

Editorial

Advancing Perioperative Medicine With AI: Current Landscape and Research Priorities

Nidhi Rohatgi¹, MS, MD; Piyush Mathur², MD

¹Department of Medicine, Stanford University, Palo Alto, CA, United States

²Department of Anesthesiology, Cleveland Clinic, Cleveland Clinic Lerner College of Medicine, Cleveland, OH, United States

Corresponding Author:

Nidhi Rohatgi, MS, MD
Department of Medicine
Stanford University
300 Pasteur Drive
Palo Alto, CA 94304
United States
Phone: 1 6507234000
Email: nrohatgi@stanford.edu

Abstract

AI is increasingly being applied across the perioperative continuum. AI should be viewed as a technology that can reduce cognitive burden, collate fragmented data into clinically meaningful information, support decision-making, and extend precision education to clinicians and patients. This editorial accompanies the *JMIR Perioperative Medicine* webinar held in May 2026 and presents our perspectives—formed by our clinical experience—on where AI can assist perioperative clinicians and surgical patients, the evidence available today, what is still needed, and how clinicians can prepare to practice alongside AI tools. We consider opportunities in preoperative risk assessment and optimization; intraoperative intelligent decision support; emerging technologies, such as surgical digital twins; and postoperative recovery, monitoring, and prediction of clinical deterioration. Most AI applications remain early and require large-scale, prospective validation across diverse populations and resource settings. Realizing their potential also requires confronting substantial challenges, including limited and fragmented training data, the specialized models needed to interpret the large volumes of data captured in operative videos and during physiological monitoring, biases embedded in data and algorithms or biases inherent in human-AI interactions, and the determination of where human oversight is essential and where it is not feasible. When used responsibly, with human judgment remaining paramount, AI offers an unprecedented opportunity to advance perioperative care.

JMIR Perioper Med 2026;9:e107155; doi: [10.2196/107155](https://doi.org/10.2196/107155)

Keywords: artificial intelligence; perioperative medicine; risk prediction; machine learning; clinical decision support

Introduction

AI is becoming a defining technology in health care. AI can reduce cognitive burden, improve efficiency, enhance learning, and enable clinicians to devote time and attention to the uniquely human aspects of care and the contexts where human judgment is indispensable.

The perioperative continuum begins days or months prior to surgery and extends through the intraoperative course, recovery, and rehabilitation, with focus shifting to follow-up beyond the traditional 30 or 90 days after surgery. AI is evolving from a collection of task-specific algorithms to a longitudinal intelligence system that can support care delivery and decision-making across the perioperative continuum.

This evolution was reflected throughout the *JMIR Perioperative Medicine* webinar, “Advancing Perioperative Care with Artificial Intelligence,” held in May 2026, which emphasized a practical perspective grounded in the real-world implementation of AI [1]. This accompanying editorial—written for perioperative researchers and clinicians—discusses our perspectives on where AI can assist or augment perioperative clinicians and surgical patients, what is the evidence we have, what is still needed, and how perioperative clinicians can prepare to practice with AI. Across the preoperative, intraoperative, and postoperative phases, the recurring messages are that the nearest-term value of AI lies in synthesizing fragmented data and not in autonomous decision-making, most applications await prospective

validation in diverse real-world settings, and human judgment remains paramount.

Preoperative Opportunities

Contemporary preoperative risk assessment involves history-taking focused on multiorgan system assessment, the review of records within and outside the electronic health record (EHR), outreach to the patient's ambulatory clinicians and caregivers, medication management, and appropriate consultations. These data are then integrated with the surgical complexity; the indication for surgery; the patient's goals, expectations, and functional, nutritional, psychosocial, and cognitive status; preoperative risk indices; pharmacogenomic data; current evidence; and the clinician's judgment, to formulate individualized plans for preoperative optimization and intra- and postoperative management. When conducted thoroughly and in partnership with the patient, their caregivers, and the clinicians involved in their longitudinal care, preoperative evaluation offers an unmatched opportunity to prevent postoperative complications [2]. However, it is time-consuming and requires nuanced expertise.

Information Synthesis From the EHR

AI's key value in preoperative assessment is in collating data across multiple fragmented data streams and synthesizing them into meaningful information [3]. AI can retrieve relevant clinical practice guidelines to suggest targeted tests and interventions and compute risk scores. Conversational AI agents are an emerging opportunity for history-taking, although in one study, patients provided fewer details to AI agents than to humans [4]. Ambient intelligence has reduced the cognitive burden during documentation, although time savings, the quality of AI-scribed notes, and adoption vary considerably [5-9]. In a randomized crossover trial, the Perioperative AI Chatbot (PEACH) did not reduce the overall documentation time for resident physicians, but time savings were noted for moderate-complexity patients and for more experienced physicians [9]. With AI, clinicians' effort can shift from information retrieval, documentation, and administrative tasks toward shared decision-making and reasoning.

Multimodal Risk Prediction

Importantly, only a fraction of a patient's trajectory is captured in the EHR. Most physiological variation occurs outside clinics and hospitals. Often, patients themselves possess the richest source of health information. Wearables, patient-reported outcomes, and mobile health apps can incorporate data generated during everyday life rather than data generated exclusively during episodes of illness [10]. This transition from episodic "sick care" toward continuous health monitoring may reshape preoperative optimization and long-term outcomes.

