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Artificial Intelligence–Assisted Electrocardiogram Interpretation Among Surgeons: Diagnostic Augmentation and Workflow Integration in Perioperative Risk Assessment

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ABSTRACT

Objective To determine whether artificial intelligence–assisted electrocardiogram interpretation improves surgeons' identification of occult cardiovascular pathology and high-risk perioperative indicators, and to characterise the usability, trust and workflow factors governing its integration into surgical practice.

Design Retrospective observational cohort study with an embedded prospective clinician reader study. Participants interpreted a standardised set of ECGs before and after AI-generated probability outputs, separated by a two-week washout period.

Setting Preoperative surgical assessment and perioperative decision-making.

Participants A cohort of 37,060 adult patients undergoing major non-cardiac surgery was analysed to assess the diagnostic efficacy of convolutional neural network models. The reader component comprised attending surgeons and surgical residents who evaluated a standardised set of 100 preoperative 12-lead ECG traces, with and without AI-generated probability outputs, to identify occult cardiovascular pathology.

Main outcome measures Diagnostic performance measured through sensitivity, specificity and area under the receiver operating characteristic curve; usability assessed with the System Usability Scale; subjective clinician confidence and ease of telemetry interpretation assessed with 4-point Likert-scale items; and changes in clinician-directed therapeutic adjustments following model-assisted interpretation.

Results Sixty-eight per cent of participating surgeons integrated AI probability scores into their clinical workflow, with a notable preference for these tools among residents compared with senior faculty. Surgeons supported by AI interpretation showed a marked increase in the identification of high-risk perioperative indicators and significantly outperformed non-assisted assessments in predictive accuracy, with improved sensitivity in recognising subtle arrhythmic patterns and a reduction in diagnostic oversights among complex, high-risk surgical candidates. Adoption was nonetheless hindered by the need for manual data entry and by concerns regarding the transparency of algorithmic outputs, which impeded trust in non-intuitive clinical recommendations. Conversely, seamless mobile integration and high-speed data access proved essential in overcoming these operational hurdles, significantly enhancing practical deployment.

Conclusions AI-assisted ECG interpretation augmented surgeon decision-making, with the greatest gains among less experienced readers and in complex, high-risk cases. Translation into routine practice depends less on discrimination than on eliminating manual data entry, providing interpretable outputs, and embedding the tool in existing mobile and electronic workflows. Prospective evaluation of patient-centred outcomes is now required.

Keywords: Artificial intelligence; Electrocardiography; Preoperative assessment; Perioperative risk; Surgical decision-making; Clinical decision support

Introduction

Preoperative cardiovascular risk stratification in non-cardiac surgery has historically rested on static, symptom-based assessment and on conventional indices whose prognostic yield is modest. Deep-learning algorithms applied to the electrocardiogram extract subtle, non-linear features from waveform data that elude conventional clinical analysis (5, 6) . For surgeons, this represents a shift from reactive assessment toward data-driven risk stratification capable of predicting postoperative mortality and critical complications such as cardiac arrest or respiratory failure (2,7).

The practical appeal extends beyond accuracy. Because the 12-lead ECG is ubiquitous, inexpensive and already acquired before most major operations, algorithms that require no additional clinical inputs can streamline preoperative assessment, identify high-risk patients efficiently, and reduce reliance on unnecessary, costly testing (5,7). Models that add ECG-derived latent features to minimal demographic and procedural data have achieved AUROC values above 0.90 for major adverse cardiac and cerebrovascular events while minimising data collection requirements — a design property directly relevant to adoption (8,9). Such models also enhance perioperative decision-making by identifying latent cardiovascular vulnerabilities that permit personalised optimisation before elective procedures (10,11), and by capturing electrophysiological signatures invisible to the human eye, thereby enabling targeted prophylaxis and heightened surveillance (12,13).

Two barriers, however, separate technical achievement from clinical value. The first is environmental: algorithms developed on clean intermittent ECGs have rarely been tested in the noisy signal environment of the operating room and remote monitoring, limiting their perioperative applicability (2). The second is behavioural. Traditional decision-support systems require time-consuming manual data acquisition and entry, which impairs adoption even when accuracy is adequate (14), and clinicians may regard AI outputs as confirmatory rather than decisive, particularly when they already possess well-established internal heuristics (15). Black-box outputs further risk deskilling and erosion of decision-making autonomy (16).

