ANESTHESIOLOGY

Openventio PUBLISHERS

Review Article

Personalized Anesthetic Planning Using Predictive Clinical Algorithms

Lukas Peeters[1*], Joao Andersson[2] and Rui Zielinska[3]

[1]*Division of Anesthesia and Intensive Care, Douro Institute of Anesthesiology and Perioperative Medicine, Portugal*
[2]*Department of Critical Care Medicine, Baltic Institute of Biomedicine, Sweden*
[3]*Department of Surgical Sciences, Baltic Institute of Biomedicine, Sweden*

ABSTRACT

Predictive clinical algorithms are increasingly being used to individualize anesthetic care, drawing on preoperative, intraoperative, and genomic data to forecast risk and guide drug selection at the level of the individual patient.

This review surveys machine-learning models for preoperative and intraoperative risk stratification, algorithms targeting specific physiologic events such as post-induction hypotension, pharmacogenomic approaches to individualized opioid and anesthetic dosing, and closed-loop systems that couple prediction to automated drug delivery.

The strongest current evidence supports narrowly scoped intraoperative event prediction and closed-loop control of anesthetic depth, both of which have short and well-characterized causal pathways from measurable inputs to outcome.

Broader complication-risk models and genotype-guided dosing protocols remain conceptually promising but are limited by insufficient external validation, workflow integration challenges, and a paucity of prospective outcome trials.

We conclude that these tools are best understood, at their current stage of development, as a calibrated adjunct to clinical judgment rather than a replacement for it, and identify the validation and integration work still needed before routine adoption.

Keywords: *personalized anesthesia; machine learning; perioperative risk prediction; pharmacogenomics; closed-loop anesthesia*

Citation: Peeters L, Andersson J and Zielinska R (2023) Personalized Anesthetic Planning Using Predictive Clinical Algorithms. Anesthesiology. 3(1):01-05.

DOI: 10.17140/2023.vol3.i01.pp01-05

Corresponding Author: *Lukas Peeters*

E-mail Address: *l.peeters@diapm.pt*

Article History: *Received 12 January 2023 | Accepted 07 February 2023 | Published 07 March 2023*

Copyright: *© 2023 Lukas Peeters, et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited (**https://creativecommons.org/licenses/by/4.0/**).*

INTRODUCTION

Anesthesiologists have always practiced a form of personalization — titrating induction agents to a patient's frailty, adjusting a regional block plan around a difficult airway, or padding a postoperative opioid

order because a patient's history of chronic pain makes standard dosing unreliable. What has changed over the last decade is not the impulse to individualize care but the tools available to do it systematically. Electronic health records now carry years of longitudinal vital signs, laboratory trends, medication histories, and structured comorbidity data on every patient walking into a preoperative clinic, and modern machine-learning methods can mine that record for patterns that a busy clinician, working from a single preoperative visit, simply cannot see. The result is a growing class of predictive clinical algorithms aimed at converting population-level risk factors into patient-specific forecasts: who will become hypotensive after induction, who will need an unplanned ICU admission, who metabolizes opioids poorly, and how much anesthetic a given patient's brain actually requires to reach an adequate depth of unconsciousness.

This review surveys that landscape as it stands for anesthetic planning specifically, rather than surgical outcome prediction more broadly. We look first at machine-learning models built on preoperative and intraoperative data to forecast perioperative risk and complications, then at algorithms aimed narrowly at intraoperative physiologic events such as post-induction hypotension, then at pharmacogenomic approaches that personalize drug selection and dosing at the molecular level, and finally at closed-loop and decision-support systems that attempt to act on these predictions in real time. We close by considering the barriers — data, validation, interpretability, and workflow — that stand between promising models and everyday anesthetic practice.

MACHINE LEARNING FOR PREOPERATIVE RISK STRATIFICATION

The most mature branch of this literature uses supervised machine learning on structured preoperative data to predict who is at elevated risk for adverse perioperative events. Xu and colleagues built a model using only preoperative variables — demographics, comorbidities, functional status, and basic laboratory values — and showed that it could stratify patients into risk tiers for a composite of postoperative complications with discrimination meaningfully better than traditional risk scores such as the ASA physical status classification or the Revised Cardiac Risk Index [1]. The appeal of a preoperative-only model is practical: it can run the moment a surgical case is scheduled, well before an anesthesiologist ever lays eyes on the patient, and can flag high-risk patients for additional preoperative optimization or a more senior anesthesia team.