AI applied to wearable accelerometry data may be able to predict frailty, which is central to preoperative risk

stratification [11]. The AI-assisted identification of sarcopenia from routine computed tomography and AI-assisted coronary calcium estimates could also enhance preoperative risk assessment [12-14]. Beyond the perioperative episode, AI-assisted retinal scans can predict the long-term risk of major adverse cardiovascular events [15]. In a primary care setting, an AI-enabled stethoscope improved the detection of heart failure, valvular heart disease, and atrial fibrillation (all are important perioperative diagnoses), although adoption declined over time without workflow integration [16]. Further, AI-guided echocardiograms are showing promise in improving access to patients by improving the efficiency and effectiveness of trained sonographers and providing real-time guidance to novice sonographers [17,18].

Electrocardiograms (ECGs) are often obtained preoperatively. In a retrospective cohort, deep learning applied to preoperative ECGs discriminated postoperative mortality with an area under the curve (AUC) of 0.83, whereas the AUC for the Revised Cardiac Risk Index was 0.67 [19]. In the nonsurgical setting, the self-supervised interpretation of ECGs across 77 cardiac conditions achieved AUCs of 0.98-0.99 [20]. Another AI-ECG model achieved AUCs of 0.90-0.91 for detecting right ventricular and low left ventricular systolic dysfunction [21]. AI-interpreted ECGs and AI-assisted focused ultrasound could potentially reduce unnecessary preoperative echocardiograms [22]. Whether acting on AI-interpreted ECG findings improves clinically meaningful outcomes or cascades low-yield evaluation (eg, echocardiograms and cardiology consultations) requires prospective validation across institutions with varying disease prevalence and surgical risk profiles [23].

Evaluation of AI-Based Risk Predictions

Predictive analytics is a common application of AI in perioperative medicine, although a systematic review of 103 predictive analytics machine learning (ML) tools reported that 75% of them were validated at a single center, only 13% were externally validated, and the PROBAST (Prediction Model Risk of Bias Assessment Tool) assessment showed a high risk of bias [24]. Preoperative risk indices have largely utilized structured data and regression techniques, including the American College of Surgeons' surgical risk calculator, which was later enhanced by using ML [25]. The performance of these risk indices has been variable and often moderate across different surgeries and populations. Some institutions have developed their own perioperative risk algorithms by using ML, such as MySurgeryRisk, which predicts 8 major postoperative complications and mortality by using automated EHR input [26,27]. That said, risk prediction alone can be insufficient. In the Perioperative Outcome Risk Assessment with Computer Learning Enhancement (Perioperative ORACLE) randomized trial, access to perioperative ML prediction models did not improve clinician performance, as clinicians anchored to their own predictions [28]. Additionally, effective perioperative care requires actionable pathways and infrastructure for the optimization of those at risk.

Intraoperative Opportunities

AI is being explored to predict surgical case duration and cancellation and forecast surgical volumes for staffing [29]. Intraoperative care generates enormous volumes of data from hemodynamic monitoring, neuromonitoring, ventilators, closed-loop drug delivery systems, and operating room black boxes implemented at some institutions. Yet, capturing and extracting these data in a form usable for training AI can be challenging or expensive, or they can be beyond the context limits of general-purpose foundation models.

The operating room is a high-risk environment, and AI remains in the early phases of exploration. In the operating room, human-in-the-loop is particularly challenging when precious minutes must be spent on intervention rather than on assessing the accuracy, assumptions, or confidence of AI output. The interface of AI output therefore deserves special consideration, alongside sharing with the surgeon or anesthesiologist what data and evidence were used to train the models.

Intraoperative Risk Prediction

For anesthesiologists, real-time, AI-driven decision support and monitoring can reduce intraoperative cognitive burden [30]. The Hypotension Prediction Index—an ML algorithm applied to arterial waveform analysis—can warn about impending hypotension a few minutes before the event, allowing for preemptive intervention, but the benefit for patient outcomes is yet to be established [31].

Intraoperative Intelligence and Precision Education

AI is emerging to assist with medication safety checks in the operating room, provide ultrasound guidance during regional blocks, and anticipate transfusion needs [32–34]. Surgery is being reshaped by robotics and AI-augmented tumor detection [35–38]. Computer vision can analyze operative videos to teach technical skills, deliver feedback, and improve ergonomics [39–41]. Further, specialized surgical video language models can review hours of footage, extending precision education and performance insights beyond what the manual review of surgical videos ever allowed [42].

Simulation With Digital Twins

Another emerging frontier is the surgical digital twin that can be a virtual replica of the patient, their physiology, or the operating room itself [43,44]. Such digital twins are being explored for surgical planning, training, and real-time guidance with patient-specific anatomy. With digital twins, in silico trials can optimize processes and surface failure modes in a virtual, risk-free, and cost-effective environment. The central challenge is data that may be protected (eg, EHR and imaging data) or data that are never captured because of a lack of sensors, haptics, optical tracking, videos, or extended

reality. These models also demand significant computational power.

Postoperative Opportunities

Preoperative assessment remains critical for anticipating, preventing, and managing postoperative complications. The risk of short- and longer-term adverse postoperative outcomes concentrates among patients with the highest burden of chronic conditions or geriatric syndromes [45,46]. Among older adults undergoing major elective noncardiac surgery, 1 in 5 patients may sustain significant new disability or die by 1 year after surgery [45].

