

Rise of the machines: How artificial intelligence could transform perioperative care delivery

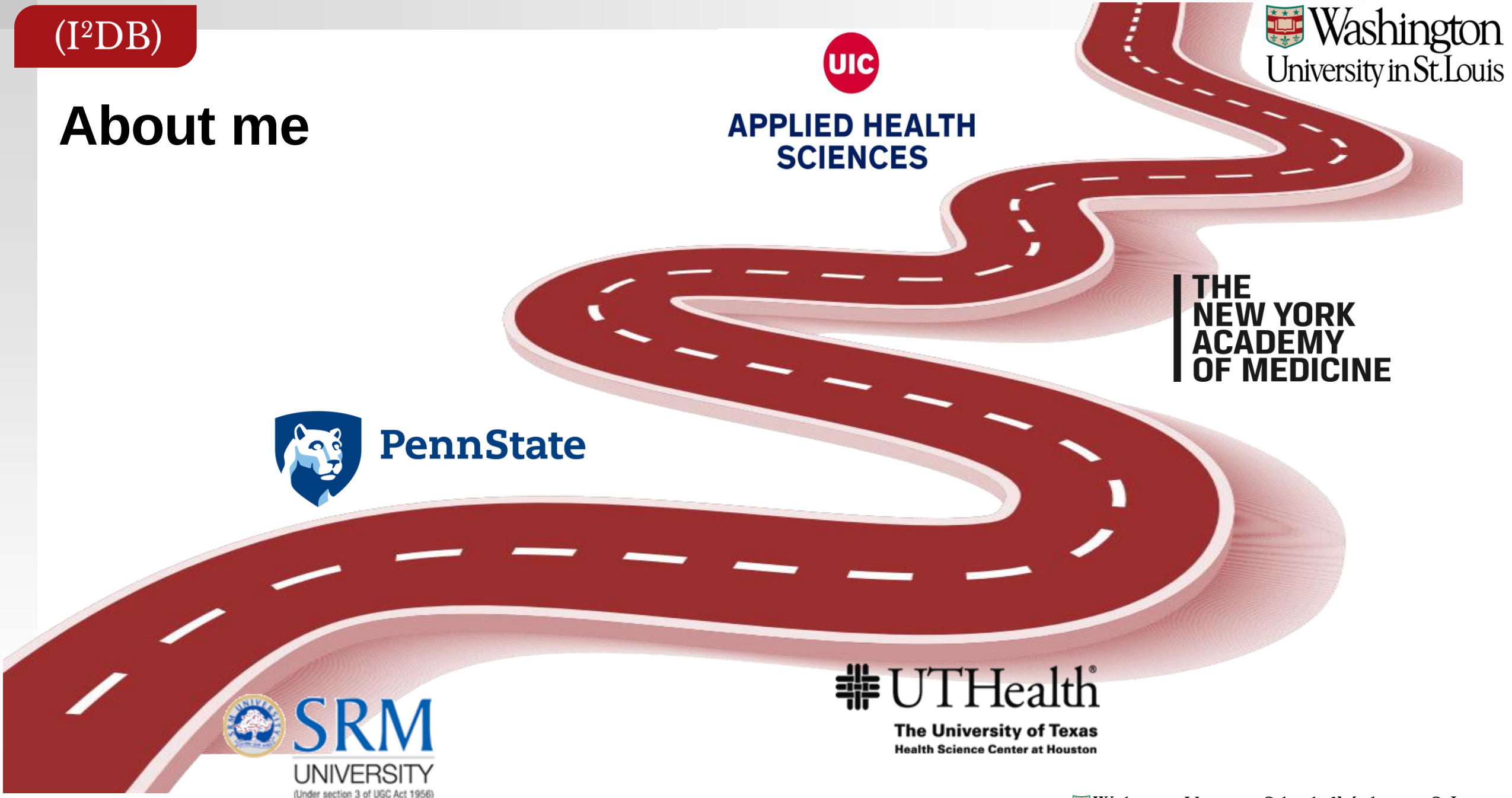
Joanna Abraham, PhD, FACMI, FAMIA
Associate Professor of Anesthesiology and Medicine

AI for Health Guest Lecture

11/9/2023

(I²DB)

About me



(I²DB)

Research Program



Handoffs and Care Transitions



Care Team Coordination



Medication Ordering and Reconciliation



Perioperative Mental Health

Telemedicine

Seminar Outline

- **Section 1**
  - Perioperative Care Workflow
  - Studies on AI Applications in Perioperative Care
- **Section 2**
  - ML in Postoperative Handoffs: Clinician Studies
  - ML in Perioperative Medicine: Public and Patient Study*
  - Lessons Learned
- **Section 3**
  - Conclusions about AI in Healthcare

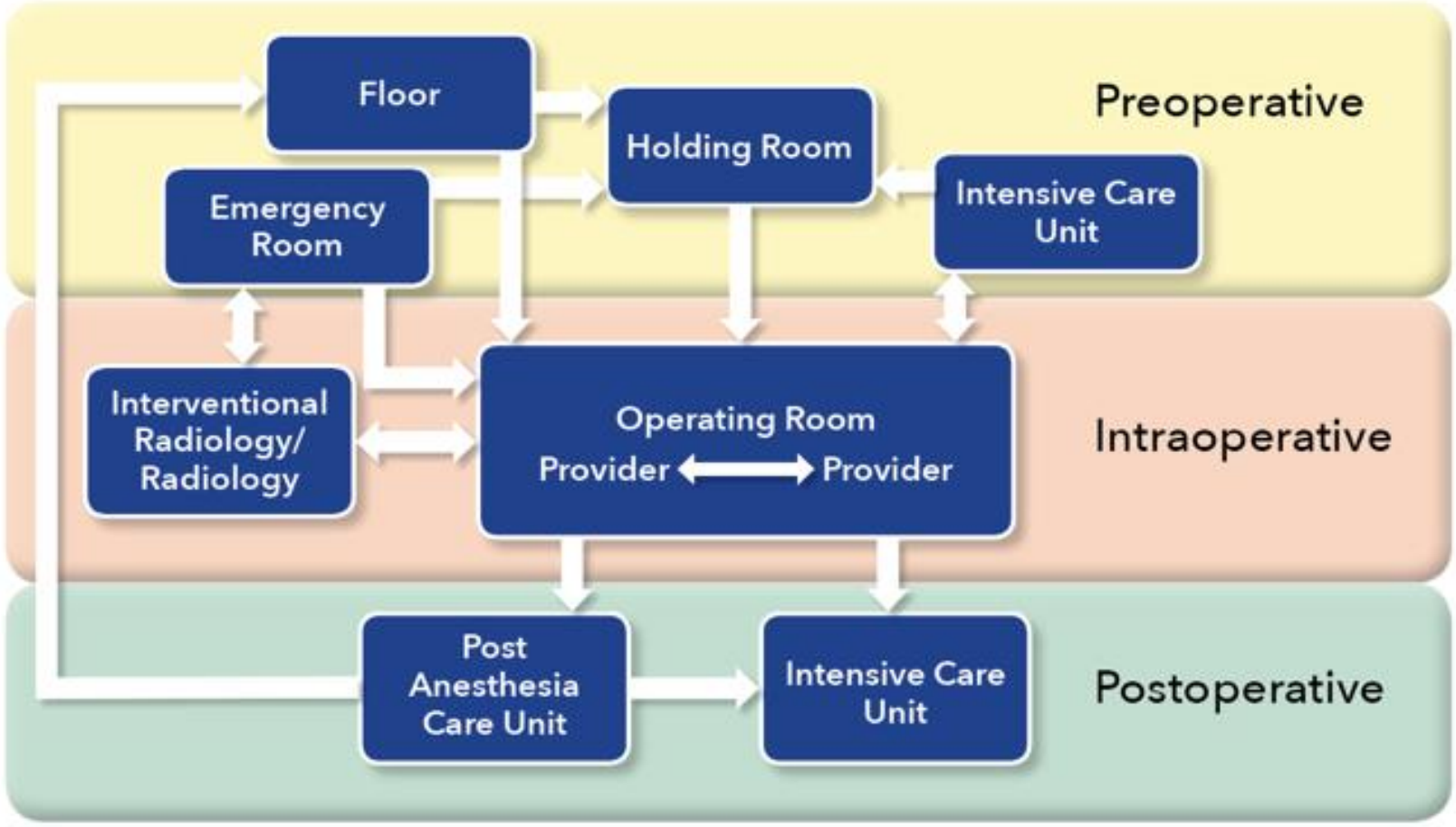
Surgeries on the Rise



300 million global surgeries
51.4 million US surgeries

PMID: 30722955
National Quality Forum. NQF-Endorsed Measures for Surgical Procedures. 2015

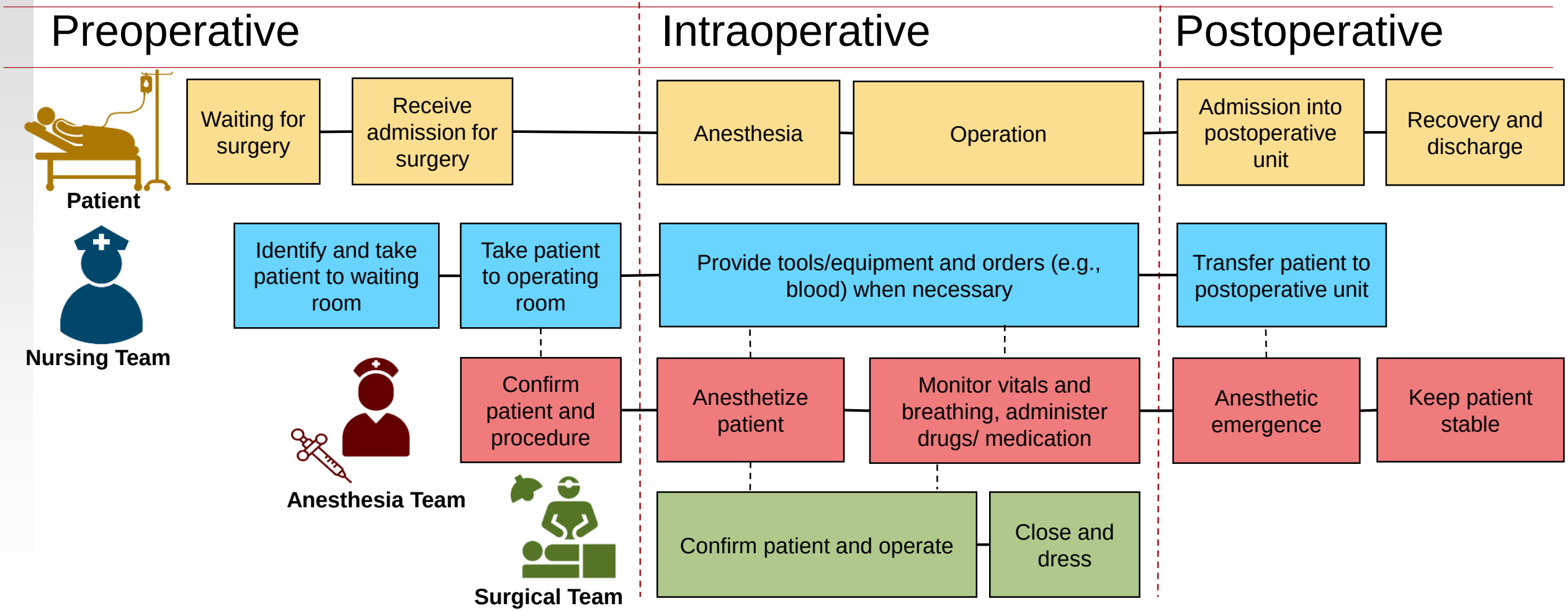
Perioperative Care Workflow



Lorinc, A, and Henson, C. "All handoffs are not the same." *What perioperative handoffs do we participate in and how are they different? APSF* 32 (2017): 29-33.

(I²DB)

Perioperative Care Workflow

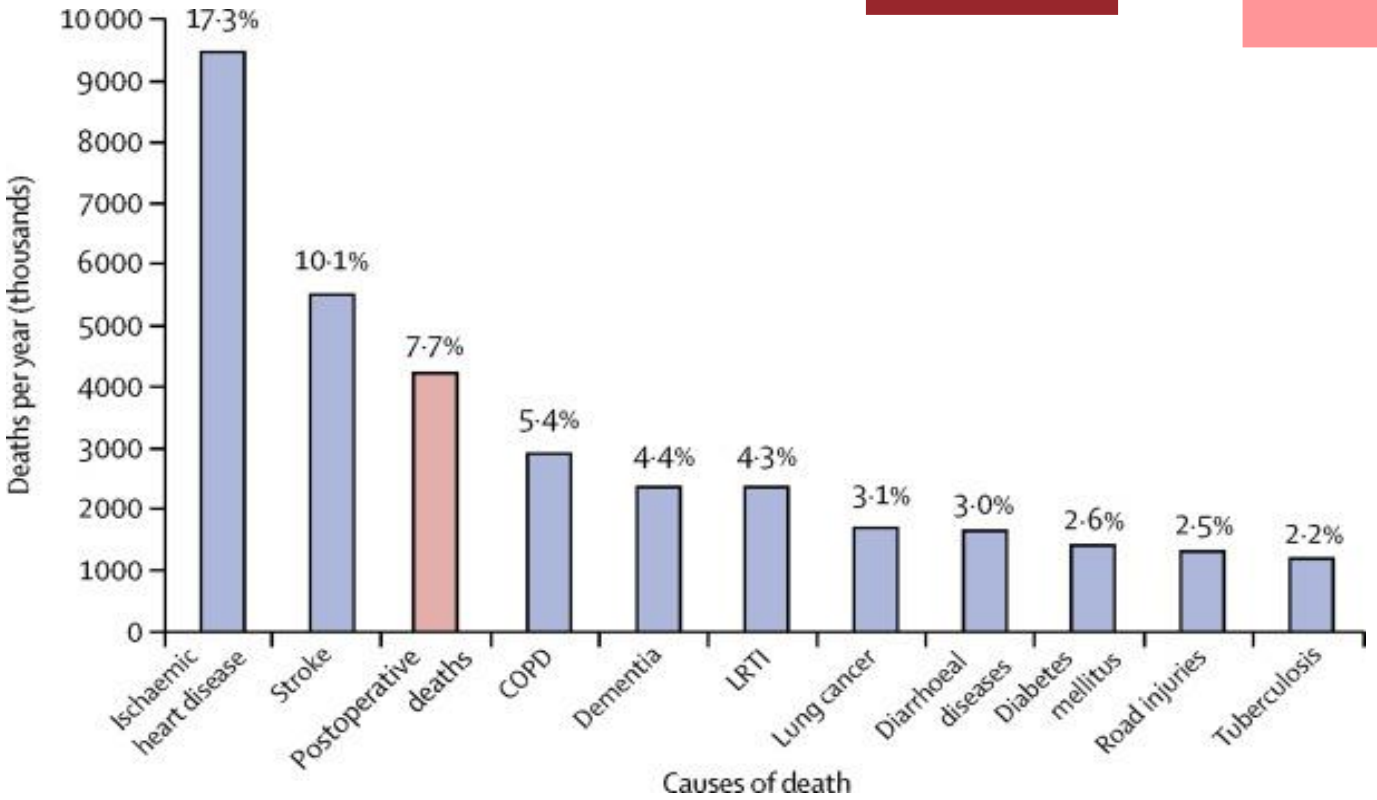


Nepogodiev D, Martin J, Biccard B, et al. Global burden of postoperative death. Lancet 2019;393(10170):401.

Postoperative Mortality and Morbidity



30-day mortality: 1-5%
1-year mortality: 5-10%





10-20%

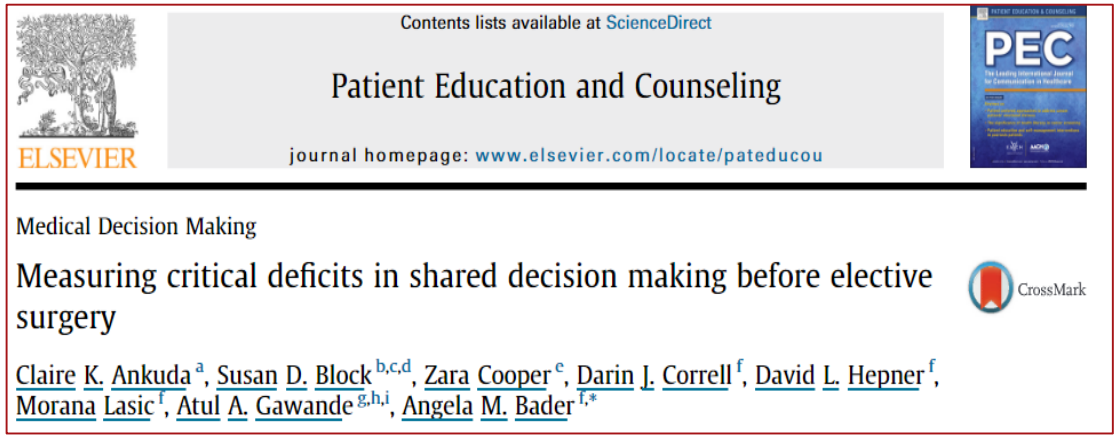
Types of Postoperative Complications

Table 1. Assessment of Death Preventability*

Category	Guidelines
Nonpreventable	Injuries or problem nonsurvivable with optimal management Evaluation and management are appropriate Suspect care does not affect classification of death but is treated as morbidity
Potentially preventable	Injuries or problem severe but survivable Evaluation and management are generally appropriate Errors in care directly or indirectly implicated in patient's death
Preventable	Injuries or problem normally survivable Evaluation and management are suspect Errors directly or indirectly cause patient's death

*From Shackford et al.[7]

Example: Preventable Complications due to Clinician Decision Making Failures



Contents lists available at ScienceDirect

Patient Education and Counseling

journal homepage: www.elsevier.com/locate/pateducou

Medical Decision Making

Measuring critical deficits in shared decision making before elective surgery

Claire K. Ankuda [a], Susan D. Block [b,c,d], Zara Cooper [e], Darin J. Correll [f], David L. Hepner [f], Morana Lasic [f], Atul A. Gawande [g,h,i], Angela M. Bader [f,*]



RESEARCH ARTICLE

WILEY Health Economics

The effect of decision fatigue on surgeons' clinical decision making

Emil Persson[1] | Kinga Barrafrem[1] | Andreas Meunier[2] | Gustav Tinghög[1,3]

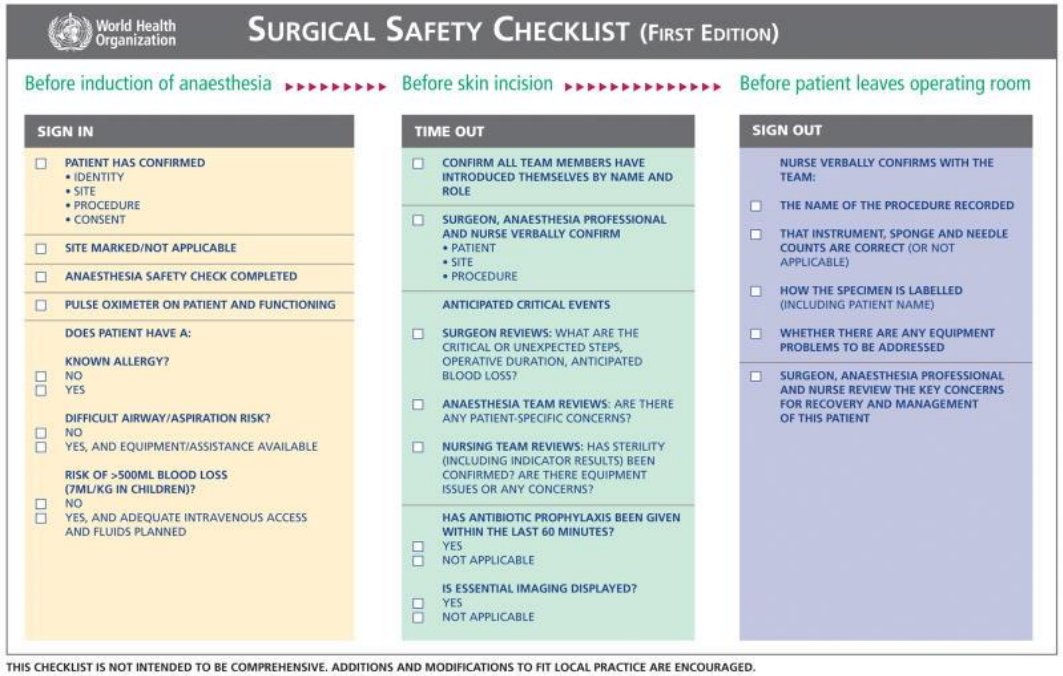
[1]Department of Management and Engineering, Division of Economics, Linköping University, Linköping, Sweden
[2]Department of Clinical and Experimental Medicine, Orthopedics, Linköping University, Linköping, Sweden
[3]National Center for Health Care Priority Setting, Division of Health Care Analysis, Linköping University 581 83, Linköping.

