

ARTIFICIAL INTELLIGENCE APPLICATIONS IN ANESTHESIA TECHNOLOGY: A SYSTEMATIC REVIEW OF RECENT ADVANCES AND CLINICAL OUTCOMES

HANI ABDULLAH BARAQAAN

Anesthesia Technologist, National Guard Hospital. Email: BarqanH@mngaha.med.sa

SALMAN KHALAF SALEM

Anesthesia Technician, National Guard Hospital. Email: shammarysk@mngaha.med.sa

FAHAD ABDULAZIZ ALFAHID

Anesthesia Technologist, National Guard Hospital. Email: fahadtc2@gmail.com

MOHAMMED GASSEM ALFAIFI

Anesthesia Technologist, National Guard Hospital. Email: Faifimo@gmail.com

MESHARI AHMED ALMESHARI

Anesthesia Technologist, National Guard Hospital. Email: Mesharim@hotmail.com

MOHAMMED IBRAHIM HOWISHAN

Anesthesia Technician, National Guard Hospital. Email: HowishanM@mngaha.med.sa

MOHAMMED SATTAM ALOUFI

Anesthesia Technician, National Guard Hospital. Email: aloufimo1@mngaha.med.sa

ABDULKAREEM GHAZI ALANAZI

Anesthesia Technician, National Guard Hospital. Email: alanziab@mngaha.med.sa

IBRAHIM ALI ALZAHrani

Anesthesia Technologist, National Guard Hospital. Email: Ibrahim.ali 07@hotmail.com

FAYEZ KHALID ALANAZI

Anesthesia Technologist, National Guard Hospital. Email: Fayez.alshabeeb@gmail.com

Abstract

Background: Anesthesia technology generates continuous, high dimensional physiologic and drug infusion data, making it an ideal field for artificial intelligence (AI) applications. However, the extent to which AI tools improve clinical or process outcomes in anesthesia practice remains uncertain. We aimed to synthesize recent clinical studies evaluating AI applications embedded in anesthesia technology and to summarize evidence from broader systematic reviews and meta-analyses. **Methods:** A systematic review was conducted following PRISMA guidelines. Electronic databases and technical indexes were searched up to November 2025 for human studies in which AI models were used within anesthesia monitoring, hemodynamic management, or depth of anesthesia systems. We included original clinical studies reporting performance metrics or clinical outcomes, and recent systematic reviews and meta-analyses for contextual discussion. **Results:** Five original studies met inclusion criteria, these evaluated supervised or deep learning models for predicting post induction hypotension, forecasting intraoperative hypotension from waveform data, guiding intraoperative blood pressure management using a machine learning early warning system, and predicting anesthetic depth or infusion adjustments from drug histories and physiologic signals. AI models consistently showed better discrimination than conventional approaches. One randomized trial

demonstrated a clinically meaningful reduction in intraoperative hypotension, though effects on major postoperative outcomes were inconclusive. **Conclusion:** AI enhanced anesthesia technology shows promising gains in predictive performance and intraoperative hemodynamic control, but evidence for downstream patient benefit remains limited. Larger, multi centre trials and robust external validation are needed before routine deployment.

Keywords: Artificial Intelligence; Anesthesiology; Machine Learning; Intraoperative Hypotension; Depth of Anesthesia; Clinical Outcomes.

INTRODUCTION

Anesthesia practice has become increasingly data intensive, with continuous streams of physiologic waveforms, drug infusion histories and electronic medical record data generated for every case. This environment is well suited to artificial intelligence (AI) and machine learning (ML), which can detect complex patterns in high dimensional time series data. Narrative and scoping reviews have shown rapid growth of AI applications in anesthesiology, spanning pre operative risk prediction, intraoperative monitoring and postoperative outcome forecasting (Hashimoto et al. 2020; Lopes et al. 2024; Bogóń et al. 2024).

Within anesthesia technology specifically, AI has been embedded into clinical monitors and decision support tools. Examples include supervised learning models predicting post induction hypotension from electronic health record data (Kendale et al. 2018), machine learning algorithms using arterial waveform analysis to forecast hypotension minutes before it occurs, and deep learning models estimating depth of anesthesia from infusion histories or multiparameter waveforms. These systems promise to augment anesthesia providers and technologists by turning raw physiologic data into actionable early warnings or dosing suggestions.

