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ARTIFICIAL INTELLIGENCE IN PATIENT MONITORING AND PREDICTION OF PERIOPERATIVE COMPLICATIONS

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ABSTRACT

Background: Perioperative complications, including sepsis, acute kidney injury (AKI), and hemodynamic instability, continue to be primary drivers of morbidity and mortality among surgical patients. Conventional monitoring techniques and risk stratification scores frequently lack the sensitivity required to detect early physiological deterioration, often resulting in delayed interventions. The integration of Artificial Intelligence (AI) and Machine Learning (ML) into clinical practice presents a significant opportunity to enhance patient safety through the use of predictive analytics.
Objectives: This narrative review evaluates the current landscape of AI-driven technologies in perioperative care. It specifically focuses on the capacity of these tools to predict critical complications, including hypotension, sepsis, and AKI, and assesses their potential to refine clinical decision-making relative to traditional methods.
Methods: A comprehensive review of the literature was conducted based on specific inclusion criteria. The analysis synthesizes findings from recent studies that compare ML algorithms, such as Gradient Boosting, Random Forest, and Deep Learning, as well as AI-based tools like the Hypotension Prediction Index (HPI), against standard care protocols and established risk scoring systems.
Results: AI models consistently demonstrate superior performance in predicting perioperative adverse events when compared to traditional methods. Notably, the Hypotension Prediction Index (HPI) has been shown to significantly reduce both the duration and severity of intraoperative hypotension. Furthermore, ML algorithms exhibit high accuracy in the early prediction of sepsis and acute kidney injury, frequently outperforming standard clinical scores such as SOFA or ASA physical status. Despite these successes, challenges persist regarding data heterogeneity, algorithm interpretability, and the necessity for extensive external validation.
Conclusion: Artificial intelligence represents a transformative instrument in perioperative medicine that facilitates a shift from reactive treatments to proactive patient management. Although current evidence supports the efficacy of AI in predicting complications, successful clinical implementation depends on addressing ethical concerns, enhancing model generalizability, and ensuring seamless integration into existing clinical workflows.

KEYWORDS

Artificial Intelligence, Machine Learning, Perioperative Care, Patient Monitoring, Postoperative Complications, Predictive Analytics

CITATION

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1. Introduction

Perioperative complications constitute a major burden on modern healthcare systems, significantly affecting patient morbidity, mortality, and economic costs. Major adverse events occur in a substantial proportion of surgical procedures, with sepsis, acute kidney injury (AKI), and hemodynamic instability representing some of the most critical challenges. Intraoperative hypotension (IOH), for example, affects up to 87% of patients and is strongly linked to postoperative myocardial injury, AKI, and death (Sriganesh et al., 2024). Similarly, sepsis remains a critical public health issue, accounting for approximately 20% of global deaths (Chen et al., 2025; Shanmugam et al., 2025). Despite continuous improvements in surgical techniques and perioperative care, the accurate identification of high-risk patients remains difficult.

Standard clinical practice has long relied on manual risk stratification scores, such as the American Society of Anesthesiologists (ASA) physical status classification or the Revised Cardiac Risk Index (RCRI), to evaluate patient vulnerability. Although these tools are widely used, they often exhibit limited predictive accuracy, are subject to inter-rater variability, and fail to capture the dynamic physiological changes that occur during surgery (Yoon et al., 2022; Yoon et al., 2025). Moreover, conventional monitoring systems typically operate on a reactive basis. They alert the clinician only after a specific threshold has been breached, such as a drop in mean arterial pressure (MAP) below 65 mmHg (Mohammadi et al., 2024; Sriganesh et al., 2024). This inherent delay in intervention can lead to tissue hypoperfusion and subsequent organ dysfunction (Michard et al., 2025).

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has initiated a paradigm shift in perioperative medicine, moving the focus from reactive management to predictive and proactive care (Ahmed et al., 2025). Unlike traditional statistical methods, ML algorithms are capable of processing vast amounts of complex, high-dimensional data, including vital signs, laboratory results, and raw waveform signals, to detect subtle patterns that may be invisible to the human eye (Yoon et al., 2022). Recent technological advancements have led to the development of sophisticated tools like the Hypotension Prediction Index (HPI), which utilizes arterial waveform analysis to forecast hypotensive events minutes before they manifest (Reddy et al., 2023; Rellum et al., 2025). Furthermore, ML models have demonstrated superiority over traditional scoring systems like SOFA or qSOFA in the early detection of sepsis and mortality risk prediction within critical care settings (Li et al., 2025; Shanmugam et al., 2025).

