

Application of AI models for preventing surgical complications: A scoping review

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Application of AI models for preventing surgical complications: A scoping review

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Abstract

Background: The impact of surgical complications is substantial and multifaceted, affecting patients, families, surgeons and healthcare systems. Despite the significant advancement in artificial intelligence (AI), there still exists a notable gap regarding prospective implementation of AI models clinically using real time data to enhance the decision-making, and the ability to intervene proactively to reduce the risk of surgical complications.

Objective: To this end, this scoping review aims to assess and analyze the adoption and use of AI models for preventing surgical complications. Furthermore, we aim to identify barriers and facilitators for the implementation and deployment at the bedside, where patient care occurs.

Methods: A literature search was conducted using online databases including IEEE Xplore, Scopus, Web of Science, MEDLINE, ProQuest, PubMed, ABI, Cochrane electronic and registries for clinical trials from January 2013 to January 27, 2025. Study characteristics and algorithm development were extracted along with performance statistics (e.g. sensitivity, area under the operating curve). Preferred Reporting Items for Scoping Reviews (PRISMA-ScR) was followed.

Results: The search yielded a total of 275 of which 19 were included for data extraction. Out of these there were ten randomized controlled trials and nine prospective studies. In three studies a web version of a calculator for predicting postoperative complications was provided. None of the 19 studies reported that the model was in clinical use. Only one study reported the perceptions of clinicians in terms of using AI models.

Conclusions: The literature demonstrates that AI models for surgical complications are not currently in use in routine practice. Barriers to use were identified as challenges of integration into daily clinical workflows and insufficient evidence regarding their clinical effectiveness.

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Original paper:

Application of AI Models for Preventing Surgical complications: A scoping review

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Keywords

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Perioperative Care

Clinical Decision Support

Abstract:

Background: The impact of surgical complications is substantial and multifaceted, affecting patients, families, surgeons and healthcare systems. Despite the significant advancement in artificial intelligence (AI), there still exists a notable gap regarding prospective implementation of AI models clinically using real time data to enhance the decision-making, and the ability to intervene proactively to reduce the risk of surgical complications. To this end, this scoping review aims to assess and analyze the adoption and use of AI models for preventing surgical complications. Furthermore, we aim to identify barriers and facilitators for the implementation and deployment at the bedside, where patient care occurs.

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Conclusion: The literature demonstrates that AI models for surgical complications are not currently in use in routine practice. Barriers to use were identified as challenges of integration into daily clinical workflows and insufficient evidence regarding their clinical effectiveness.

Introduction:

With more than 320 million surgeries performed annually worldwide, there is a global responsibility to enhance the quality of surgical care ¹. Surgical complications, whether minor or severe, often lead to reoperations, morbidity and prolonged hospital stay ^{2,3}. Death following surgery occurs up to 5 % of the time and every tenth patient experiences preventable surgical complications ¹. Adverse events also impact surgeons as a second victim, and health care resources utilization rises notably ⁴. The extra cost of surgical complications ranges from 3.5 to 10 billion dollars yearly and is associated with an average increase in hospital stay of 11 days ⁵. Despite attempts with optimized clinical pathways to reduce the frequency of surgical complications, complications persist ^{6,7}.

Artificial intelligence (AI) is transforming the field of surgery, offering unprecedented advancements

in precision, efficiency, and patient outcomes⁸. By leveraging the power of machine learning, natural language processing, and computer vision, AI has the possibility to enhance various aspects of surgical practice from preoperative planning to intraoperative guidance and postoperative care⁹.

During pre-operative discussions, the surgeon and patient must weigh the benefits of surgery against the risks. AI can rapidly process large amounts of health data, unburdening health personnel, and enhance their ability to help better inform their patients¹⁰.