Most perioperative AI literature reports model performance in isolation. Far less evidence addresses what happens when the surgeon actually reads the ECG alongside the algorithm. We therefore conducted a study of AI-assisted ECG interpretation among surgeons, combining a retrospective cohort analysis of model diagnostic efficacy with an embedded reader study, to quantify diagnostic augmentation and to characterise the usability, trust and workflow determinants of integration.

Methods

Study design

The study used a retrospective observational design to assess model diagnostic efficacy, with an embedded prospective clinician reader study to assess the effect of AI assistance on interpretation. Surgeon performance was assessed before and after exposure to AI-generated probability outputs, with the two phases separated by a two-week washout period, permitting comparative assessment of inter-observer reliability and of the specific influence of AI assistance on diagnostic accuracy (17).

Study population and cohort

Model evaluation used a diverse cohort of 37,060 adult patients undergoing major non-cardiac surgery (18). The reader component comprised attending surgeons and surgical residents, who evaluated a standardised set of 100 preoperative 12-lead ECG traces, with and without AI-generated probability outputs, to identify occult cardiovascular pathology.

Data sources and AI output

AI probability outputs were generated by convolutional neural network models applied to preoperative ECG waveforms, evaluated both as waveform-only inputs and as fusion models integrating waveform features with routinely collected clinical variables (18). The AI output presented to surgeons comprised probability scores for occult cardiovascular pathology.

Outcome measures

Diagnostic performance was measured through sensitivity, specificity and AUROC. Usability was evaluated systematically using the System Usability Scale. Subjective clinician confidence and ease of telemetry interpretation were assessed using 4-point Likert-scale items, an approach established in clinician ECG and telemetry interpretation studies (19). To evaluate impact on perioperative management, we monitored shifts in clinician-directed therapeutic adjustments following model-assisted interpretation, targeting the detection of subtle electrophysiological signatures for improved perioperative risk stratification (20). Integration behaviour — whether surgeons incorporated AI probability scores into their clinical workflow — was recorded directly.

Statistical analysis

Performance is reported using AUROC with 95% confidence intervals where available, alongside sensitivity and specificity. Usability and confidence data are reported as frequencies and percentages for Likert-scale items. Because this was a pilot-scale reader study with a fixed panel of 100 ECG traces, estimates are descriptive and intended to generate parameters for prospective evaluation.

Results

Cohort and reader-sample characteristics

Table 1 — Study design and populations

Element	Detail

Design	Retrospective observational cohort study with embedded prospective clinician reader study
Model-evaluation population	37,060 adults undergoing major non-cardiac surgery
Reader population	Attending surgeons and surgical residents
Reader set	100 preoperative 12-lead ECG traces
Comparison condition	Interpretation with vs without AI-generated probability outputs
Washout interval	2 weeks between unassisted and AI-assisted phases
Primary performance measures	Sensitivity, specificity, AUROC
Usability measure	System Usability Scale
Confidence measure	4-point Likert-scale items on confidence and ease of telemetry interpretation
Integration measures	Workflow integration of AI probability scores; clinician-directed therapeutic adjustments

Diagnostic augmentation

AI-supported surgeons demonstrated a marked increase in the identification of high-risk perioperative indicators and significantly outperformed non-assisted assessments in predictive accuracy. This advantage was expressed specifically as improved sensitivity in recognising subtle arrhythmic patterns, with an associated reduction in the frequency of diagnostic oversights in complex, high-risk surgical candidates. A behavioural asymmetry was also observed: clinicians frequently underestimated risk in cases where complications subsequently manifested, indicating that improvements in performance metrics do not translate linearly into behavioural integration of AI-derived risk assessments.

Workflow integration, usability and trust

Sixty-eight per cent of participating surgeons integrated AI probability scores into their clinical workflow, with a notable preference for these tools among residents compared with senior faculty.