Abstract

The depleting effect of repeated decision making is often referred to as decision fatigue. Understanding how decision fatigue affects medical decision making is important for achieving both efficiency and fairness in health care. In this study, we investigate the potential role of decision fatigue in orthopedic surgeons' decisions to operate, exploiting a natural experiment whereby patient allocation to time slots is plausibly randomized at the level of the patient.

(I²DB)

Strategies to Prevent Postoperative Complications



World Health Organization

SURGICAL SAFETY CHECKLIST (FIRST EDITION)

Before induction of anaesthesia ▸▸▸▸▸▸▸▸▸ Before skin incision ▸▸▸▸▸▸▸▸▸▸▸▸▸ Before patient leaves operating room

SIGN IN

- ☐ PATIENT HAS CONFIRMED
  - IDENTITY
  - SITE
  - PROCEDURE
  - CONSENT
- ☐ SITE MARKED/NOT APPLICABLE
- ☐ ANAESTHESIA SAFETY CHECK COMPLETED
- ☐ PULSE OXIMETER ON PATIENT AND FUNCTIONING
- DOES PATIENT HAVE A:

KNOWN ALLERGY?
- ☐ NO
- ☐ YES

DIFFICULT AIRWAY/ASPIRATION RISK?
- ☐ NO
- ☐ YES, AND EQUIPMENT/ASSISTANCE AVAILABLE

RISK OF >500ML BLOOD LOSS (7ML/KG IN CHILDREN)?
- ☐ NO
- ☐ YES, AND ADEQUATE INTRAVENOUS ACCESS AND FLUIDS PLANNED

TIME OUT

- ☐ CONFIRM ALL TEAM MEMBERS HAVE INTRODUCED THEMSELVES BY NAME AND ROLE
- ☐ SURGEON, ANAESTHESIA PROFESSIONAL AND NURSE VERBALLY CONFIRM
  - PATIENT
  - SITE
  - PROCEDURE

ANTICIPATED CRITICAL EVENTS
- ☐ SURGEON REVIEWS: WHAT ARE THE CRITICAL OR UNEXPECTED STEPS, OPERATIVE DURATION, ANTICIPATED BLOOD LOSS?
- ☐ ANAESTHESIA TEAM REVIEWS: ARE THERE ANY PATIENT-SPECIFIC CONCERNS?
- ☐ NURSING TEAM REVIEWS: HAS STERILITY (INCLUDING INDICATOR RESULTS) BEEN CONFIRMED? ARE THERE EQUIPMENT ISSUES OR ANY CONCERNS?

HAS ANTIBIOTIC PROPHYLAXIS BEEN GIVEN WITHIN THE LAST 60 MINUTES?
- ☐ YES
- ☐ NOT APPLICABLE

IS ESSENTIAL IMAGING DISPLAYED?
- ☐ YES
- ☐ NOT APPLICABLE

SIGN OUT

NURSE VERBALLY CONFIRMS WITH THE TEAM:
- ☐ THE NAME OF THE PROCEDURE RECORDED
- ☐ THAT INSTRUMENT, SPONGE AND NEEDLE COUNTS ARE CORRECT (OR NOT APPLICABLE)
- ☐ HOW THE SPECIMEN IS LABELLED (INCLUDING PATIENT NAME)
- ☐ WHETHER THERE ARE ANY EQUIPMENT PROBLEMS TO BE ADDRESSED
- ☐ SURGEON, ANAESTHESIA PROFESSIONAL AND NURSE REVIEW THE KEY CONCERNS FOR RECOVERY AND MANAGEMENT OF THIS PATIENT

THIS CHECKLIST IS NOT INTENDED TO BE COMPREHENSIVE. ADDITIONS AND MODIFICATIONS TO FIT LOCAL PRACTICE ARE ENCOURAGED.

Systematic review

Training situational awareness to reduce surgical errors in the operating room

M. Graafland[1], J. M. C. Schraagen[2,3], M. A. Boermeester[1], W. A. Bemelman[1] and M. P. Schijven[1]

[1]Department of Surgery, Academic Medical Centre, Amsterdam, [2]Netherlands Organization for Applied Scientific Research (TNO), Soesterberg, and [3]Faculty of Behavioural, Management and Social Sciences, University of Twente, Twente, The Netherlands

Correspondence to: Dr M. P. Schijven, Department of Surgery, Academic Medical Centre, PO Box 22660, 1100 DD Amsterdam, The Netherlands (e-mail: m.p.schijven@amc.uva.nl)

ELSEVIER

World Neurosurgery

Volume 82, Issues 1–2, July–August 2014, Pages e21-e29



Education & Training

The Science of Medical Decision Making: Neurosurgery, Errors, and Personal Cognitive Strategies for Improving Quality of Care

Kyle M. Fargen, William A. Friedman

uis

(I²DB)

Exploring Innovative Methods to Address Postoperative Complications

Table 1. Assessment of Death Preventability*

Category	Guidelines
Nonpreventable	Injuries or problem nonsurvivable with optimal management Evaluation and management are appropriate Suspect care does not affect classification of death but is treated as morbidity
Potentially preventable	Injuries or problem severe but survivable Evaluation and management are generally appropriate Errors in care directly or indirectly implicated in patient's death
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*From Shackford et al.[7]


AI

Potential Role for AI in Perioperative Care

Pre-operative

- Surgical planning
  - Prepare for risks and complications
- Provides estimate of surgery duration
- Resource allocation and planning
- Hospital stay after anesthesia

Intra-operative

- Tracks patient vitals
  - Respiration rate
  - Blood pressure
- Detects abnormalities in vitals

Post-operative

- Monitor signs of deterioration post-operatively
- Forecast outcomes of post-operative complications
- Predicts likelihood of hospital readmission

Retrospective Studies on ML in Perioperative Care

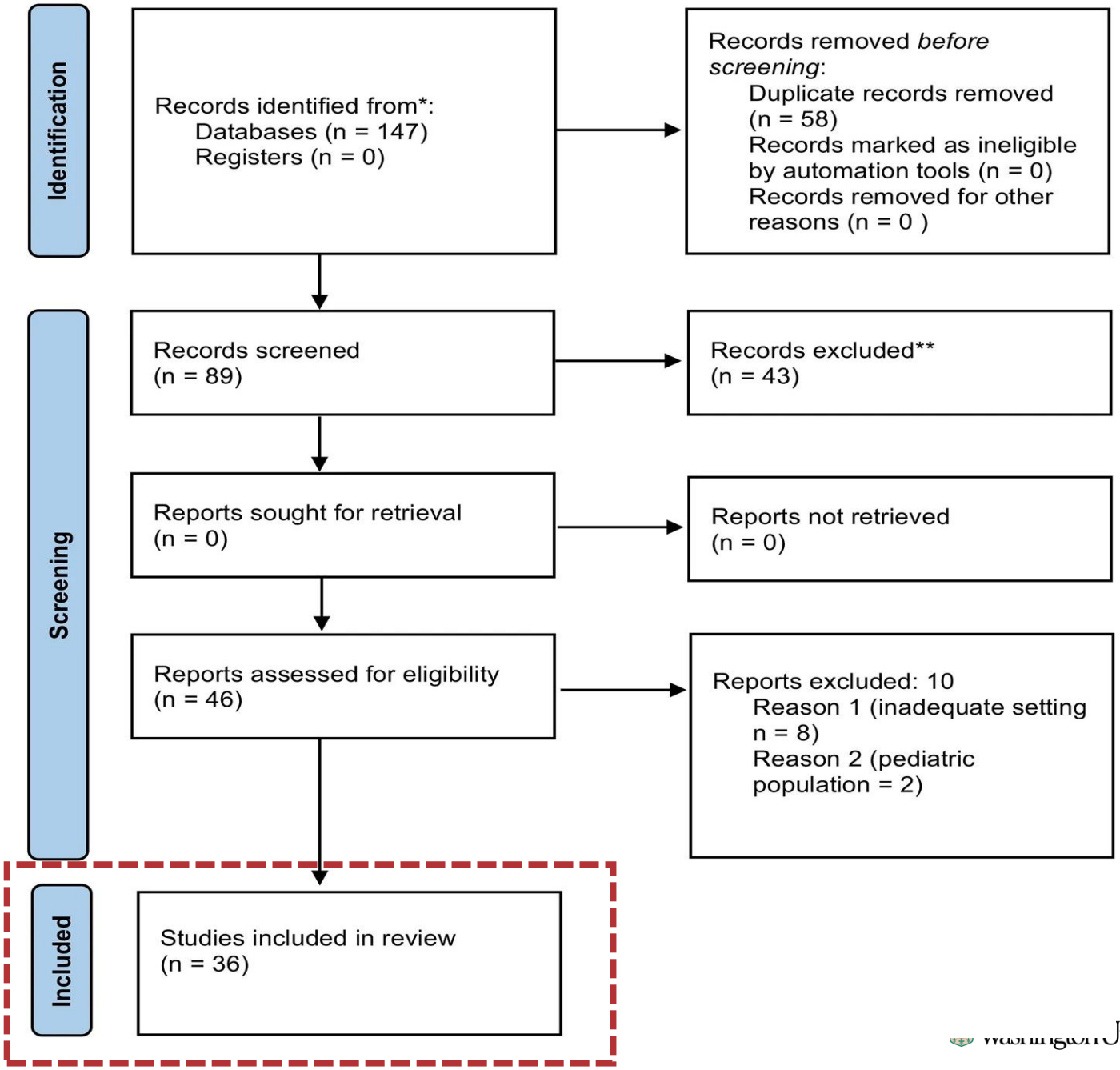
- Review on ML studies evaluating outcomes in perioperative care

Study Design: Experimental



Bellini, V., Valente, M., Bertorelli, G., Pifferi, B., Craca, M., Mordonini, M., ... & Bignami, E. (2022). Machine learning in perioperative medicine: a systematic review. *Journal of Anesthesia, Analgesia and Critical Care*, *2*(1), 2.

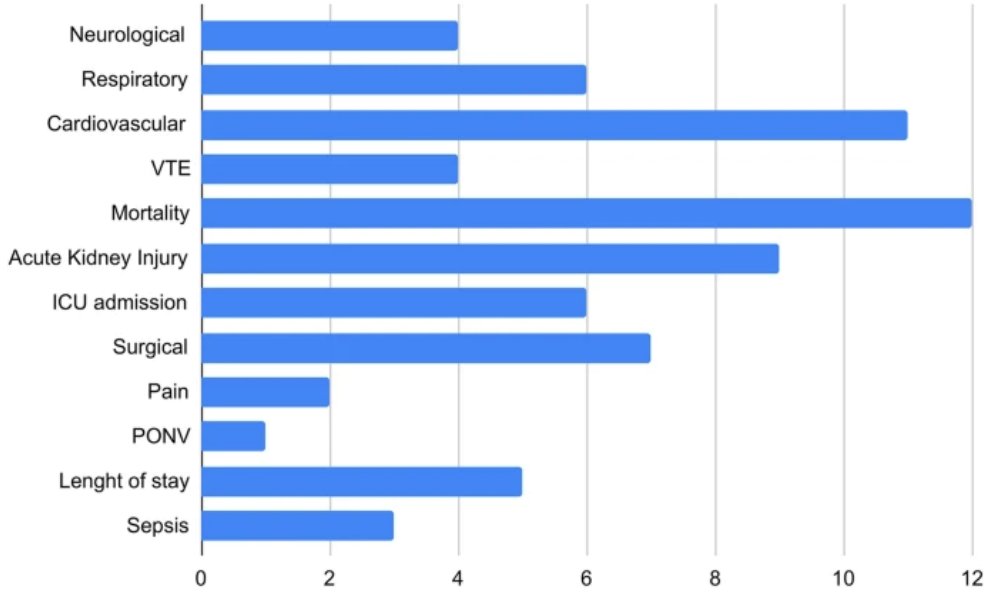
PRISMA


Identification
Records identified from*:
Databases (n = 147)
Registers (n = 0)
Records removed *before screening*:
Duplicate records removed (n = 58)
Records marked as ineligible by automation tools (n = 0)
Records removed for other reasons (n = 0)
Screening
Records screened
(n = 89)
Records excluded**
(n = 43)
Reports sought for retrieval
(n = 0)
Reports not retrieved
(n = 0)
Reports assessed for eligibility
(n = 46)
Reports excluded: 10
Reason 1 (inadequate setting n = 8)
Reason 2 (pediatric population = 2)
Included
Studies included in review
(n = 36)

(I²DB)

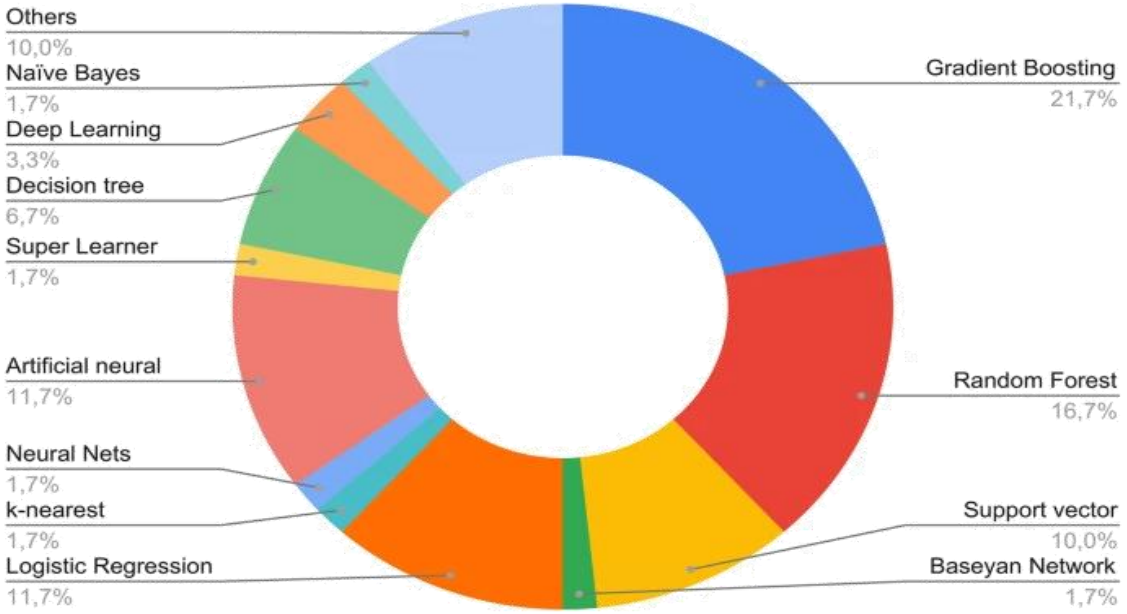
Retrospective Studies on ML in Perioperative Care

Perioperative Outcomes Studied



Main outcomes (preoperative/intraoperative) considered in our analysis

Most frequently used algorithms



Presentation of the main types of machine learning methods used in the analysis of our studies

Open Access Protocol

BMJ Open

Using machine learning techniques to develop forecasting algorithms for postoperative complications: protocol for a retrospective study

Bradley A Fritz,[1] Yixin Chen,[2] Teresa M Murray-Torres,[1] Stephen Gregory,[1] Arbi Ben Abdallah,[1] Alex Kronzer,[1] Sherry Lynn McKinnon,[1] Thaddeus Budelier,[1] Daniel L Helsten,[1] Troy S Wildes,[1] Anshuman Sharma,[1] Michael Simon Avidan[1]

BJA

British Journal of Anaesthesia, 123 (5): 688–695 (2019)

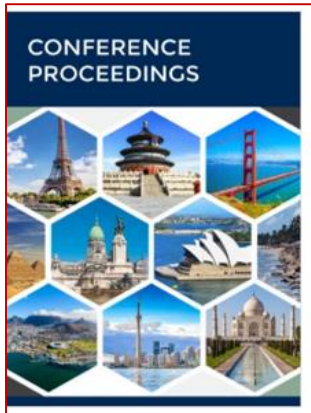
doi: 10.1016/j.bja.2019.07.025

Advance Access Publication Date: 23 September 2019

Quality and Patient Safety

Deep-learning model for predicting 30-day postoperative mortality

Bradley A. Fritz[1,*,†], Zhicheng Cui[2,†], Muhan Zhang[2], Yujie He[2], Yixin Chen[2], Alex Kronzer[1], Arbi Ben Abdallah[1], Christopher R. King[1] and Michael S. Avidan[1]



Home / Proceedings / ICDM / ICDM 2022

2022 IEEE International Conference on Data Mining (ICDM)

Self-explaining Hierarchical Model for Intraoperative Time Series

Year: 2022, Pages: 1041-1046
DOI Bookmark: 10.1109/ICDM54844.2022.00128

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Chenyang Lu, Washington University in St. Louis,McKelvey School of Engineering

Details



Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining

5033 Pages

ACM Conferences

SECTION

Perioperative Predictions with Interpretable Latent Representation

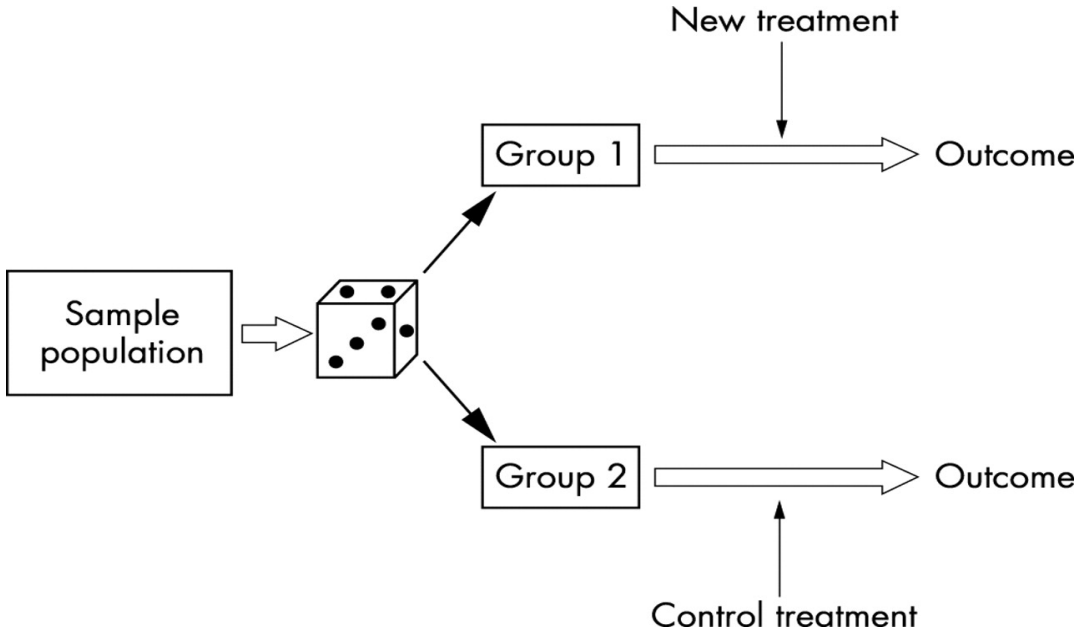
View summary

Bing Xue, York Jiao, Thomas Kannampallil, Bradley Fritz, Christopher King, Joanna Abraham, Michael Avidan and Chenyang Lu ... Hide

Prospective Studies on ML in Perioperative Care

- Review on RCT studies evaluating ML-augmented interventions in perioperative settings and impact on perioperative outcomes