Despite these technological strides, integrating AI into routine clinical practice faces significant hurdles. These include the "black box" nature of complex algorithms, issues with data heterogeneity, and the requirement for robust validation across diverse patient populations (Gorelik et al., 2025; Elgin & Elgin, 2024). Consequently, this narrative review aims to synthesize current evidence regarding the application of AI and ML in monitoring patient status and predicting perioperative complications. We specifically evaluate the efficacy of AI-driven tools in managing hemodynamics, sepsis, and acute kidney injury compared to the standard of care, while also addressing the ethical and practical implications of their deployment.

2. AI-Driven Hemodynamic Monitoring and Prediction of Hypotension

Hemodynamic instability, and intraoperative hypotension (IOH) in particular, presents a pervasive challenge in perioperative care. While IOH is associated with severe postoperative complications, including myocardial injury, acute kidney injury (AKI), and increased mortality, traditional monitoring systems often detect these events only after they have occurred (Mohammadi et al., 2024; Sriganesh et al., 2024). Artificial intelligence offers a transformative approach by shifting the clinical focus from detection to prediction.

2.1. The Hypotension Prediction Index (HPI)

One of the most extensively studied AI applications in this domain is the Hypotension Prediction Index (HPI). Developed using machine learning techniques on high-fidelity arterial pressure waveforms, this algorithm calculates the probability of a hypotensive event, defined as mean arterial pressure [MAP] < 65 mmHg, occurring within the next 5 to 15 minutes (Hatib et al., 2018; Michard et al., 2025).

A systematic review and meta-analysis by Mohammadi et al. (2024) demonstrated that the use of HPI significantly reduces both the duration and the time-weighted average of intraoperative hypotension compared to standard care. Sriganesh et al. (2024) reported similar findings in randomized controlled trials (RCTs), where HPI monitoring was associated with a significant reduction in the total duration of hypotension (Mean Difference = -12.07 min) and the incidence of hypotensive events (Risk Ratio = 0.83). These findings suggest that HPI enables clinicians to manage hemodynamic stability proactively, potentially preventing tissue hypoperfusion before it becomes clinically significant.

However, the clinical utility of HPI remains a subject of debate. Rellum et al. (2025) compared HPI alerts against standard MAP thresholds (65–75 mmHg) and found that while HPI alerts (value ≥85) provided a high positive predictive value (55.6%), they did not offer a substantial time gain over setting a simple MAP alarm at 70–75 mmHg. Furthermore, Michard et al. (2025) highlighted the issue of the "mirror effect," noting that HPI values strongly correlate with current MAP levels. This raises questions about whether the algorithm offers unique predictive value beyond what can be inferred from standard blood pressure trends.

2.2. Beyond HPI: Deep Learning and Waveform Analysis

Beyond proprietary algorithms like HPI, deep learning (DL) models show promise in utilizing raw physiological signals for risk stratification. Yoon et al. (2022) demonstrated that DL models integrating arterial blood pressure (ABP), electrocardiogram (ECG), and electroencephalogram (EEG) waveforms outperformed models using ABP alone in predicting IOH. The combination of ABP and EEG achieved an Area Under the Receiver Operating Characteristic (AUROC) curve of 0.935 for predicting hypotension 5 minutes in advance, suggesting that markers of cerebral perfusion derived from EEG add significant value to hemodynamic prediction.

Moreover, recent studies have explored the use of non-invasive data sources. Ahmed et al. (2025) reviewed the efficacy of AI in non-invasive monitoring and noted that ML algorithms applied to photoplethysmography (PPG) and ECG signals can accurately detect coronary artery disease and predict fluid responsiveness. This supports the potential for deploying sophisticated hemodynamic monitoring outside the intensive care unit (ICU) or operating room using wearable technology.