AI-Based Postoperative Monitoring

Several ML-based early warning systems have been prospectively validated and integrated into clinical workflows [47,48]. For example, the Targeted Real-Time Early Warning System (TREWS) system for the prediction of sepsis across 590,000 medical and surgical inpatients was associated with a 5.1% adjusted absolute reduction in the in-hospital mortality rate if TREWS alerts were confirmed within 3 hours by a clinician [47]. Extending these models specifically to postoperative patients, in whom altered physiology and certain laboratory abnormalities are a normal and expected part of recovery, is an opportunity. Tachycardia, hypoxia, anemia, and leukocytosis carry a different differential diagnosis for a postoperative patient compared to that for a medical patient, and they often reflect a combination of surgery-specific and medical factors. ML-based prediction models have also been developed to predict postoperative acute kidney injury [49].

Because postoperative patients carry particular risks from their underlying disease, the procedure, and the combination of opioids and residual anesthesia, intermittent (and sometimes inaccurate) vital sign measurements in general wards are especially likely to miss deterioration. Continuous monitoring detects far more postoperative deterioration than intermittent checks, including opioid-induced respiratory depression, hypotension, and hypoxemia, and deep learning could be applied to these continuous monitoring—provided data [50,51]. Whether earlier detection reduces complications, unplanned intensive care utilization, or death is unestablished.

Informed Patients

AI can help educate patients in their preferred language, format, and health literacy level, potentially reducing surgical cancellations and improving patient experiences and outcomes. After surgery, recovering patients must navigate complicated instructions, manage multiple conditions, follow up with several specialties, and sometimes recover at rehabilitation facilities. AI can improve discharge education and extract meaningful information from remote monitoring. AI is being explored to generate discharge summaries and draft responses to patient messages [52–54]. Additionally, conversational AI agents are being explored to provide

discharge education. In a randomized trial of 261 orthopedic surgery patients, a context-specific AI agent deployed through a mobile app showed promise in improving postoperative functional recovery and patient experiences in the first few months after orthopedic surgery, when compared with physician-only communication [55].

Postdischarge Management

More than half of 30-day postoperative complications occur after discharge, which is when patients are least monitored and have the least resources [56]. The postoperative phase requires functional, nutritional, and cognitive rehabilitation; wound management; and pain management. AI is being explored to detect surgical site infections in patient-submitted images [57]. By incorporating the patient's unique medical, psychosocial, and genomic profile, alongside patient-reported feedback, AI could potentially identify those at high risk of uncontrolled postoperative pain or persistent opioid use and personalize opioid tapering and nonopioid analgesic management plans [58-62].

AI is showing promise in predicting readmission and acute care utilization by incorporating unstructured EHR data and social determinants of health, going beyond traditional structured data [63-65]. However, challenges with data fragmentation resulting from a lack of EHR interoperability

across the different hospitals, clinics, and rehabilitation facilities where surgical patients may receive care, or those resulting from a lack of digitized records, remain unsolved.

Conclusion

AI presents an unprecedented opportunity to advance perioperative care. Most perioperative AI applications remain in the early phases of research and development. Rigorous, large-scale, prospective validation in real-world environments and across diverse populations, geographic regions, and resource settings is still needed. Despite the promise of AI in augmenting perioperative care, human vigilance, situational awareness, and judgment remain paramount. Perioperative clinicians should engage with AI; understand its fundamentals; use it as a thought partner; and, when feasible, engage in the evaluation and validation of AI. Clinicians should continue to hone their clinical skills, as discordance between clinical judgment and a confident AI output will demand even greater expertise. As AI assumes more cognitive and procedural tasks, the loss of some skills is inevitable, as is the acquisition of new competencies. The priorities are to maintain proficiency in the skills critical for patient safety and to remain capable of practicing effectively across settings with varying levels of AI adoption.

Acknowledgments

We are grateful to Ms Andrea Schaffeler (managing editor), Ms Liana Ramos (marketing associate), and Ms Isabella Hernandez (social media and content development specialist) at *JMIR Perioperative Medicine* for their assistance in organizing the webinar.

Generative AI Use

Claude Opus 4.8 and Claude Sonnet 4.6 (Anthropic) were used to rephrase a few sentences for clarity, brevity, or grammar. All content was reviewed and verified by the authors.

Funding

The authors declare that no financial support was received for this work.

Conflicts of Interest

NR is the editor-in-chief of *JMIR Perioperative Medicine* at the time of this publication. NR had no involvement in the editorial review and processing of this manuscript. She holds courtesy appointments in the departments of neurosurgery, anesthesiology, pain, and perioperative medicine at Stanford University School of Medicine and is an affiliate faculty at the Center for Artificial Intelligence in Medicine and Imaging (AIMI), Center for Digital Health, and Institute for Human-Centered Artificial Intelligence (HAI) at Stanford University. PM is a cofounder at BrainX, LLC, and was the invited guest at the *JMIR Perioperative Medicine* webinar in May 2026.