Models that add intraoperative data — hemodynamic trends, anesthetic depth, fluid and vasopressor administration — perform even better, unsurprisingly, since they capture how a patient's physiology actually responds once the case is underway rather than only how it looks on paper beforehand. A large JAMA Network Open study evaluated exactly this comparison, training separate models on preoperative-only and combined preoperative-plus-intraoperative feature sets to predict a range of postoperative complications including acute kidney injury, delirium, and prolonged ventilation, and found consistently improved discrimination once intraoperative trajectory data was incorporated [2]. This has an obvious clinical implication for anesthetic planning: risk is not fixed at the preoperative visit but continues to evolve across the case, which argues for models that can be re-run intraoperatively rather than a single static preoperative score.

Cardiac anesthesia has been an especially active area for these methods, given the density of monitoring data already collected during cardiopulmonary bypass and the high stakes of hemodynamic instability in this population. A recent review catalogued applications spanning risk prediction, intraoperative hemodynamic forecasting, and postoperative recovery trajectories in cardiac surgical patients, and described institutions increasingly using machine-learning outputs to inform decisions about invasive monitoring, vasoactive drug selection, and ICU disposition planning before the patient ever reaches the operating room [3]. Similar model families have been extended to ambulatory anesthesia, where the goal is almost the opposite — identifying which patients are low enough risk to safely proceed with same-day discharge pathways rather than flagging patients for escalated monitoring [4]. Commentary aimed at practicing clinicians has framed this shift toward algorithm-informed perioperative planning as one of the more concrete near-term payoffs of artificial intelligence in anesthesia, precisely because it slots into decisions — preoperative triage, monitoring intensity, staffing — that anesthesiologists already make every day [5].

PREDICTING INTRAOPERATIVE PHYSIOLOGIC EVENTS

A second and more granular strand of work targets specific intraoperative events rather than broad postoperative complication categories. Post-induction hypotension is the paradigm case: it is common, it happens quickly enough that reactive management is often too late, and it has been repeatedly linked to downstream harm including acute kidney injury and myocardial injury. Machine-learning models trained on preoperative characteristics and induction-agent choice have shown reasonable ability to predict which patients will experience a clinically significant blood pressure drop within the first several minutes after induction, well before the drop itself occurs [6]. A more recent preprint extended this approach with richer feature sets and reported further gains in predictive performance, underscoring that this remains an active area of methodological refinement rather than a solved problem [7].

Other intraoperative and early postoperative targets have received similar attention. One study developed a machine-learning approach to predict postoperative infection risk specifically among patients requiring intravenous neurotargeted drugs without mechanical ventilation, an population where standard infection-risk tools are poorly calibrated [8]. Deep-learning approaches have also been applied to the dosing problem itself rather than only to outcome prediction — one study used a deep-learning framework to model the relationship between anesthetic dosing and drug efficacy, aiming to move beyond weight-based or age-based dosing heuristics toward models that account for the nonlinear ways individual patients actually respond to induction and maintenance agents [9]. Reviews summarizing the broader field of anesthetic complication prediction have noted that model performance for these narrow physiologic targets tends to be higher than for broad complication categories, likely because the causal pathway from measurable inputs to a specific event like hypotension is shorter and less confounded by unmeasured surgical and systemic factors [10,11]. A broader synthesis of precision perioperative care similarly places event-level prediction, rather than global complication scoring, as the segment of this literature closest to informing real-time anesthetic decisions [12].

PHARMACOGENOMICS AND INDIVIDUALIZED DRUG SELECTION

Predictive algorithms built from clinical and physiologic data are only one axis of personalization; the other operates at the level of genetics. Interindividual variability in response to anesthetic and analgesic drugs has a substantial pharmacogenomic component, and this has been recognized in the anesthesia literature for well over a decade. Early reviews documented how polymorphisms affecting opioid receptor function and drug-metabolizing enzymes explain much of the variability clinicians observe at the bedside — why one patient sails through a standard morphine-based postoperative regimen while another remains in severe pain on the same dose, or conversely experiences profound respiratory depression [13].

The genes most consistently implicated include those encoding cytochrome P450 enzymes, particularly CYP2D6, which governs the bioactivation of codeine and tramadol into their active metabolites; variation here produces the well-described spectrum from poor metabolizers who get little analgesic benefit to ultrarapid metabolizers who are at risk of toxicity from the same nominal dose [14]. The OPRM1 gene, encoding the mu-opioid receptor, and COMT, involved in catecholamine and pain-signaling pathways, have similarly been linked to differences in opioid requirement and pain sensitivity across large observational cohorts [15]. A recent synthesis of this literature framed pharmacogenetic opioid dosing as one of the more actionable near-term applications of precision medicine in anesthesia, in part because clinical genotyping panels covering the relevant variants are now commercially available and increasingly affordable, even though prospective trials demonstrating outcome benefit from genotype-guided dosing protocols remain comparatively sparse [16].