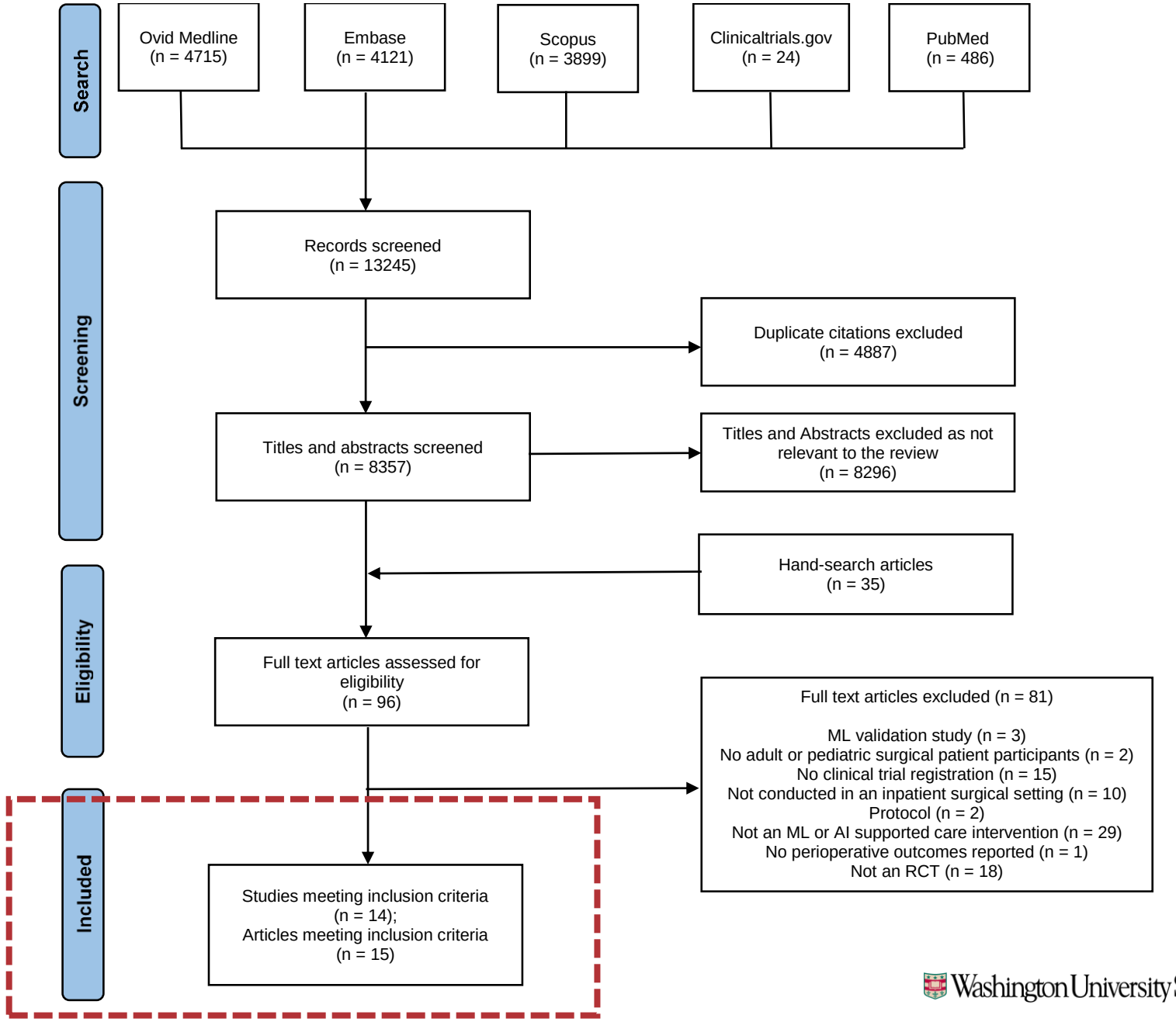
Study Design: Randomized Clinical Trial



Mehta, D., Huang, G., Pedamallu, L., Abraham, J. (*under prep*). Machine learning augmented tools in perioperative medicine: a systematic review and meta-analysis

(I²DB)

PRISMA


Search
Ovid Medline (n = 4715)
Embase (n = 4121)
Scopus (n = 3899)
Clinicaltrials.gov (n = 24)
PubMed (n = 486)
Screening
Records screened (n = 13245)
Duplicate citations excluded (n = 4887)
Titles and abstracts screened (n = 8357)
Titles and Abstracts excluded as not relevant to the review (n = 8296)
Hand-search articles (n = 35)
Eligibility
Full text articles assessed for eligibility (n = 96)
Full text articles excluded (n = 81)
ML validation study (n = 3)
No adult or pediatric surgical patient participants (n = 2)
No clinical trial registration (n = 15)
Not conducted in an inpatient surgical setting (n = 10)
Protocol (n = 2)
Not an ML or AI supported care intervention (n = 29)
No perioperative outcomes reported (n = 1)
Not an RCT (n = 18)
Included
Studies meeting inclusion criteria (n = 14);
Articles meeting inclusion criteria (n = 15)

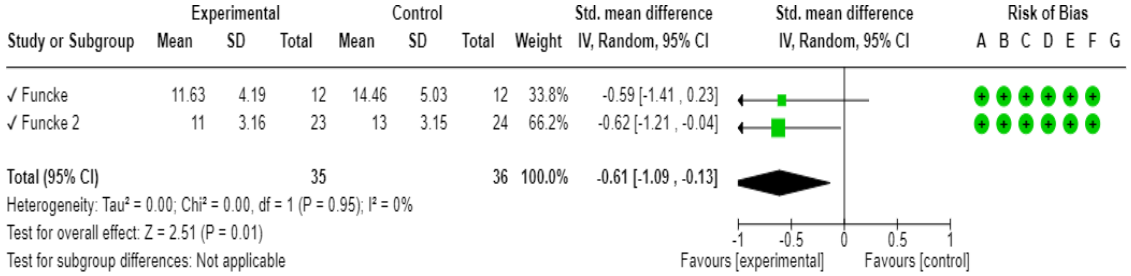
(I²DB)

Nociception Level Index (NOL)

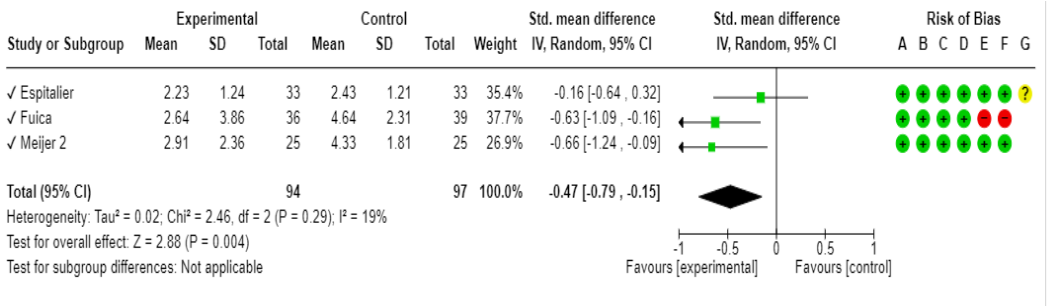


- **Nociception**: Neural response to potentially tissue damaging stimuli
- **Problem**: Pain due to improper opioid dosing
- **NOL index**: An artificial intelligence-driven, multi-parameter index designed for monitoring nociception during surgery

End of narcotics to extubation time

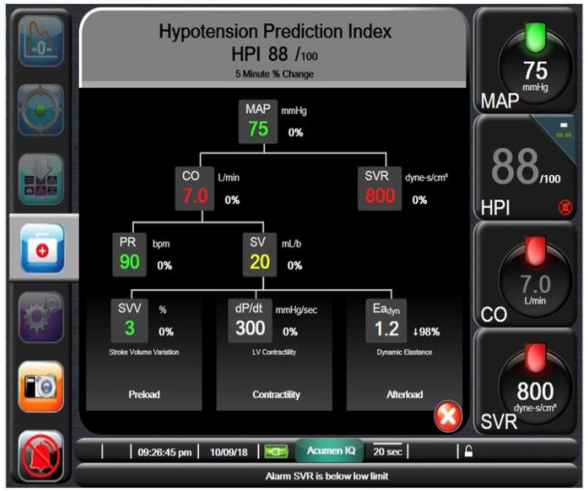


Mean pain score in PACU



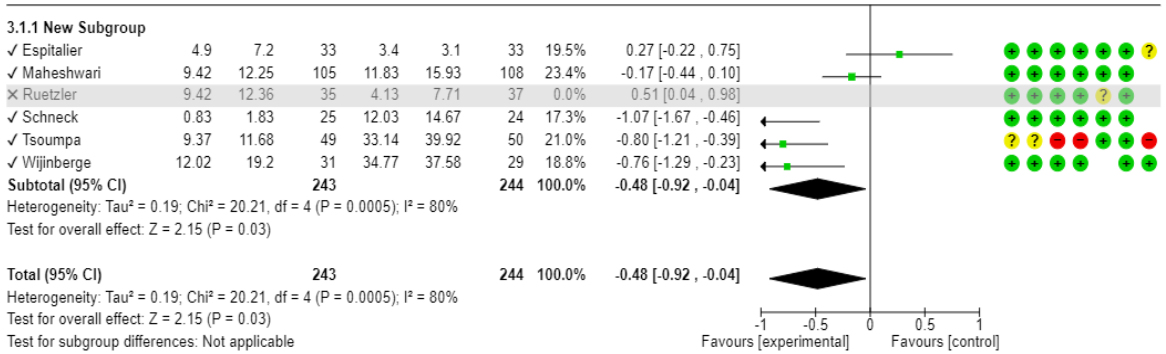
(I²DB)

Hypotensive Prediction Index (HPI)

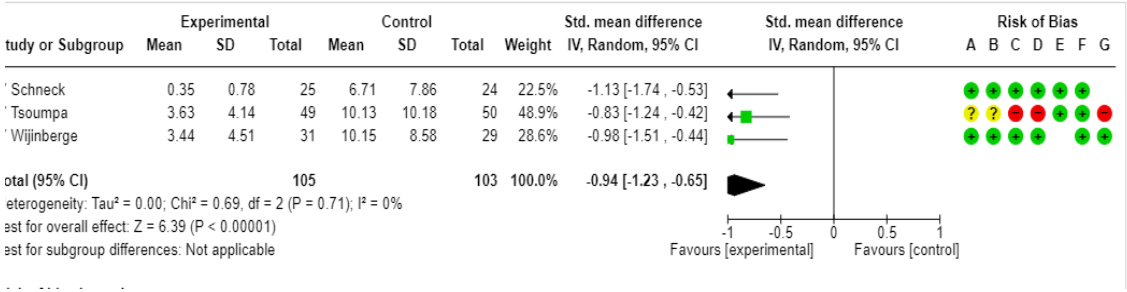


- **Problem**: Low blood pressure during surgery
- **HPI**: An algorithm designed to predict hypotension based on arterial waveform features
- HPI uses a arterial catheter to provide clinicians with alerts regarding the short-term risk of hypotensive events

Duration of Hypotension



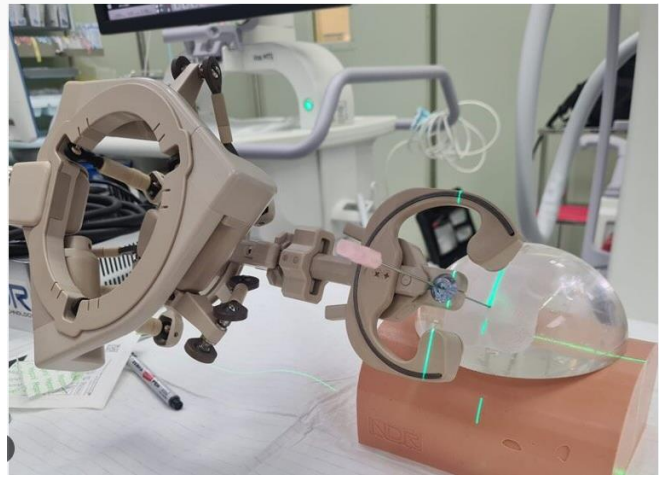
Hypotension as percentage of surgery time



Washington University School of Medicine in St. Louis

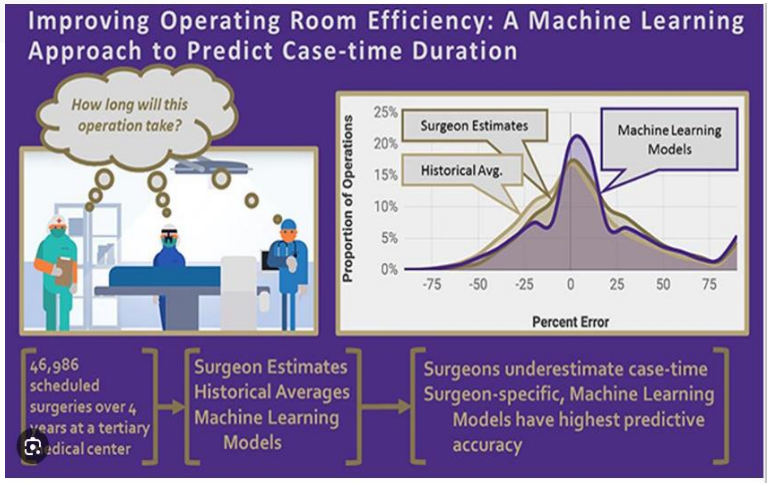
(I²DB)

Robotic-Assisted Fluoroscopic (RAF)



- **Problem**: Needle puncture frequency and duration during mini-percutaneous nephrolithotomy (PCNL) surgeries
- **RAF with ultrasound-guided (US) renal access**: uses a robotic technique called ANT-X that automates needle puncture trajectory using AI platform
- **Findings**: Significant improvement with RAF in decreasing mean number of needle punctures, in improving resident ability to obtain success and needle puncture duration

Surgical Case Duration



- **Problem**: Delays in surgeries and resources
- **ML Case-time Duration**: Machine learning–assisted surgical predictions 1 day before surgery
- **Findings**: Significantly improved accuracy in predicting case duration reduced patient wait time, no difference in time between cases (i.e., turnover time or surgeon wait time), reduced pre-surgical length of stay; and decreased the unnecessary use of pre-surgical re-sources

(I²DB)

Leveraging ML for Augmenting Postoperative Handoffs

(I²DB)

Postoperative Patient Transfers

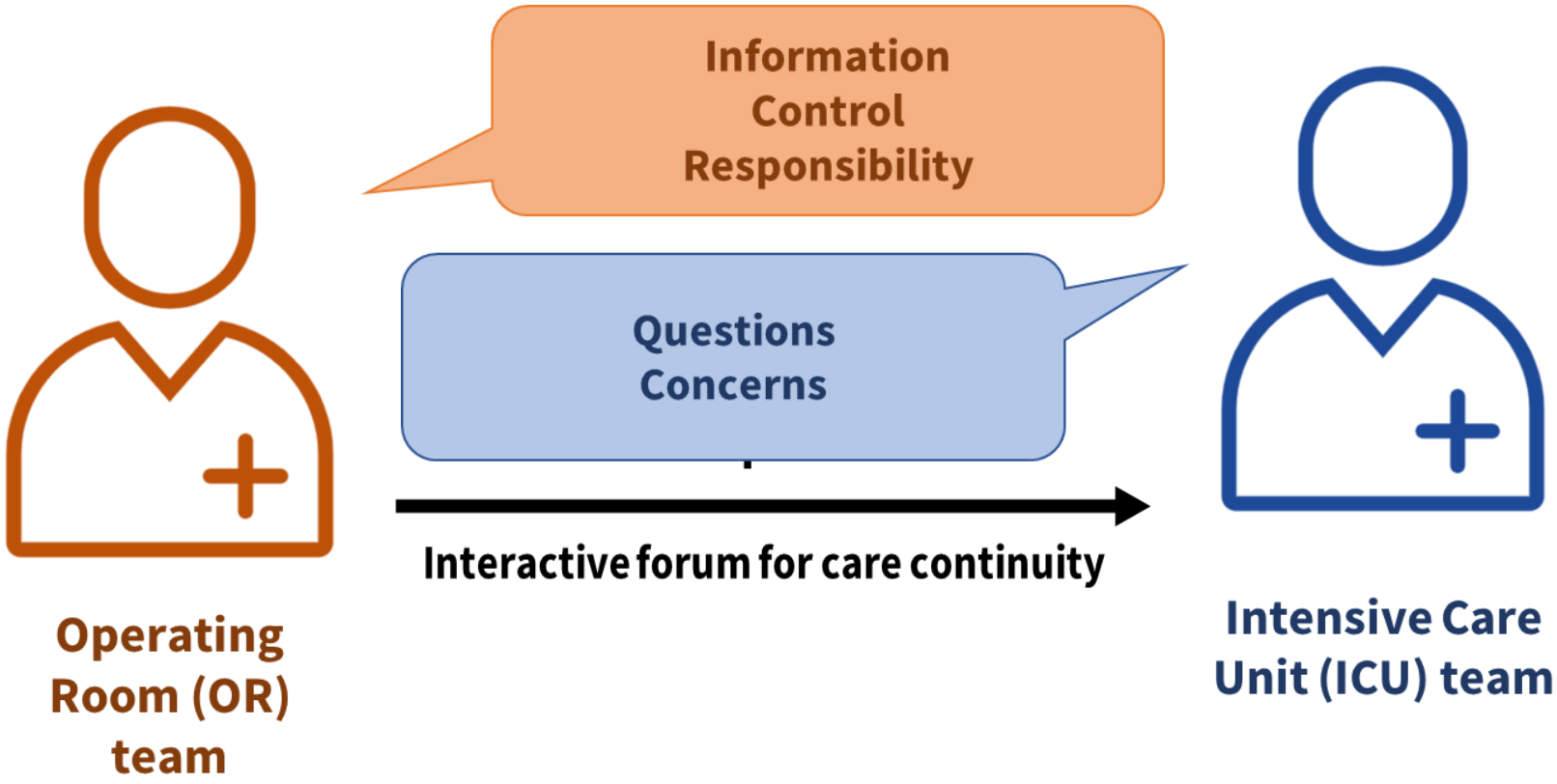
Operating Room Team



Intensive Care Unit Team

PMID: 18582931; 30722955; 28738985
National Quality Forum. Surgery, Spring 2019 Review Cycle: CDP Report. 2020.

Postoperative Handoffs



PMID: 2a1701043; 23703824

Sentinel Event Alert

A complimentary publication of The Joint Commission
Issue 58, September 12, 2017

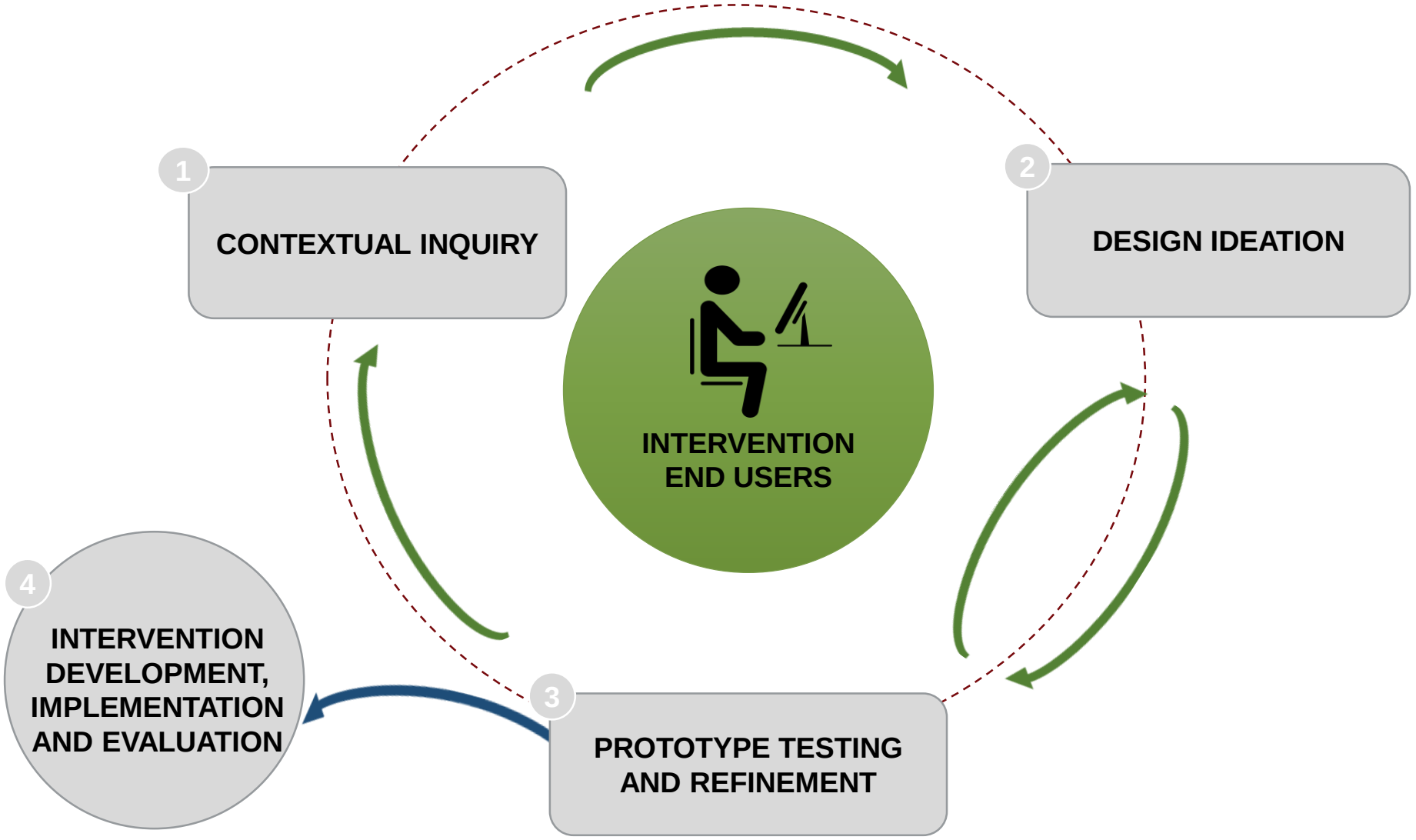
Published for Joint Commission-accredited organizations and interested health care professionals, *Sentinel Event Alert* identifies specific types of sentinel and adverse events and high risk conditions, describes their common underlying causes, and recommends steps to reduce risk and prevent future occurrences.