AI models, primarily machine learning algorithms, have been developed with an aim to improve patients' outcomes after surgery, optimizing processes and enhancing decision-making. These algorithms analyze patterns and their relationship to determine complex combinations that can indicate the patient's risk for surgical complications. There is a notable gap in studies focusing on the adaption and actual clinical use of these AI models¹¹⁻¹⁹. Existing literature is focused on the retrospective development of models aimed at preventing surgical complications. There are several reasons why these models have not been widely adopted in actual clinical use, including but not limited to the lack of validation, differences in culture and behavior, organizational structure, and the unavailability of data^{20,21}. Currently, there is a gap in the literature to evaluate the clinical use of AI models specifically, hence, this review aims to give an overview of the published studies. Previously published reviews have focused exclusively on studies involving the development and validation of models conducted using retrospective data²²⁻²⁴. Our focus is rather to uncover AI models that have been prospectively tested in the surgical setting, and to pinpoint barriers and facilitators to inform the implementation of AI tools for preventing surgical complications.

Methods:

We used a scoping review protocol with a review methodology that addressed key concepts, types of evidence, and a gap in the literature by systematically searching, selecting, and synthesizing existing knowledge²⁵. We used the framework proposed by Pollock et. al. to follow the five phases: 1) develop the review objective 2) applying the eligibility criteria 3) selecting the articles 4) extracting data and 5) reporting the results²⁶. The research team comprised both surgeons and machine learning engineers. The primary research question was “Which AI models have been tested clinically to predict surgical complications?” The secondary question was “If not yet implemented in clinical use, are there any in the horizon that could be easily implemented?”

To address the research questions, online databases and registries including Scopus, Cumulative Index to Nursing and Allied Health Literature (CINAHL), the Cochrane library, PubMed, Medline, Web of Science, Embase, Epistemonikos and IEEE were queried. Mendeley (version) was used to import all citations. Preferred Reporting Items for Scoping Reviews (PRISMA-ScR) was followed²⁷.

The list of search terms was then defined based on several discussion rounds between the authors. The following search terms were used: ("Artificial intelligence" OR "Machine learning" OR "AI tool" OR "AI" OR "Validated algorithm" OR "AI models") AND ("Predict" OR "Prediction tool" OR "Prediction index" OR "Clinical decision support tool") AND ("postoperative complication" OR "surgical adverse event" OR "adverse surgical outcome"). A librarian performed the search and the primary investigator (KM) and co-investigator (ELJ) read the abstracts from the search results. Inclusion criteria included: 1) evaluation of the model in a clinical environment, 2) published between 2011 – January 2025 3) published in English language 4) evaluated an AI model aiming to prevent surgical complications. The exclusion criteria were: (1) non-English, (2) articles containing future applications of AI only, (3) AI used not for surgical complications and (4) no full-text

availability.