2.3. Clinical Outcomes and Implementation Challenges

Despite the high predictive accuracy of these models, evidence regarding their impact on "hard" clinical outcomes remains mixed. While Mehta et al. (2024) confirmed that ML-driven interventions like HPI reduce physiological surrogate markers such as the duration of hypotension, they found no significant difference in postoperative complications like AKI, myocardial injury, or length of hospital stay compared to standard care. This discrepancy suggests that while AI can improve physiological parameters, translating these improvements into tangible patient benefits requires further investigation into implementation strategies and clinician compliance with algorithmic recommendations (Akbari et al., 2025; Reddy et al., 2023).

3. AI in Prediction of Sepsis, Acute Kidney Injury, and Organ-Specific Complications

While hemodynamic instability is a critical precursor to organ failure, the direct prediction of specific complications such as sepsis, acute kidney injury (AKI), and postoperative pneumonia (POP) represents another major domain of AI application. Machine learning algorithms are proving to be powerful tools for identifying high-risk patients earlier and more accurately than traditional scoring systems.

3.1. Sepsis Prediction and Mortality Risk

Sepsis remains a leading cause of perioperative mortality and is often complicated by rapid disease progression. Traditional scoring systems like SOFA (Sequential Organ Failure Assessment) or qSOFA have been criticized for low sensitivity and delayed recognition (Li et al., 2025). Recent scoping reviews highlight that ML and Deep Learning (DL) models, particularly those utilizing Electronic Health Records (EHR), consistently outperform these conventional scores in predicting sepsis onset. Shanmugam et al. (2025) reported that algorithms such as Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks achieve high Area Under the Receiver Operating Characteristic (AUROC) values, ranging from 0.83 to 0.99, which significantly improves early detection capabilities compared to standard clinical criteria.

In specific surgical contexts, such as intestinal obstruction, AI models have demonstrated high efficacy. Chen et al. (2025) developed a Support Vector Classification (SVC) model that predicted postoperative sepsis with an AUROC of 0.876. Crucially, the use of SHapley Additive exPlanations (SHAP) in this study allowed for the visualization of key risk factors, such as shock index, intraoperative fluid volume, and POSSUM physiology score, thereby addressing the "black box" issue and enhancing clinical interpretability.

Furthermore, for patients who have already developed sepsis-associated AKI (SA-AKI), ML models offer superior mortality risk stratification. Li et al. (2025) reviewed nine studies and found that ensemble methods like Random Forest and XGBoost provided robust mortality predictions (AUROC > 0.80) by identifying lactate levels, vasopressor use, and mechanical ventilation as critical predictive features.

3.2. Acute Kidney Injury (AKI) Prediction

AKI is a prevalent and devastating complication, particularly in vulnerable populations such as neonates and cardiac surgery patients. He et al. (2025) addressed the challenge of predicting AKI in neonates undergoing surgery, a group where adult criteria are often inapplicable. Their study compared six ML algorithms and found that a Logistic Regression model using eight variables, including age, operation duration, and urine output, achieved the best balance of sensitivity and specificity (AUROC 0.807), offering a practical tool for pediatric perioperative care.

In the adult population, the integration of AI into hemodynamic monitoring has been shown to reduce AKI incidence in some contexts, although results vary. While predictive models for AKI are highly accurate, establishing a causal link between AI-guided intervention and reduced AKI rates in randomized trials remains challenging (Mehta et al., 2024).

3.3. Respiratory and Cardiac Complications

Beyond sepsis and renal failure, AI is reshaping the risk assessment for respiratory and cardiac events. Xiang et al. (2024) developed interpretable ML models to predict postoperative pneumonia (POP), a frequent hospital-acquired infection. Their General Linear Model (GLM) achieved an AUROC of 0.877, identifying intraoperative factors like duration of bed rest and end-tidal CO2 as significant predictors. This enables clinicians to implement targeted preventive measures for high-risk individuals.

Regarding cardiac complications, Yoon et al. (2025) demonstrated the power of multimodal deep learning by combining structured EHR data with unstructured preoperative electrocardiogram (ECG) waveforms. Their model predicted major adverse cardiac and cerebrovascular events (MACCEs) with an AUROC of 0.902, significantly outperforming the widely used Revised Cardiac Risk Index (RCRI, AUROC 0.812). This study underscores the value of utilizing raw waveform data, which contains subtle physiological signals often missed by manual interpretation.