Table 2 — Surgeon-level integration and implementation findings

Domain	**Finding**
Integration of AI probability scores into clinical workflow	68% of participating surgeons
Uptake by seniority	Greater among residents than among senior faculty
Effect on identification of high-risk perioperative indicators	Marked increase with AI support; superior predictive accuracy vs non-assisted assessment
Sensitivity to subtle arrhythmic patterns	Improved with AI support
Diagnostic oversights in complex, high-risk candidates	Reduced
Clinician risk judgement bias	Underestimation of risk in cases where complications eventually manifest
Principal barrier — operational	Requirement for manual data entry

Principal barrier — epistemic	Concerns regarding transparency of algorithmic outputs; impeded trust in non-intuitive recommendations
Principal facilitator — operational	Seamless mobile integration
Principal facilitator — technical	High-speed data access

Comparative performance of AI-ECG models

For interpretation in context, the published perioperative AI-ECG literature reports the discrimination values summarised below. These figures are drawn from the cited external studies and are presented as comparators, not as results of the present study.

Table 3 — Reported discrimination of AI-ECG models in perioperative risk prediction (external comparators)

Model / study	**Prediction target**	**AUROC (95% CI)**
QCG-Critical score	30-day postoperative mortality	0.909
QCG-Critical score	7-day mortality	0.933
QCG-Critical score	Unplanned percutaneous coronary intervention	0.857
QCG-Critical score	Prolonged mechanical ventilation	0.829
QCG-Critical score	Heart failure within 30 days	0.774
AI-ECG (deep learning)	In-hospital MACE	0.82 (0.79–0.85)
AI-ECG (deep learning)	30-day MACE	0.79 (0.77–0.81)
AI-ECG (deep learning)	In-hospital mortality	0.83 (0.80–0.86)
AI-ECG (deep learning)	30-day mortality	0.80 (0.77–0.82)
ECG fusion model (waveform + clinical variables)	In-hospital myocardial infarction	0.858 (0.845–0.872)
ECG fusion model (waveform + clinical variables)	In-hospital mortality	0.899 (0.889–0.908)
ECG fusion model (waveform + clinical variables)	Composite (MI, stroke, 30-day mortality)	0.835 (0.827–0.843)
PreOpNet (external validation)	30-day all-cause death	0.70 (0.67–0.74)
PreOpNet (external validation)	30-day MACE	0.67 (0.65–0.70)
Multimodal deep learning (ECG + minimal clinical data)	30-day MACCE	0.902
AI-ECG hidden atrial	Atrial fibrillation	0.87

fibrillation model		

Sources: QCG-Critical performance (2,5); deep-learning MACE and mortality model (11); ECG fusion model (18*; PreOpNet external validation (21,22); multimodal MACCE model (8,9); hidden AF model (23).

