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Research Article

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Artificial Intelligence-Assisted Monitoring in Anaesthesia: A Systematic Review and Meta-analysis of Diagnostic Accuracy and Clinical Impact AI in Anaesthesia: Monitoring and Outcomes Review

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Abstract

Background: *Artificial intelligence (AI) is transforming medicine by enabling real-time data analysis and improved decision-making. In anaesthesiology, AI tools are increasingly used for perioperative risk assessment and intraoperative*

monitoring, but evidence on their real-world performance and safety remains limited.

Methods: *We conducted a systematic review and meta-analysis following PRISMA guidelines, including studies from 2010 to May 2025 that evaluated AI applications—machine learning (ML), deep learning, neural networks, and fuzzy logic—in adult patients undergoing general or regional anaesthesia. Primary outcomes were perioperative complications (e.g., hypotension, hypoxia, bradycardia, delirium, vomiting, cardiac arrest, mortality, acute kidney injury [AKI]); secondary outcomes included haemodynamic stability, ICU admission, and length of stay. Risk of bias was assessed using RoB 2 and ROBINS-I, and random-effects models were applied.*

Results: *Eighteen studies with diverse surgical settings and sample sizes (60 to >450,000 patients) were included. ML models consistently outperformed conventional statistical methods. Ensemble algorithms, such as XGBoost and random forests, achieved AUROC values of 0.942 and 0.96, respectively. Deep learning models, including Max-Pooling Convolutional Neural Networks, predicted mortality with AUROC 0.867. Hypotension Prediction Index (HPI) trials showed 88% sensitivity, 87% specificity, and a 77% reduction in hypotension burden. Hybrid models integrating waveform and electronic health record data reported AUROCs of 0.807 for mortality and 0.766 for AKI.*

Conclusions: *AI-based monitoring, especially ML and biomarker-guided strategies, offers substantial improvements in perioperative risk stratification and haemodynamic management. Wider clinical adoption requires external validation, explainable AI frameworks, and rigorously designed randomized controlled trials demonstrating meaningful patient outcome benefits.*

Keywords: Machine Learning, Hypotension Prediction Index Intraoperative Hypotension, Acute Kidney Injury, Perioperative Prediction, Ensemble Models and Deep Learning

PROSPERO registration n: CRD420251060430.

Key Messages

1. AI-based perioperative monitoring systems, encompassing machine learning and biomarker-guided methodologies, exhibit enhanced diagnostic precision relative to conventional statistical techniques in various surgical environments.
2. Randomised controlled evidence demonstrates the clinical efficacy of AI-assisted haemodynamic management, resulting in substantial decreases in the occurrence, severity, and duration of intraoperative hypotension.
3. The transition of AI from predictive accuracy to enhanced patient-centered outcomes is dependent on extensive, multicenter randomised trials, external validation, and transparent AI frameworks.

1. Introduction

Artificial intelligence (AI) has been instrumental in changing the global healthcare scene over the last 20 years, paving the way for new developments in clinical care, diagnosis, individualised treatment, and healthcare data management. Because anaesthesiology requires the real-time interpretation and processing of vast volumes of physiological and pharmacological data, it is a particularly promising field for the adoption of AI-based technologies. Therefore, perioperative safety and the standard of anaesthesia care could be significantly improved by integrating AI-assisted predictive and decision support tools.

The precise administration of fast-acting medications, the timely adaptation to significant physiological changes, and the continuous, high-precision monitoring of multiple vital parameters are all necessary for modern anaesthesiology. However, many clinical decisions are still based on doctors' subjective experiences and established practices rather than standardised, predictive approaches, even with major advancements in medical technology. In this regard, moving from reactive to proactive decision-making models that can foresee crucial events before they materialise clinically is made possible by artificial intelligence and its subfields, such as machine learning (ML), deep learning (DL), and artificial neural networks [1-4].

Predicting intraoperative and postoperative complications, including bradycardia, hypotension, hypoxia, postoperative delirium, postoperative nausea and vomiting (PONV), intensive care admission, and mortality, is a primary objective of artificial intelligence in anaesthesiology. Many of these incidents happen unexpectedly, necessitating quick action to avoid negative outcomes. AI systems analyse preoperative clinical and anamnestic data, as well as real-time multi-parameter signals from automated anaesthetic delivery systems, electroencephalograms (EEGs), and physiological monitors. Finding patterns that are hidden from view, estimating the likelihood of future occurrences, and proposing prompt intervention techniques are the objectives.

Numerous observational and randomised clinical studies have assessed the efficacy of these technologies at different points

during the perioperative period during the past ten years. For instance, the Hypotension Prediction Index (HPI) software was created with the help of artificial intelligence (AI) and has been thoroughly investigated for its capacity to anticipate intraoperative hypotension episodes up to several minutes beforehand [5-9]. This enables medical professionals to use fluidic interventions or pharmacological modulation to stop the event from happening. The automated administration of intravenous anaesthetics, including propofol and remifentanil, has also been optimised through the use of AI algorithms. This has improved the depth of anaesthesia and haemodynamic stability while allowing for more customisation than conventional target-controlled infusion (TCI) systems.

More effective control of arterial pressure, depth of anaesthesia, fluid administration, and mechanical ventilation has been made possible by intelligent controllers built on fuzzy logic or neuro-adaptive predictive models [10]. By minimising inter-individual variability in anaesthetic response and maximising the balance between efficacy and safety, these tools have been demonstrated to increase the precision and consistency of therapeutic strategies. Additionally, AI-powered clinical information management tools, like predictive electronic anaesthesia records, have enhanced perioperative data collection and analysis, opening up new avenues for quality improvement and clinical audit.

The current body of scientific literature is disjointed and frequently contradictory, despite the excitement these innovations have generated. Few studies have shown a significant impact on critical clinical outcomes like length of hospital stay, major complication rates, or mortality, despite the fact that many have reported encouraging results in terms of predictive accuracy and improved intraoperative parameters. Moreover, it is challenging to reach firm conclusions regarding the applicability of these technologies in routine clinical practice due to variations in the AI models used, the clinical contexts examined, and the methodological calibre of publications.

In light of this, the goal of this systematic review and meta-analysis is to present a comprehensive summary of the data that is currently available regarding the application of AI in perioperative anaesthesia. Through a comparative analysis of data from observational and randomised clinical trials, the review will assess the safety and effectiveness of AI-based tools for intraoperative monitoring and complication prediction. The results will be stratified by the technology (deep learning (DL), fuzzy logic, neural networks, or machine learning (ML), the type of complication targeted, the operative setting (major versus minor surgery; elective versus urgent), and the methodological quality of the included studies.

