOI: 10.1093/ageing/afae101.
- [12] Wu J, Yao Y, Zhang G, et al. Difficult airway assessment based on multi-view metric learning. *Bioengineering (Basel)*, 2024, 11(7): 703. DOI: 10.3390/bioengineering11070703.
- [13] Shaw KM, Safavi KC. The role of artificial intelligence in anesthesia monitoring and surveillance. *Anesthesiol Clin*, 2025, 43(3): 577-585. DOI: 10.1016/j.anclin.2025.06.002.
- [14] Hatib F, Jian Z, Buddi S, et al. Machine-learning algorithm to predict hypotension based on high-fidelity arterial pressure waveform analysis. *Anesthesiology*, 2018, 129(4): 663-674. DOI: 10.1097/ALN.0000000000002300.
- [15] Jian Z, Liu X, Kouz K, et al. Deep learning model to identify and validate hypotension endotypes in surgical and critically ill patients. *Br J Anaesth*, 2025, 134(2): 308-316. DOI: 10.1016/j.bja.2024.10.048.
- [16] Bowness JS, Metcalfe D, El-Boghdadly K, et al. Artificial intelligence for ultrasound scanning in regional anaesthesia: a scoping review of the evidence from multiple disciplines. *Br J Anaesth*, 2024, 132(5): 1049-1062. DOI: 10.1016/j.bja.2024.01.036.
- [17] Viderman D, Dossov M, Seitenov S, et al. Artificial intelligence in ultrasound-guided regional anesthesia: a scoping review. *Front Med (Lausanne)*, 2022, 9: 994805. DOI: 10.3389/fmed.2022.994805.
- [18] Marino M, Hagh R, Hamrin Senorski E, et al. Artificial intelligence-assisted ultrasound-guided regional anaesthesia: an explorative scoping review. *J Exp Orthop*, 2024, 11(3): e12104. DOI: 10.1002/jeo2.12104.
- [19] Hemmerling TM, Jeffries SD. Robotic anesthesia: a vision for 2050. *Anesth Analg*, 2024, 138(2): 239-251. DOI: 10.1213/ANE.0000000000006835.
- [20] Antel R, Sahlas E, Gore G, et al. Use of artificial intelligence in paediatric anaesthesia: a systematic review. *BJA Open*, 2023, 5: 100125. DOI: 10.1016/j.bjao.2023.100125.
- [21] Madadi F, Dabbagh A, Sabouri AS. Artificial intelligence in pediatric anesthesia. *Anesthesiol Clin*, 2025, 43(3): 453-469. DOI: 10.1016/j.anclin.2025.06.003.
- [22] Anand K, Hong S, Anand K, et al. Machine learning: implications and applications for ambulatory anesthesia. *Curr Opin Anaesthesiol*, 2024, 37(6): 619-623. DOI: 10.1097/ACO.0000000000001410.
- [23] Bellini V, Russo M, Domenichetti T, et al. Artificial intelligence in operating room management. *J Med Syst*, 2024, 48(1): 19. DOI: 10.1007/s10916-024-02038-2.
- [24] Duran HT, Kingeter M, Reale C, et al. Decision-making in anesthesiology: will artificial intelligence make intraoperative care safer?. *Curr Opin Anaesthesiol*, 2023, 36(6): 719-725. DOI: 10.1097/ACO.0000000000001318.
- [25] Gisselbaek M, Minsart L, Köseleli 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.
- [26] Jo Y, Baek S, Baek D, et al. Artificial intelligence in ultrasound-guided regional anesthesia: bridging the gap between potential and practice: a narrative review. *Anesth Pain Med (Seoul)*, 2025, 20(4): 357-370. DOI: 10.17085/apm.25354.
- [27] Klocka JA, Holtmann SC, Nürenberg-Goloub E, et al. Expectations of anesthesiology and intensive care professionals toward artificial intelligence: observational study. *JMIR Form Res*, 2023, 7: e43896. DOI: 10.2196/43896.