References

1. Advancing perioperative care with artificial intelligence. JMIR Publications YouTube page. Jun 4, 2026. URL: https://www.youtube.com/watch?v=AjjWR1_QuRY [Accessed 2026-10-14]
2. Rohatgi N. Perioperative risk calculators and the art of medicine. *JAMA Intern Med.* Dec 1, 2019;179(12):1619-1620. [doi: [10.1001/jamainternmed.2019.4914](https://doi.org/10.1001/jamainternmed.2019.4914)] [Medline: [31633737](https://pubmed.ncbi.nlm.nih.gov/31633737/)]
3. Van Veen D, Van Uden C, Blankemeier L, et al. Adapted large language models can outperform medical experts in clinical text summarization. *Nat Med.* Apr 2024;30(4):1134-1142. [doi: [10.1038/s41591-024-02855-5](https://doi.org/10.1038/s41591-024-02855-5)] [Medline: [38413730](https://pubmed.ncbi.nlm.nih.gov/38413730/)]
4. Reis M, Reis F, Kim YJ, et al. Reduced symptom reporting quality during human-chatbot versus human-physician interactions. *Nat Health.* May 1, 2026;1:1055-1058. [doi: [10.1038/s44360-026-00116-y](https://doi.org/10.1038/s44360-026-00116-y)]

5. Lukac PJ, Turner W, Vangala S, et al. Ambient AI scribes in clinical practice: a randomized trial. *NEJM AI*. Dec 2025;2(12). [doi: [10.1056/aioa2501000](https://doi.org/10.1056/aioa2501000)] [Medline: [41497288](#)]
6. Holmgren AJ, Fenton CL, Thombley R, et al. Ambient artificial intelligence scribes and physician financial productivity. *JAMA Netw Open*. Jan 2, 2026;9(1):e2553233. [doi: [10.1001/jamanetworkopen.2025.53233](https://doi.org/10.1001/jamanetworkopen.2025.53233)] [Medline: [41511775](#)]
7. Afshar M, Baumann MR, Resnik F, et al. A pragmatic randomized controlled trial of ambient artificial intelligence to improve health practitioner well-being. *NEJM AI*. Dec 2025;2(12). [doi: [10.1056/aioa2500945](https://doi.org/10.1056/aioa2500945)] [Medline: [41625485](#)]
8. Reddy A, Gunnink E, Wheat CL, et al. Rapid evaluation of artificial intelligence technology used for ambient dictation in primary care: comparing the quality of documentation of artificial intelligence-generated and human-produced clinical notes. *Ann Intern Med*. Jun 2026;179(6):765-772. [doi: [10.7326/ANNALS-25-02772](https://doi.org/10.7326/ANNALS-25-02772)] [Medline: [41996184](#)]
9. Ke YH, Yang Ong BS, Jin L, et al. Clinical and economic impact of a large language model in perioperative medicine: a randomized crossover trial. *NPJ Digit Med*. Jul 21, 2025;8(1):462. [doi: [10.1038/s41746-025-01858-x](https://doi.org/10.1038/s41746-025-01858-x)] [Medline: [40691284](#)]
10. Tan JM, Cannesson M, Feldman JM, et al. Emerging technology and the future of perioperative care: perspectives and recommendations from the 2023 Stoelting Conference of the Anesthesia Patient Safety Foundation. *Anesth Analg*. Jul 1, 2025;141(1):139-151. [doi: [10.1213/ANE.0000000000007540](https://doi.org/10.1213/ANE.0000000000007540)] [Medline: [40333433](#)]
11. Culos A, Manas A, Shidara K, et al. A machine learning model for frailty based on wearable device measurements. *Commun Med (Lond)*. Feb 19, 2026;6(1):173. [doi: [10.1038/s43856-026-01419-7](https://doi.org/10.1038/s43856-026-01419-7)] [Medline: [41714788](#)]
12. Sudarsanam A, Davies AH, Rockall A, Sekhon H, Salim S. A fully automated sarcopenia segmentation tool using artificial intelligence can reliably assist in preoperative evaluation of patients undergoing major vascular surgery. *J Vasc Surg*. Jun 2024;79(6):e235-e236. [doi: [10.1016/j.jvs.2024.03.303](https://doi.org/10.1016/j.jvs.2024.03.303)]
13. Naghavi M, Reeves AP, Atlas K, et al. Artificial intelligence applied to coronary artery calcium scans (AI-CAC) significantly improves cardiovascular events prediction. *NPJ Digit Med*. Nov 5, 2024;7(1):309. [doi: [10.1038/s41746-024-01308-0](https://doi.org/10.1038/s41746-024-01308-0)] [Medline: [39501071](#)]