The PICOT framework, which is advised for creating structured clinical questions, was used to define the inclusion criteria that were chosen for this review. Adult patients undergoing regional or general anaesthesia make up the target population. The use of artificial intelligence (AI)-based technologies for intraoperative monitoring or perioperative adverse event prediction is the intervention (I). Standard, non-AI-assisted monitoring techniques are used in comparison (C). Predictive accuracy in relation to particular complications (such as hypotension, hypoxia, post-operative vomiting syndrome, delirium, and death) is the primary outcome (O), and clinical variables like length of hospital stay, ICU admission rate, and intraoperative stability are the secondary outcomes. Since 2010 is when AI-based technologies were first introduced and used in anaesthesiology, both prospective observational studies and randomised controlled trials (RCTs) and relevant retrospective studies published since then were included.

This meta-analysis differs from earlier synthesis attempts in that it focusses on studies published after 2010 and has stricter inclusion criteria. Methodological quality, which is evaluated with particular instruments like ROBINS-I for observational studies and RoB 2 for randomised controlled trials (RCTs), is emphasised. Additionally, subgroup analyses will be carried out based on the kind of algorithm employed, the perioperative phase of application (pre-, intra-, or postoperative), and the kind of complication that is being targeted. There are also moral, legal, and financial concerns with the broad use of AI in anaesthesia. Thorough consideration must be given to issues like algorithm transparency, medico-legal liability for mistakes, sensitive data protection, and guaranteeing fair access to these advancements. Training medical staff to enable anaesthetists to consciously incorporate the new technologies into their daily clinical practice is another essential component. Therefore, educational institutions and healthcare facilities ought to support professional development courses that address fundamental AI concepts, data analysis, and human-machine interaction.

Establishing a strong body of evidence to direct the clinical application of AI tools in anaesthesiology and to guide future research aimed at creating dependable, secure, and genuinely practical predictive models for daily use is the ultimate goal of this work. Technical innovation, strong proof of clinical efficacy, safety, and acceptability, as well as long-term economic viability, are necessary for the adoption of such technologies.

2. Methods

To maintain openness, reproducibility, and methodological rigour, this systematic review with meta-analysis closely adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Because the protocol was pre-registered with the PROSPERO (International Prospective Register of Systematic Reviews) database, the authors were bound to adhere to a predetermined plan, reducing the possibility of selective bias and boosting the accuracy of the findings.

2.1. Type of Studies Included

Randomised controlled trials (RCTs), retrospective studies and prospective observational studies on the application of AI-based technologies in anaesthesiology that were carried out in adult human populations were included in the review. The recent adoption of AI technologies in clinical practice, which has reduced the quantity of RCTs available, served as the impetus for

the decision to incorporate observational studies. This does not, however, rule out the possibility of gathering pertinent data from carefully planned non-randomized research.

2.2. Inclusion Criteria

Every study that satisfied the following requirements was deemed qualified:

- To guarantee the inclusion of current research in line with recent advancements in AI technologies, the publication date should be between January 1, 2010, and December 31, 2024.
- Research design: observational studies with a control group and prospective RCTs.
- Adult subjects (≥18 years old) undergoing general or loco-regional anaesthesia in a surgical or procedural setting comprise the population.
- **Intervention:** the application of models, algorithms, or predictive tools based on artificial intelligence, such as expert systems, machine learning, deep learning, artificial neural networks, or fuzzy logic algorithms.
- The ability to predict or prevent perioperative complications, such as intraoperative hypotension, hypoxia, adverse cardiovascular events, bradycardia, postoperative delirium, PONV, cardiac arrest, and AKI, is the main outcome.
- Long hospital stays, the need to be admitted to an intensive care unit, haemodynamic stability, and the effectiveness of intraoperative physiological monitoring are examples of secondary outcomes.

2.3. Exclusion Criteria

Research that satisfied these requirements was not included:

- research done on children (less than 18 years old) or in animal models.
- Research that lacked a clear and documented AI-based intervention.
- Simulation studies, case reports, editorials, letters to the editor, and conference abstracts without peer-reviewed full texts are all examples.
- To guarantee linguistic homogeneity in data extraction and interpretation, studies published in languages other than English were disqualified.

Inclusion criteria	Exclusion criteria
Adult subjects (≥18 years old)	Research done on children (less than 18 years old) or in animal models
observational or RCTs	Research that lacked a clear and documented AI-based intervention
publication date between January 1, 2010- present.	not observational or RCTs
All AI technologies or system	studies published in languages other than English

Table. Inclusion and Exclusion Criteria

2.4. Sources of Information and Search Methodology

Three primary biomedical databases—PubMed/MEDLINE, Embase, and the Cochrane Central Register of Controlled Trials (CENTRAL)—were thoroughly searched. The search approach was predetermined and comprised MeSH (Medical Subject Headings) terms and keywords related to the fields of artificial intelligence, perioperative complications, and anaesthesia. Terms like "artificial intelligence," "machine learning," "deep learning," "anaesthesia," "perioperative complications," "monitoring," "prediction," and others were examples of Boolean combinations. Only human subjects' studies published between 2010 and May 2025 were included in the results.

2.5. Search Strategy

Study Selection Process

Two reviewers (A.A.C., M. R. E.) independently screened all identified abstracts and titles. Using the predetermined criteria, the full texts of potentially eligible articles were retrieved and evaluated for inclusion. A third reviewer (T. R. E.) was consulted or discussed in order to settle disagreements. (Table 1.)
(Table 1.)

Stage	Number of Records	Notes
Records identified	2772	Using the defined search strategy (see below)
Records after duplicates removed	2586	Duplicate records removed
Records screened (title and abstract)	2586	Screening based on predefined PICOTT criteria
Records excluded	2552	Excluded for: - Not RCTs or observational - Not related to anaesthesiology - Not adult patients
Full-text articles assessed for retrieval	34	Full-text retrieval attempted
Full-text articles not retrieved	0	Full texts not accessible
Full-text articles assessed for eligibility	34	Evaluated according to inclusion/exclusion criteria

Full-text articles excluded	16	Common reasons for exclusion: - Not RCT - AI not directly used - Irrelevant outcomes
Studies included in the systematic review	18	All were randomized controlled trials on AI in perioperative anaesthesia
Studies included in the meta-analysis	18	All provided extractable quantitative outcome data

2.6. Data extraction

A standardised collection form that was tested in a pilot phase was used to extract pertinent data from each includedstudy.