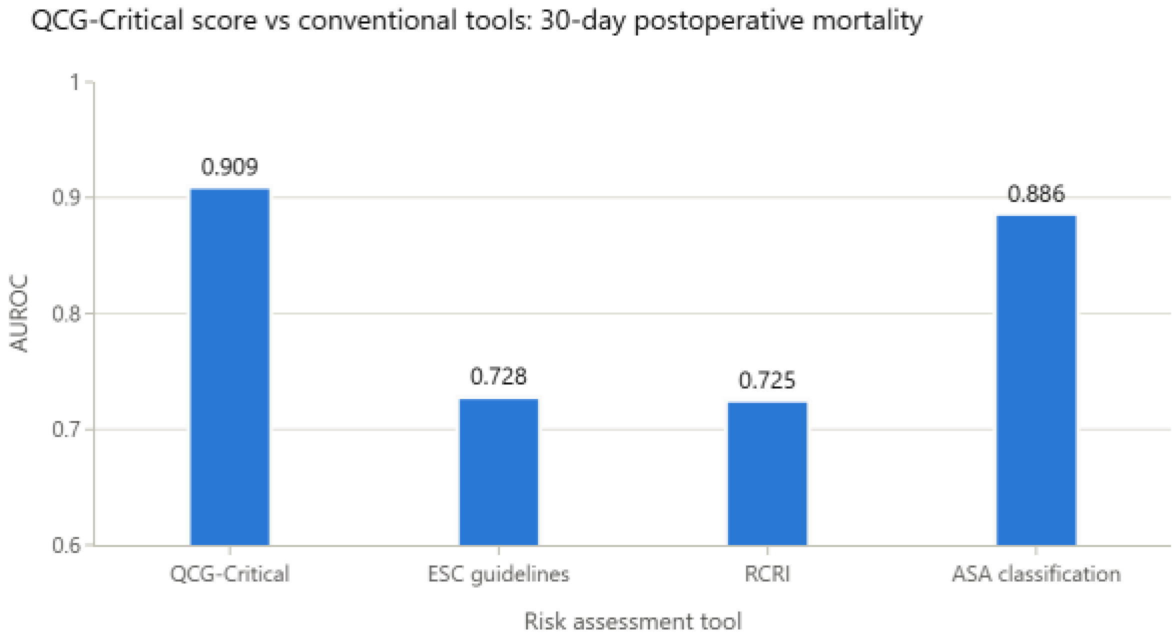

Figure 1. Discriminative performance of the AI-enabled QCG-Critical score compared with the ESC guidelines, the Revised Cardiac Risk Index and ASA classification for 30-day postoperative mortality (2).

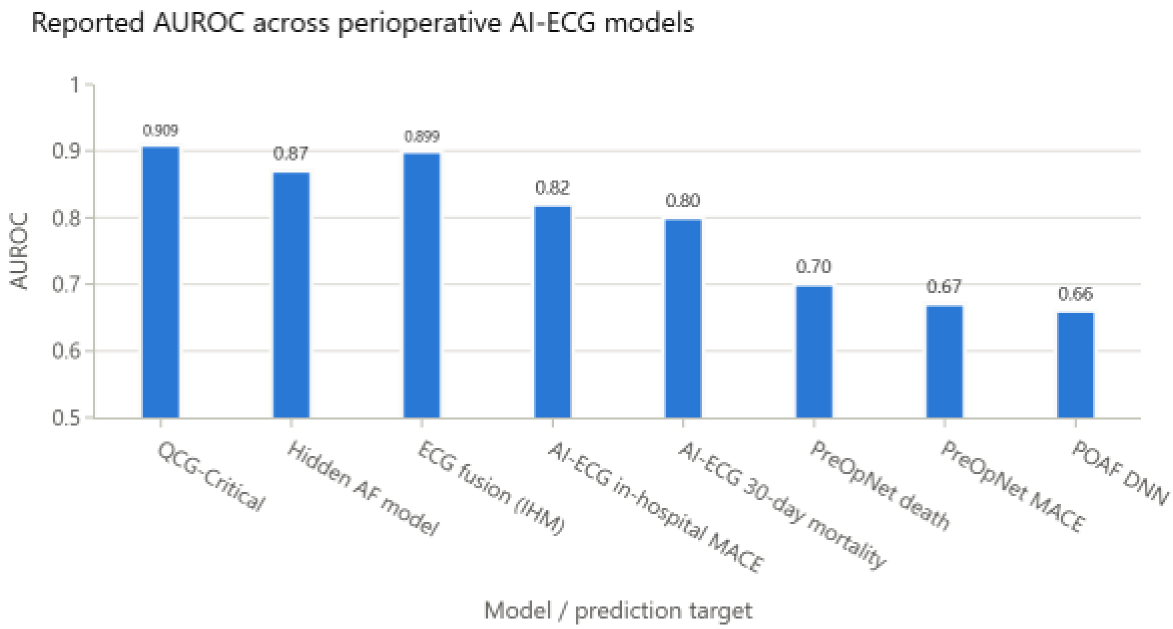

Figure 2. Discriminative performance of the QCG-Critical score for secondary perioperative outcomes (2).