A recent textbook chapter on pharmacogenomics in anesthesia framed genotype-informed dosing as most defensible for drugs with a narrow therapeutic window and well-characterized metabolic pathway, opioids and neuromuscular blockers chief among them, while cautioning that evidence for volatile-agent and propofol dosing remains comparatively preliminary [17]. Beyond opioids, pharmacogenomic variation affects other core anesthetic agents. Butyrylcholinesterase deficiency alters the duration of succinylcholine-induced paralysis; variants in genes governing propofol and volatile anesthetic pharmacodynamics have been proposed as partial explanations for the wide clinical range in anesthetic requirement that experienced clinicians already intuit but cannot yet quantify at the bedside [18,19]. Pediatric anesthesia in particular has drawn attention to this gap, since children display even greater pharmacokinetic and pharmacodynamic variability than adults and cannot always report pain or sedation depth reliably, making genotype-informed planning an appealing complement to purely weight-based dosing in this population [20].

CLOSED-LOOP SYSTEMS AND REAL-TIME DECISION SUPPORT

Prediction alone changes little if it does not translate into action at the point of care, and a parallel line of engineering work has focused on closing that loop — using continuous physiologic monitoring to drive automated or semi-automated adjustment of anesthetic delivery. Closed-loop target-controlled infusion of propofol, guided by processed EEG indices such as the bispectral index, was one of the earliest demonstrations that an algorithm could titrate anesthetic depth as well as or better than a human clinician working from the same monitor, maintaining tighter control around a target depth of anesthesia and reducing both overdose and underdose excursions [21]. A subsequent systematic review and meta-analysis of randomized trials comparing closed-loop to manually controlled propofol infusion confirmed improved control of depth of anesthesia, along with more consistent hemodynamic parameters, across a range of surgical settings [22].

More recent closed-loop platforms have expanded beyond hypnotic depth alone to incorporate multiple drug classes and physiologic targets simultaneously, including automated vasopressor titration to a mean arterial pressure target and coordinated control of analgesia alongside hypnosis [23]. These systems represent a natural extension of the predictive models

discussed above: a system that can forecast an impending hypotensive event is far more valuable if it is coupled to a delivery mechanism that can pre-emptively adjust vasopressor or fluid administration rather than simply alerting a clinician who may be occupied elsewhere in the room. Explainability has emerged as a recurring concern as these systems move toward deployment; reviews have argued that anesthesiologists are reasonably reluctant to cede titration decisions to algorithms whose internal logic cannot be inspected, and have called for interpretable model architectures or post-hoc explanation methods that let clinicians understand why a given recommendation was made rather than treating the model as an unaccountable black box [24].

BARRIERS TO CLINICAL TRANSLATION

Despite genuine methodological progress, the gap between a well-performing model in a retrospective validation cohort and a tool that changes practice at the bedside remains wide. A recent scoping review of artificial intelligence for perioperative anesthetic complication prediction catalogued dozens of published models but found that the large majority had never been prospectively validated, let alone tested in a randomized fashion against usual clinical decision-making, and that external validation across institutions — essential given how much local case mix, equipment, and practice patterns vary — was the exception rather than the rule [25]. Models trained on a single academic center's population and monitoring equipment can perform poorly when transplanted to a community hospital with a different patient demographic and different intraoperative documentation habits, a form of dataset shift that is well recognized in the broader medical-AI literature but is only beginning to be systematically addressed in anesthesia-specific work.

Workflow integration is a related and underappreciated obstacle. A model that requires a clinician to manually enter data into a separate interface, rather than drawing automatically from the anesthesia information management system already running in the room, is unlikely to be used consistently regardless of its underlying accuracy. A recent commentary on translating AI prediction into anesthesia practice argued that the technical performance of a model is now, in many cases, less of a bottleneck than the human-factors and systems-integration work needed to put a prediction in front of the right person at the right moment in a format they will actually act on [26]. Reimbursement, medicolegal liability for algorithm-informed decisions, and the practical question of who is responsible when a model's recommendation and a clinician's judgment diverge are all still largely unresolved, and will need institutional and regulatory attention independent of further gains in model accuracy.

Pharmacogenomic approaches face a related but distinct set of barriers. Genotyping turnaround time has historically exceeded the timeline of same-day or urgent surgery, though pre-emptive panel genotyping — performed once and stored in the record for future use, analogous to blood type — has been proposed as a workaround. Cost-effectiveness data specific to perioperative genotype-guided dosing remain limited, and professional societies have been cautious about recommending routine preoperative pharmacogenomic testing outside of patients with a specific history suggesting atypical drug response, such as a prior anesthetic awareness event or unexplained opioid treatment failure.