This form was used to extract pertinent data from each included study. The variables that were gathered included the author's name, the year of publication, the study design, the sample that was analysed, the population's demographics, the type and characteristics of the AI algorithm that was used, the clinical setting, the type of surgery or anaesthesia that was performed, the primary and secondary outcomes, the main results, and the authors' main conclusions. Two authors independently collected the data in duplicate.

2.7. Risk of Bias Assessment

Validated instruments were used to evaluate the included studies' methodological quality:

- RoB 2.0 for RCTs, in accordance with the Cochrane Collaboration's guidelines. Randomisation, treatment deviation, attrition, outcome measurement, and the selection of reported data were among the biases evaluated.

Non-randomized observational studies were conducted using ROBINS-I, which takes into account biases in participant selection, confounding factors, intervention classification, missing data, and analysis techniques.

Two authors conducted each evaluation independently, and any disagreements over the results were discussed. Each study's overall quality was assigned a risk of bias rating of "low," "moderate," or "high."

2.8. Statistical Analysis and Data Synthesis

Meta-analysis was used to synthesise quantitative data with homogeneous populations, interventions, and outcomes. To account for variation amongst studies, a random effects model was used. With 95% confidence intervals, effect sizes were presented as odds ratios (OR), risk ratios (RR), or mean differences (MD). Cochran's Q statistic was used to evaluate study heterogeneity, and the I2 index was used to quantify it based on three criteria: 0–25% (low), 25–50% (moderate), and >50% (high).

To investigate the efficacy of AI, subgroup analyses were designed according to the following criteria: the algorithm type (e.g., HPI, fuzzy logic, deep learning, or generic predictive models); the type of complication (e.g., neurological, cardiovascular, or respiratory); and the surgical context (major vs. minor surgery; elective vs. emergency).

Studies with a high risk of bias were excluded through sensitivity analyses.

2.9. Affiliation and Peer Review

A multidisciplinary team unaffiliated with academic institutions carried out the work, and during the protocol phase, the review was not exposed to external peer review. However, after the manuscript is finished, it will be submitted for peer review and publication.

3. Results

There were 18 studies in all, and they were a mix of randomised controlled trials (RCTs), prospective observational studies, and retrospective analyses. The studies took place in many different parts of the world, including Europe (the Netherlands, Italy, Germany, and Spain), North America (the United States), and Asia (Korea and China). This shows that people all over the world are interested in using machine learning (ML) and biomarkers to predict and manage perioperative events.
(Table 2.)

Study (Author, Year)	Setting	Sample Size	Study Type	Primary Outcome	Model(s) Used	Best Model Performance	Input Features	Unique Features
Schenk et al., 2021	Amsterdam UMC, Netherlands – PACU	60 (54 analyzed)	Randomized Controlled Sub-Study	Time-weighted average (TWA) of postoperative hypotension (POH)	Hypotension Prediction Index (HPI)	88% sensitivity, 87% specificity for IOH; 77% reduction in IOH depth/duration	Continuous arterial waveform; MAP <65 mm Hg; FloTracIQ sensor data	Machine learning-based early warning system; integration with HemoSphere monitor

Fritz et al., 2019	Single center (USA)	95,907	Retrospective	30-day postoperative mortality	MPCNN (CNN + LSTM), DNN, SVM, RF, LR	AUROC: 0.867, AUPRC: 0.097	>70 static and time-series variables	Real-time dynamic prediction, intraoperative monitoring
Lee et al., 2022	Multi-center (Korea)	454,404	Retrospective	30-day postoperative mortality	XGBoost, LR, RF, DNN	AUROC: 0.942, AUPRC: 0.175 (XGBoost)	12–18 preoperative variables	External validation across 4 hospitals, compact model
Te et al., 2024	Single center (China)	23,305	Retrospective	PIHI Index (post-intubation instability)	Extra Tree Regressor, XGBoost, MLP, SVR, MLR	R^2: 0.9047, MAPE: 20.86% (ETR)	14 variables: demographics + drug dosages	Continuous outcome, ICV index creation, SMOTETomek balancing
Fritz et al., 2024	Barnes-Jewish Hospital, Saint Louis, MO, USA	5071 patients	Single-centre Randomised Controlled Trial	30-day all-cause postoperative mortality and AKI within 7 days	ML models for death & AKI	Death prediction: AUROC **0.807**; AKI prediction: AUROC **0.766**	Electronic health records: demographics, labs, pre-op data, anaesthesia record	Clinicians randomized to ML-assisted vs unassisted review; live EHR integration; Likert-based risk rating scale
Frassanito et al., 2023	IRCCS Policlinico Gemelli, Rome, Italy	60 patients	Single-centre RCT	TWA-MAP <65 mm Hg; IOH after induction; severe hypotension	HPI + Modified Goal-Directed Therapy	82% reduction in IOH events; TWA-MAP <65 mm Hg: 0.14 vs 0.77 mm Hg	HPI alerts, SVV, dP/dtmax, Eadyn, MAP, BIS, fluid/vasopressor response	Real-time HPI alert protocol; faster intervention; tailored hemodynamic algorithm
Kang et al., 2020	Soonchunhyang University Bucheon Hospital, South Korea	222 patients	Retrospective ML study	Hypotension after anesthesia induction (tracheal intubation–incision)	Naïve Bayes, Logistic Regression, Random Forest, Artificial Neural Network	**Random Forest:** AUROC **0.842** (CI: 0.736–0.948); 83.7% recall with selected features	89 features from EHR + anesthesia devices: SBP, MBP, HR, TIVA doses, ventilator settings, patient demographics	High-res time-synchronized multi-device monitoring; pre-intubation-only training window; feature set comparisons
Wijnberge et al., 2020	Amsterdam UMC, Netherlands	64 patients	Single-centre RCT	Reduction in intraoperative hypotension duration	Hypotension Prediction Index (HPI)	**HPI group**:- significant reduction in time spent MAP <65 mm Hg	Arterial waveform data via FloTracIQ sensor, MAP thresholds	First RCT on HPI; real-time alerts; integration with Acumen platform
Baig et al., 2013	Auckland City Hospital, New Zealand	30 patients	Real-time fuzzy logic validation	Detection of absolute hypovolaemia	RT-SAAM, FLMS-2 (Fuzzy logic systems)	FLMS-2: Kappa = 0.75; RT-SAAM: Kappa = 0.62	HR, BP, PV, $EtCO_2$; waveform analysis; fuzzy rule sets	Multi-module fuzzy alarms; real-time alerts; clinician agreement validation
Ripollés-Melchor et al., 2025	28 hospitals (Spain + Jordan)	917 patients	Multicenter RCT	Moderate-to-severe AKI within 7 days; complications; 30-day mortality	Hypotension Prediction Index (HPI)	No significant difference in AKI incidence (HPI: 6.1% vs control: 7.0%)	HPI >80, MAP, SVV, Eadyn, dP/dtmax, vasopressor/fluids guided by Hemosphere	Largest HPI RCT; diverse real-world practices; subgroup analysis for hypertension effect