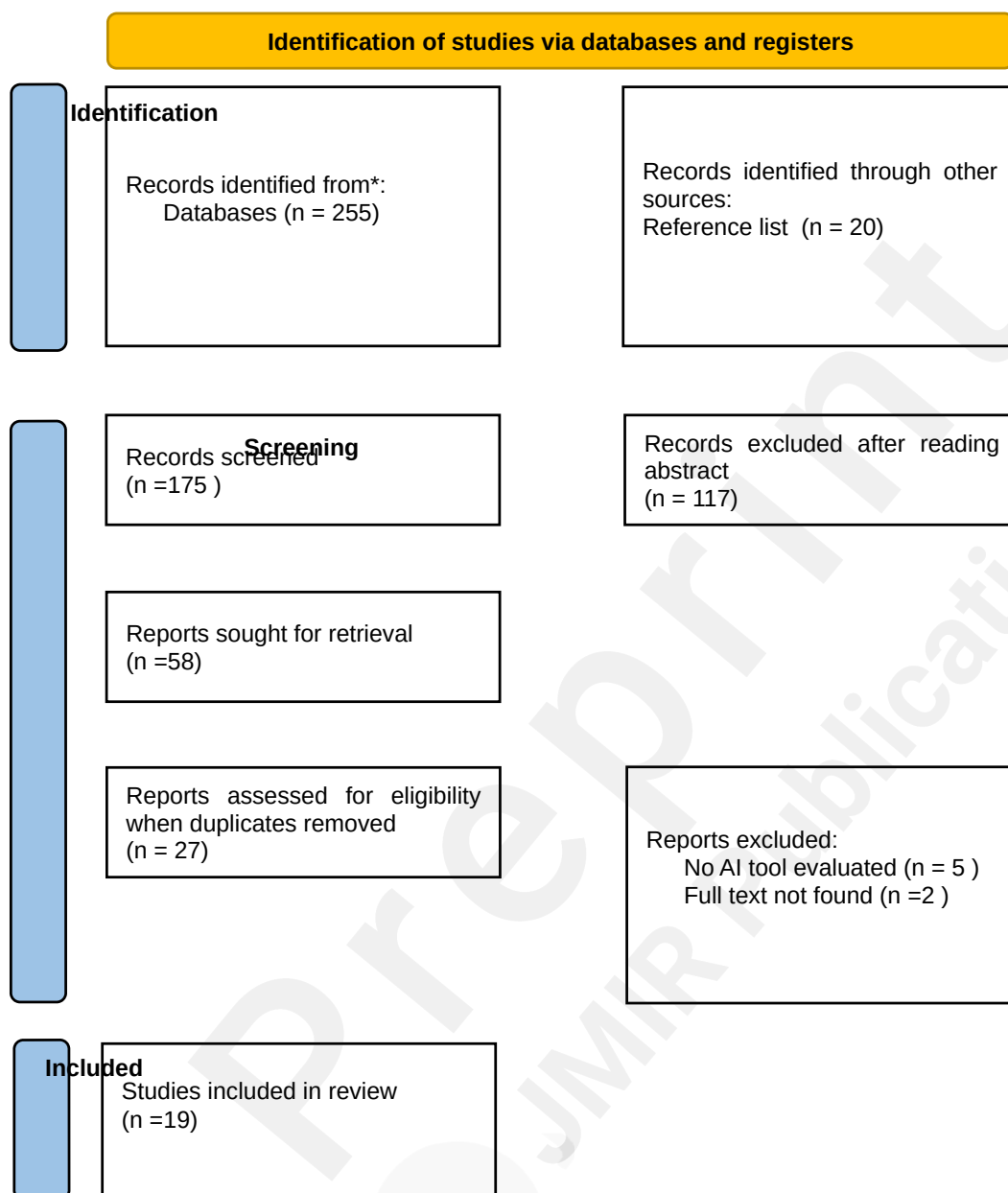
Data extraction:

Two reviewers (KM and ELJ) independently screened and selected studies eligible for inclusion. Disagreements were arbitrated with a third reviewer (CTO). The reporting quality was assessed by using the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD)²⁸. The checklist includes 22 items with the potential answer options: "yes", "no", and "not applicable.". The two reviewers assessed the selected studies for compliance with the items described in the TRIPOD checklist regarding study design, predictor selector, outcome, applied model and validation. The final articles were reviewed in depth, recording x, y, z which was exported to Excel. The characteristics of studies that reported on the use of AI to predict surgical complications were summarized in tabular form.

Results

A Modified Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)²⁹ flow diagram of the scoping review is provided in Figure 1. From 255 articles garnered in the initial search and 20 more from reference lists, 19 articles met the selection (Table 1). Seven of the studies originated in the USA while 10 were from Europe and 2 from Asia. There were 58 articles left after reading the abstracts excluding those not fulfilling the inclusion criteria. 31 articles were removed due to duplicates and additional 7 because they lacked an AI model or a prospective testing phase. One study included only adolescents with 59 participants. The 19 articles were published between 2013 and 2025. There were ten RCT's and nine prospective studies.