Inadequate hand-off communication

Health care professionals typically take great pride and exert painstaking effort to meet patient needs and provide the best possible care. Unfortunately, too often, this diligence and attentiveness falters when the patient is handed off, or transitioned, to another health care provider for continuing care, treatment or services. A common problem regarding hand-offs, or hand-overs, centers on communication: expectations can be out of balance between the sender* of the information and the receiver.[1] This misalignment is where the problem often occurs in hand-off communication.

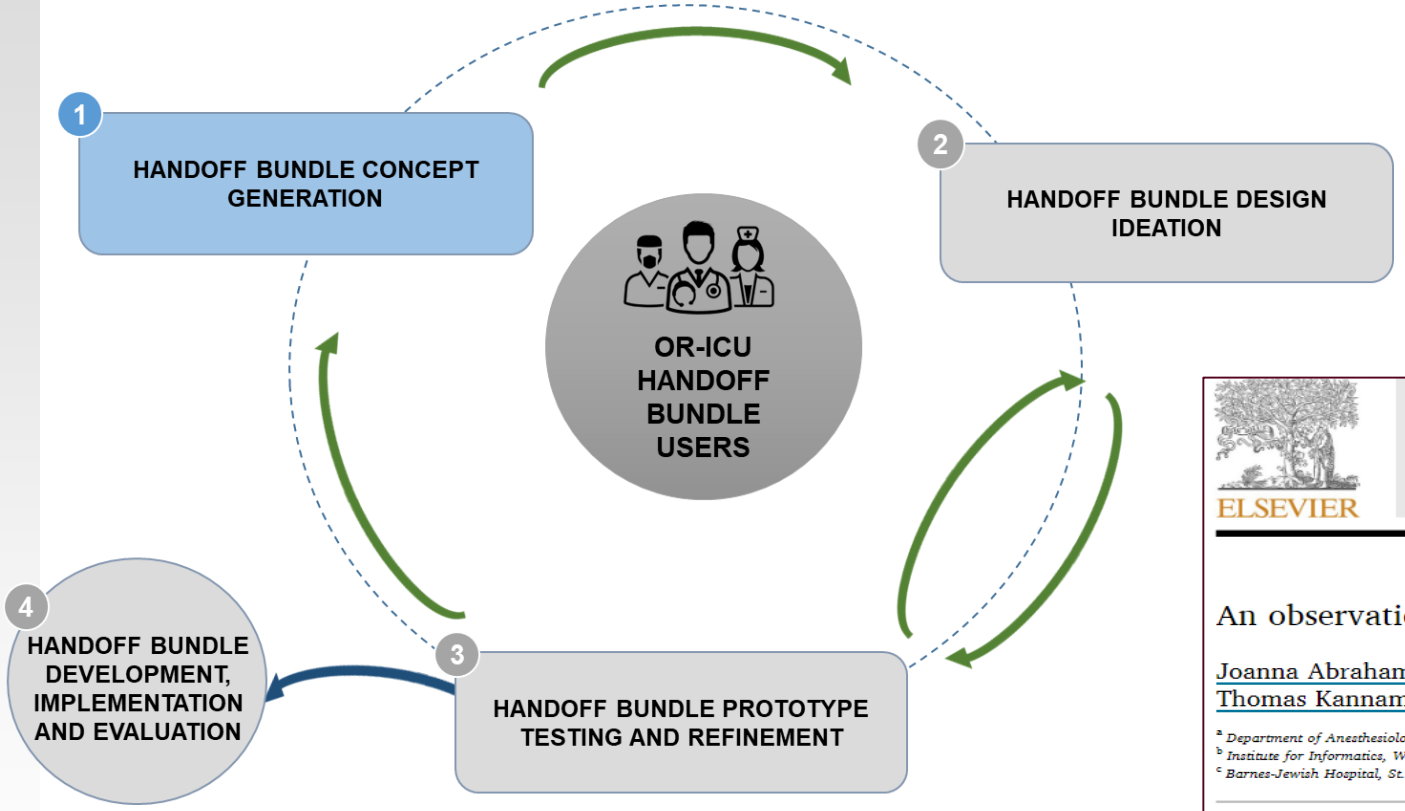
(I²DB)

User-Centered Design (UCD) Approach



(I²DB)

UCD Step 1



Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

An observational study of postoperative handoff standardization failures

Joanna Abraham [a,b,*], Alicia Meng [a], Carrie Sona [c], Troy Wildes [a], Michael Avidan [a], Thomas Kannampallil [a,b]

[a] Department of Anesthesiology, Washington University School of Medicine, St Louis, MO, United States
[b] Institute for Informatics, Washington University School of Medicine, St Louis, MO, United States
[c] Barnes-Jewish Hospital, St. Louis, MO, United States

ARTICLE INFO

Keywords:
Patient transfer
Surgical patients
Communication
Compliance
Safety

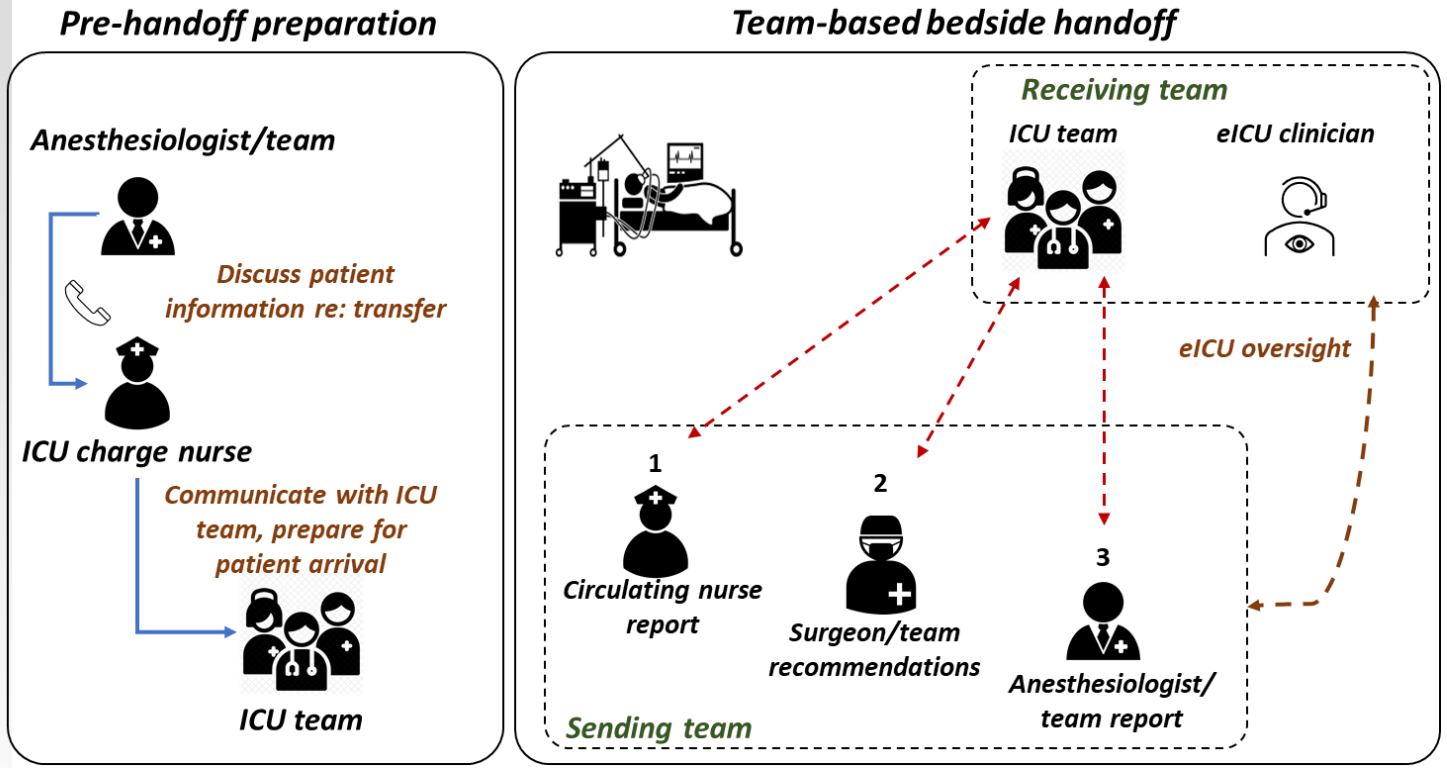
ABSTRACT

Background: Patient handoffs from an operating room (OR) to an intensive care unit (ICU) require precise co-ordination among surgical, anesthesia, and critical care teams. Although several standardized handoff strategies have been developed, their sustainability remains is poor. Little is known regarding factors that impede handoff standardization.

Purpose: Our objectives are three-fold: (1) highlight compliance failures with standardized handoffs; (2) identify factors contributing to compliance failures; and (3) develop guidelines for sustainable handoff interventions and processes.

(I²DB)

Postoperative Standardized Handoff Bundle



Protocol

- RN introduces self, followed by anesthesia provider, surgeon, and ICU team member
- Verification of patient name via words by anesthesia provider and armband by RN
- Critical hookups by RN and RT: 1. A-Line or NIBP, 2. SpO2, 3. ECG, 4. Chest tube or ventriculostomy
- Simultaneously vent and ETCO2: immediate patient care needs discussion only
- Critical hookup completion verified: anesthesia provider says, "it is safe to being report. Is everyone present?"
- Verification that all necessary team members are present: patient's RN, RT, surgical team member, ICU team member

Checklist

Anesthesia

- Surgery performed
- Type of anesthesia provided
- Allergies/CODE status
- Isolation status as applicable
- Airway and oxygenation/ventilation: intubation technique, abnormalities, issues, etc.
- Hemodynamics: intra-op issues, vasopressors
- Anesthesiology team identifies functional IV access line
- Fluid balance and blood products: big issues (anuria, massive EBL, etc.)
- Paralytic status: relaxed, reversed, and procedures (blocks, spinal, etc.)
- Labs and meds: issues
- Anesthesia complications/special considerations
- PMH and PSH including pertinent pre-op medications
- THE THING I AM MOST CONCERNED ABOUT IN THIS PATIENT IS:
- Any questions?
- Hand report template to surgery team member

Surgery

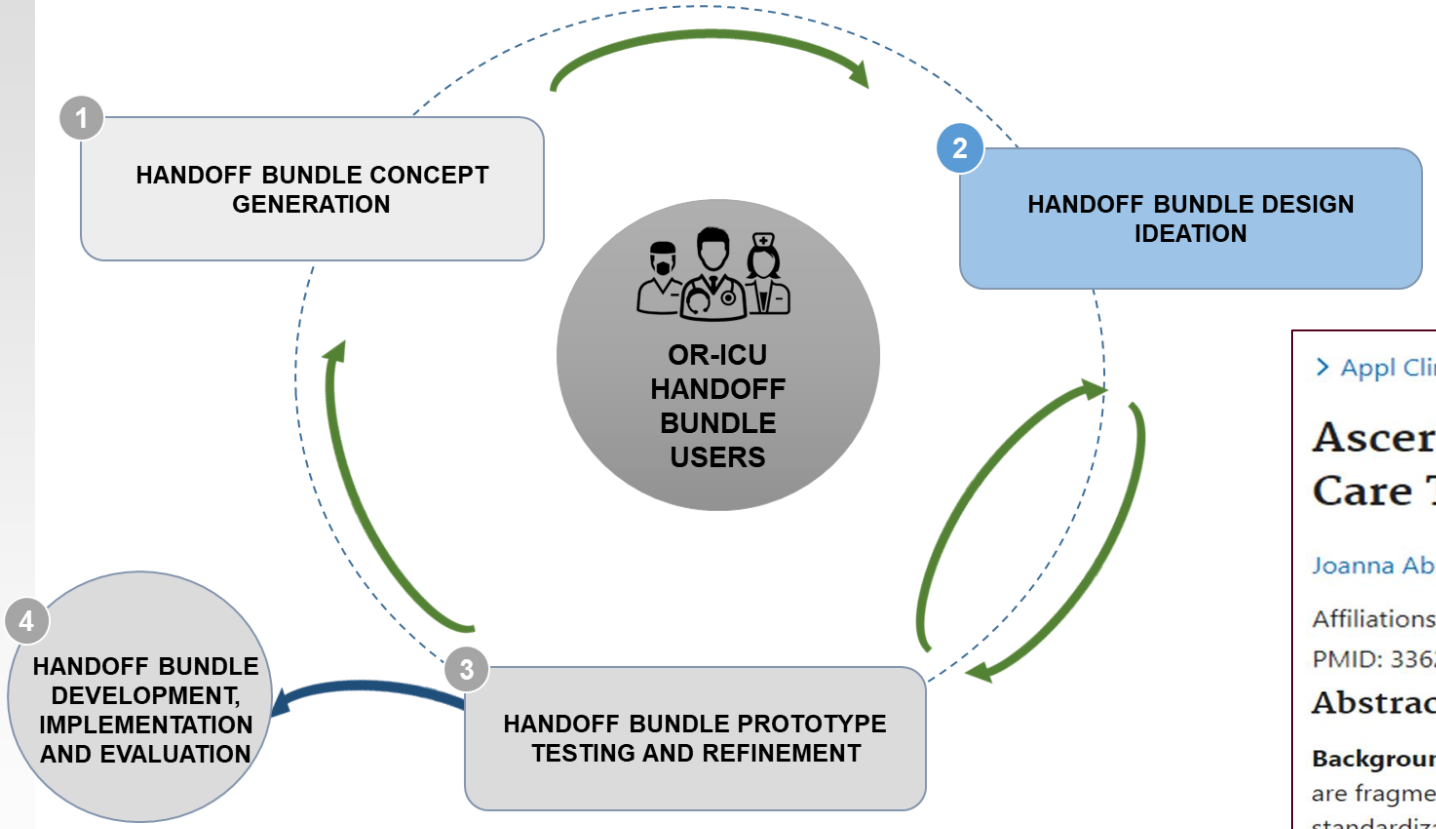
- Actual surgery performed
- Surgical findings (anticipated and unanticipated)
- Drains/tubes
- Special instructions (such as chest tubes to suction for 12 hours, do not reposition NGT)
- Any IRSI or no count or incorrect count case and decision made to defer radiographs due to patient condition
- Surgical complications/special considerations
- THE THING I AM MOST CONCERNED ABOUT IN THIS PATIENT IS:
- Any questions?

The ICU team is now in charge of the patient

Compliance to Standardized Handoff Bundle

Audits by eICU	# of cases (out of 302)
Number of cases that called 30 mins prior to ICU transfer	66.2%
Team member introductions given	66.8%
Team members used checklist during handoffs	37.5%
Surgery team left their contact information	54.5%
Handoff duration	53 (<5 mins); 218 (5-10 mins); 30 (>10 mins)
Handoff quality	**9 (1); 90 (2); 113 (3); 88 (4)**

UCD Step 2



Appl Clin Inform. 2021 Jan;12(1):107-115. doi: 10.1055/s-0040-1721780. Epub 2021 Feb 24.

Ascertaining Design Requirements for Postoperative Care Transition Interventions

Joanna Abraham [1 2], Christopher R King [1], Alicia Meng [1]

Affiliations + expand

PMID: 33626584 PMCID: PMC7904383 DOI: 10.1055/s-0040-1721780

Abstract

Background: Handoffs or care transitions from the operating room (OR) to intensive care unit (ICU) are fragmented and vulnerable to communication errors. Although protocols and checklists for standardization help reduce errors, such interventions suffer from limited sustainability. An unexplored aspect is the potential role of developing personalized postoperative transition interventions using artificial intelligence (AI)-generated risks.

Objectives: This study was aimed to (1) identify factors affecting sustainability of handoff standardization, (2) utilize a human-centered approach to develop design ideas and prototyping

Process-Based Protocol Requirements

- **Establish an active role for eICU clinicians during handoffs**

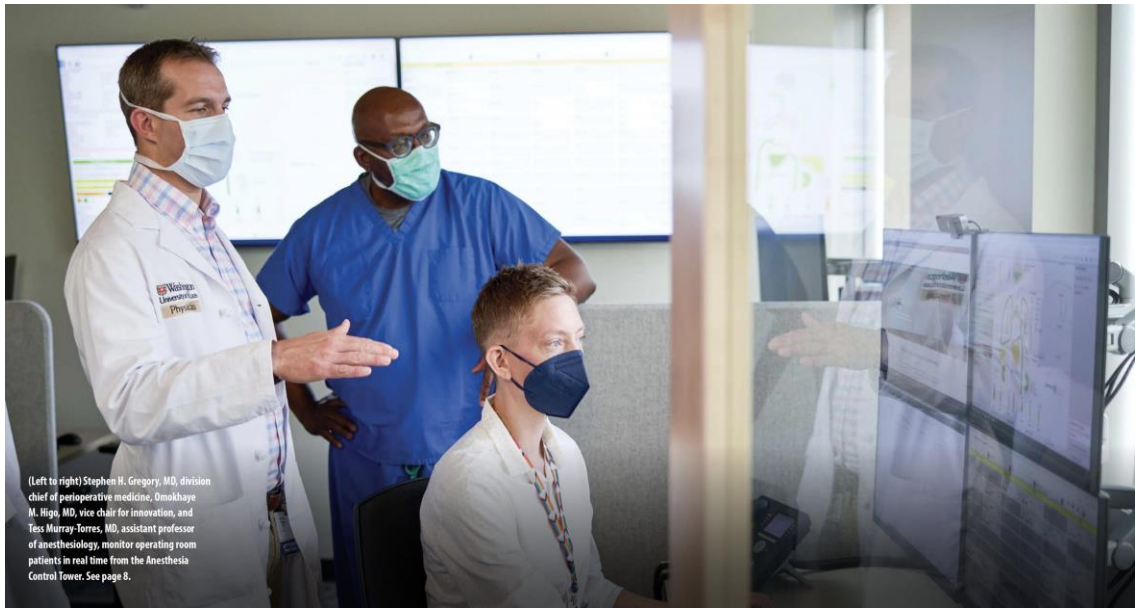


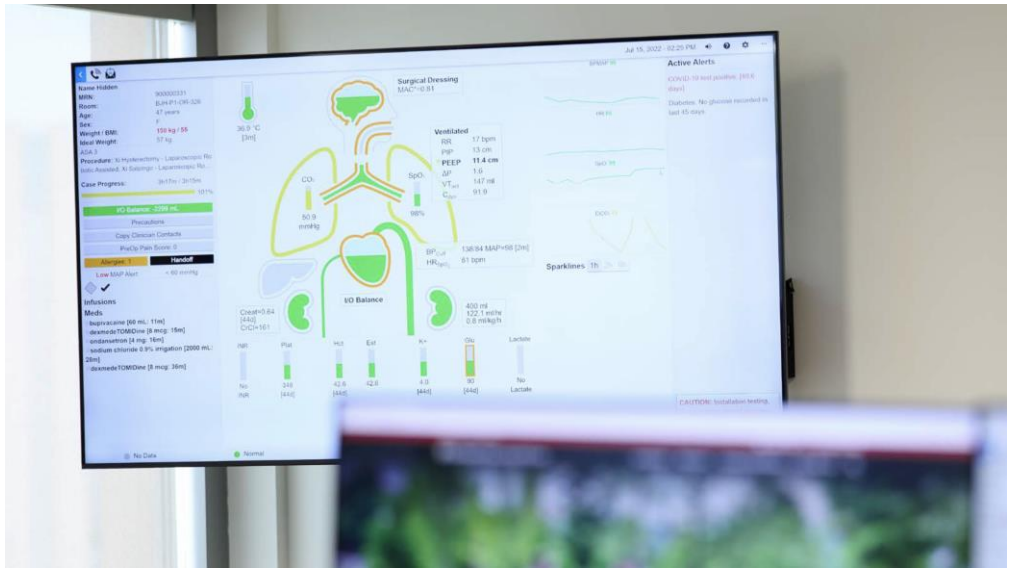
"I think that (an active role) could be a good role for the eICU. To kind of **police the handoff process**. I think it would be more feasible for the eICU nurse to monitor this than the bedside nurse or the bedside physician." (Anest 3)