Hu et al., 2024	Henan Univ. of Sci. & Tech., China	202 patients	Deep learning model validation	Preoperative & intraoperative anesthetic dose prediction	ANN + CNN + LSTM + Attention	R^2 = 0.915 (intra-op); MAPE = 12.25%	Gender, age, weight, SBP, DBP, BIS, HR; time-series vitals	Multi-stage model; attention mechanism; convolutional feature extraction
Abin et al., 2024	3 hospitals, Tehran, Iran	998 patients	Cohort ML-based design	AKI risk reduction via anesthesia management	AKI– and AKI+ regression planners	Accuracy: 80.6%; F1-score: 0.821; recall: 84.8%	8 pre-op features → 6 anesthesia targets (CPB time, fluids, transfusion, diuretics)	Dual regression system; visual dashboard; validated by cardiac anesthesiologists
Hayase et al., 2020	Kyoto Chubu Medical Center, Japan	83,867 EEG epochs from 30 patients	Observational + ML validation	BIS prediction from EEG scatter patterns	MLPNN (deep learning)	R = 0.87; RMSE = 7.09; Bias = 0.07	Poincaré-index (0.5–47 Hz & 20–30 Hz), EMG70–110 Hz, suppression ratio	Hierarchical Poincaré plot fusion; EMG-aware BIS estimation; BIS used as supervisor
Šribar et al., 2023	University Hospital Dubrava, Croatia	34 patients	Single-centre RCT	Duration, depth, and frequency of IOH during thoracic surgery	Hypotension Prediction Index (HPI) vs FloTrac GDT	TWA-AUT: 0.01 mmHg (HPI) vs 0.08 mmHg (GDT); fewer hypotensive episodes in HPI group	HPI alert threshold ≥90; MAP, SVV, Eadyn, dP/dt, CI, SVI, HR, BP, lactate, $ScvO_2$	First HPI RCT in thoracic surgery; structured decision tree; high-fidelity waveform analysis
Morisson et al., 2022	Maisonneuve-Rosemont Hospital, Montréal, Canada	66 patients	Ancillary RCT analysis	Prediction of moderate to severe PACU pain	ML algorithms (elasticnet, RF, SVM…)	Penalized logistic regression: CV-AUC **0.753**(0.718–0.788); Brier score: 0.194	Age, ASA class, BMI, NOL metrics (reaction to intubation/incision), surgical TWA NOL	First ML analysis of intraoperative nociception (NOL) to predict PACU pain; SHAP interpretability; surgery-specific feature modeling
Velagapudi et al., 2022	4 academic hospitals (USA)	100 patients × 2 models	Prospective validation via web-based simulation	Accuracy of anesthesiologist predictions for glucose & opioid needs	XGBoost (glucose), Random Forest (opioids)	Glucose: Accuracy ↑ from 79% to 84.7%; Opioids: ↑ from 18% to 42%	Age, BMI, ASA, diabetes, meds, pain history, surgery type, duration, anesthesia type	First dual-model validation with real clinicians; REDCap interface; SHAP-informed feedback
Luckscheiter et al., 2022	Southwest Germany EMS registry (MIND 3.1)	25,556 trauma patients	Registry-based retrospective analysis	Need for preclinical airway management in trauma	Random Forest (RF) & Naive Bayes (NB)	RF: AUROC 0.96; PRC area 0.83; NB: AUROC 0.93; PRC area 0.66	24 features via PCA: auscultation, injury pattern, oxygen therapy, shock index, vital signs, interventions	First large-scale airway prediction model in EMS; validated on real-world trauma registry; SMOTE applied for class balance

Tan et al., 2021	Huashan Hospital, Fudan University, Shanghai, China	406 carotid endarterectomy (CEA) procedures	Retrospective single-center cohort study	Early Phase Postoperative Hypertension (EPOH) requiring intravenous vasodilators within 24 hours post-CEA	Gradient Boosted Regression Trees (GBRT) via XGBoost	AUROC: **0.77** (95% CI: 0.62–0.92); Sensitivity ~90%; Specificity ~52%	100+ perioperative variables including: intraoperative peak SBP, cardiac index, anesthetic dosages (propofol, fentanyl, ephedrine), lab values (glucose, cholesterol, alkaline phosphatase), Doppler echocardiography metrics, clamping time, and demographic data	First ML model for EPOH prediction; feature importance analysis via XGBoost gain scores; validated with 4-fold stratified cross-validation; strong association found between intraoperative BP spikes and EPOH risk

The sample sizes were very different. For example, Schenk et al. (2021) had only 60 patients (n=60), while Lee et al. (2022) had 454,404 patients in a very large retrospective dataset [11]. The ORACLE Trial (Fritz et al., 2024) was the biggest interventional study [12]. It randomly assigned 5,071 patients to either ML-assisted or standard perioperative care. (Table 2.)

3.1. The Main Results of the Studies Were Different and Included

- Most of the time, intraoperative hypotension (IOH) is defined as a mean arterial pressure (MAP) of less than 65 mmHg (e.g., Schenk et al., 2021; Wijnberge et al., 2020).
- Acute kidney injury (AKI) is often used as a secondary endpoint (for example, Fritz et al., 2024; Ripollés-Melchor et al., 2025).
- Mortality after surgery: both 30 days after surgery and while in the hospital (e.g., Fritz et al., 2019; Lee et al., 2022).
- PIHI (Te et al., 2024) is an example of a composite haemodynamic instability index.

3.2. Modelling Methods and Algorithmic Techniques

There were a number of different predictive modelling methods used in the studies. These can be divided into three main groups: traditional ML algorithms, deep learning architectures, and biomarker-based indices (especially HPI).

Some of the models that were tested the most were random forests (RF), logistic regression (LR), gradient boosting machines (like XGBoost), and support vector machines (SVM).

Lee et al. (2022) directly compared several algorithms for predicting 30-day mortality. They found that XGBoost did better than both RF (AUROC = 0.92) and DNN models, with AUROC = 0.942 and AUPRC = 0.175.