Figure 1 PRISMA flow chart



From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

For more information, visit: <http://www.prisma-statement.org/>

Table 1 Demographics of the included articles

Author/year of publication	Country of origin	Clinical domain	Number of enrolled/planned participants	Type of study
Wijnberge/2020 ³⁰	Netherland	Non-cardiac surgery	60	Unblinded randomized clinical trial 1) early warning system with HPI 2) standard care
Lorente/2023 ³¹	Spain	High-risk surgical patients for elective major abdominal surgery	80	Parallel-arm double-blinded multicenter randomized trial 1) HPI protocol 2) standard care
Schneck/ 2020 ³²	Germany	Patients undergoing primary hip arthroplasty.	99	Single center randomized blinded prospective trial 1)Therapy algorithm HPI 2) Standard care 3) Historic control group
Bao/2024 ³³	USA	Patients with ASA 3 or 4 moderate or high-risk non-cardiac surgery > 3 hours.	425, post hoc 457 vs 15796	Prospective single-arm multicenter (n=11) trial Study 1) continuous blood pressure measurements from study monitors compared to historical cohort with standard care Study 2) subset of trial participants versus a propensity score-weighted contemporaneous comparison group
Tsoumpa/2021 ³⁴	Greece	Moderate or high-risk non-cardiac surgery	99	Single center prospective randomized trial 1)HPI with hemodynamic treatment protocol 2) Standard care
Cylwik/ 2024 ³⁵	Poland	Patients undergoing oncological gastrointestinal surgery with ASA 3 or 4	46	Prospectively single center were HPI was used for 50 patients
Murabito/2022 ³⁶	Italy	Patients for elective laparotomic major general surgery	40	Single center pilot randomized clinical trial 1) early warning system 2) standard care
Šribar/2023 ³⁷	Kroatia	Patients for elective major thoracic surgery with one lung ventilation	34	Prospective randomized single-center blinded trial 1) "machine learning algorithm" (AcumenIQ) 2) "conventional pulse contour analysis" (Flotrac)
Maheshwari/2020 ³⁸	USA	Patients with ASA 3 or 4 for moderate or high-risk noncardiac surgery	214	Randomized multi center control trial (n=2) 1) HPI guided group 2) Standard care
Andrzejewska/	Poland	Patients undergoing	59 adolescents	Prospective single-center, non-randomized, case-

2023 ³⁹		posterior fusion for adolescent idiopathic scoliosis		control study 1) Goal-directed therapy with HPI 2) Standard care
Ren/2022 ⁴⁰	USA	Pre surgery	67 surgeons assessed 100 cases with the tool	Prospective
Bilimoria/2013 ⁴¹	USA	Pre surgery	80 surgeons testing the tool on 10 cases	Prospective
Bronsart/2020 ⁴²	USA	Pre surgery	197 patients assessed by 9 surgeons but 166 were assessed by the tool	Convergent prospective mixed-methods with both quantitative and qualitative data
Moheb/2023 ⁴³	USA	Emergency surgery	150 patients, 15 surgeons in each group	Prospective, non-blinded, single center 1) prediction with use of POTTER 2) standard prediction
Ferre/2023 ⁴⁴	France	Pre surgery	389	Single-center prospective observational study
Kouz/2023 ⁴⁵	France, Germany, Italy, Spain, and United Kingdom	Elective major noncardiac surgery	702	European multicentre (n=12) prospective observational trial
Fritz/2024 ⁴⁶	USA	Patients for elective surgery during daytime weekdays	5071	Single-centre prospective randomized clinical trial 1) AlertWatch + ML display 2) Standard care
Yik/2024 ⁴⁷	Singapore	Elective major gastrointestinal surgery	36	Prospective cohort study
Li/2024 ⁴⁸	China	Patient underwent surgical procedure with general anaesthesia and mechanical ventilation	307	Prospective cohort in a single center

The outcomes of the AI models are outlined in table 2. The majority of studies (n=10) used the outcome of duration of hypotension as the studied outcome. Four studies used the outcome of

generic risk of complications (n=4), kidney injury was another common outcome to three studies. One study had the level of troponin and proBNP as a proxy target for complications. Included in the risk stratification was prediction of mortality and morbidity. The main population studied was high-risk patients in four studies, with a subspecialty lens of non-cardiac surgical patients.