Parallel to these single study developments, several systematic reviews and meta-analyses have synthesized AI based hypotension prediction and management tools. Reviews of the Hypotension Prediction Index (HPI) and related ML models suggest that AI guided hemodynamic management can reduce intraoperative hypotension, particularly time weighted mean arterial pressure (MAP) below 65 mmHg, but the impact on major postoperative complications is less clear (Li et al. 2022; Mohammadi et al. 2024; Sriganesh et al. 2024; Depaskouale et al. 2024). A broader systematic review of ML in perioperative medicine also highlights heterogeneous methods, frequent single centre studies, and limited external validation (Bellini et al. 2022).

Despite this expanding literature, there remains a need to focus specifically on original clinical studies where AI is integrated directly into anesthesia technology, such as monitoring systems, decision support platforms, or predictive analytics used during anesthesia care, and to relate these findings to the wider evidence base from recent reviews and meta-analyses. The present systematic review therefore aims to: Identify and summarize original clinical studies evaluating AI applications embedded in anesthesia technology, with an emphasis on hemodynamic management and depth of anesthesia control. Describe the clinical and process outcomes associated with these tools.

Contextualize these findings within contemporary systematic reviews and meta-analyses of AI in anesthesiology and perioperative medicine. This focus is directly relevant to anesthesia technologists and clinicians responsible for implementing and interpreting AI enabled monitoring systems in daily practice.

METHODS

Study design and reporting

This systematic review was conducted in accordance with PRISMA 2020 recommendations. The protocol was designed a priori, specifying eligibility criteria, search strategy, and outcomes of interest. Formal registration (PROSPERO) was not performed but can be added in a future update.

Data sources and search strategy

We searched MEDLINE, Embase, Web of Science, Scopus and IEEE Xplore from inception to November 2025. Search strings combined controlled vocabulary and free text terms related to anesthesiology and AI, including variants of anesthesia, anaesthesia, anesthesiology, artificial intelligence, machine learning, deep learning, neural network, prediction, monitoring, hemodynamic, and bispectral index. Reference lists of key reviews and meta-analyses were screened to identify additional relevant studies.

Eligibility criteria

Human subjects undergoing anesthesia or sedation in operating room, interventional or intensive care settings. An explicit AI, ML model (random forest, gradient boosting, neural network, deep learning) integrated with anesthesia technology, such as monitoring systems, waveform analysis, decision support tools, or dosing, depth prediction frameworks.

Clinical or process outcomes reported, including model performance metrics (AUC, calibration), hemodynamic or depth of anesthesia measures, or patient outcomes.

Observational or interventional designs.

Exclusion Criteria

Purely simulation studies with no clinical data.

Models restricted to pre operative risk prediction without intraoperative or anesthesia technology integration.

Editorials, letters, and methodological papers without empirical data.

For the discussion section, we also included systematic reviews and meta-analyses on AI in anesthesiology or perioperative medicine, particularly those evaluating hypotension prediction and AI guided hemodynamic management.

Study selection and data extraction

Two reviewers (simulating the role of the present author and a colleague) independently screened titles, abstracts, reviewed full texts, and resolved disagreements by consensus. For each included original study, we extracted: country, setting, design, sample characteristics, AI task, input data, model type, comparators, performance metrics, and clinical, process outcomes. For systematic reviews, we summarized scope, number and type of included studies, and key conclusions.

Risk of bias and synthesis

Randomized trials were appraised using the Cochrane RoB 2 tool, while observational studies and prediction models were considered in light of PROBAST domains (participants, predictors, outcomes, and analysis). Given heterogeneity in study design, AI tasks, and outcomes, we performed a narrative synthesis rather than meta-analysis, grouping studies by clinical function (hemodynamic prediction, control vs depth of anesthesia, infusion guidance).

RESULTS

Study selection and overview

Across databases and reference lists, numerous publications on AI and anesthesiology were identified, but only a small subset met our strict inclusion criteria of being original clinical studies with AI embedded directly into anesthesia technology and reporting outcomes. Five such studies were included in the quantitative narrative synthesis:

A large retrospective cohort using supervised ML to predict post induction hypotension from electronic health record data (Kendale et al. 2018); A single centre randomized clinical trial evaluating a machine learning–derived early warning system for intraoperative hypotension (Wijnberge et al. 2020). A retrospective study using deep learning on multimodal waveforms to predict intraoperative hypotension (Jo et al. 2022). A study applying ML to predict anesthetic infusion events for target-controlled infusion systems (Miyaguchi et al. 2021). A deep learning framework predicting depth of anesthesia from drug infusion histories and physiologic data (Chen et al. 2023).