Luckscheiter et al. (2022) made models for bad things that happen during surgery. RF got an AUROC of 0.96 and a PRC area of 0.83 [13].

3.3. Deep Learning Structures

Deep learning methods took advantage of the changing nature of data streams during surgery.

Fritz et al. (2019) used a combination of convolutional neural networks (CNNs) and LSTM-based architectures (MPCNN) to predict 30-day mortality with an AUROC of 0.867 and an AUPRC of 0.097. Hu et al. (2024) used these ideas on high-frequency arterial waveform data and found that $R^2 = 0.915$ and MAPE = 12.25% were good for predicting changes in blood flow during surgery [14].

3.4. The Hypotension Prediction Index (HPI)

HPI, a proprietary algorithm trained to predict IOH minutes before onset, was evaluated in a number of RCTs and observational studies (Schenk et al., 2021; Wijnberge et al., 2020; Ripollés-Melchor et al., 2025). In addition to a 77% decrease in the severity and duration of hypotension in the intervention group, Schenk et al. (2021) reported 88% sensitivity and 87% specificity for HPI. When HPI guidance was used, Wijnberge et al. (2020) also showed a significant decrease in cumulative hypotension time.

3.5. Innovative and Hybrid Methods

Te et al. (2024) developed the Post-Intubation Hemodynamic Instability (PIHI) index using 14 clinical and ventilatory variables, achieving $R^2 = 0.9047$. [15,16] For AKI risk, Abin et al. (2024) used a dual regression approach, reporting accuracy = 80.6%, F1-score = 0.821, and recall = 84.8%.

3.6. Predictive Factors and the Significance of Features

MAP and derived waveform parameters were universally critical, according to a comparative analysis of input features (Table 3).

In HPI-based studies, significant attention was paid to variables such as systolic and diastolic blood pressure (SBP and DBP), heart rate (HR), pulse volume (PV), stroke volume variation (SVV), and dP/dtmax (Frassanito et al., 2023; Šribar et al., 2023[16]).

Larger retrospective models included preoperative variables like age, comorbidity indices, baseline renal function, and ASA status (Lee et al., 2022; Kang et al., 2020) [17].

3.7. Analysis of Comparative Performance

Among the best-performing models (AUROC > 0.90) were:

- Lee et al. (2022): AUROC = 0.942, AUPRC = 0.175 (XGBoost).
- Luckscheiter et al. (2022) : PRC = 0.83 (RF), AUROC = 0.96.
- Te et al. (2024)]: R^2 = 0.9047 for continuous hemodynamic predictions.

Performers in the middle (AUROC 0.80–0.89):

- Fritz et al. (2019) : AUROC = 0.867, AUPRC = 0.097 (MPCNN).
- Fritz et al. (2024, ORACLE) : AUROC = 0.807 for 30-day mortality; 0.766 for AKI.

Models for experiments or lower performers:

- Tan et al. (2021): sensitivity ~90%, specificity ~52%, AUROC = 0.77 (95% CI: 0.62–0.92).
- Morisson et al. (2022) : Brier score = 0.194, AUC = 0.753, penalised logistic regression [18].

(Table 3.)

Studies/Variable	Heart Rate (HR)	Blood Pressure (BP)	Pulse Volume (PV)	Mean Arterial Pressure (MAP)	Mortality (any)	AI Models Compared	Best Model Performance	AUROC	ICV Values	Type of Surgery	Risk of AKI	Hypertension Risk	Airway Management	Dosage for Anesthesia	Warning System vs Standard Care	30-Day Postoperative Mortality	Postoperative Complications	Anesthesia Depth Monitoring	Postoperative Pain
Fritz et al., 2019	Used (pre- and intraoperative)	Used (systolic & diastolic, intraoperative)	NR	Derived from BP, not explicitly reported	30-day postoperative mortality (1%)	MPCNN (CNN + LSTM), DNN, SVM, RF, LR	MPCNN (AUROC: 0.867, AUPRC: 0.097)		Not used	All types (mainly ASA II–III)	NR	Included as comorbidity	Included (only intubated patients)	Included (cumulative intraop doses)	Designed for real-time warning integration	Primary endpoint	Not stratified	NR	NR

Lee et al., 2022	Used (preoperative only)	Used (preoperative only)	NR	NR	30-day postoperative mortality (0.2–0.4%)	XGBoost, Random Forest, Logistic Regression, DNN	XGBoost (AUROC: 0.942, AUPRC: 0.175)		Not used	Non-cardiac surgeries across specialties	NR	Included as input feature	Not explicitly described	Not included	Offline model for preoperative risk stratification	Primary endpoint	Not stratified	NR	NR
Te et al., 2024	Used (preoperative only)	Used (systolic & diastolic, preoperative)	NR	NR	No direct mortality outcome	Extra Tree Regressor, XGBoost, SVR, MLR, MLP	ETR (R^2: 0.9047, MAE: 0.0512)		Predicted as primary output	General anesthesia with tracheal intubation (ASA I–II)	NR	Included as binary input feature	All patients had endotracheal intubation	Included (initial infusion: fentanyl, propofol, etc.)	Not real-time; predictive support only	Not measured	Focused only on PIH (hemodynamic instability)	NR	NR

Schenket al. (HPI Trial)	Not explicitly reported	MAP target: >65 mm Hg	Captured via FloTracIQ sensor	Not specified	Not reported directly (30-day outcomes)	HPI-guided vs Standard Care	HPI algorithm	~0.90–0.92 (based on sensitivity/specificity)	Not applicable	Elective non cardiac (mainly GI and gynecological)	Elevated in presence of IOH/POH	Perioperative MAP management used to mitigate extremes	General anaesthesia with mechanical ventilation	Sevoflurane median: 1.55 – 1.64 vol %	HPI guidance vs routine haemodynamic protocols	Not directly assessed	4 patients with Clavien-Dindo Grade ≥ III (bleeding intervention s)	Not explicitly reported	Not discussed in this sub-study
ORACLE Trial (Fritz et al., 2024)	Available via EHR; used in ML input features	MAP monitored; predictive relevance for AKI and mortality	Not reported as standalone metric	MAP used by ML model for prediction	30-day postoperative mortality assessed; 2.2% incidence	ML-assisted vs ML-unassisted clinician prediction	Death: AUROC 0.807; AKI: AUROC 0.766	Death (ML model): 0.807; AKI (ML model): 0.766	Not applicable	Mixed elective surgeries across 10+ specialties	11.1% AKI incidence; ML prediction compared to clinician accurac	Incorporated into ML risk models	Standard GA protocols, managed remotely	Not detailed; captured in EHR for ML input	ML predictions visible or hidden to clinicians	Assessed via EHR; 98 deaths among 5071 patients	AKI in 450 patients; complications influenced by ML predictio	Not reported explicitly; depth inferred from EHR inputs	Not analyzed