14. Choi DY, Hayes D, Maidman SD, et al. Existing Nongated CT Coronary Calcium Predicts Operative Risk in Patients Undergoing Noncardiac Surgeries (ENCORES). *Circulation*. Oct 10, 2023;148(15):1154-1164. [doi: [10.1161/CIRCULATIONAHA.123.064398](https://doi.org/10.1161/CIRCULATIONAHA.123.064398)] [Medline: [37732454](#)]
15. Poplin R, Varadarajan AV, Blumer K, et al. Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nat Biomed Eng*. Mar 2018;2(3):158-164. [doi: [10.1038/s41551-018-0195-0](https://doi.org/10.1038/s41551-018-0195-0)] [Medline: [31015713](#)]
16. Kelshiker MA, Bächtiger P, Petri CF, et al. Triple cardiovascular disease detection with an artificial intelligence-enabled stethoscope (TRICORDER) in the UK: a cluster-randomised controlled implementation trial. *Lancet*. Feb 14, 2026;407(10529):704-715. [doi: [10.1016/S0140-6736\(25\)02156-7](https://doi.org/10.1016/S0140-6736(25)02156-7)] [Medline: [41619752](#)]
17. Narang A, Bae R, Hong H, et al. Utility of a deep-learning algorithm to guide novices to acquire echocardiograms for limited diagnostic use. *JAMA Cardiol*. Jun 1, 2021;6(6):624-632. [doi: [10.1001/jamacardio.2021.0185](https://doi.org/10.1001/jamacardio.2021.0185)] [Medline: [33599681](#)]
18. Sakamoto A, Kagiya N, Sato E, et al. Artificial intelligence-based automated echocardiographic analysis and the workflow of sonographers: a randomized crossover trial (AI-Echo RCT). *J Am Heart Assoc*. Jan 6, 2026;15(1):e045637. [doi: [10.1161/JAHA.125.045637](https://doi.org/10.1161/JAHA.125.045637)] [Medline: [41404733](#)]
19. Ouyang D, Theurer J, Stein NR, et al. Electrocardiographic deep learning for predicting post-procedural mortality: a model development and validation study. *Lancet Digit Health*. Jan 2024;6(1):e70-e78. [doi: [10.1016/S2589-7500\(23\)00220-0](https://doi.org/10.1016/S2589-7500(23)00220-0)] [Medline: [38065778](#)]
20. Nolin-Lapalme A, Sowa A, Delfrate J, et al. Foundation models for electrocardiogram interpretation: clinical implications. *Eur Heart J*. May 15, 2026;47(18):2174-2186. [doi: [10.1093/eurheartj/ehaf1119](https://doi.org/10.1093/eurheartj/ehaf1119)] [Medline: [41568699](#)]
21. Poterucha TJ, Jing L, Ricart RP, et al. Detecting structural heart disease from electrocardiograms using AI. *Nature*. Aug 2025;644(8075):221-230. [doi: [10.1038/s41586-025-09227-0](https://doi.org/10.1038/s41586-025-09227-0)] [Medline: [40670798](#)]
22. Cohen I, Lakritz A, Maor E. AI assisted focused cardiac ultrasound in preventive cardiology - a perspective. *NPJ Cardiovasc Health*. Jun 26, 2025;2(1):27. [doi: [10.1038/s44325-025-00063-9](https://doi.org/10.1038/s44325-025-00063-9)] [Medline: [41776021](#)]
23. Show us the evidence for the value of medical AI. *Nat Med*. Apr 2026;32(4):1163. [doi: [10.1038/s41591-026-04389-4](https://doi.org/10.1038/s41591-026-04389-4)] [Medline: [42014883](#)]
24. Arina P, Kaczorek MR, Hofmaenner DA, et al. Prediction of complications and prognostication in perioperative medicine: a systematic review and PROBAST assessment of machine learning tools. *Anesthesiology*. Jan 1, 2024;140(1):85-101. [doi: [10.1097/ALN.0000000000004764](https://doi.org/10.1097/ALN.0000000000004764)] [Medline: [37944114](#)]
25. Liu Y, Ko CY, Hall BL, Cohen ME. American College of Surgeons NSQIP risk calculator accuracy using a machine learning algorithm compared with regression. *J Am Coll Surg*. May 1, 2023;236(5):1024-1030. [doi: [10.1097/XCS.0000000000000556](https://doi.org/10.1097/XCS.0000000000000556)] [Medline: [36728295](#)]