Process-Based Protocol Requirements

- **Envision a new role for eOR clinicians during handoffs**

> **(eOR) would help [with handoffs]... Especially since ..we look at the surgical notes and the different clinicians' notes. We kind of look at everything.** We [eOR] really don't just stick with anesthesia notes – we usually go further." (eOR 2)



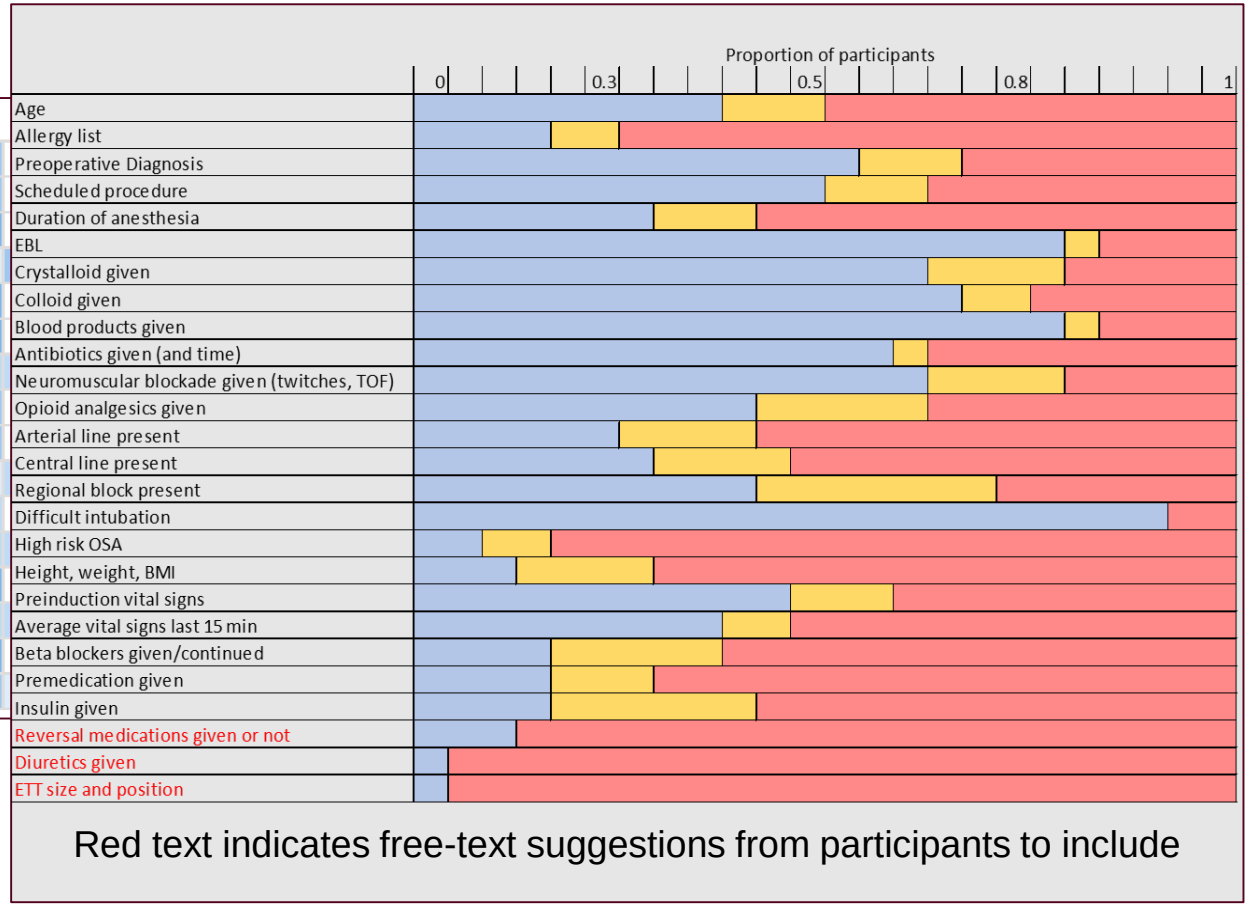


(I²DB)

Information Checklist Requirements

Core elements
Flexible elements
Unnecessary elements

	Core/Necessary ...
Age	3
Allergy list	3
Preoperative diagnosis	4
Scheduled Procedure	1
EBL	4
Blood products given	4
Antibiotics given	2
Crystalloid given	3
Colloid given	3
High risk OSA	1
Height, weight, and BMI	2
Average vital signs last 15 minutes	2
ETT size and position	4
Skin closure/integrity	2
Actual surgery performed	4
Drains/tubes (location, type, functi...	3



Red text indicates free-text suggestions from participants to include

Core Elements

- Age
- True procedure
- Recent intubation/difficult airway
- Anesthesia details (duration of anesthesia, EBL, blood products, regional block)
- OSA risk
- Reactions to medication intra-op
- History of paralytics' issues
- Malignant hyperthermia
- Post-op care plan/discharge plan
- Surgeon notes (expectations for next dose, serious complications)
- Positioning restrictions
- Post-operative imaging
- Fluids
- Antibiotics
- Restrictions (bed rest, diet)
- Short term concerns
- Drain orders
- Clinical overview (baseline, perception of patient status in relation to baseline)
- Extubation plan
- Risk of atrial fibrillation
- Risk of stroke
- Volume status
- Tubes

Flexible Elements

- Intra-op abnormalities
- Opioids
- 30-day mortality
- Method of intubation used intra-operatively
- Risk of AKI
- Risk of VTE
- Risk of pneumonia
- Length of ICU stay
- Dressing changes
- Urine output
- Repeated surgery
- Repeated debridement
- Difficulty of closing
- Reaction to anesthesia/medications
- Interventions for the floor
- Desaturation events
- Vasopressors
- Cardiology consult

Information Checklist Requirements

"**Some [patient] issues [and complications] don't fit neatly into the standardized** [handoff] structure." (Anest 5)

- **Flexible report tailored to specific patient risks/issues over a standardized structure**

"I put more of the **harder to find details** of the anesthesia. I put the stuff that I always want to hear on handoff, but that Or you have to go through if you weren't there for handoff or it wasn't documented well, it disappears.
I feel like a lot of **[standardized patient information] will just clutter up the [report]** and make it much harder to get the **couple big things** you want to see out of it." (ICU Fellow 2)

Information Checklist Requirements

- **Prefer to see elevated risks**

"I think **only ones elevated** because I can't see a reason if we don't include them [low risks], what is the consequence of not knowing?" (ICU Fellow 1)

"Yeah. I feel like for all these, I really **only care if they're at significantly higher risk** and then maybe if they're at significantly lower risk of afib in cardiac surgery patients. Other than that, **I don't care if it's about average.** I guess if they're at significantly elevated risk above the average for the procedure or if they're just at significantly elevated risk" (ICU Fellow 2)

Information Checklist Requirements

"I would care more about **why [a patient is at risk]**… You would want to know the elevated risk of mortality, even though all patients of that surgery have an elevated risk." – Fellow 1

- **Risk factors contributing to risks**

"I think we wanna know **why [complications happen] so we can prevent it early**. I think that would be helpful." (ICU RN 1)

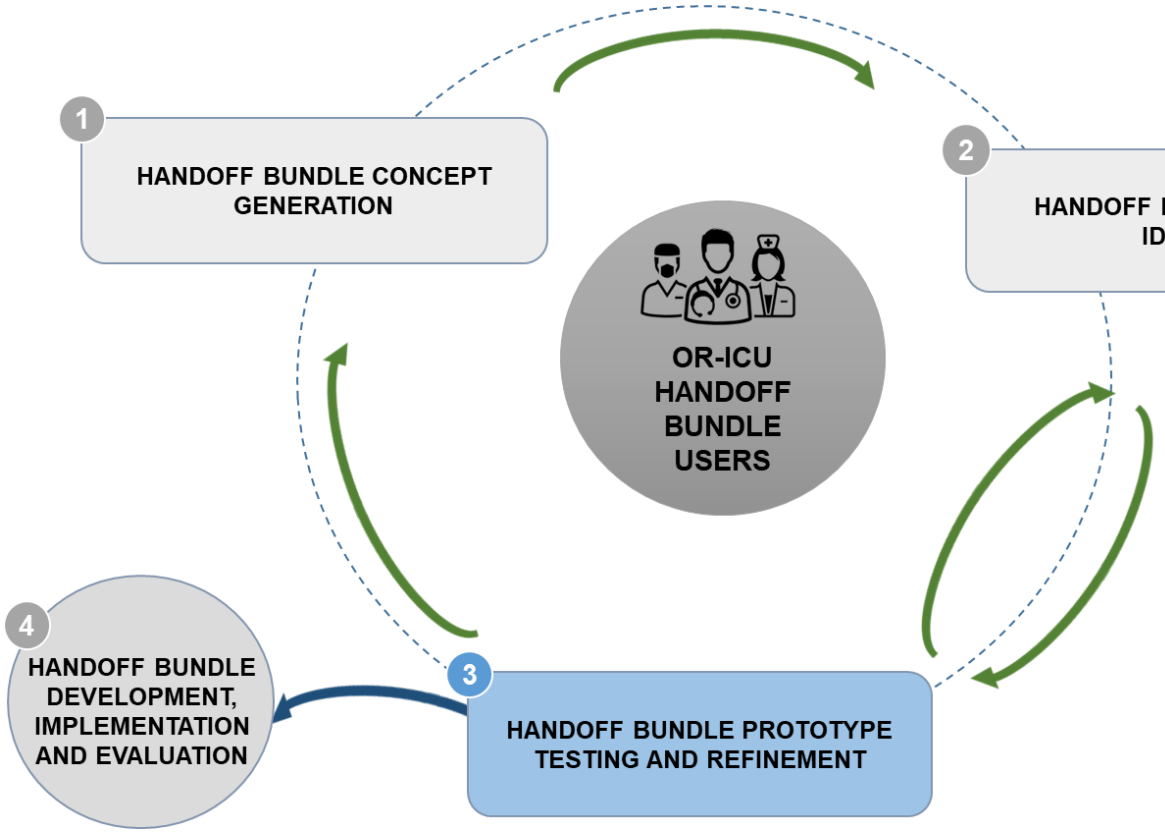
"I don't really care if they have a 1% increased chance of mortality. But **if it's for a reason that might change something you do**?" (ICU Fellow 2)

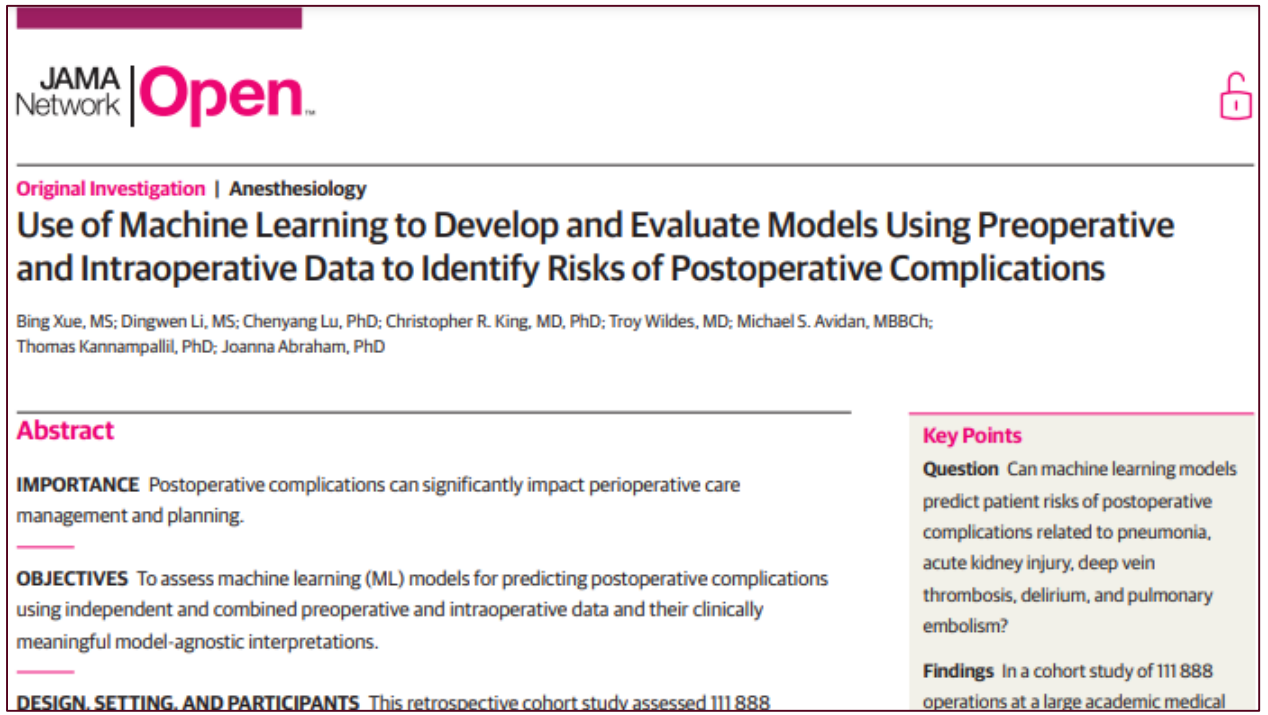
"I think I would only care about **the factors that would keep them in the ICU**" (ICU Fellow 3)

- **Modifiable patient risks and suggestions for mitigating risks**

"What **should the blood pressure be to decrease risk, right**? Or if this patient is already mechanically ventilated, what should the CO2 be to decrease risk? " (Anesth 7).

UCD Step 3





JAMA Network | Open

Original Investigation | Anesthesiology

Use of Machine Learning to Develop and Evaluate Models Using Preoperative and Intraoperative Data to Identify Risks of Postoperative Complications

Bing Xue, MS; Dingwen Li, MS; Chenyang Lu, PhD; Christopher R. King, MD, PhD; Troy Wildes, MD; Michael S. Avidan, MBBCh; Thomas Kannampallil, PhD; Joanna Abraham, PhD

Abstract

IMPORTANCE Postoperative complications can significantly impact perioperative care management and planning.

OBJECTIVES To assess machine learning (ML) models for predicting postoperative complications using independent and combined preoperative and intraoperative data and their clinically meaningful model-agnostic interpretations.

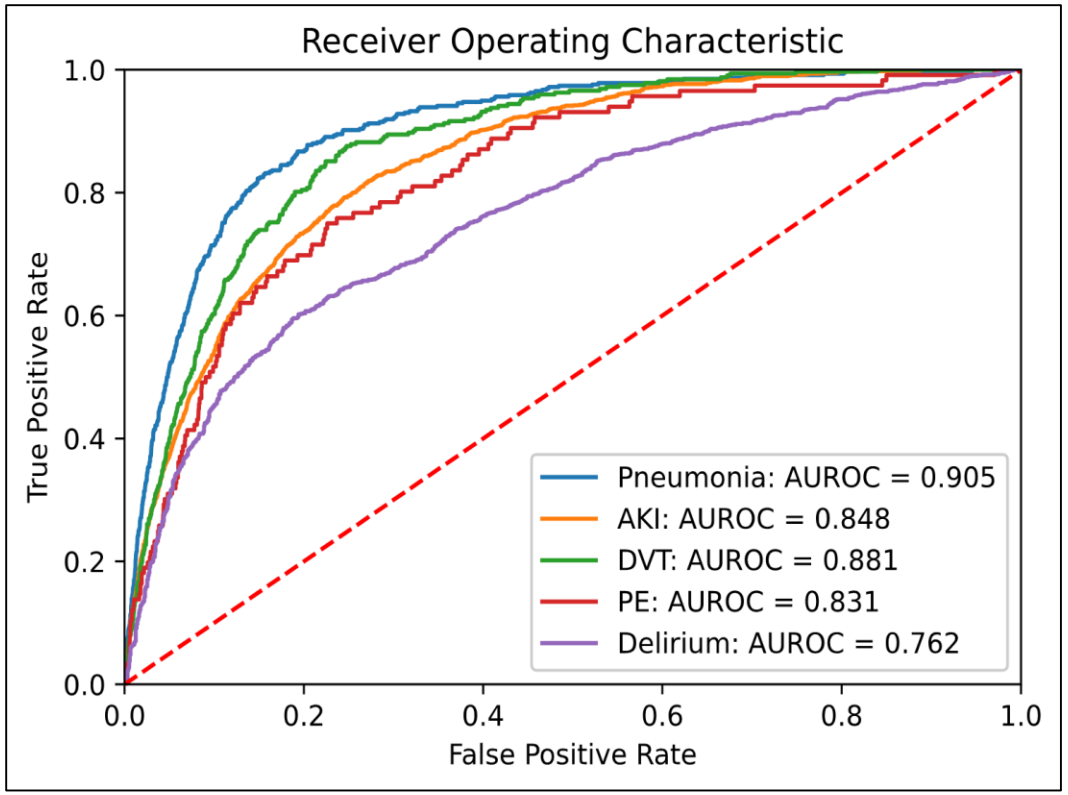
DESIGN, SETTING, AND PARTICIPANTS This retrospective cohort study assessed 111 888

Key Points

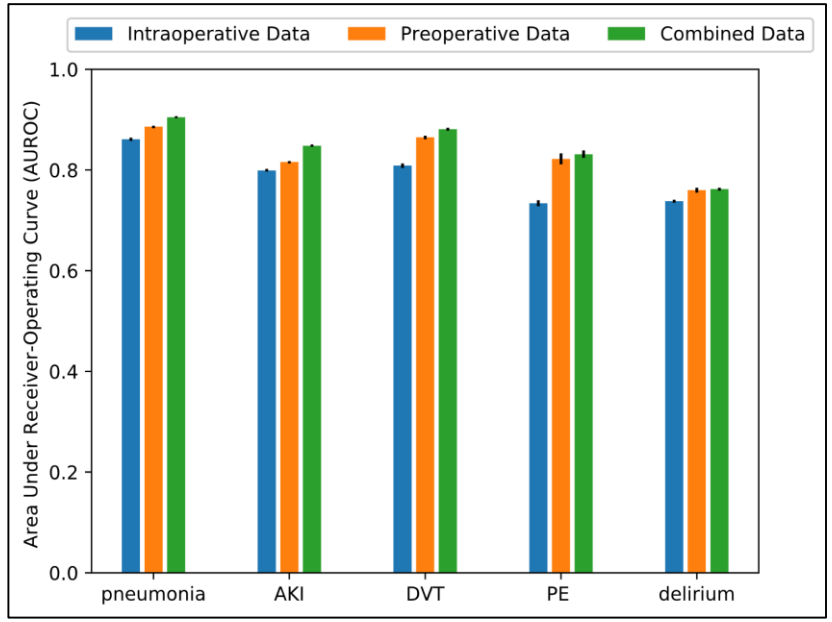
Question Can machine learning models predict patient risks of postoperative complications related to pneumonia, acute kidney injury, deep vein thrombosis, delirium, and pulmonary embolism?