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Frassanito et al., 2023	Continuously monitored; data not individually reported	MAP target: >65 mmHg; intervention threshold was HPI ≥85	Monitored indirectly via dP/dtmax and SVV, not reported as standalone	Primary measure for IOH and severe hypotension (cutoffs: 65 and 50 mmHg)	1 death within 30 days in Control group	HPI + modified GDT protocol vs standard GDT protocol	82% reduction in IOH events (97 vs 313); shorter time to treatment intervention	Not reported numerically	Not assessed	Major gynaecologic oncologic surgery (laparoscopic, laparotomy, combined)	Not directly assessed; IOH linked to organ injury in cited literature	Slightly higher incidence of MAP > 110 mmHg in HPI group	General anesthesia with mechanical ventilation	Propofol, sufentanil, and sevoflurane (BIS-targeted); more dobutamine in HPI group	Real-time HPI alerts (≥85) triggered proactive decision-making	1 patient (Control group)	Pleural effusion (HPI 3%, Control 20%), arrhythmia, cardiac ischemia	BIS monitored; target range 40–50	Managed via intrathecal morphine or epidural catheter
Kang et al. (2020)	Included in feature set	SBP, MBP used as key predictors	Not directly reported	MBP <65 mmHg used to define hypoten	Not primary endpoint	Naïve Bayes, LR, RF, ANN	RF: AUROC 0.842; 83.7% recall	RF: 0.842 (CI: 0.736–0.948)	Not applicable	Laparoscopic cholecystectomy	Not assessed	Hypertension included in comorbidity feat	GA with TIVA and intubation	Propofol/remifentanil via TCI pump	ML model trained on pre-intubation data	Not assessed	Not reported	BIS used; not analyzed	Not reported

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Wijnberge et al. (2020)	Monitored via arterial waveform	MAP <65 mm Hg threshold for intervention	FloTracIQ waveform analysis	Primary outcome: MAP <65 mm Hg duration	Not statistically powered for mortality	HPI vs conventional care	Significant reduction in MAP <65 mm Hg duration	Not reported; prior studies suggest >0.9	Not applicable	High-risk non cardiac surgery	Not assessed	MAP control strategy used to prevent extremes	GA with invasive monitoring	Not detailed	Real-time HPI alerts triggered early intervention	Not statistically powered	Not reported	Not specified	Not reported
Baig et al. (2013)	Used as a fuzzy input for hypovolaemia diagnosis	BP waveform analysis with fuzzy thresholds	PV from plethysmograph used in fuzzy rule engine	Central to alarm generation logic	Compared clinical impact using Kappa agreement	RT-SAAM, FLMS-2 (Fuzzy logic expert systems)	Kappa agreement: FLMS-2 = 0.75; RT-SAAM = 0.62	Not used; Kappa statistic for diagnostic agreement	Not applicable	Moderate-to-high blood loss procedures	Not directly evaluated	Rule-based flagging of elevated BP	Not detailed	Not specified	Multi-layer fuzzy alerts: probabilistic, SPV, fuzzy rule	Monitored indirectly via user feedback	Diagnostic accuracy validated with clinician agreement	Not part of fuzzy system logic	Pain control studied in other fuzzy systems

Ripollés-Melchor et al. (2025)	Monitored; not analyzed separately	MAP <65 mm Hg threshold; HPI alert at >80	dP/dtmax and SVV used in HPI algorithm	Primary outcome: AKI linked to MAP <65 mm Hg	30-day mortality: 1.1% (HPI) vs 0.9% (control)	HPI-guided vs real-world standard care	No significant AKI reduction; RR = 0.89; P = 0.66	Not reported; primary outcome analyzed via RR	Not applicable	Moderate-to-high risk elective abdominal surgery	Primary endpoint; no significant reduction	Subgroup analysis showed trend in non-hypertensives	GA with BIS; ventilation standardized	Balanced crystalloid; ephedrine, norepinephrine used	HPI alert at >80 triggered algorithmic intervention	1.1% (HPI) vs 0.9% (control); no significant difference	31.9% (HPI) vs 29.7% (control); no significant difference	BIS used in both groups	Not analyzed
Hu et al. (2024)	Used as input to CNN and LSTM	SBP & DBP used for dose prediction	Extracted via CNN feature layers	Trend modeled via LSTM	Not evaluated	ANN + CNN + LSTM with attention	R^2 = 0.915 (intra-op); MAPE = 12.25%	Not applicable; regression focus	Not applicable	Various; not stratified	Not assessed	Not stratified	GA assumed; not detailed	Etomidate, atracurium, sufentanil predicted	AI dosing model; attention highlights key features	Not evaluated	Not reported	BIS input collected; not output variable	Not analyzed
Abin et al. (20	Input to dual	Cr used as inpu	Not directly mod	Used to stratify	5–10% AKI	Dual regressi	Accuracy = 80.6	Not reported;	Not applicable	Cardiac surgery	Primary end	HTN include	GA assumed;	CPB time,	AKI + and AKI	5–10% AKI	AKI severity trac	Not modeled	Not analyzed

24)	regression model	t; MAP indirectly modeled	eled	AKI risk	-related mortality cited	on models (AKI+ / AKI–)	%; F1 = 0.821; recall = 84.8%	regression-based		(CABG, valve, transplant)	point; AKI + vs AKI – modeling	d in PMH features	not detailed	fluids, diuretics, transfusions predicted	– planners + visual dashboard	-related mortality cited	ked via Cr levels (KDIGO)		
Hayase et al. (2020)	Captured; used as context for EEG patterns	Related to BIS accuracy via EMG contamination	Not directly used; EEG-derived via 20–30Hz targeted frequency	Indirectly related to EMG/BIS fidelity at low and high depth	Not assessed	Poincaré-index fusion via MLPNN (deep learning approach)	R = 0.87, RMSE = 7.09 (PredBIS vs mBIS correlation)	Not reported; linear regression used for validation	Not applicable	Mixed (30 patients, including spinal and GA cases)	Not analyzed	EMG artifacts >80 BIS signal problematic in light anesthesia	GA with BIS; some spinal with propofol	Severflurane, remifentanil, propofol; muscle relaxant use stratified	Poincaré-index–driven MLPNN alerts; layered EEG analysis	Not analyzed	Not assessed	BIS + EEG scatter via Poincaré indices	Not evaluated
Šribar et al. (20	Monitored; higher	MAP <65 mmHg	Derived via wavefor	Primary endpoin	1 death (Acume	HPI vs FloTrac	TWA-AUT: 0.01	Not reported; TW	Not applicable	Major thoracic (lun	1 case (Flotrac gro	MAP ≥65 mmHg	GA with one-lung vent	Propofol, sufentan	HPI alert ≥90 + deci	1 death (Acume	No MI, CVI, or AKI	BIS used; MAC	Epidural or IV sufentanil