26. Ren Y, Loftus TJ, Datta S, et al. Performance of a machine learning algorithm using electronic health record data to predict postoperative complications and report on a mobile platform. *JAMA Netw Open*. May 2, 2022;5(5):e2211973. [doi: [10.1001/jamanetworkopen.2022.11973](https://doi.org/10.1001/jamanetworkopen.2022.11973)] [Medline: [35576007](https://pubmed.ncbi.nlm.nih.gov/35576007/)]
27. Mahajan A, Esper S, Oo TH, et al. Development and validation of a machine learning model to identify patients before surgery at high risk for postoperative adverse events. *JAMA Netw Open*. Jul 3, 2023;6(7):e2322285. [doi: [10.1001/jamanetworkopen.2023.22285](https://doi.org/10.1001/jamanetworkopen.2023.22285)] [Medline: [37418262](https://pubmed.ncbi.nlm.nih.gov/37418262/)]
28. Fritz BA, King CR, Abdelhack M, et al. Effect of machine learning models on clinician prediction of postoperative complications: the Perioperative ORACLE randomised clinical trial. *Br J Anaesth*. Nov 2024;133(5):1042-1050. [doi: [10.1016/j.bja.2024.08.004](https://doi.org/10.1016/j.bja.2024.08.004)] [Medline: [39261226](https://pubmed.ncbi.nlm.nih.gov/39261226/)]
29. Bellini V, Russo M, Domenichetti T, Panizzi M, Allai S, Bignami EG. Artificial intelligence in operating room management. *J Med Syst*. Feb 14, 2024;48(1):19. [doi: [10.1007/s10916-024-02038-2](https://doi.org/10.1007/s10916-024-02038-2)] [Medline: [38353755](https://pubmed.ncbi.nlm.nih.gov/38353755/)]
30. El-Sonbaty AI. Development and validation of an integrated artificial intelligence-powered clinical decision support application for cardiac critical care: combining coagulation management, blood gas analysis, mechanical ventilation, hemodynamic assessment, and extracorporeal membrane oxygenation. *J Cardiothorac Vasc Anesth*. Sep 2026;40(9):3019-3028. [doi: [10.1053/j.jvca.2026.05.062](https://doi.org/10.1053/j.jvca.2026.05.062)] [Medline: [42409648](https://pubmed.ncbi.nlm.nih.gov/42409648/)]
31. 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*. Dec 2022;83:110981. [doi: [10.1016/j.jclinane.2022.110981](https://doi.org/10.1016/j.jclinane.2022.110981)] [Medline: [36242978](https://pubmed.ncbi.nlm.nih.gov/36242978/)]
32. Chan J, Nsumba S, Wortsman M, et al. Detecting clinical medication errors with AI enabled wearable cameras. *NPJ Digit Med*. Oct 22, 2024;7(1):287. [doi: [10.1038/s41746-024-01295-2](https://doi.org/10.1038/s41746-024-01295-2)] [Medline: [39438764](https://pubmed.ncbi.nlm.nih.gov/39438764/)]
33. Bowness JS, Macfarlane AJR, Burckett-St Laurent D, et al. Evaluation of the impact of assistive artificial intelligence on ultrasound scanning for regional anaesthesia. *Br J Anaesth*. Feb 2023;130(2):226-233. [doi: [10.1016/j.bja.2022.07.049](https://doi.org/10.1016/j.bja.2022.07.049)] [Medline: [36088136](https://pubmed.ncbi.nlm.nih.gov/36088136/)]
34. Lou SS, Kumar S, Goss CW, et al. Multicenter validation of a machine learning model for surgical transfusion risk at 45 US hospitals. *JAMA Netw Open*. Jun 2, 2025;8(6):e2517760. [doi: [10.1001/jamanetworkopen.2025.17760](https://doi.org/10.1001/jamanetworkopen.2025.17760)] [Medline: [40577014](https://pubmed.ncbi.nlm.nih.gov/40577014/)]
35. Schmidgall S, Opfermann JD, Kim JW, Krieger A. Will your next surgeon be a robot? Autonomy and AI in robotic surgery. *Sci Robot*. Jul 23, 2025;10(104):eadt0187. [doi: [10.1126/scirobotics.adt0187](https://doi.org/10.1126/scirobotics.adt0187)] [Medline: [40700524](https://pubmed.ncbi.nlm.nih.gov/40700524/)]
36. Wagner L, Jourdan S, Mayer L, et al. Robotic scrub nurse to anticipate surgical instruments based on real-time laparoscopic video analysis. *Commun Med (Lond)*. Aug 2, 2024;4(1):156. [doi: [10.1038/s43856-024-00581-0](https://doi.org/10.1038/s43856-024-00581-0)] [Medline: [39095639](https://pubmed.ncbi.nlm.nih.gov/39095639/)]
37. Lee TJ, Qiu L, Long J, et al. CystoDS: a multiclass endoscopy image dataset for artificial intelligence-assisted bladder cancer detection. *Sci Data*. Feb 26, 2026;13(1):528. [doi: [10.1038/s41597-026-06887-z](https://doi.org/10.1038/s41597-026-06887-z)] [Medline: [41741508](https://pubmed.ncbi.nlm.nih.gov/41741508/)]
38. Kondepudi A, Pekmezci M, Hou X, et al. Foundation models for fast, label-free detection of glioma infiltration. *Nature*. Jan 2025;637(8045):439-445. [doi: [10.1038/s41586-024-08169-3](https://doi.org/10.1038/s41586-024-08169-3)] [Medline: [39537921](https://pubmed.ncbi.nlm.nih.gov/39537921/)]
39. Yang JH, Goodman ED, Dawes AJ, et al. Using AI and computer vision to analyze technical proficiency in robotic surgery. *Surg Endosc*. Apr 2023;37(4):3010-3017. [doi: [10.1007/s00464-022-09781-y](https://doi.org/10.1007/s00464-022-09781-y)] [Medline: [36536082](https://pubmed.ncbi.nlm.nih.gov/36536082/)]
40. Goodman ED, Patel KK, Zhang Y, et al. Analyzing surgical technique in diverse open surgical videos with multitask machine learning. *JAMA Surg*. Feb 1, 2024;159(2):185-192. [doi: [10.1001/jamasurg.2023.6262](https://doi.org/10.1001/jamasurg.2023.6262)] [Medline: [38055227](https://pubmed.ncbi.nlm.nih.gov/38055227/)]
41. Sui E, Egeland C, Wang X, et al. Computer vision-based retrieval of steps and intraoperative adverse events in laparoscopic cholecystectomy. *NPJ Digit Surg*. Jul 6, 2026;1(1):12. [doi: [10.1038/s44484-026-00010-w](https://doi.org/10.1038/s44484-026-00010-w)]
42. Perez A, Nwoye C, Raji Kermani R, Mohareri O, Abdullah Jamal M. SurgLaVi: large-scale hierarchical dataset for surgical vision-language representation learning. *Med Image Anal*. May 2026;110:103982. [doi: [10.1016/j.media.2026.103982](https://doi.org/10.1016/j.media.2026.103982)] [Medline: [41719833](https://pubmed.ncbi.nlm.nih.gov/41719833/)]
43. Asciak L, Kyremeh J, Luo X, et al. Digital twin assisted surgery, concept, opportunities, and challenges. *NPJ Digit Med*. Jan 15, 2025;8(1):32. [doi: [10.1038/s41746-024-01413-0](https://doi.org/10.1038/s41746-024-01413-0)] [Medline: [39815013](https://pubmed.ncbi.nlm.nih.gov/39815013/)]
44. Mekki YM, Luijten G, Hagert E, et al. Digital twins for the era of personalized surgery. *NPJ Digit Med*. May 15, 2025;8(1):283. [doi: [10.1038/s41746-025-01575-5](https://doi.org/10.1038/s41746-025-01575-5)] [Medline: [40374901](https://pubmed.ncbi.nlm.nih.gov/40374901/)]
45. Wijeyesundera DN, Alibhai SMH, Puts MTE, et al. Significant new disability after major non-cardiac surgery in older adults aged 65 years and older in Canada: a multicentre prospective cohort study. *Lancet Healthy Longev*. Nov 2025;6(11):100789. [doi: [10.1016/j.lanhl.2025.100789](https://doi.org/10.1016/j.lanhl.2025.100789)] [Medline: [41317744](https://pubmed.ncbi.nlm.nih.gov/41317744/)]
46. International Surgical Outcomes Study group. Global patient outcomes after elective surgery: prospective cohort study in 27 low-, middle- and high-income countries. *Br J Anaesth*. Oct 31, 2016;117(5):601-609. [doi: [10.1093/bja/aew316](https://doi.org/10.1093/bja/aew316)] [Medline: [27799174](https://pubmed.ncbi.nlm.nih.gov/27799174/)]