Table 2

Predicted outcome	Author/year of publication	Features	Name of the AI tool	Performance metrics	Web based calculators available
Duration of hypotension	Wijnberge/2020 ³⁰	Arterial pressure waveform (28 variables)	Hypotension prediction Index (HPI)	Median average hypotension 1) 0.10mmHg vs 2) 0.44 mmHg but no differences in number of hypotension episodes. The algorithm (Hypotension Prediction Index) tested with AUC = 0.5	None, but algorithm can be found ⁴⁹
Duration of hypotension	Lorente/2023 ³¹	Intraoperative time-weighted average of MAP <65 mm Hg, number of hypotension episodes, total time of hypotension, biomarkers of acute kidney distress, tissue oxygenation	Hypotension prediction Index (HPI)	Reduced intraoperative hypotension but no differences in oxygen saturation and acute kidney injury	None, but the algorithm can be found ⁴⁹
Duration of hypotension	Schneck/ 2020 ³²		Hypotension Prediction Index (HPI)	Reduced the incidence and duration of hypotensive events	None, but the algorithm can be found ⁴⁹
Duration of hypotension	Bao/2024 ³³	Arterial pressure waveform and demographics,	Hypotension Prediction Index (HPI)	58 % reduction of MAP< 65 mmHg. In post hoc analysis 35 % reduction in minutes of	None, but algorithm can be found here ⁴⁹

		comorbidity, procedures and acute kidney injury for post hoc analysis		hypotension. No difference in AKI 13.8 vs 15.8 %.	
Duration of hypotension	Tsoumpa/ 2021 ³⁴	Intraoperative time-weighted average of MAP <65 mm Hg, number and time of hypotension, amount of medicines, i.v fluid, transfusion, morbidity and complications	Hypotension Prediction Index (HPI)	3 fold decrease in hypotension but increase in hypertension. No differences in complications or LOS or use of medicine/i.v.	None, but algorithm can be found here ⁴⁹
Dynamics of troponin and proBNP and AKI	Cylwik/ 2024 ³⁵	Pre and postoperatively proBNP and troponin and acute kidney injury	Hypotension Prediction Index (HPI)	Hypotension associated with acute kidney injury but not with myocardial injury	None, but algorithm can be found ⁴⁹
Duration of hypotension	Murabito/ 2022 ³⁶	Time weighted average of hypotension and biomarkers	Hypotension Prediction Index (HPI)	Use of HPI reduced the intraoperative hypotension and biomarker for brain and oxidative stress	None, but algorithm can be found ⁴⁹
Duration of hypotension	Šribar/ 2023 ³⁷	Time weighted average of hypotension, i.v fluids, medicines, ICU stay, length of stay, acute kidney injury, coronary syndrome or cerebrovascular infarction	Hypotension Prediction Index (HPI)	Use of HPI reduced the number and duration of hypotension with median time of hypotension from 105 min to 22 min	None, but the algorithm can be found ⁴⁹
Duration of hypotension	Maheshwari/ 2020 ³⁸	Arterial pressure waveform	Hypotension Prediction Index (HPI)	HPI predicted hypotension but could not reduce hypotension neither were there any differences in intra	None, but algorithm can be found ⁴⁹