Findings In a cohort study of 111 888 operations at a large academic medical

Risk Prediction of Postoperative Complications

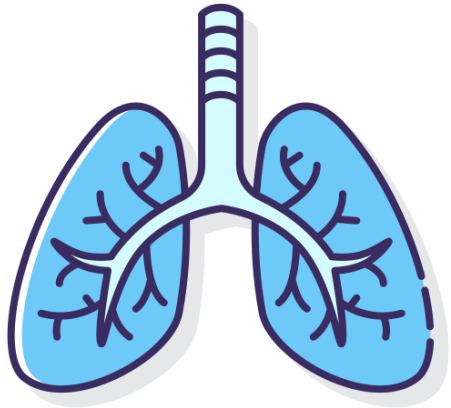


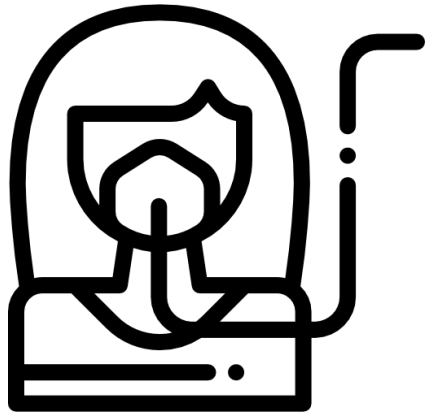
- Acute kidney injury (AKI)
- Delirium
- Deep vein thrombosis (DVT)
- Pulmonary embolism (PE)
- Pneumonia



Example: Potential Use of Postoperative Risk Prediction during Handoffs

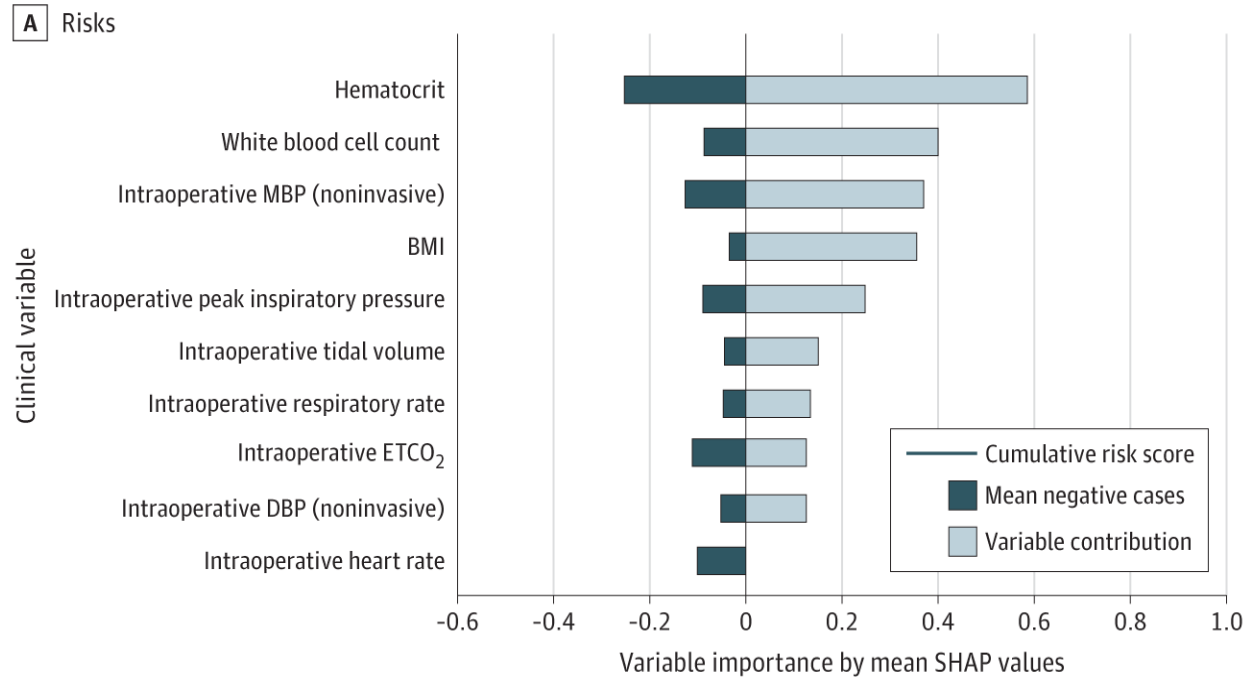
- A 65-year-old patient with fever, a history of chronic obstructive pulmonary disease, heavy smoking, and elevated liver enzymes is admitted for an open pneumonectomy
- An epidural is placed preoperatively. The patient is given a moderate dose of phenylephrine intraoperatively (maximum dose, 0.8 μg/kg per minute) and 2.5 L of crystalloid fluids, and a right chest tube is placed
- The patient is extubated in the operating room and transferred to the intensive care unit with a high-flow face mask (9 L of oxygen)



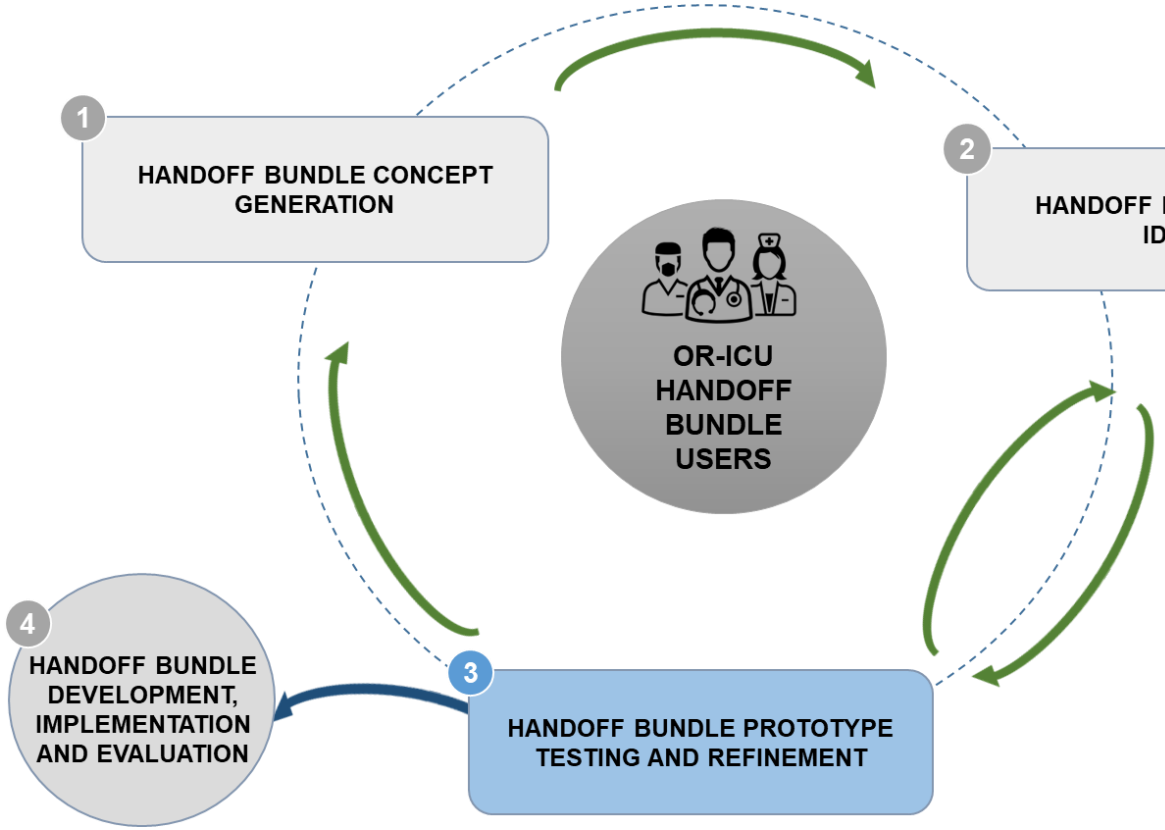


Example: Risk Explanation

- GBT model (AUROC=0.905) predicted this patient to be at **high-risk for pneumonia**
- **ML risk factors**
  - Patient's history of anemia (hematocrit)
  - Elevated white blood cell count
  - Low body mass index (BMI)
  - Tidal volume and respiratory rate signals
- Inform **potential postoperative care plans**
  - Early mobilization, pulmonary hygiene, incentive spirometry, scheduled bronchodilators, supplemental oxygen, a low threshold for antibiotic therapy



UCD Step 3



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Integrating machine learning predictions for perioperative risk management: Towards an empirical design of a flexible-standardized risk assessment tool

Joanna Abraham [a,b,*], Brian Bartek [a], Alicia Meng [b], Christopher Ryan King [b], Bing Xue [c], Chenyang Lu [d], Michael S. Avidan [b]

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[c] Department of Electrical & Systems Engineering, McKelvey School of Engineering, Washington University in St Louis, MO, United States
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ARTICLE INFO

Keywords:
Artificial Intelligence
Surgery
Critical Care
Complications

ABSTRACT

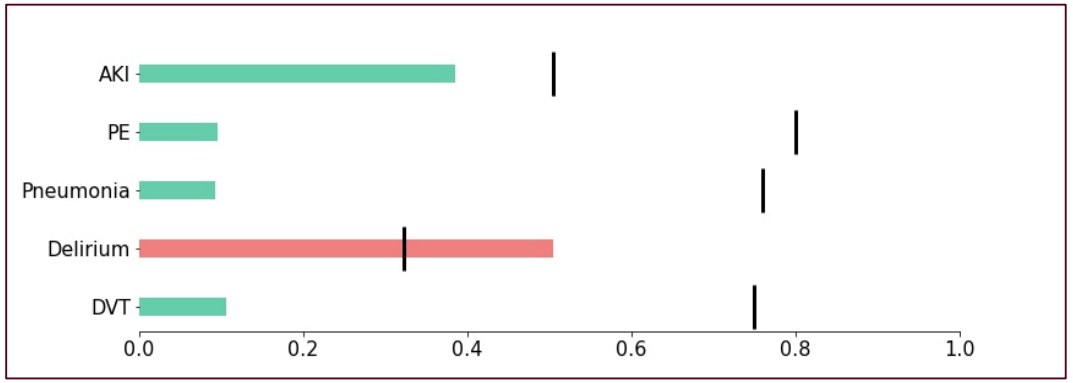
Background: Surgical patients are complex, vulnerable, and prone to postoperative complications that can potentially be mitigated with quality perioperative risk assessment and management. Several institutions have incorporated machine learning (ML) into their patient care to improve awareness and support clinician decision-making along the perioperative spectrum. Recent research suggests that ML risk prediction can support peri-operative patient risk monitoring and management across several situations, including the operating room (OR) to intensive care unit (ICU) handoffs.

Objectives: Our study objectives were threefold: (1) evaluate whether ML-generated postoperative predictions are concordant with clinician-generated risk rankings for acute kidney injury, delirium, pneumonia, deep vein thrombosis, and pulmonary embolism, and establish their associated risk factors; (2) ascertain clinician end-user

ML Risk: Visualization Format

Postop Complications	Predicted likelihood risk for complication	Accuracy of prediction
AKI	13	78
Delirium	49	66
DVT	4	92
Pulmonary embolism	6	97
Pneumonia	10	92

- **Tables and graphs to display risk predictions**



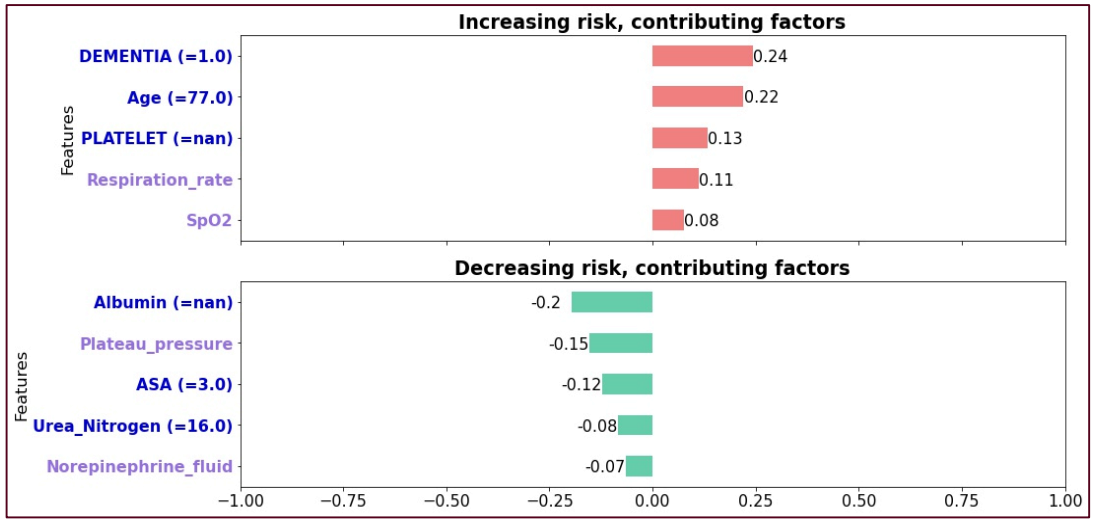
- **Pop-up to explain risk calculations**

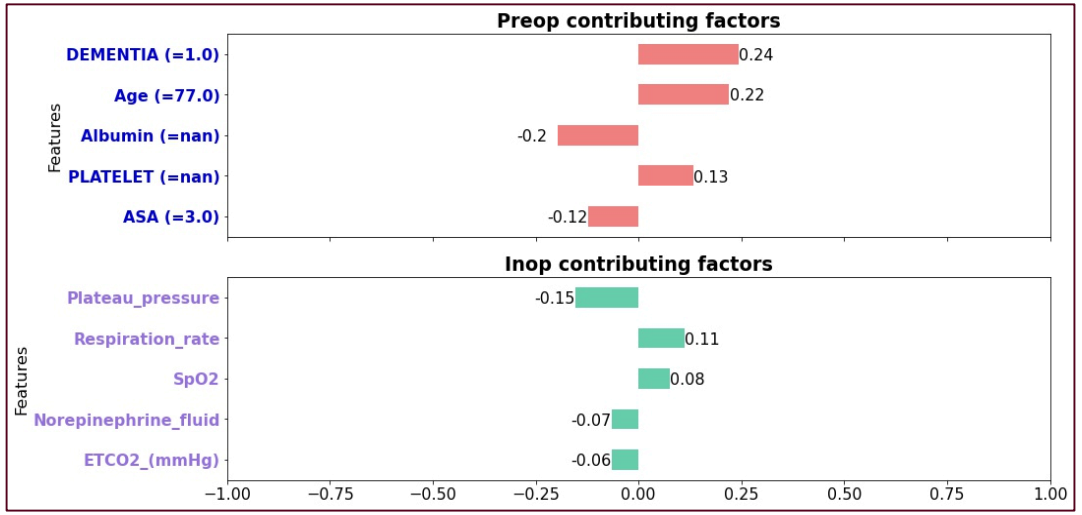
"…. If I need to **supplement my knowledge**, then I would like a **hover-to-discover**." (C2, Anest/Crit Care)

ML Risk Factors: Visualization Format

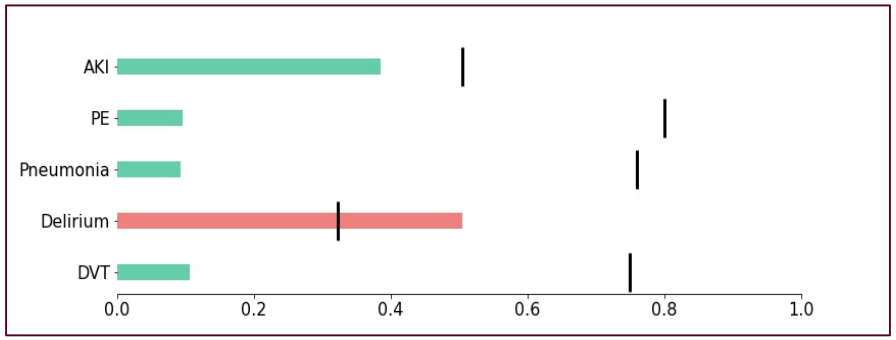
- **Risk factors grouping – decreasing and increasing risks over pre-op and intra-op risks**

"I think grouping it **according to those that increase, and those that decrease**." (C12, Anest)





ML Risk: Content



Postop Complications	Predicted likelihood risk for complication	Accuracy of prediction
AKI	13	78
Delirium	49	66
DVT	4	92
Pulmonary embolism	6	97
Pneumonia	10	92

"You could consider showing a **confidence interval**, maybe using an **error bar** on the bar chart." (C5, Anest)

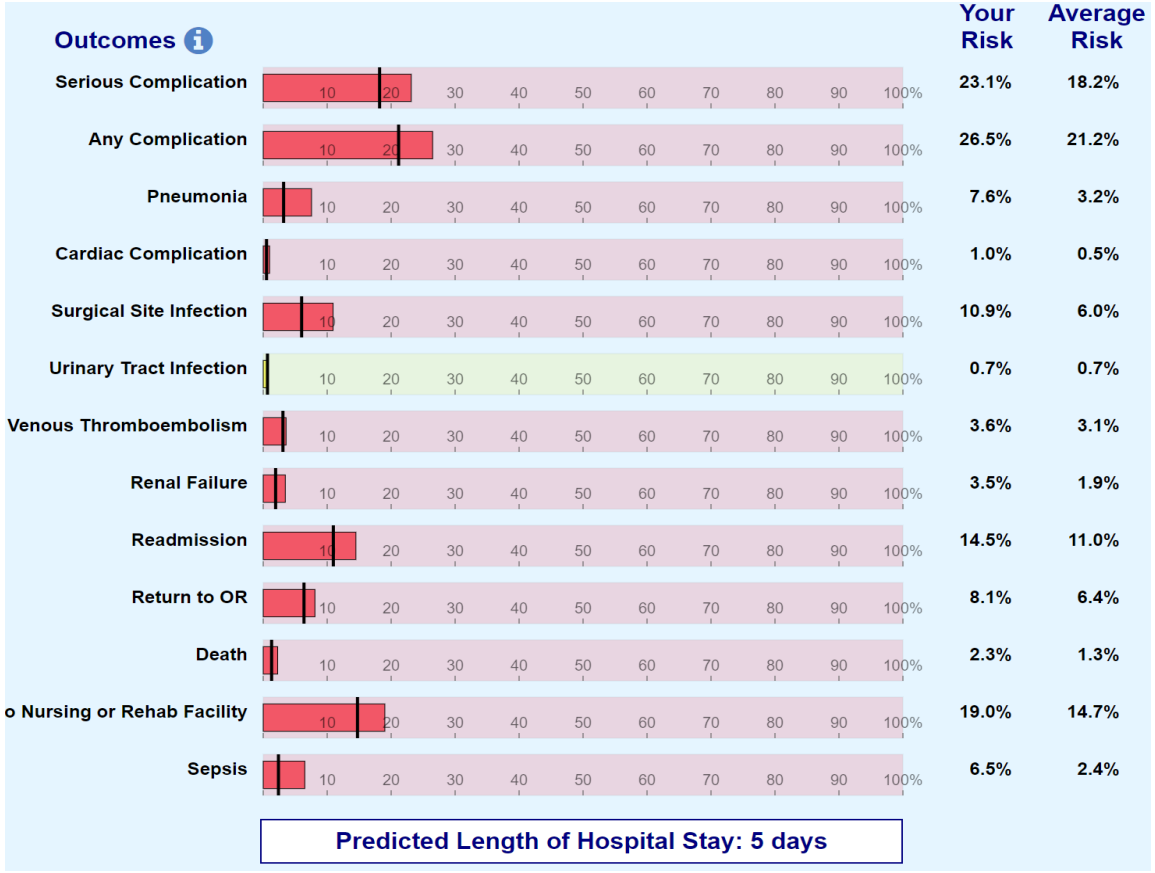
- **Providing confidence interval and percentages of prediction accuracy**

- **Identifying clinically meaningful risk thresholds**

If you **set [the alert threshold] too low**, you'll get way more alerts than might be clinically present. And you'll likely get fatigued and potentially [ignore alerts]. **If you set them too high,** you make it unlikely that these would be prevented." (C12, Anest)

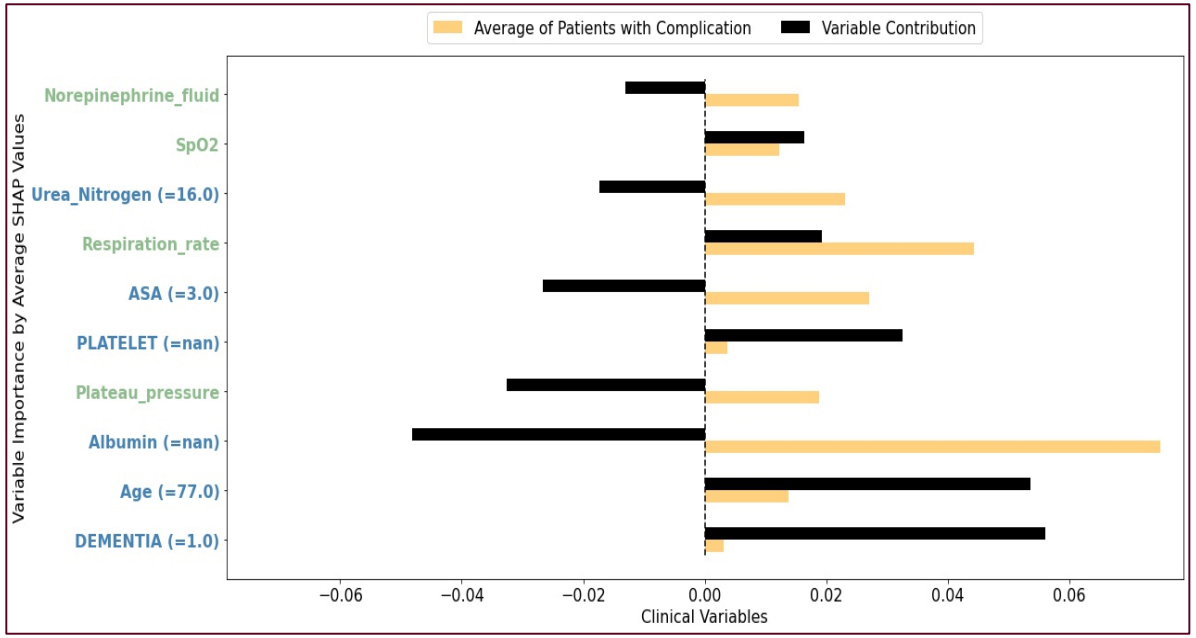
ML Risk: Content

- **Comparisons between current and average patients preoperatively and intraoperatively are useful**