23)	baseline in HPI group	threshold	m analysis	t	nIQ group)	GDT	vs 0.08 mm Hg	A used		g/esophagus)	up)	target	ilation	il, sevoflurane	sion tree	nIQ group)	in HPI group	0.8–1	
Moriss on et al. (2022)	Included in NOL algorithm	MAP indirectly modeled via NOL	Part of NOL algorithm	NOL-based thresholds (10–25)	Not assessed	ML algorithms (elastic net, RF, SVM …)	CV-AUC 0.753 (0.718–0.788); Brier score 0.194	CV-AUC 0.753	Not applicable	Gynecologic laparoscopy	Not assessed	Not stratified	GA with intubation	Fentanyl guided by NOL	NOL-guided fentanyl vs MAP/HR-based care	Not assessed	63.6% had moderate to severe PACU pain	BIS used	
Velagapudi et al. (2022)	Included in ML input features and NOL reaction anal	Implicit in case parameters; MAP not modeled directly	Not reported; NOL-based surrogate features likel	Used indirectly via preoperative ASA status and	Not assessed	XGBoost for glucose prediction; Random Forest for	Glucose: Accuracy ↑ from 79% to 84.7%; Opi	Opioid model cross-validated AUROC: **0.753**	Not applicable	Mixed ambulatory and inpatient procedures	Not evaluated	Implied in diabetes/glucose control models	Intubated GA; not stratified	Fentanyl dosing modified based on NOL and ML aid	ML predictions presented via REDCap interface;	Not assessed	Focused on pain and glucose misestimation; not tracked	BIS used; not modeled	Primary outcome: ML-aided prediction of opioid requirement

	ysis		y considered	surgery type		opioid need	oids: Accuracy ↑ from 18% to 42%								used as reference		for mally		
Lucksc heiter et al., 2022	Included as a key input feature; ranked third in importance in RF model	Systolic BP used; top-ranked feature in RF model	Not directly modeled; inferred via shock index and auscultation	Not explicitly modeled; indirectly reflected via systolic BP and shock index	Not assessed	Random Forest (RF) vs Naive Bayes (NB)	RF: AUROC 0.96; PRC area 0.83; NB: AUROC 0.93; PRC area 0.66	RF: 0.96 (95% CI: 0.96–0.97); NB: 0.93 (95% CI: 0.92–0.93)	Not applicable	Not surgical; prehospital trauma registry (EMS-based)	Not evaluated	Indirectly modeled via systolic BP and shock index	**Primary endpoint**; 5.7% of patients required prehospital airway management	Not modeled; airway management inferred via interventions and medications	ML model trained on EMS registry data; no real-time alerts deployed	Not assessed	Not assessed; prehospital setting only	Not applicable	Not assessed

Tan et al., 2021	Preoperative HR measured; slightly higher in EPOH group (not statistically significant)	SBP >160 mmHg defines EPOH; intraoperative and postoperative peak SBP/DBP significantly higher in EPOH group	Not directly modeled; MAP variability and vasoactive response indirectly involved	Not calculated directly; SBP/DBP trends used as surrogates for hypertensive patterns	No deaths occurred during hospital stay in either group	Gradient Boosted Regression Trees (GBRT) via XGBoost	Mean AUROC: **0.77** (95% CI: 0.62–0.92); Sensitivity ~90%; Specificity 0.52	0.77 (cross-validation average)	Not applicable	Carotid endarterectomy (CEA) under general anesthesia	Not assessed	EPOH risk specifically modeled; intraoperative BP spikes highly predictive	GA with standard intubation; not a variable in prediction	Sevoflurane, propofol, fentanyl, phenylephrine, ephedrine tracked; their dosages used as input features	ML model validated retrospectively; no live alert integration	Not assessed	Stroke: 5 cases; CHS: 4 cases (all in EPOH group); Cerebral hemorrhage: 2 cases (both EPOH)	Not modeled directly; BIS not reported	Not assessed

4. Discussion

This review emphasises how ML-based perioperative prediction models perform better than conventional techniques in terms of clinical utility and accuracy. Logistic regression is clearly outperformed by ensemble models such as XGBoost (AUROC up to 0.942) and RF (AUROC 0.96). By utilising time-series data, deep learning architectures provide additional incremental benefits.

Since several RCTs showed significant decreases in IOH burden, confirming the idea of predictive haemodynamic monitoring, the Hypotension Prediction Index (HPI) is noteworthy for its real-time clinical applicability. The idea that IOH is a modifiable intraoperative risk factor and that proactive ML-guided interventions can lessen its severity and duration is supported by this data.

4.1. ML-Driven vs. Biomarker-Based Models Biomarker-based methods (HPI)

Using arterial waveform analysis, provide timely, actionable alerts proven to lower IOH in clinical settings [19].
Reliance on proprietary algorithms and a comparatively limited prediction scope (hypotension only) are among thelimitations.

4.2. Models Powered by Machine Learning

Predict broader outcomes (mortality, AKI, composite complications) by integrating multi-modal data sources. Show improved discriminative abilities.

Model complexity, interpretability, and the requirement for sizable, superior datasets are among the difficulties.

4.3. Clinical Consequences

The findings of this synthesis point to a potential paradigm shift in perioperative care: predictive analytics, like capnography or pulse oximetry, may soon be used as a routine supplement to anaesthesia monitoring.

Proactive management techniques like prompt vasopressor titration, fluid optimisation, and renal protection protocols may be made possible by machine learning (ML) models integrated into anaesthesia information management systems (AIMS).

4.4. The Evidence's Limitations

Heterogeneity in outcome definitions, inconsistent performance metric reporting, and a small number of highly effective RCTs focussing on hard endpoints (mortality, AKI, myocardial injury) limit the body of evidence. Few studies evaluated cost-effectiveness or implementation feasibility in standard clinical practice, and proprietary algorithms like HPI further restrict reproducibility.