Duration of hypotension	Andrzejewska/2023 ³⁹	Surgical time, i.v fluids, blood values, length of stay, cardiac and neurological complications	Hypotension Prediction Index (HPI)	or postoperative variables Median hypotension time 8 min (HPI group) vs 40 min. Less time to extubation time for HPI group (median 5 vs 27.5 min). None cardiac and neurological complication in the HPI group, while it was 4 in the control group.	
Duration of hypotension	Kouz/2023 ⁴⁵	Acute myocardial injury, acute kidney injury, death within 30 days after surgery, hospital re-admission within 30 days after surgery.	Hypotension Prediction Index (HPI)	The median number of ≥ 1 min episodes of a MAP < 65 mm Hg was 1. median time-weighted average MAP < 65 of 0.03 mm Hg. 3% had acute myocardial injury, 9% had acute kidney injury. Postoperative mortality within 30 days after surgery was observed in 2%.	None, but algorithm can be found ⁴⁹
Risk for complications	Ren/2022 ⁴⁰	285 inputs, 8 outcomes: complications and death	My Surgery Risk	AUC; no higher AUC after using the model. Surgeon predictive performance did not change significantly after viewing predictions generated by the algorithm.	https://prismap.medicine.ufl.edu/x/com-dom-prisma-p.sites.medinfo.ufl.edu/MySurgeryRisk.html Algorithm Development ⁵⁰
Risk for complications	Bilimoria/2013 ⁴¹	21 preoperative factors, 8 outcomes: mortality, morbidity and 6 others	ACS NSQIP Surgical Risk Calculator	Agreement between surgeons and the tool	https://riskcalculator.facs.org/RiskCalculator/ Algorithm development ⁵¹
Decision support tool	Bronsart/2020 ⁴²	Mortality, overall morbidity, unplanned readmission, 19 preoperative variables	SURPAS	Descriptive, SURPAS was helpful	None, but algorithm can be found ⁵²
Risk for	Moheb/2023 ⁴³	8 variables?	POTTER	POTTER outperformed	None, but the algorithm can

complication				surgeons	be found ¹⁴
Stratifying the perioperative risk score	Ferre/2023 ⁴⁴	25 variables	MyRISK	Patients and surgeons satisfactions and MyRISK score correlated to complication	None, but validated in the same study.
Risk for mortality and kidney failure	Fritz/2024 ⁴⁶	Variables within comorbidity, preoperative vital sign, preoperative labs, intraoperative time series and medication and fluids	Periop ORACLE	Clinicians using the algorithm to predict complications	None, but the algorithm can be found ⁵³
Risk for adverse surgical outcome	Yik/2024 ⁴⁷	Intramuscular adipose tissue as a proxy for muscle quality obtained by ultrasound	MuscleSound®	Clinicians using the tool can have a robust diagnostic tool to help predict surgical risk and outcomes.	None
Risk for postoperative pulmonary complications	Li/2024 ⁴⁸	20 variables	PPC -score	Real-time identification of surgical patients' risk of postoperative pulmonary complications could help personalize intraoperative ventilatory strategies and reduce postoperative pulmonary complications.	https://aorm.wchscu.cn/

Table 3 The most frequently cited barriers and facilitators in each of the studies.

Author/year of publication	Barriers	Facilitators
Wijnberge/2020 ³⁰	Early warning system software needed (Flotrac IQ pressure transducer	Intraoperatively observer so the personnel adhered to the protocol.

	connected to the HemoSphere monitor)	
Lorente/ 2023³¹	Defining the correct range for normal blood pressure. FloTrac® sensor (GDHT protocol) and AcumenIQ® sensor (HPI protocol) needed.	PI checked for adherence to the study protocol
Schneck/ 2020³²	Both groups were monitored by the same equipment, but in the control group the monitoring by the HPI were blinded for the anesthesiologists.	Implementation of HPI was considered uncomplicated providing a high user compliance
Bao/ 2024³³	FloTrac IQ sensor and EV1000 platform needed	Ignoring alarm was allowed in the trial
Tsoumpa/ 2021³⁴	Acumen Flo-Traq transducer and EV1000 platform needed	An observer was present to record surgery- and anesthesia-related details
Cylwik/ 2024³⁵	Need the HemoSphere monitoring platform, equipped with the Acumen™ IQ sensor	Anesthesiologists had received official training in the use of HPI software
Kouz/2023⁴⁵	Acumen™ IQ sensor (Edwards Lifesciences) and the HemoSphere monitoring platform is needed	Each center had a clinical routine for hypotension
Murabito/ 2022³⁶	FloTrac IQ sensor with EWS software needed	Pharmacological intervention was recorded by an external observer
Šribar/ 2023³⁷	Hemosphere monitoring platform using either AcumenIQ or Flotrac sensors is needed	Pilot trial with five in each group
Maheshwari/ 2020³⁸	EV1000 is needed	A research member ensured the waveform was acceptable using fast flush test
Andrzejewska/ 2023³⁹	Acumen sensor and Hemosphere monitor are needed	Fast flush test was performed
Ren/2022⁴⁰	Fully automated data entry	Model outputs were