ML Risk Factors: Content

- **Presenting relative risk compared to the population and absolute risks**



"I think probably the best way [to assess patient risk] is **within the context of other patients getting the same procedure**… If people are providing care for patients getting that procedure a lot, **they know when this patient separates themselves from others getting the same procedure and they know when they may need to escalate certain preventative or surveillance measures**." (C1, Anest)

Shows you where you are in the population as well as red, yellow, green, or something like **I think both of those are valuable**. A lot of times, especially if you're having a **discussion with family** about risks of stuff surgeries, further surgeries or a further course of action, **having the absolute values could be useful**." (ICU Fellow 1)

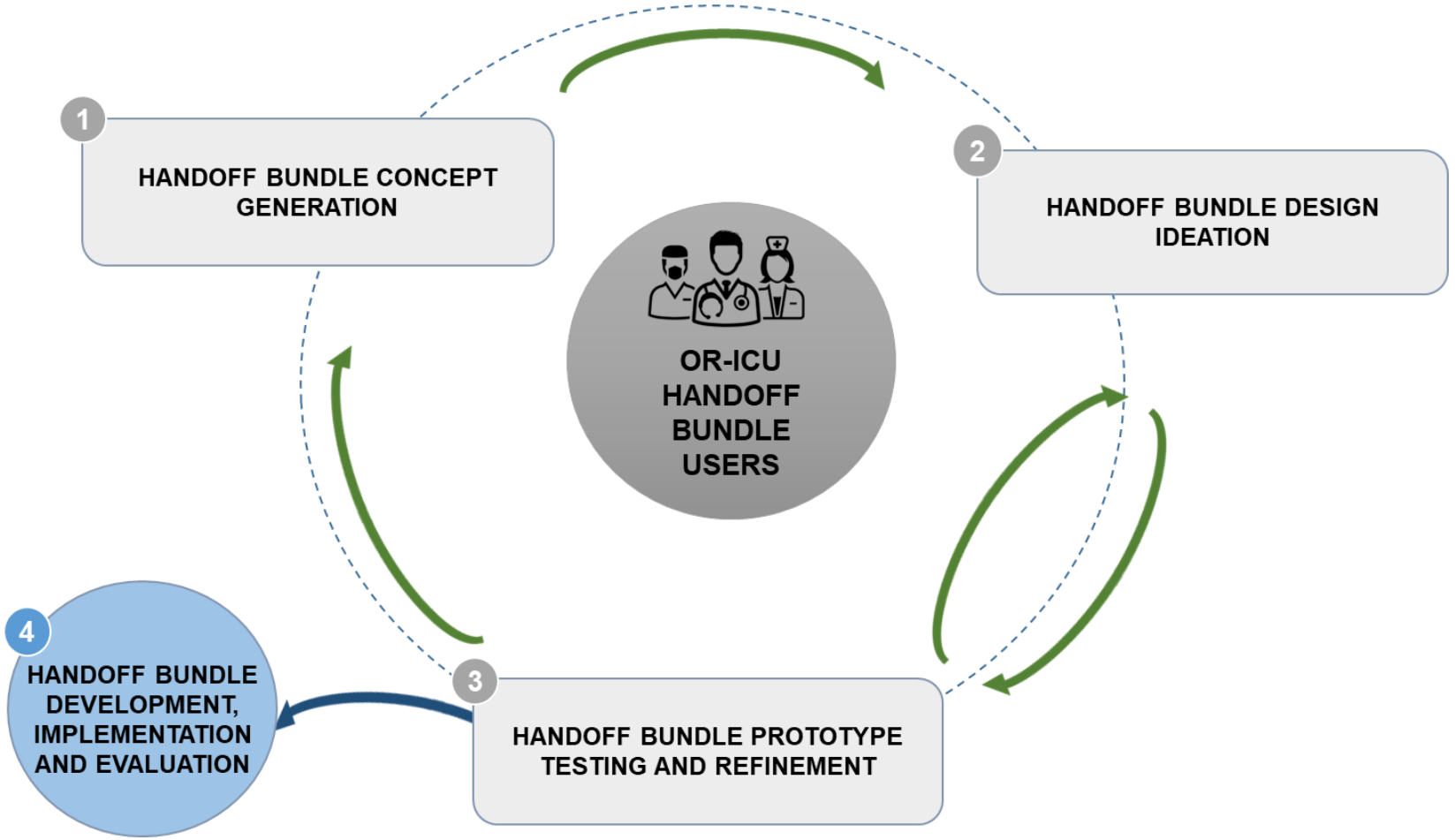
Implementation Strategies for Clinicians

- **Incorporate ML at several timepoints along the perioperative spectrum**
- **Offer training and education on ML model interpretation**
- **Refine ML based on clinician feedback reports**

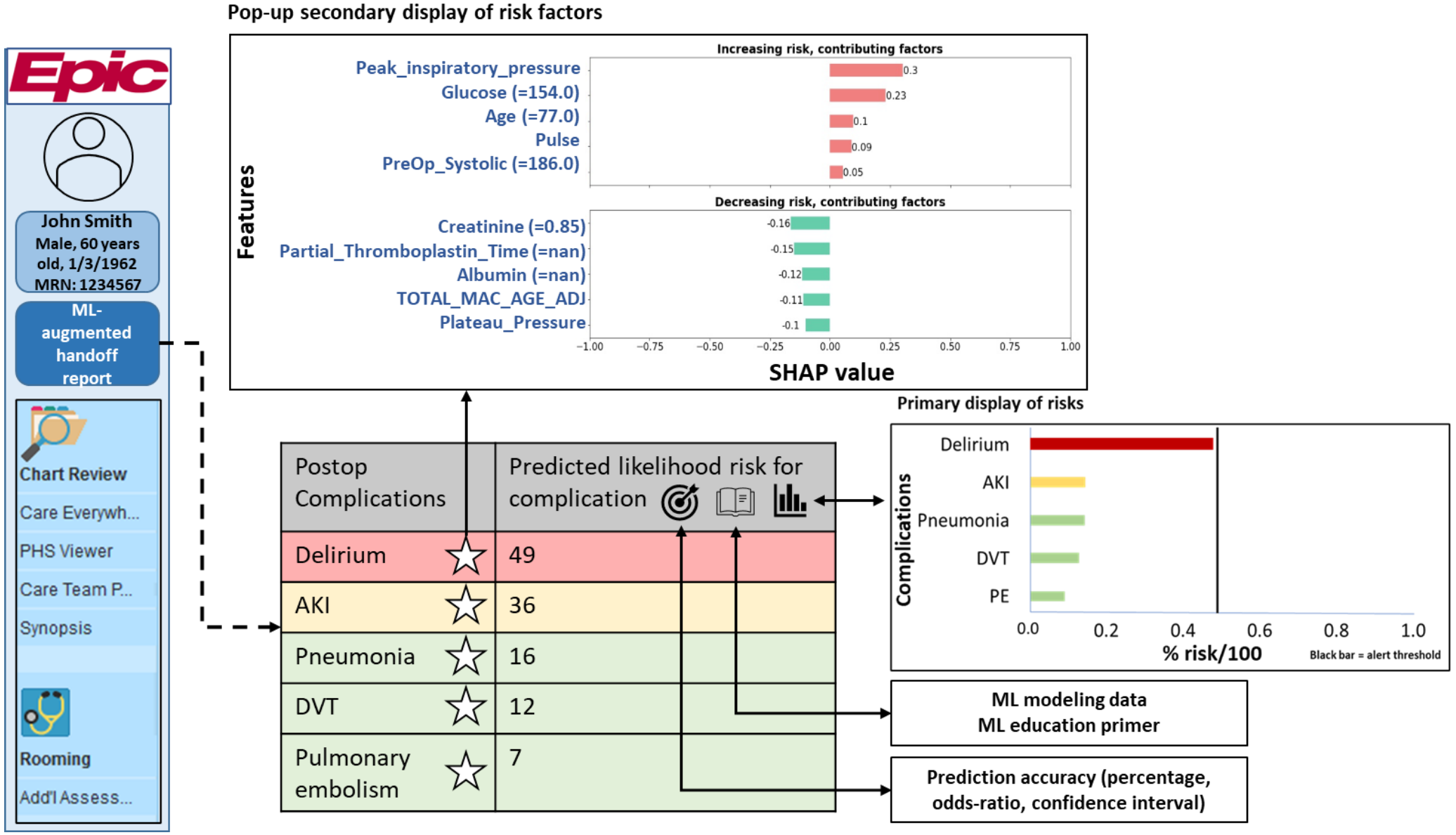
"The journey with the patient starts way before the surgery itself - you actually see the patient preoperatively, so you know what the patient actually walks into the clinic with. So, **all the preoperative contributing factors is something which we will look out for. And we'll discuss with the patient. So, to us that that is something which is very, very important."** (C10,Surgeon)

"If I was trained and familiar with the graph… I think that would probably be quicker and easier to use." (C4, CRNA)

UCD Step 4: Ongoing Work

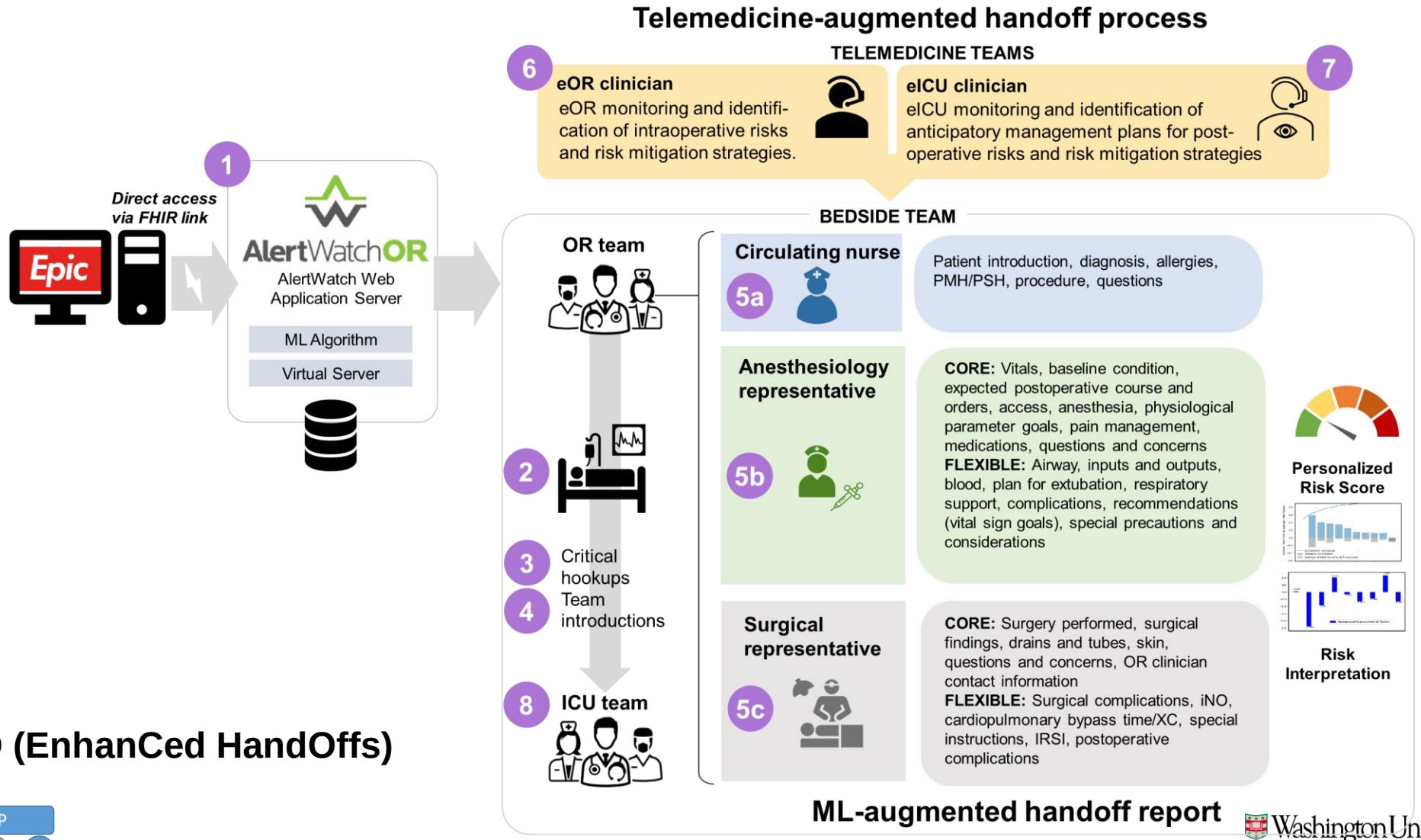


(I²DB)


Pop-up secondary display of risk factors
Epic
John Smith
Male, 60 years old, 1/3/1962
MRN: 1234567
ML-augmented handoff report
Chart Review
Care Everywh...
PHS Viewer
Care Team P...
Synopsis
Rooming
Add'l Assess...
Increasing risk, contributing factors
Peak_inspiratory_pressure
Glucose (=154.0)
Age (=77.0)
Pulse
PreOp_Systolic (=186.0)
0.3
0.23
0.1
0.09
0.05
Decreasing risk, contributing factors
Creatinine (=0.85)
Partial_Thromboplastin_Time (=nan)
Albumin (=nan)
TOTAL_MAC_AGE_ADJ
Plateau_Pressure
-0.16
-0.15
-0.12
-0.11
-0.1
Features
−1.00 −0.75 −0.50 −0.25 0.00 0.25 0.50 0.75 1.00
SHAP value
Postop Complications
Predicted likelihood risk for complication
Delirium 49
AKI 36
Pneumonia 16
DVT 12
Pulmonary embolism 7
Primary display of risks
Delirium
AKI
Pneumonia
DVT
PE
Complications
0.0 0.2 0.4 0.6 0.8 1.0
% risk/100
Black bar = alert threshold
ML modeling data
ML education primer
Prediction accuracy (percentage, odds-ratio, confidence interval)

(I²DB)

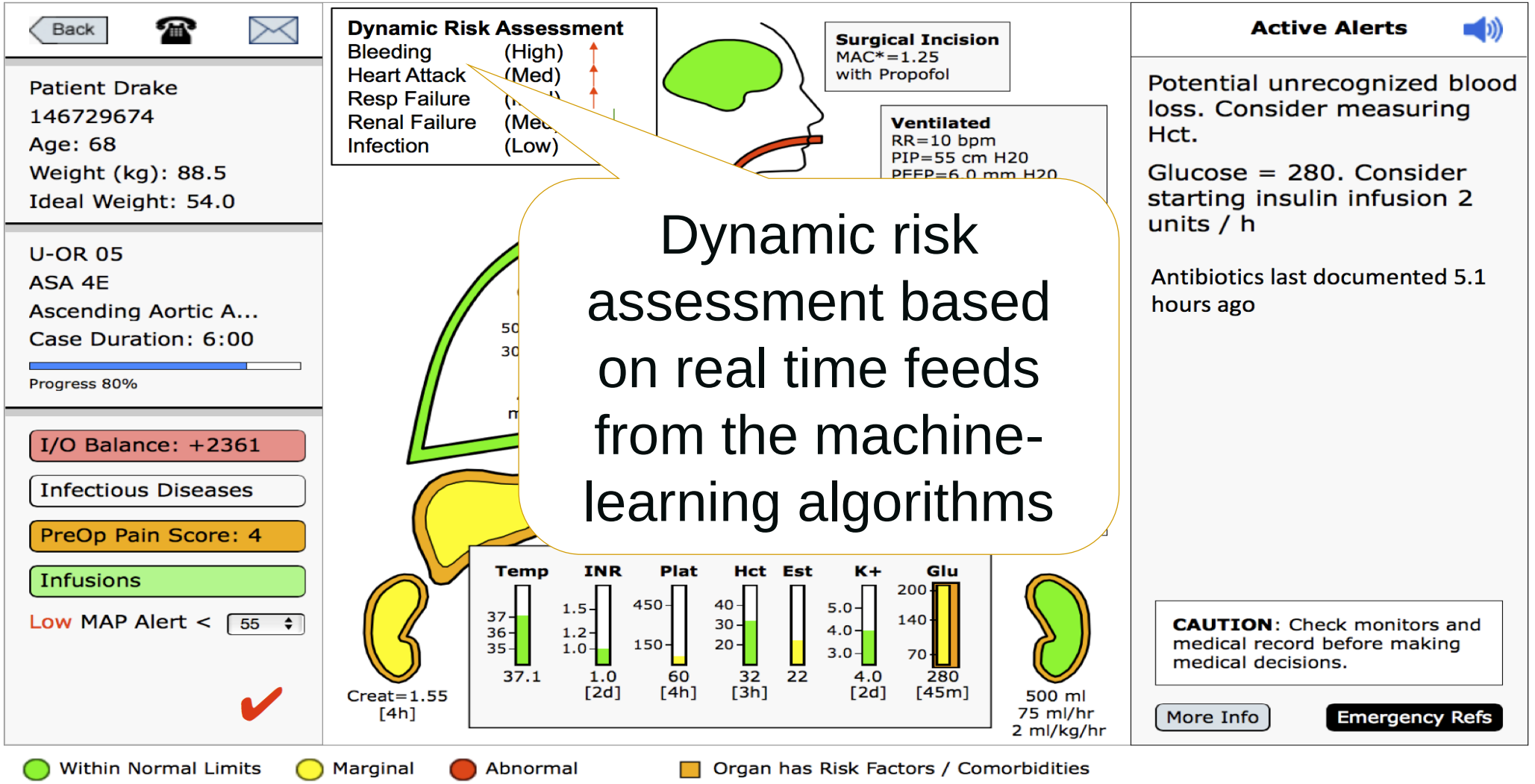
ML-Augmented Handoff Model



ECHO (EnhanCed HandOffs)

(I²DB)

AlertWatch CDSS



(I²DB)

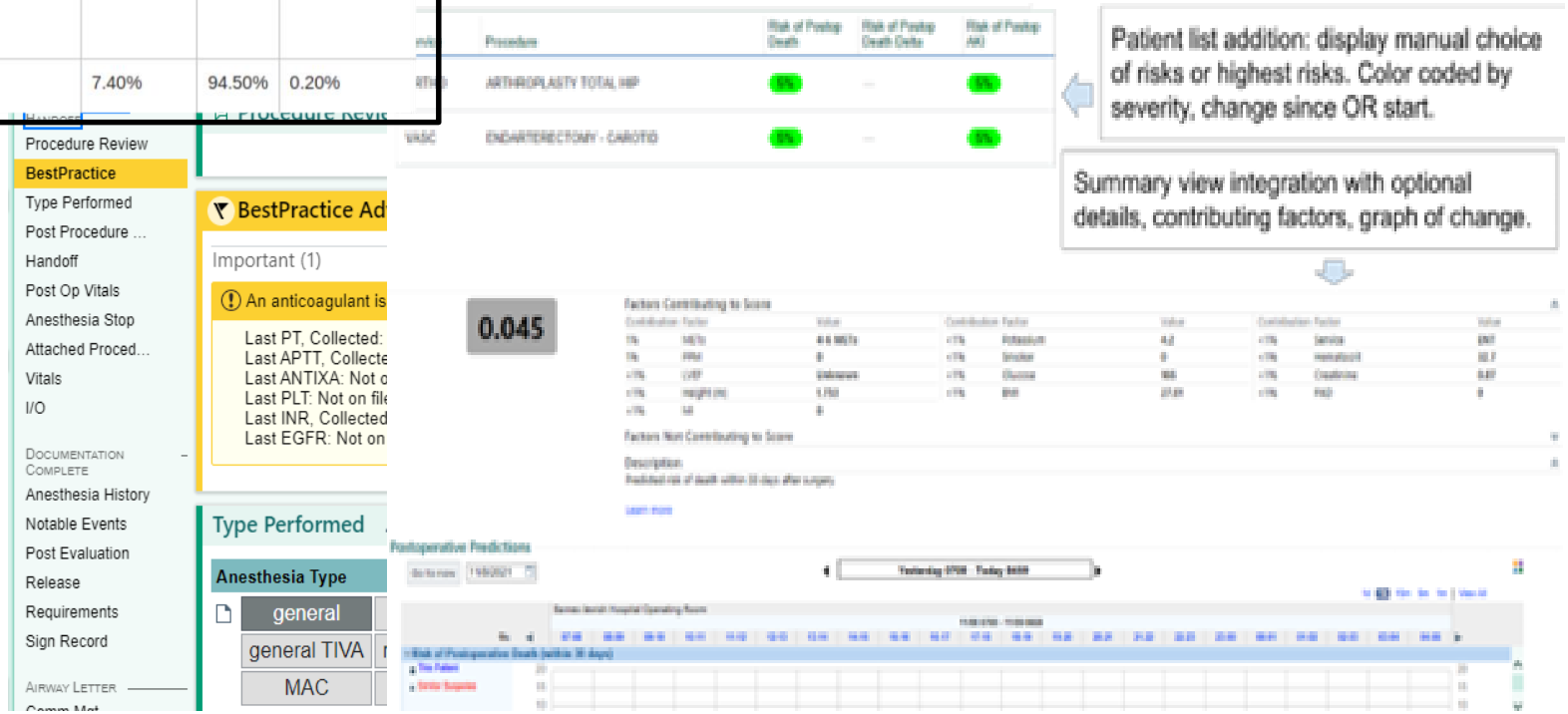
Epic Inraoperative and Postoperative CDSS



Ryan King, MD, PhD

Figure 5: Anesthesia Control Tower ML Dashboard with patient information redacted. Yellow highlight implies "ready for review." Additional columns not shown for space.