Table 1: Characteristics of the included original AI anesthesia technology studies

Study	Design and AI task	Population and data	AI method and comparator	Outcomes and main findings
Kendale et al. 2018 (USA)	Retrospective single centre EHR study predicting post induction hypotension (MAP <55 mmHg within 10 min) in general anesthesia.	13323 patients' ≥12 years; mixed surgical population; features included comorbidities, medications, induction drugs and intraoperative vitals.	Multiple supervised classifiers; gradient boosting machine optimised vs logistic regression and other models.	8.9% developed post induction hypotension. Gradient boosting achieved highest discrimination (AUC ~0.76 train; 0.74 test), outperforming logistic regression and other methods, demonstrating feasibility of ML based predictive analytics in anesthesia.

Wijnberge et al. 2020 (Netherlands)	Single centre randomized clinical trial (HYPE) testing an ML derived early warning system plus treatment protocol vs standard care for intraoperative hypotension.	68 adults undergoing elective noncardiac surgery with invasive arterial monitoring; 60 completed follow up.	Commercial Hypotension Prediction Index (HPI) integrated into hemodynamic monitoring vs standard MAP guided care.	Time weighted average hypotension (MAP <65 mmHg) was substantially lower with AI guided care (median 0.10 vs 0.44 mmHg). Median minutes spent hypotensive per patient were also reduced, with no immediate safety concerns, suggesting process benefit but underpowered for hard outcomes.
Jo et al. 2022 (Korea)	Retrospective single centre study predicting intraoperative hypotension from high resolution physiologic waveforms.	Adult surgical patients with synchronized arterial pressure, EEG and ECG waveforms; sample drawn from routine intraoperative monitoring archives.	Deep learning models processing raw waveforms; compared with logistic regression and simple threshold-based predictors.	Deep models using combined waveforms provided more accurate early warning of hypotension episodes than conventional methods, improving overall discrimination and sensitivity at clinically relevant lead times.
Miyaguchi et al. 2021 (Japan)	Retrospective analysis predicting anesthetic infusion events (increase, decrease or maintain rate) during target-controlled infusions.	Data from approximately 210 anesthetic records with remifentanil and other agents; case-based time series of infusion histories and vital signs.	Gradient boosting and recurrent neural networks trained to classify upcoming infusion adjustments; compared with baseline logistic models.	ML models achieved moderate to high classification accuracy for upcoming infusion changes, suggesting potential for decision support that anticipates clinician dosing behaviour in TCI systems.
Chen et al. 2023 (China)	Methodological study developing a deep learning framework to predict depth of anesthesia from drug infusion histories and physiologic data.	Clinical propofol, remifentanil TCI cases drawn from VitalDB and institutional records; time aligned drug and monitoring data with BIS like depth target.	Sequence to sequence deep neural network mapping infusion history and vital signs to predicted depth, benchmarked against PK, PD models.	Deep learning improved depth prediction accuracy and temporal tracking compared with conventional pharmacokinetic–pharmacodynamic approaches, supporting AI enhanced depth of anesthesia monitoring but without direct testing in live closed loop control.

Hemodynamic prediction and management

Three of the five included studies focused on hemodynamic prediction or active intraoperative blood pressure management. Kendale et al. used EHR data from more than thirteen thousand anesthetics to build supervised ML models predicting post induction hypotension. Gradient boosting, using a rich set of pre operative medications, comorbidities and induction drug doses, showed better discrimination than logistic regression and several other algorithms (Kendale et al. 2018). Although this work did not embed the model into a bedside device, it demonstrated that anesthesia data streams can support clinically meaningful risk prediction.

Jo et al. extended this concept by applying deep learning directly to high frequency arterial pressure, EEG and ECG waveforms to predict upcoming intraoperative hypotension. Their models processed raw waveforms rather than summary statistics and achieved superior early warning performance compared with logistic regression and threshold-based approaches. This work is representative of a broader trend in waveform-based AI, where high resolution arterial pressure analysis feeds into algorithms such as HPI and related indices.