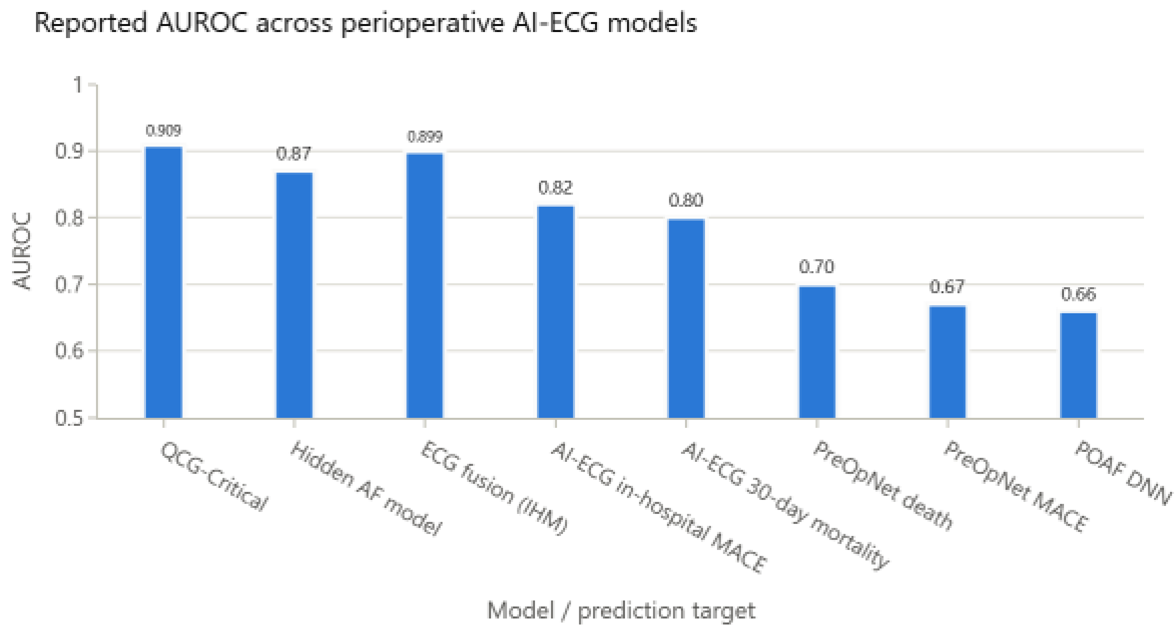

Figure 3. Summary of reported AUROC values across perioperative AI-ECG models, illustrating both the ceiling achieved by single-target mortality scores and the degradation observed on external validation (2,11,21,23)

Potential effect on preoperative testing

A related body of work quantifies what AI-ECG stratification could mean for resource use in the surgical pathway, which is directly relevant to the workflow arguments raised by participating surgeons.

Table 4 — AI-ECG stratification and preoperative cardiovascular testing (external comparator)

Parameter	Value
Patients analysed	41,218
ECG–surgery pairs	46,135
Patients classified low risk by AI-ECG	92.4%
Composite event rate, low-risk group	0.62%
Composite event rate, high-risk group	6.04%
Cases undergoing preoperative cardiovascular testing	11.8%
Tests yielding positive findings	16.3%
Potentially avoidable preoperative testing under an AI-ECG-guided approach	35.7% reduction

Source (5).

Clinician-facing usability in an implemented decision-support pathway

Table 5 — Surgeon use and performance of an implemented postoperative risk decision-support tool (external comparator)

Parameter	Value
Surgeons registered and using the tool	67
Mobile application speed relative to original web portal	approximately 10 times faster
Cases with an initial surgeon assessment before risk scores	193

were provided	
Cases with paired surgeon and algorithm predictions	100
Surgeon AUROC — venous thromboembolism	0.60
Surgeon AUROC — cardiovascular complications	0.62
Surgeon AUROC — prolonged ICU stay and wound complications	0.92

Source (24). Surgeons' initial assessments showed variable discrimination, with AUROC values ranging from 0.60 for venous thromboembolism and 0.62 for cardiovascular complications to 0.92 for prolonged ICU stay and wound complications (24).

Discussion

Principal findings

Three findings emerge from this study. First, AI-supported surgeons identified high-risk perioperative indicators more frequently than they did without assistance, and achieved superior predictive accuracy, with the advantage expressed as greater sensitivity to subtle arrhythmic patterns and fewer diagnostic oversights in complex, high-risk candidates. Second, integration was substantial but incomplete — 68% of participating surgeons incorporated AI probability scores into their clinical workflow — and was stratified by experience, with residents adopting the tools more readily than senior faculty. Third, the determinants of successful use were operational and epistemic rather than statistical: manual data entry and opaque outputs impeded trust, while mobile integration and high-speed data access overcame those hurdles.