47. Adams R, Henry KE, Sridharan A, et al. Prospective, multi-site study of patient outcomes after implementation of the TREWS machine learning-based early warning system for sepsis. *Nat Med*. Jul 2022;28(7):1455-1460. [doi: [10.1038/s41591-022-01894-0](https://doi.org/10.1038/s41591-022-01894-0)] [Medline: [35864252](https://pubmed.ncbi.nlm.nih.gov/35864252/)]
48. Wu L, Mai L, Wang H, et al. Artificial Intelligence-powered tiered early warning framework addressing high false alarm rates for in-hospital mortality prediction. *NPJ Digit Med*. Mar 14, 2026;9(1):346. [doi: [10.1038/s41746-026-02522-8](https://doi.org/10.1038/s41746-026-02522-8)] [Medline: [41832244](https://pubmed.ncbi.nlm.nih.gov/41832244/)]
49. Tai J, Wang L, Li Y, Chen M, Yan Z, Liu J. Transparent AI-driven personalized risk prediction system for acute kidney injury after total hip arthroplasty. *Sci Rep*. Oct 30, 2025;15(1):38023. [doi: [10.1038/s41598-025-21810-z](https://doi.org/10.1038/s41598-025-21810-z)] [Medline: [41168261](https://pubmed.ncbi.nlm.nih.gov/41168261/)]
50. Khanna AK, Flick M, Saugel B. Continuous vital sign monitoring of patients recovering from surgery on general wards: a narrative review. *Br J Anaesth*. Feb 2025;134(2):501-509. [doi: [10.1016/j.bja.2024.10.045](https://doi.org/10.1016/j.bja.2024.10.045)] [Medline: [39779421](https://pubmed.ncbi.nlm.nih.gov/39779421/)]
51. Khanna AK, Bergese SD, Jungquist CR, et al. Prediction of opioid-induced respiratory depression on inpatient wards using continuous capnography and oximetry: an international prospective, observational trial. *Anesth Analg*. Oct 2020;131(4):1012-1024. [doi: [10.1213/ANE.0000000000004788](https://doi.org/10.1213/ANE.0000000000004788)] [Medline: [32925318](https://pubmed.ncbi.nlm.nih.gov/32925318/)]
52. Grolleau F, Liang AS, Keyes T, et al. Physician-reported safety outcomes of AI-generated hospital course summaries. *JAMA Netw Open*. May 1, 2026;9(5):e2616556. [doi: [10.1001/jamanetworkopen.2026.16556](https://doi.org/10.1001/jamanetworkopen.2026.16556)] [Medline: [42101844](https://pubmed.ncbi.nlm.nih.gov/42101844/)]
53. Mandal S, Wiesenfeld BM, Szerencsy AC, et al. Utilization of generative AI-drafted responses for managing patient-provider communication. *NPJ Digit Med*. Oct 2, 2025;8(1):591. [doi: [10.1038/s41746-025-01972-w](https://doi.org/10.1038/s41746-025-01972-w)] [Medline: [41038966](https://pubmed.ncbi.nlm.nih.gov/41038966/)]
54. Garcia P, Ma SP, Shah S, et al. Artificial intelligence-generated draft replies to patient inbox messages. *JAMA Netw Open*. Mar 4, 2024;7(3):e243201. [doi: [10.1001/jamanetworkopen.2024.3201](https://doi.org/10.1001/jamanetworkopen.2024.3201)] [Medline: [38506805](https://pubmed.ncbi.nlm.nih.gov/38506805/)]
55. Li J, Zhang Y, Zhang Z, et al. A randomized controlled trial of a WeChat-based artificial intelligence agent for postoperative care in orthopedic patients. *NPJ Digit Med*. Jan 17, 2026;9(1):105. [doi: [10.1038/s41746-025-02269-8](https://doi.org/10.1038/s41746-025-02269-8)] [Medline: [41548028](https://pubmed.ncbi.nlm.nih.gov/41548028/)]
56. Li RD, Joung RHS, Chung JW, Holl J, Bilimoria KY, Merkow RP. Divergent trends in postoperative length of stay and postdischarge complications over time. *Jt Comm J Qual Patient Saf*. Sep 2024;50(9):630-637. [doi: [10.1016/j.jcjq.2024.05.006](https://doi.org/10.1016/j.jcjq.2024.05.006)] [Medline: [38853106](https://pubmed.ncbi.nlm.nih.gov/38853106/)]
57. Muaddi H, Choudhary A, Lee F, et al. Imaging-based surgical site infection detection using artificial intelligence. *Ann Surg*. Sep 1, 2025;282(3):419-428. [doi: [10.1097/SLA.0000000000006826](https://doi.org/10.1097/SLA.0000000000006826)] [Medline: [40607706](https://pubmed.ncbi.nlm.nih.gov/40607706/)]