	and mobile device outputs require a system architecture as a scalable real-time platform.	provided to mobile device applications.
Bilimoria/2013 ⁴¹	Variables are manually added in the calculator	Allows clinicians to increase the risk of surgery within the confidence interval for the predicted risk
Bronsert/2020 ⁴²	Variables are manually added in the calculator	Increase the interaction between the patient and the surgeon and make the patients able to understand the procedure and risk of the surgery.
Moheb/2023 ⁴³	Variables are manually added in the calculator	Improved the surgeons prediction
Ferre/2023 ⁴⁴	A digital questionnaire had to be filled out by the patients	The risk were visual illustrated with green (low), orange (intermediate) and red (high).
Fritz/2024 ⁴⁶	Variables are manually added in the calculator	No facilitator identified
Yik/2024 ⁴⁷	Need an ultrasound and the software Musclesound	Bedside, easy to use.
Li/2024 ⁴⁸	Data developed on an elderly demographic	Easy to use, available online

Discussion

This scoping review identified some promising AI models that help the clinicians improve the outcome for surgical patients. Although the models have demonstrated their usefulness there is still some limitations of the models when it comes to clinical use. MySurgeryRisk, a tool developed by researchers at the University of Florida, using machine learning to process vast amounts of patient data and clinical metrics, appears to be a promising predictive AI tool with a high degree of accuracy. It is designed to provide real-time, actionable insights to surgeons, leading to better

patient outcomes and optimized resource allocation^{40,50}. The downside of this model is that their prediction is mostly linear and does not account for variables that together should be weighted more when it comes to calculating the risk. The HPI prediction model of hypotension demonstrated promising results in preventing surgical adverse outcomes. The augmentORTM Portal developed by Asensus Surgical specifically evaluates the surgeon's performance and identify areas for improvement. This could reduce surgical complications by enhancing the technical skills of the surgeons⁵⁴, but has yet to be trialed clinically. The implementation of AI in predicting surgical complications is marked by these innovative approaches and promising results, yet its integration into routine clinical practice faces barrier^{9,55}.

Barriers that impede the widespread adoption of potentially transformative AI models in healthcare are several^{56,57}. Firstly, the quality and comprehensiveness of the data used to train these models are critical. AI models require extensive, well-annotated clinical data to learn effectively, and this data must be continually updated to reflect new medical knowledge and practices⁵⁶. Integrating AI models into existing healthcare IT infrastructures can be technically challenging and costly, necessitating significant upfront investment and ongoing maintenance, as well as extensive training of health care providers⁵⁸. There are also substantial regulatory hurdles. AI models must undergo rigorous testing and approval processes to ensure they meet all clinical safety and efficacy standards. Ethical considerations, such as protecting patient privacy and addressing potential biases in AI algorithms, which must be carefully managed to prevent disparities in healthcare outcomes⁵⁹. For instance, in the review by de Keijzer evaluating the HPI highlighted that despite the potential of AI to transform clinical decision-making, there is a significant translational gap from proof-of-concept to clinical utility⁶⁰. This gap is often due to regulatory uncertainties, organizational challenges, and attitudinal barriers among healthcare professionals. These barriers slow the uptake

and adoption of AI models, even in cases where they have proved to significantly benefit patient care, such as in managing stroke complications ⁶¹.

Another reason for resistance to implementation of AI is skepticism of healthcare professionals towards AI models. Clinicians are cautious about relying on AI for decision-making, concerned that it may overlook individual patient nuances or erode their clinical autonomy^{62,63}. Additionally, the economic implications cannot be overlooked. The development, testing, and deployment of AI systems require substantial financial resources, which can be a barrier for less well-funded healthcare institutions ⁶⁴. Last, there's a worry that AI could become a substitute rather than a support for clinical decision-making, potentially leading to an erosion of the clinicians professional skills ⁶³.