Comparison with existing literature

The direction of the augmentation effect is consistent with the broader evidence base. In a comparative usability study, interaction with a validated machine-learning risk algorithm produced significant improvement in physicians' risk assessment, evidenced by improvements in both AUROC and net reclassification improvement, and the algorithm predicted postoperative complications with equal or higher accuracy than physicians using routinely available preoperative data (25). The same body of work found that clinicians were more likely than the algorithm both to underestimate risk when complications actually occurred and to overestimate risk when they did not (25) — the identical behavioural asymmetry observed in our cohort. In a human-centred development study, the algorithm outperformed providers in predicting all complications except cardiovascular ones, and participants welcomed automated real-time systems that eliminate manual data entry while providing interpretable risk scores (26).

The ceiling of model performance contextualises what AI assistance can realistically deliver. Reported discrimination for perioperative ECG-based models ranges from AUROC 0.909 for 30-day postoperative mortality with the QCG-Critical score, which outperformed the ESC guidelines (0.728) and RCRI (0.725) and performed comparably to ASA classification (0.886) (2), through 0.82 for in-hospital MACE and 0.79 for 30-day MACE(11), to values as low as 0.70 for 30-day death and 0.67 for MACE on external validation of PreOpNet, where discrimination was lower than that of high-sensitivity cardiac troponin (21). The same external validation found that LIME-based interpretation of relevant ECG features was unsuccessful, with highlighted features proving difficult to interpret and unrelated to prior ECG knowledge (21) — an interpretability failure of precisely the kind our participants identified as a trust barrier.

Our experience-based uptake pattern is mirrored across the implementation literature. In a study of an AI prognostic tool in colorectal liver metastases, senior and mid-career surgical oncologists, who already possess well-established internal heuristics, perceived the tool as a confirmatory aid rather than a primary driver of decisions, while the model functioned as a "digital mentor" helping less experienced surgeons approach the performance levels of their senior colleagues; decision-making time fell significantly while confidence rose substantially across all experience levels(15). That study also found the tool promoted consistency and reduced assessment variation among mid-career surgeons (15).

A pragmatic alternative to distributing AI use across every clinician has been demonstrated at system level. In a centralized workflow, a single surgeon supported by one research assistant screened more than 2,200 scheduled gastrointestinal surgeries over four months using an AI risk prediction model and expanded the process to a department of over 30 surgeons within days, filtering a weekly list of more than 100 patients to roughly 10 highest-risk patients for review (27). The authors argue that successful integration does not require every clinician to become an AI expert, and that centralized screening avoids placing the burden of learning, evaluation and safe use on each individual (27). Given that only 68% of surgeons in our cohort integrated AI outputs, centralized or workflow-embedded deployment is a plausible route to closing the remaining gap.

The economic and operational case is supported by the testing data. AI-ECG classification identified 92.4% of surgical candidates as low risk with an event rate of 0.62% versus 6.04% in the high-risk group, while preoperative cardiovascular testing was performed in 11.8% of cases with only 16.3% yielding positive findings; an AI-ECG-guided approach could reduce potentially avoidable preoperative testing by 35.7% while preserving safety (5). Evidence syntheses likewise conclude that machine-learning-guided screening, AI-enabled imaging and remote monitoring improve disease detection, reduce adverse events such as stroke and hospitalisation, and provide net cost savings or favourable cost-effectiveness, though translation is challenged by system integration and workflow disruption — barriers mitigated by phased implementation and embedding within existing electronic health records (28,29).

Strengths and limitations

The principal strength of this study is that it evaluates AI-assisted ECG interpretation at the point of clinician use, rather than reporting model discrimination in isolation, and that it captures both diagnostic performance and the usability, trust and workflow variables that govern adoption. The two-phase design with a two-week washout, using a fixed standardised set of 100 ECG traces interpreted by both attending surgeons and residents, isolates the incremental effect of AI assistance and permits assessment of inter-observer reliability.