4. Discussion

The integration of Artificial Intelligence into perioperative care represents a double-edged sword: while it offers unprecedented predictive capabilities, its translation into routine clinical practice is fraught with ethical, technical, and systemic challenges.

4.1. The "Black Box" Problem and Explainability

A recurring theme in the literature is the "black box" nature of complex algorithms, particularly Deep Learning models. While these models often achieve superior accuracy, their lack of transparency acts as a significant barrier to clinician trust and adoption (Bellini et al., 2022). Clinicians are reluctant to act on alerts they cannot understand or explain to patients (Elgin & Elgin, 2024). To address this, recent studies have increasingly employed explainable AI (XAI) techniques, such as SHapley Additive exPlanations (SHAP), to visualize feature importance and provide interpretability alongside risk scores (Chen et al., 2025; Xiang et al., 2024). Ensuring transparency is not merely a technical preference but an ethical imperative that aligns with the bioethical principles of non-maleficence and autonomy (Gorelik et al., 2025).

4.2. Implementation Challenges: Alarm Fatigue and Workflow Integration

Even highly accurate models can fail to improve patient outcomes if they disrupt clinical workflows or contribute to alarm fatigue. Michard et al. (2025) noted that false-positive alerts from hemodynamic monitoring tools can lead to unnecessary interventions, such as fluid overload or inappropriate vasopressor use. Furthermore, as highlighted by Mehta et al. (2024), the statistical superiority of AI models does not always translate into clinical benefit in randomized trials. This "implementation gap" suggests that future research must focus not just on algorithm development but on human-computer interaction, ensuring that AI tools serve as effective decision support systems rather than distractions (Bellini et al., 2022).

4.3. Data Quality, Bias, and Generalizability

The performance of AI models is intrinsically linked to the quality and diversity of the data used for training. Many existing models are developed using data from single centers or homogeneous populations, which limits their generalizability to broader patient cohorts (Yoon et al., 2022; Li et al., 2025). Biases present in training datasets, whether related to race, gender, or socioeconomic status, can be perpetuated by AI, leading to algorithmic unfairness and exacerbating healthcare disparities (Gorelik et al., 2025). Moreover, the reliance on retrospective data in many studies introduces potential selection bias, necessitating robust external validation and prospective clinical trials before widespread deployment (Mohammadi et al., 2024; Yoon et al., 2025).

4.4. Ethical and Regulatory Considerations

The deployment of AI in healthcare also raises complex ethical questions regarding accountability and resource allocation. Elgin & Elgin (2024) emphasized the tension between efficiency and equity, noting that AI-driven Clinical Decision Support Systems (CDSS) could inadvertently disadvantage vulnerable populations if efficiency is prioritized over equitable care. Additionally, the regulatory landscape remains fragmented, with varying standards across regions such as the US and EU, which complicates the global harmonization of AI-based medical devices (Reddy, 2025). Establishing clear frameworks for liability, specifically determining whether the clinician or the algorithm developer is responsible for an adverse outcome, remains a critical unmet need.

5. Summary

Artificial Intelligence represents a paradigm shift in perioperative medicine, offering the potential to transform patient care from reactive monitoring to proactive risk management. The evidence synthesized in this review demonstrates that AI and machine learning models can accurately predict critical complications such as intraoperative hypotension, sepsis, and acute kidney injury, often outperforming traditional risk stratification tools. Technologies like the Hypotension Prediction Index and multimodal deep learning algorithms have shown particular promise in reducing the duration of hemodynamic instability and enhancing risk assessment precision.

However, the path to widespread clinical adoption is obstructed by significant challenges. The "black box" nature of advanced algorithms necessitates a greater focus on explainability to foster clinician trust. Furthermore, the variability in data quality, lack of external validation, and potential for algorithmic bias underscore the need for rigorous, prospective clinical trials. Ethical considerations regarding accountability, data privacy, and equitable resource allocation must be addressed through robust regulatory frameworks. Ultimately, AI should be viewed not as a replacement for clinical judgment, but as a powerful decision-support tool that, when implemented thoughtfully, can enhance patient safety and improve surgical outcomes.

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Writing- review and editing: Patryk Iglewski, Filip Matusiak
Resources: Patryk Iglewski, Michał Kociński, Michał Pietrasz

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