Moreover, research exploring clinicians' perceptions of AI underscores their concerns regarding workload, risk, trust, and the integration of AI into clinical settings. Many clinicians fear that AI may increase their workload or change their workflow in ways that could compromise patient care. They also voice concerns about the risks of relying too heavily on technology that may not always account for the complex realities of medical practice ⁶⁵. Manual data entry is not feasible if the number of features is even moderately high. There must be a bridge between the AI models and the electronic health charts, minimizing the effort for the clinicians to use the models. The integration should be a seamless solution preferably as automated data pipelines would facilitate implementations.

Based on the literature and our scoping review, we believe that there are opportunities to overcome these barriers and improve surgical safety using AI across different domains to predict adverse outcomes. We collated numerous of studies results in particular where AI may have greatest impact

in specific areas where the complications have been narrowed down to one area, such as hypotension, tissue oxygen saturation and graft loss (table 2).

Regarding hypotension specifically, HPI generates a number ranging from 0-100 where 85 will trigger an alarm on the Acumen™ Hypotension Prediction Index software (Edwards Lifesciences; Irvine, CA, USA) to indicate the likelihood of hypotension will occur⁴⁹. The alarm display support to the clinicians to diagnose the cause and initial causal treatments. The hypotension is defined as mean arterial pressure (MAP) of less than 65 mmHG for at least one minute. There have been several evaluations of the index^{66,67}, as well as an RCT showing the efficacy of the HPI⁶⁸. Retrospective studies have demonstrated that HPI reduces hypotension⁶⁹ which is associated with acute kidney injury and myocardial injury^{70,71} as well as decreases mechanical ventilation time and length of ICU stay⁷². To monitor the effect of HPI, an European registry has been established⁷³. HPI is also used in a protocol to measure the oxygen saturation and predict free flap survival⁷⁴.

Table 2 Evaluation of the potential of AI tool to predict surgical complications

Patient domain	Name of tool	Likelihood of impact
Hypotension	HPI	High
Tissue oxygen saturation	HPI	Medium
Real time assessment	augmentOR, PPC	Medium
Risk of graft loss	HPI	Medium
Risk of mortality	periopORACLE	Medium
Risk of overall complications	MySurgeryRisk, ACS	Low
	NSQIP, POTTER, MyRisk,	
	MuscleSound	
Decision to undergo surgery	SURPAS	Low

Our scoping review revealed that there are some AI models that have both been clinically tested and are easy for others to implement as they are available through a web-based calculator, such as

the MySurgeryRisk. The studies demonstrated that the AI models had promising performance based on their prospective testing. Also, the domain of tissue oxygen saturation have a substantial likelihood of impact since some of these studies also include the hypotension parameter ⁷⁴. For the domain of overall risk prediction, several studies have shown promising results demonstrating that this also have moderate likelihood of impact along with graft loss and risk of mortality. When it comes to decisions to proceed surgery there is less likelihood for impact due to the complexity of the inputs into the prediction model. A specific challenge with using AI for surgical decisions is the difficulty of integrating complex AI predictions into the nuanced and highly individualized process of surgical planning. AI models must accurately interpret and analyze medical images, patient history, and other data to suggest surgical interventions. However, clinical judgment required for surgical decisions often involves factors beyond what AI can currently predict, such as patient preferences, surgeon experience, and intraoperative findings. Thus, while AI can support decision-making, it cannot fully replicate the expert judgment of experienced surgeons ⁷⁵. The AI model could also lack generalizability as performance will be affected by the clinical context where the solution is implemented.

Conclusion

While AI holds significant promise for enhancing surgical safety and efficiency by predicting complications, its broader adoption depends on overcoming multifaceted challenges such as cost, surgeons suspicion and adaption into clinical use. Continued technological advancements, alongside strategic policy frameworks and educational efforts aimed at building trust among healthcare providers could bridge this gap.

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