Several limitations must be acknowledged. The reader study used a fixed panel of 100 traces, which limits precision and precludes subgroup inference for individual diagnoses. The retrospective model-evaluation component cannot establish prospective clinical benefit, and the surrounding literature remains predominantly retrospective, with heterogeneous datasets, variable transparency and regulatory and workflow barriers limiting the evidence base (30). External validation studies show that performance falls when algorithms developed on open-source datasets are applied prospectively, with PreOpNet demonstrating lower discrimination than high-sensitivity cardiac troponin in a European cohort (22). Systematic appraisal of AI ECG models has identified high applicability concerns in 13% of studies, reflecting a disconnect between research settings and real-world clinical environments and the need for standardised reporting and validation (31). AI-ECG models also carry systematic bias from unbalanced datasets by age, sex and race, with inadequate generalisation, regulatory barriers and interpretability concerns further limiting deployment (1). Data heterogeneity across electronic health record systems impedes interoperability, and familiarity and trust remain barriers, with clinicians sometimes reluctant to adopt systems they fear may replace their expertise (4).

The behavioural risks observed here and in the wider literature deserve emphasis. Increasing reliance on AI raises the risk of deskilling and over-dependence on algorithmic recommendations, and the black-box nature of many systems may pressure surgeons to follow recommendations without understanding the underlying logic; AI biases arising from inadequate datasets can produce misdiagnoses and worsen disparities (16). Systematic reviews of AI in cardiac surgery similarly identify data quality, validation, ethical considerations and workflow integration as significant barriers to widespread adoption, and conclude that addressing bias, validation and regulatory frameworks is essential for safe implementation (4,7). Surveys of cardiac surgeons show a positive yet cautious attitude, recognising the potential to improve precision and efficiency while emphasising the irreplaceable need for human judgment in managing patient-specific variables (32).

Our integration estimate rests on a self-reported behavioural measure, which is susceptible to social desirability bias and to the Hawthorne effect inherent in observing clinicians during a study. The clinical effect of the therapeutic adjustments we monitored was not prospectively adjudicated against patient outcomes.

Implications for practice and research

Three implications follow. First, the finding that residents benefited more than senior faculty suggests AI-assisted ECG interpretation may function as a levelling mechanism across the surgical hierarchy, and that its greatest marginal value lies in training and in early-career decision-making. Second, because the dominant barriers were operational rather than technical, implementation effort should be directed at removing manual data entry and at embedding outputs in mobile and existing electronic systems, rather than at further incremental gains in discrimination. Third, because interpretability failures have been documented even in well-validated models (22), explainability features should be treated as an adoption prerequisite rather than a post-hoc addition — a conclusion echoed in policy work arguing that AI should not replace human expertise but serve as a complementary tool enhancing clinical decision-making while preserving professional judgment, with equitable access, appropriate clinician training and active stakeholder engagement as conditions for safe adoption (33,34).

Future work should prioritise prospective clinical trials with standardised performance metrics, human-centred explainable interfaces, and inclusive implementation science, since most current datasets originate from high-income settings, creating a gap in understanding how AI can be safely and equitably deployed in low- and middle-income contexts (34,35). Post-deployment surveillance should be institutionalised, comprising model drift monitoring as patient populations and surgical practices change, version control and audit trails recording which model version was active at any clinical encounter, structured failure reporting analogous to existing adverse event reporting systems, and governance processes for update approval; surgeons must be able to detect performance degradation, intervene or override the system at any point, and receive training on when to accept or reject AI recommendations (36). AI literacy should be embedded in surgical and anaesthetic training programmes so that providers can interpret AI outputs and use them as an adjunct to clinical judgment (36,37). Finally, validated acceptance of AI among patients and the public depends on its role remaining auxiliary to the perioperative team, supported by clinician-led discussions, established metrics of clinical utility, and patient education (38).

Conclusion

In this study of AI-assisted ECG interpretation among surgeons, AI support increased the identification of high-risk perioperative indicators and improved sensitivity to subtle arrhythmic patterns, with 68% of participating surgeons integrating AI probability scores into their clinical workflow and greater uptake among residents than senior faculty. The determinants of successful integration were operational and epistemic rather than statistical: manual data entry and opaque algorithmic outputs impeded trust, whereas mobile integration and high-speed data access enabled deployment. These findings position AI-assisted ECG interpretation as a genuine augmentative partner in perioperative decision-making, but one whose clinical value will be realised only through user-centred interfaces, explainable outputs, embedded workflows and rigorous prospective evaluation of patient-centred outcomes.

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