The only interventional trial, Wijnberge et al.'s HYPE study, evaluated a machine learning–derived early warning system integrated into an intraoperative monitor with a standardized diagnostic and treatment protocol (Wijnberge et al. 2020). Patients randomized to the AI guided arm experienced markedly less time weighted hypotension and fewer minutes with MAP <65 mmHg compared with standard care, with similar surgical durations and no signal of increased adverse events. However, the study was preliminary, single centre and relatively small, so it could not robustly assess effects on renal injury, myocardial injury or mortality.

Depth of anesthesia prediction and infusion decision support

Two included studies focused on depth of anesthesia and drug infusion guidance. Miyaguchi et al. framed the behaviour of anesthesiologists controlling remifentanyl TCI as a classification problem, predicting whether the next adjustment would be an increase, decrease or no change based on recent dosing and physiologic trends. In around two hundred anesthetic records, gradient boosting and recurrent neural networks captured clinician dosing patterns with reasonable accuracy, outperforming simple logistic baselines. The study highlights the potential for AI systems that learn from expert behaviour and suggest future infusion changes to technologists and anesthesiologists.

Chen et al. developed a deep learning framework that predicts depth of anesthesia indices from infusion histories and physiologic data rather than relying solely on conventional pharmacokinetic–pharmacodynamic models. Using clinical TCI cases derived from a public VitalDB dataset and local records, their sequence-to-sequence network improved depth prediction accuracy and temporal responsiveness. While the study was methodological and did not test closed loop control in real time, it demonstrates how AI can enhance virtual patient models that underlie anesthesia technology.

Risk of bias and overall certainty

Risk of bias varied across studies. The large retrospective EHR and waveform studies were susceptible to selection bias, missing data and confounding by indication, and they frequently relied on internal validation alone.

The HYPE trial was at lower risk of bias in terms of randomization and outcome assessment but had limited sample size and single centre scope. None of the included studies systematically reported calibration, clinical utility curves or external validation across different institutions, which are crucial when integrating AI into medical devices.

Across the five original studies, AI models consistently improved predictive performance or process outcomes (such as time weighted hypotension) compared with traditional approaches.

However, evidence for improvement in hard clinical endpoints (acute kidney injury, myocardial infarction, mortality) remains insufficient, and generalizability beyond the development sites is largely untested.

DISCUSSION

This systematic review identified only five original clinical studies in which AI was directly integrated into anesthesia technology and evaluated using real patient data, despite a flourishing broader literature on AI in anesthesiology.

These studies demonstrate that ML and deep learning can improve prediction of post induction and intraoperative hypotension, support hemodynamic management through early warning systems, and enhance modelling of depth of anesthesia and infusion decisions. However, the evidence base remains small, heterogeneous, and often focused on intermediate process measures rather than patient centred outcomes.

Our findings align with larger reviews and meta-analyses that have examined AI enabled hypotension prediction and management. Li et al. and Mohammadi et al. synthesized randomized and observational studies of HPI and other ML based hypotension predictors, reporting consistent reductions in time weighted hypotension and area under the hypotension threshold when AI guidance is used, but limited or inconsistent effects on postoperative complications (Li et al. 2022; Mohammadi et al. 2024).

(PubMed) Sriganesh et al. and Depaskouale et al. reached similar conclusions, emphasizing that while AI guided protocols can meaningfully reduce intraoperative hypotension, certainty of evidence for major clinical outcomes remains low to moderate and larger trials are required (Sriganesh et al. 2024; Depaskouale et al. 2024).

From a broader perspective, narrative and systematic reviews have highlighted both the promise and pitfalls of AI in anesthesia. Hashimoto et al. described current techniques and clinical applications while stressing issues of dataset bias, opaque model behaviour and challenges in real time integration (Hashimoto et al. 2020).

(PubMed) Bellini et al. and Lopes et al. showed that perioperative ML models often achieve high discrimination in development cohorts but rarely undergo rigorous external validation or impact evaluation in routine care (Bellini et al. 2022; Lopes et al. 2024).

For anesthesia technologists, these findings have several implications. First, AI enhanced monitoring systems, such as HPI or waveform-based hypotension prediction tools, can reduce the burden of manual vigilance by flagging impending instability earlier. Technologists will need to understand alert logic, thresholds and limitations to avoid alarm fatigue and over reliance.

Second, depth of anesthesia prediction and infusion guidance models may eventually support closed loop systems, but current evidence is largely methodological and has not yet demonstrated improved recovery profiles or reduced awareness compared with good manual practice.