CONCLUSION

Personalized anesthetic planning is no longer a purely aspirational phrase; it describes a set of tools — preoperative risk models, intraoperative event predictors, pharmacogenomic panels, and closed-loop delivery systems — that are already deployed in some centers and under active study in many more. The strongest evidence currently sits with narrowly scoped intraoperative predictions, such as post-induction hypotension, and with closed-loop control of anesthetic depth, both of which have a relatively short and well-characterized causal pathway from input data to outcome. Broader complication-prediction models and pharmacogenomic dosing protocols are conceptually promising and increasingly well supported by observational data, but still await the prospective, multicenter validation that would justify routine use. For the practicing anesthesiologist, the near-term value of this literature is less about ceding judgment to an algorithm and more about having a better-calibrated second opinion — one built from a much larger dataset than any individual clinician could hold in memory — available at the moments in a case when that extra signal matters most.

DECLARATIONS

Acknowledgements

The authors thank their respective departments for the time and resources that supported the preparation of this review.

Funding

This review received no external funding from public, commercial, or not-for-profit funding agencies.

Conflict of Interest

The authors declare that they have no conflicts of interest relevant to the content of this review.

Author Contributions

Lukas Peeters conceived the review and drafted the initial manuscript. Joao Andersson performed the literature search and contributed the sections on pharmacogenomics and closed-loop systems. Rui Zielinska contributed the sections on machine-learning

risk prediction and clinical translation, and all authors critically revised the manuscript and approved the final version.

Ethics Statement

This is a literature review that did not involve new human or animal research; no ethics committee approval was required.

Data Availability

No new data were generated for this review. All sources discussed are publicly available published articles cited in the reference list.

REFERENCES

1. Enabling personalized perioperative risk prediction by using a machine-learning model based on preoperative data (2023) Scientific Reports, DOI:10.1038/s41598-023-33981-8.
2. Use of Machine Learning to Develop and Evaluate Models Using Preoperative and Intraoperative Data to Identify Risks of Postoperative Complications (2020) JAMA Network Open.
3. Applications of Artificial Intelligence and Machine Learning in Cardiac Anesthesia Across the Continuum of Perioperative Care (2024) Academic Medicine & Surgery.
4. Machine learning: implications and applications for ambulatory anesthesia (2024) Current Opinion in Anaesthesiology.
5. Artificial Intelligence Driven Innovation in Anesthesia for Personalized Perioperative Care (2024) medtigo Journal.
6. Prediction of Postinduction Hypotension by Machine Learning (2023) Erasmus University Rotterdam publication.
7. Post Induction Hypotension prediction during general anesthesia using machine learning (2025) medRxiv preprint.
8. Machine learning for infection risk prediction in postoperative patients with non-mechanical ventilation and intravenous neurotargeted drugs (2022) PMC, PMID:35855872.
9. Intelligent algorithm based on deep learning to predict the dosage for anesthesia: A study on prediction of drug efficacy based on deep learning (2024) PMC, PMID:38774280.
10. Artificial intelligence in predicting anesthetic complications: current techniques, clinical applications, and limitations (2025) PMID:42248065.
11. Machine learning applications in perioperative medicine review (2023) Journal of Clinical Medicine.
12. Precision anesthesia and perioperative care review (2024) Current Anesthesiology Reports, DOI:10.1007/s40140-024-00674-5.
13. Pharmacogenomics and anaesthesia: explaining the variability in response to opiates (2007) PMID:17378023.
14. The Role of Pharmacogenomics in Anesthesia Pharmacology (2016) PMID:27935783.
15. Genetics of perioperative pain management (2019) PMC, PMID:31572027.
16. Reviewing pharmacogenetics to advance precision medicine for opioids (2021) Neuropharmacology.
17. Pharmacogenomics in Anesthesia (2024) Springer Nature, Book Chapter.
18. Pharmacogenomics in Anesthesia: Tailoring Anesthetic Agents to Genetic Variations (2023) Auctores.
19. Pharmacogenomics and Personalized Medicine review (2012) Pharmacogenomics and Personalized Medicine.
20. Personalized pediatric anesthesia and pain management: problem-based review (2024) ScholarWorks IUPUI.
21. Closed-loop Control of Anesthesia Using Bispectral Index (2002) Anesthesiology.
22. Bispectral index monitoring of the clinical effects of propofol closed-loop target-controlled infusion: Systematic review and meta-analysis of randomized controlled trials (2021) Medicine (Baltimore).
23. Closed-Loop Anesthesia: Advances in Automated Drug Delivery and Perioperative Monitoring (2025) PMC.
24. Explainable artificial intelligence in anesthesiology prediction models: bridging the gap from black-box algorithms to clinical decision support (2026) Frontiers in Medicine.
25. Artificial intelligence for predicting perioperative anaesthetic complications and supporting clinical decision-making: a scoping review (2025) PMID:42622976.
26. From prediction to practice: closing the translation gap in artificial intelligence for anesthesia (2025) PMC.