Room Name	Description	akigr1	cardiac	death_in_30	DVT_PE	ICU	post_dialysis
BJH OR POD 2 ROOM 209	###LAPAROSCOPIC CHOLECYSTECTOMY	2.90%	1.60%	0.10%	8.80%	5.20%	0.10%
BJH OR POD 3 ROOM 301	EXPLORATION LIVER TRANSPLANT WITH WASHOUT LIVER BIOPSY AND BILE DUCT REVISION	67.10%	6.90%	7.60%	1.20%	93.40%	0.90%
BJH OR POD 2 ROOM 211	TRACHEOSTOMY PERCUTANEOUS	40.30%	2.70%	3.50%	7.40%	94.50%	0.20%



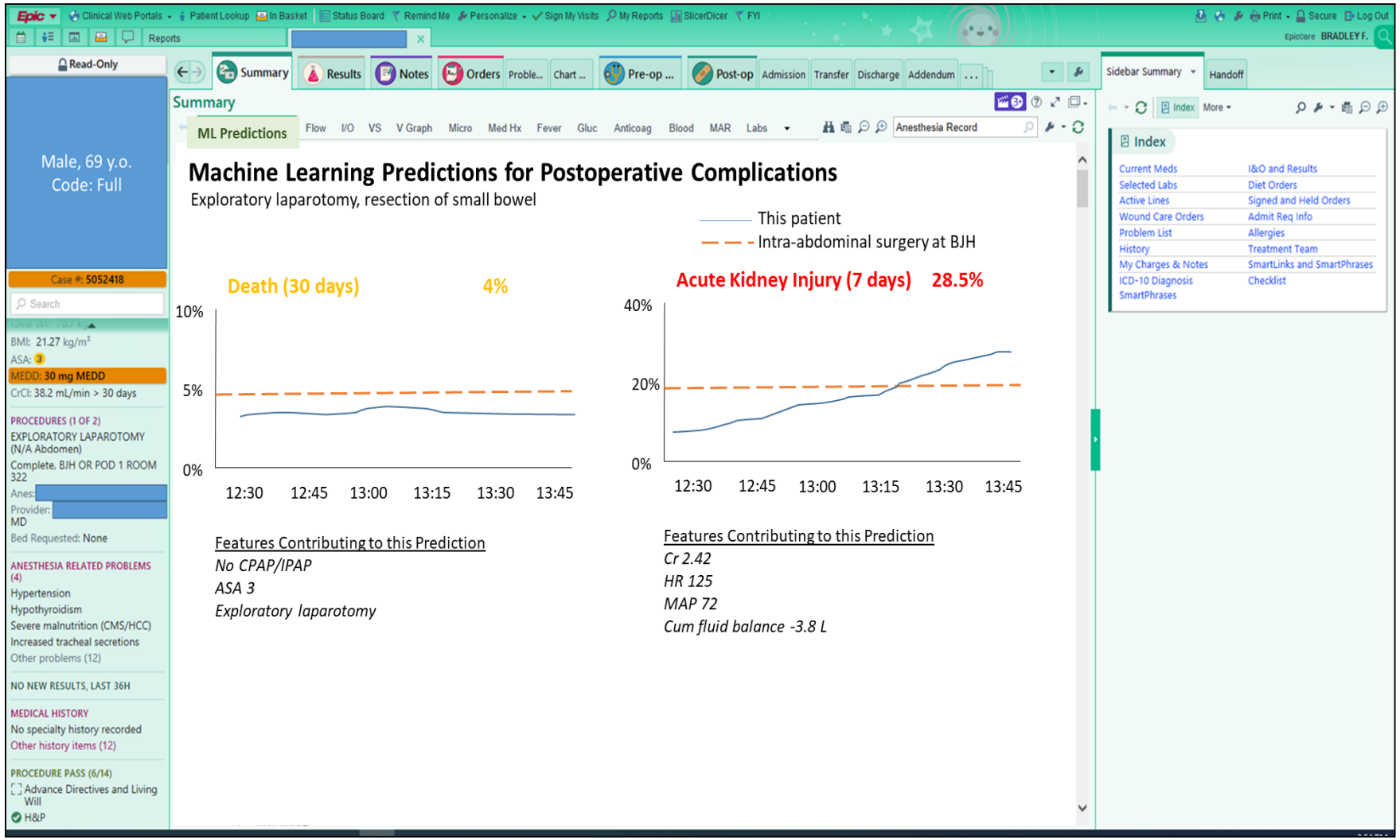
King CR, Shambe A, Abraham J. Potential uses of AI for perioperative nursing handoffs: a qualitative study. JAMIA Open. 2023 Mar 16;6(1):ooad015. PMID: 36935899; PMCID: PMC10019806.

(I²DB)

Epic Intraoperative CDSS



Brad Fritz, MD



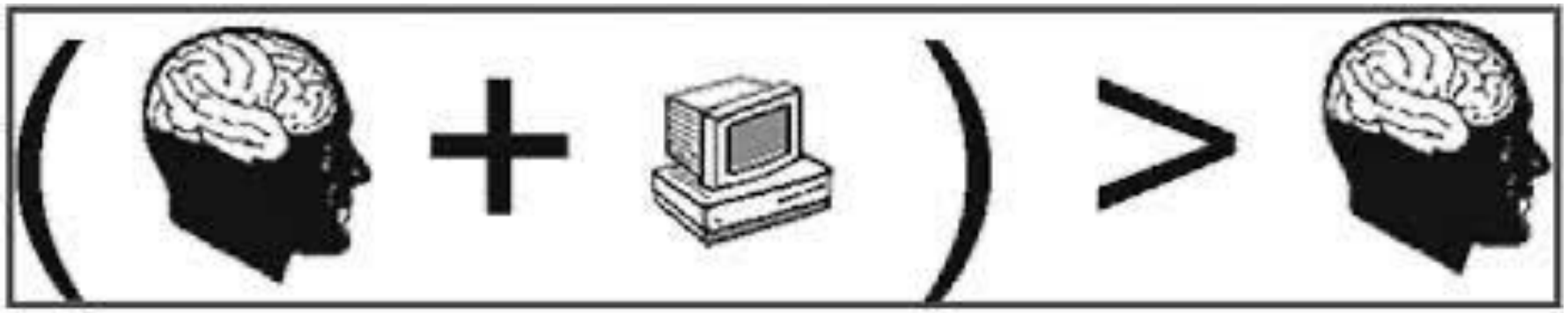
Fritz BA, Pugazenthi S, Budelier TP, Tellor Pennington BR, King CR, Avidan MS, Abraham J. User-Centered Design of a Machine Learning Dashboard for Prediction of Postoperative Complications. Anesth Analg. 2023 Jun 20. PMID: 37339083.

Washington University School of Medicine in St. Louis

Conclusion

Paradigm Shift on Role of Computers in Healthcare





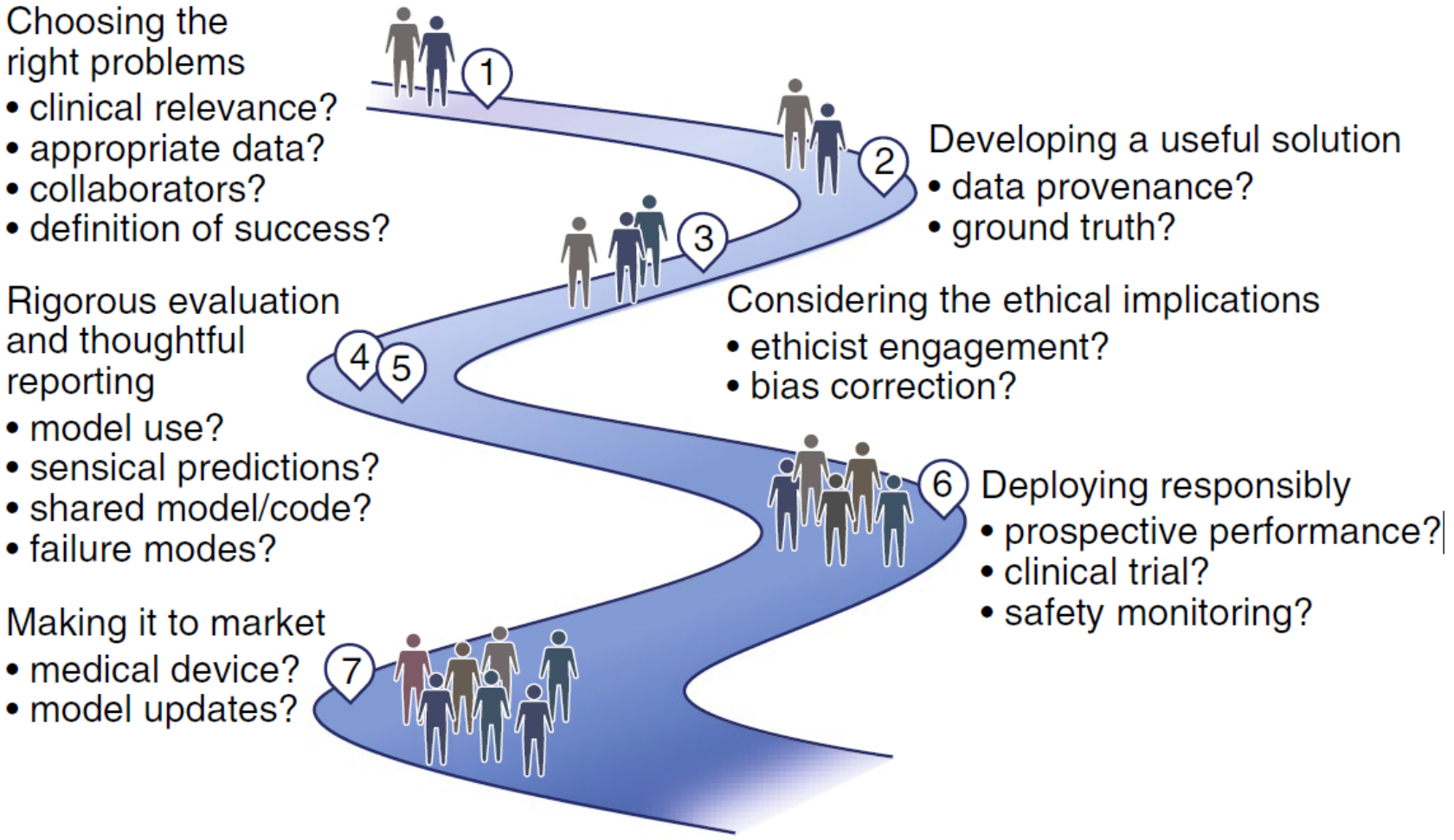
Charles P. Friedman, PhD





James J. Cimino, MD

Roadmap for Deploying Effective ML Systems in Healthcare



Wiens, Jenna, et al. "Do no harm: a roadmap for responsible machine learning for health care." *Nature medicine*

Methods for Deploying AI in Healthcare

From Code to Bedside: Implementing Artificial Intelligence Using Quality Improvement Methods

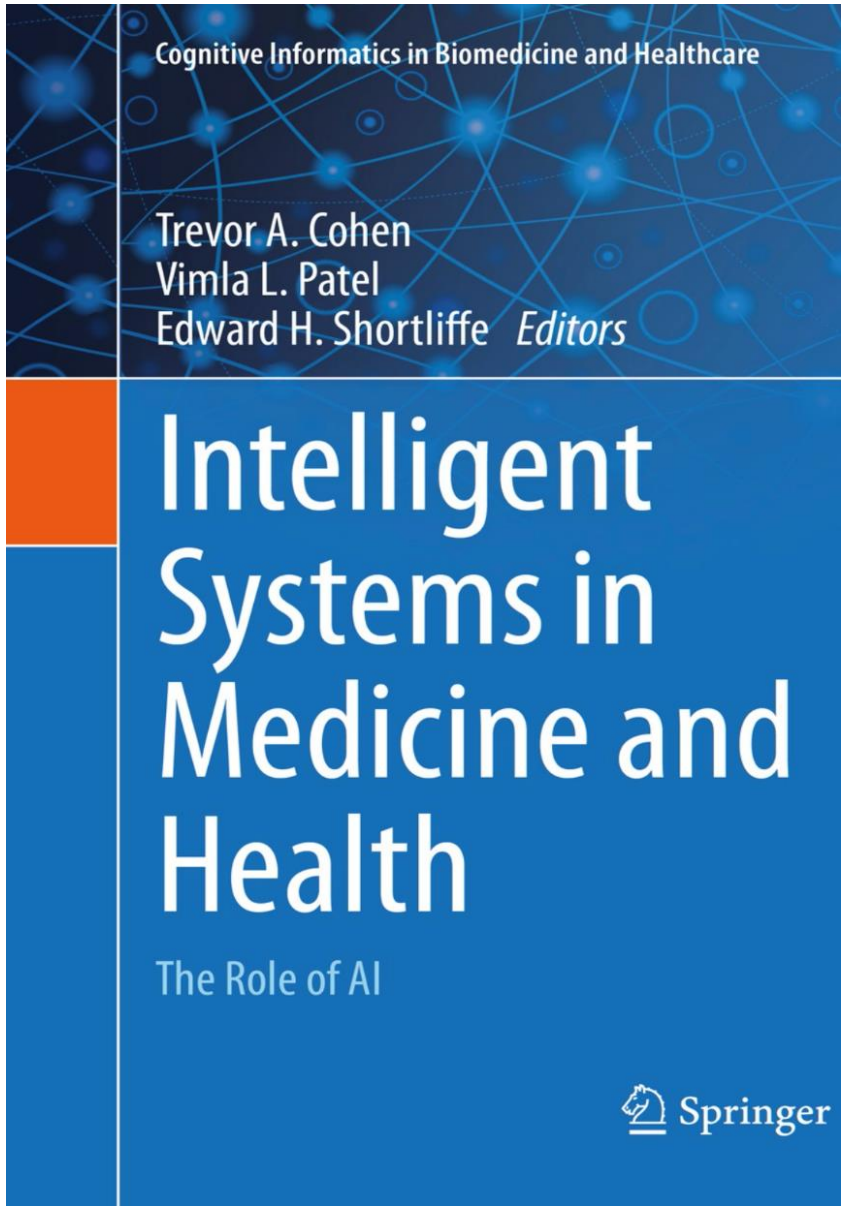
Margaret Smith, MBA, Amelia Sattler, MD, Grace Hong, and Steven Lin, MD

Stanford Healthcare AI Applied Research Team, Division of Primary Care and Population Health, Department of Medicine, Stanford University School of Medicine, Stanford, CA, USA.

Despite increasing interest in how artificial intelligence (AI) can augment and improve healthcare delivery, the development of new AI models continues to outpace adoption in existing healthcare processes. Integration is difficult because current approaches separate the develop-

With all the hype, the challenges of AI adoption in healthcare are coming into focus. Regulation, data quality, privacy, and interoperability[4] are some of the most cited challenges. Yet, when senior leaders are asked what factors most often

(I²DB)



Call to Action: Human-centered AI: Aligning AI systems with human intent

(I²DB)

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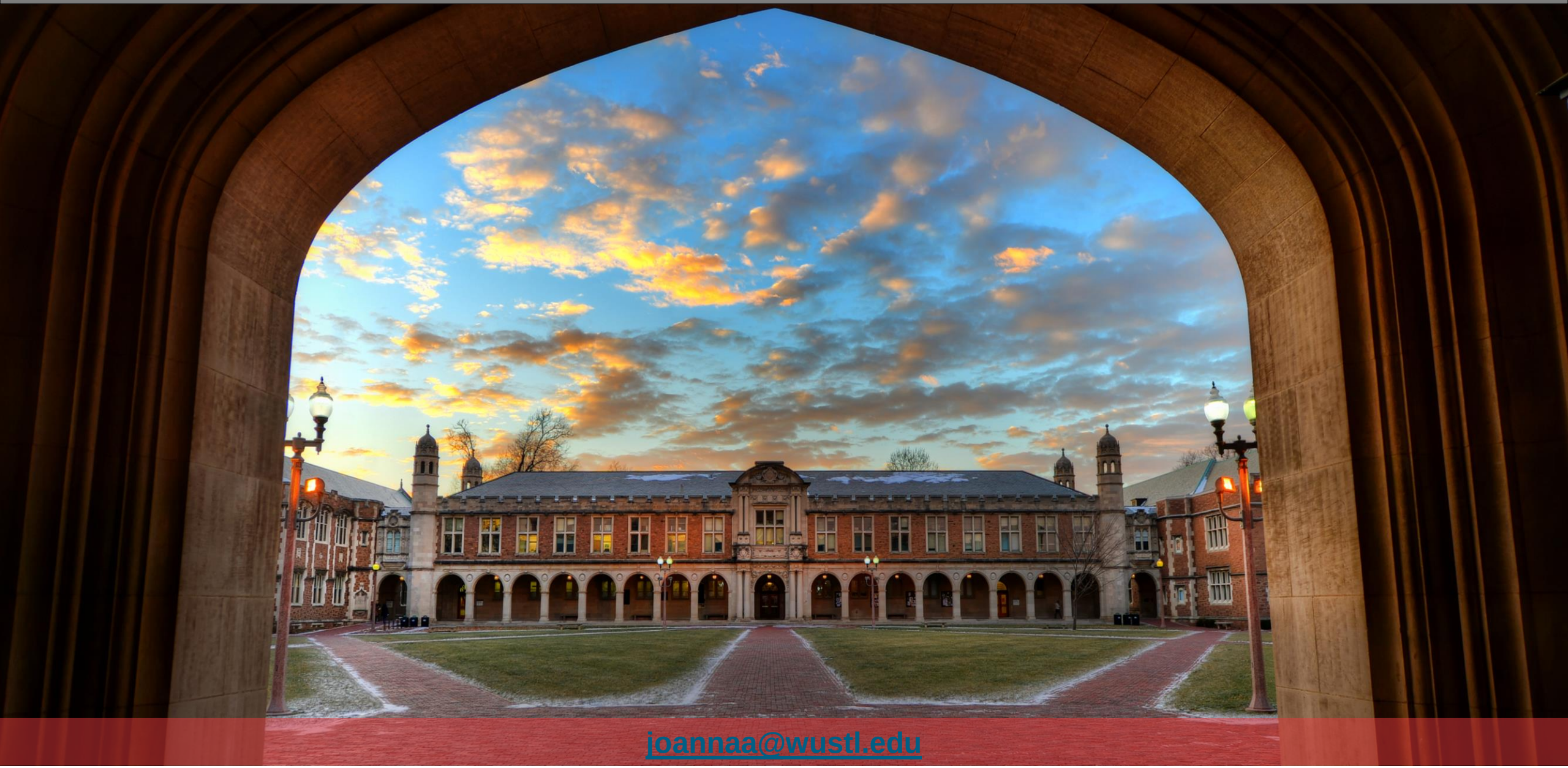
Funding


AHRQ


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Questions or Comments?



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