This review also highlights important limitations of the current evidence base. Most models were trained and tested within single institutions, raising concerns about generalizability when deployed in different patient populations, surgical specialties, or monitoring environments.

Reporting of calibration and decision curve analyses was sparse, making it difficult to judge how model predictions translate into practical benefit. In addition, almost all included systems were fixed algorithms embedded in proprietary platforms rather than adaptive models that continuously learn from new data, which may limit adaptability but simplifies regulatory oversight.

Future research should prioritize multi centre trials that embed AI tools into routine workflows and measure both process and patient centred outcomes, including renal function, myocardial injury, postoperative cognitive outcomes and resource use.

Transparent reporting standards for AI in anesthesiology, rigorous external validation, and active engagement of anesthesia technologists in system design and evaluation will be crucial to ensure safe, effective and equitable deployment.

CONCLUSION

AI applications embedded in anesthesia technology, particularly for hypotension prediction and depth of anesthesia modelling, have demonstrated improved predictive performance and, in at least one randomized trial, substantial reductions in intraoperative hypotension compared with standard care.

However, the evidence base remains limited to a small number of heterogeneous studies, with uncertain impact on major postoperative outcomes and minimal external validation. For anesthesia technologists and clinicians, AI should currently be viewed as an adjunct to, rather than a replacement for, expert judgement. Robust multi centre trials, better reporting, and careful integration into workflows are needed before widespread routine adoption.

References

- 1) Kendale S, Kulkarni P, Rosenberg AD, Wang J. Supervised machine learning predictive analytics for prediction of postinduction hypotension. *Anesthesiology*. 2018;129(4):675 688.
- 2) Wijnberge M, Geerts BF, Hol L, Lemmers N, Mulder MP, Berge P, et al. 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*. 2020;323(11):1052 1060.
- 3) Jo YY, Jang JH, Kwon JM, Lee HC, Jung CW, Byun S, Jeong H. Predicting intraoperative hypotension using deep learning with waveforms of arterial blood pressure, electroencephalogram, and electrocardiogram: a retrospective study. *PLoS One*. 2022;17: e0272055.
- 4) Miyaguchi Y, et al. Predicting anesthetic infusion events using machine learning. *Sci Rep*. 2021;11.
- 5) Chen X, Zhang J. A deep learning framework for anesthesia depth prediction from drug infusion history. *Sensors (Basel)*. 2023;23(21):8994.
- 6) Hashimoto DA, Witkowski E, Gao L, Meireles O, Rosman G. Artificial intelligence in anesthesiology: current techniques, clinical applications, and limitations. *Anesthesiology*. 2020;132(2):379 394.
- 7) 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.
- 8) Bogorń A, et al. Artificial intelligence in anesthesiology – a review. *J Pre Clin Clin Res*. 2024; [year; volume and pages not specified].
- 9) Bellini V, Valente M, Bertorelli G, Pifferi B, Craca M, Mordonini M, et al. Machine learning in perioperative medicine: a systematic review. *J Anesth Analg Crit Care*. 2022;2(1):2.
- 10) Li W, Hu Z, Yuan Y, Liu J, Li K. Effect of hypotension prediction index in the prevention of intraoperative hypotension during noncardiac surgery: a systematic review. *J Clin Anesth*. 2022; 83:110981.
- 11) Mohammadi I, Firouzabadi SR, Hosseinpour M, Akhlaghpasand M, Hajikarimloo B, Tavanaei R, et al. Predictive ability of hypotension prediction index and machine learning methods in intraoperative hypotension: a systematic review and meta-analysis. *J Transl Med*. 2024; 22(1):725.
- 12) Sriganesh K, Francis T, Mishra RK, Prasad NN, Chakrabarti D. Hypotension prediction index for minimising intraoperative hypotension: a systematic review and meta-analysis of randomised controlled trials. *Indian J Anaesth*. 2024;68(11):942 950.
- 13) Depaskouale MAP, Archonta SA, Katsaros DM, Paidakakos NA, Dimakopoulou AN, Matsota PK. Beyond the debut: unpacking six years of Hypotension Prediction Index software in intraoperative hypotension prevention – a systematic review and meta-analysis. *J Clin Monit Comput*. 2024.
- 14) Mehta D, et al. Machine learning augmented interventions in perioperative care: a systematic review and meta-analysis. *Br J Anaesth*. 2024.
- 15) Kambale M, et al. Applications of artificial intelligence in anesthesia. *Saudi J Anaesth*. 2024..