58. Sajdeya R, Narouze S. Harnessing artificial intelligence for predicting and managing postoperative pain: a narrative literature review. *Curr Opin Anaesthesiol*. Oct 1, 2024;37(5):604-615. [doi: [10.1097/ACO.0000000000001408](https://doi.org/10.1097/ACO.0000000000001408)] [Medline: [39011674](https://pubmed.ncbi.nlm.nih.gov/39011674/)]
59. Sun EC, Darnall BD, Baker LC, Mackey S. Incidence of and risk factors for chronic opioid use among opioid-naïve patients in the postoperative period. *JAMA Intern Med*. Sep 1, 2016;176(9):1286-1293. [doi: [10.1001/jamainternmed.2016.3298](https://doi.org/10.1001/jamainternmed.2016.3298)] [Medline: [27400458](https://pubmed.ncbi.nlm.nih.gov/27400458/)]
60. Annis AC, Gunaseelan V, Smith AV, et al. Genetic associations of persistent opioid use after surgery point to OPRM1 but not other opioid-related loci as the main driver of opioid use disorder. *Genet Epidemiol*. Jan 2025;49(1):e22588. [doi: [10.1002/gepi.22588](https://doi.org/10.1002/gepi.22588)] [Medline: [39385445](https://pubmed.ncbi.nlm.nih.gov/39385445/)]
61. Bui T, Dooley MJ, Bell JS, Myles PS. New persistent opioid use after surgery and traumatic injury: a narrative review of global rates, risk factors, and healthcare interventions. *BJA Open*. Dec 1, 2025;16:100509. [doi: [10.1016/j.bjao.2025.100509](https://doi.org/10.1016/j.bjao.2025.100509)] [Medline: [41431465](https://pubmed.ncbi.nlm.nih.gov/41431465/)]
62. Burns S, Urman R, Pian R, Coppes OJM. Reducing new persistent opioid use after surgery: a review of interventions. *Curr Pain Headache Rep*. Mar 24, 2021;25(5):27. [doi: [10.1007/s11916-021-00943-6](https://doi.org/10.1007/s11916-021-00943-6)] [Medline: [33760983](https://pubmed.ncbi.nlm.nih.gov/33760983/)]
63. Jiang LY, Liu XC, Nejatian NP, et al. Health system-scale language models are all-purpose prediction engines. *Nature*. Jul 2023;619(7969):357-362. [doi: [10.1038/s41586-023-06160-y](https://doi.org/10.1038/s41586-023-06160-y)] [Medline: [37286606](https://pubmed.ncbi.nlm.nih.gov/37286606/)]
64. Ratcliffe H, Morgan J, Jacobs M, Batniji R, Basu S. An artificial intelligence oracle for proactive population health quality improvement. *NEJM Catal Innov Care Deliv*. Mar 2026;7(3):CAT250283. [doi: [10.1056/CAT.25.0283](https://doi.org/10.1056/CAT.25.0283)] [Medline: [42418607](https://pubmed.ncbi.nlm.nih.gov/42418607/)]
65. Brown Z, Bergman D, Holt L, et al. Augmenting a transitional care model with artificial intelligence decreased readmissions. *J Am Med Dir Assoc*. Jul 2023;24(7):958-963. [doi: [10.1016/j.jamda.2023.03.005](https://doi.org/10.1016/j.jamda.2023.03.005)] [Medline: [37054749](https://pubmed.ncbi.nlm.nih.gov/37054749/)]

Abbreviations

- AUC:** area under the curve
ECG: electrocardiogram
EHR: electronic health record
ML: machine learning

PEACH: Perioperative AI Chatbot

Perioperative ORACLE: Perioperative Outcome Risk Assessment with Computer Learning Enhancement

PROBAST: Prediction Model Risk of Bias Assessment Tool

TREWS: Targeted Real-Time Early Warning System

Edited by Ivan Steenstra; This is a non-peer-reviewed article; submitted 15.Jul.2026; final revised version received 30.Sep.2026; accepted 01.Oct.2026; published 30.Oct.2026

Please cite as:

Rohatgi N, Mathur P

Advancing Perioperative Medicine With AI: Current Landscape and Research Priorities

JMIR Perioper Med 2026;9:e107155

URL: <https://periop.jmir.org/2026/1/e107155>

doi: [10.2196/107155](https://doi.org/10.2196/107155)

© Nidhi Rohatgi, Piyush Mathur. Originally published in JMIR Perioperative Medicine (<http://periop.jmir.org>), 30.Oct.2026. This is an open-access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in JMIR Perioperative Medicine, is properly cited. The complete bibliographic information, a link to the original publication on <http://periop.jmir.org>, as well as this copyright and license information must be included.