4.5. Prospects for the Future

Multicenter, sufficiently powered RCTs assessing clinically significant endpoints should be the top priority for future research. Explainable AI (XAI) to increase clinician trust and transparency combining machine learning models with biomarker-based indices to provide hybrid real-time decision support.

Health economics studies to assess implementation logistics and cost-effectiveness.

To guarantee generalisability, external validation is conducted across a variety of populations.

5. Conclusion

Perioperative risk management is about to be redefined by machine learning and biomarker-based monitoring. These models reliably forecast and reduce intraoperative complications more successfully than conventional techniques by utilising real-time waveform data, EHR variables, and sophisticated analytics. Large-scale retrospective studies validate the scalability of ML-based approaches, while HPI-guided trials demonstrate the clinical utility and viability of predictive monitoring.

However, strong proof of better patient outcomes—rather than merely surrogate metrics—will be necessary for wider adoption. In order to guarantee that predictive alerts result in significant clinical actions that lower morbidity and mortality, future research should focus on integrating ML algorithms into perioperative care pathways.

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Declaration of interests

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References

1. Kang, A. R., Lee, J., Jung, W., Lee, M., Park, S. Y., et al. (2020). Development of a prediction model for hypotension after induction of anesthesia using machine learning. *PLOS ONE, 15*(4), e0231172.
2. Fritz, B. A., Cui, Z., Zhang, M., He, Y., Chen, Y., et al. (2019). Deep-learning model for predicting 30-day postoperative mortality. *British Journal of Anaesthesia, 123*(5), 688–695.
3. Fritz, B. A., King, C. R., Abdelhack, M., Chen, Y., Kronzer, A., et al. (2024). Effect of machine learning models on clinician prediction of postoperative complications: The Perioperative ORACLE randomised clinical trial. *British Journal of Anaesthesia, 133*(5), 1042–1050.
4. Hayase, K., Hayashi, K., & Sawa, T. (2020). Hierarchical Poincaré analysis for anaesthesia monitoring. *Journal of*

Clinical Monitoring and Computing, 34(6), 1321–1330.
5. Wijnberge, M., Geerts, B. F., Hol, L., Lemmers, N., Mulder, M. P., et al. (2020). Effect of a machine learning–derived early warning system for intraoperative hypotension vs standard care on depth and duration of intraoperative hypotension during elective noncardiac surgery: The HYPE randomized clinical trial. *JAMA, 323*(11), 1052–1060.
6. Ripollés-Melchor, J., Tomé-Roca, J. L., Zorrilla-Vaca, A., Aldecoa, C., Colomina, M. J., et al. (2025). Hemodynamic management guided by the Hypotension Prediction Index in abdominal surgery: A multicenter randomized clinical trial. *Anesthesiology, 142*(4), 639–654.
7. Schenk, J., Wijnberge, M., Maaskant, J. M., Hollmann, M. W., Hol, L., et al. (2021). Effect of Hypotension Prediction Index-guided intraoperative haemodynamic care on depth and duration of postoperative hypotension: A sub-study of the Hypotension Prediction trial. *British Journal of Anaesthesia, 127*(5), 681–688.
8. Frassanito, L., Giuri, P. P., Vassalli, F., Piersanti, A., Garcia, M. I. M., et al. (2023). Hypotension Prediction Index guided goal-directed therapy and the amount of hypotension during major gynaecologic oncologic surgery: A randomized controlled clinical trial. *Journal of Clinical Monitoring and Computing, 37*(4), 1081–1093.
9. Šribar, A., Sokolović Jurinjak, I., Almahariq, H., Bandić, I., Matošević, J., et al. (2023). Hypotension prediction index guided versus conventional goal-directed therapy to reduce intraoperative hypotension during thoracic surgery: A randomized trial. *BMC Anesthesiology, 23*, 101.
10. Mansoor Baig, M., Gholamhosseini, H., & Harrison, M. J. (2013). Fuzzy logic based anaesthesia monitoring systems for the detection of absolute hypovolaemia. *Computer Methods and Programs in Biomedicine, 43*(6), 683–692.
11. Lee, S. W., Lee, H. C., Suh, J., Lee, K. H., Lee, H., et al. (2022). Multi-center validation of machine learning model for preoperative prediction of postoperative mortality. *NPJ Digital Medicine, 5*(1), 91.
12. Te, R., Zhu, B., Ma, H., Zhang, X., Chen, S., et al. (2024). Machine learning approach for predicting post-intubation hemodynamic instability (PIHI) index values: Towards enhanced perioperative anesthesia quality and safety. *BMC Anesthesiology, 24*(1), 136.
13. Luckscheiter, A., Zink, W., Lohs, T., Eisenberger, J., Thiel, M., et al. (2022). Machine learning for the prediction of preclinical airway management in injured patients: A registry-based trial. *Clinical and Experimental Emergency Medicine, 9*(4), 304–313.
14. Hu, Z., Pan, G., Wang, X., & Li, K. (2024). Intelligent algorithm based on deep learning to predict the dosage for anesthesia: A study on prediction of drug efficacy based on deep learning. *Health Science Reports, 7,* e2113.
15. Abin, A. A., Molla, A., Ejmalian, A., Nabavi, S., Memari, B., et al. (2024). Anesthetic management recommendations using a machine learning algorithm to reduce the risk of acute kidney injury after cardiac surgeries. *Anesthesiology and Pain Medicine, 14*(3), e143853.
16. Tan, J., Wang, Q., Shi, W., Liang, K., Yu, B., et al. (2021). A machine learning approach for predicting early phase postoperative hypertension in patients undergoing carotid endarterectomy. *Annals of Vascular Surgery, 71*, 121–131.
17. Morisson, L., Nadeau-Vallee, D. M., Espitalier, F., Laferrière-Langlois, P., Idrissi, M., et al. (2023). Prediction of acute postoperative pain based on intraoperative nociception level (NOL) index values: The impact of machine learning-based analysis. *Journal of Clinical Monitoring and Computing, 37*, 337–344.
18. Velagapudi, M., Nair, A. A., Strodtbeck, W., Flynn, D. N., Howell, K., et al. (2023). Evaluation of machine learning models as decision aids for anesthesiologists. *Journal of Clinical Monitoring and Computing, 37*, 155–163.
19. U.S. Food and Drug Administration. (2021). Good machine learning practice for medical device development: Guiding principles.