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
About me
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
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.
Postoperative Mortality and Morbidity

30-day mortality: 1-5%
1-year mortality: 5-10%
# Types of Postoperative Complications

<table>
<thead>
<tr>
<th>Category</th>
<th>Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonpreventable</td>
<td>Injuries or problem nonsurvivable with optimal management</td>
</tr>
<tr>
<td></td>
<td>Evaluation and management are appropriate</td>
</tr>
<tr>
<td></td>
<td>Suspect care does not affect classification of death but is treated as morbidity</td>
</tr>
<tr>
<td>Potentially preventable</td>
<td>Injuries or problem severe but survivable</td>
</tr>
<tr>
<td></td>
<td>Evaluation and management are generally appropriate</td>
</tr>
<tr>
<td></td>
<td>Errors in care directly or indirectly implicated in patient’s death</td>
</tr>
<tr>
<td>Preventable</td>
<td>Injuries or problem normally survivable</td>
</tr>
<tr>
<td></td>
<td>Evaluation and management are suspect</td>
</tr>
<tr>
<td></td>
<td>Errors directly or indirectly cause patient’s death</td>
</tr>
</tbody>
</table>

*From Shackford et al.*
Example: Preventable Complications due to Clinician Decision Making Failures
Strategies to Prevent Postoperative Complications

SURGICAL SAFETY CHECKLIST (FIRST EDITION)

Before induction of anaesthesia
- ○ PATIENT HAS CONSENTED
- ○ CONSENT
- ○ V.F.
- ○ PREOPERATIVE MEDICATIONS PROPERLY ADMINISTERED
- ○ PATIENT TACHYCARDIA NOT APPLICABLE
- ○ ANAESTHESIA SAFETY CHECK COMPLETED
- ○ PULSE OXIMETER ON PATIENT AND FUNCTIONING
- ○ ○ PATIENT HAVE A.
- ○ ○ KNOWLEDGE OF SURGERY?
- ○ ○ YES
- ○ ○ NO
- ○ ○ ANCILLARY MEDICATIONS ADMINISTERED
- ○ ○ NEW OF VITAL SIGNS OBTAINED
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.

Before skin incision
- ○ CONFIRM ALL TEAM MEMBERS HAVE IDENTIFIED THEMSELVES BY NAME AND ROLE
- ○ SURGEON, ANAESTHETIST, PROFESSIONAL, AND NURSE VENTILATE CONFIRMED
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.

Before patient leaves operating room
- ○ SURGEON, ANAESTHETIST, PROFESSIONAL, AND NURSE VENTILATE CONFIRMED
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.
- ○ ○ V.F.

SIGN OUT
- ○ ○ NAME OF THE PROCEDURE RECORD
- ○ ○ THE NAME OF THE PROFESSIONAL RECORD
- ○ ○ THE NAME OF THE PROFESSIONAL RECORD
- ○ ○ THE NAME OF THE PROFESSIONAL RECORD
- ○ ○ THE NAME OF THE PROFESSIONAL RECORD
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- ○ ○ THE NAME OF THE PROFESSIONAL RECORD

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. Graat1, J. M. C. Schraagen1,3, M. A. Boermeester1, W. A. Bemelman1 and M. P. Schijven1

1Department of Surgery, Academic Medical Centre, Amsterdam, 2Department of Neurosurgery, Academic Medical Centre, Amsterdam, 3Department of Anesthesiology, Academic Medical Centre, Amsterdam, Amsterdam, The Netherlands.

World Neurosurgery
Volume 82, Issues 1-2, July-August 2019, Pages e21–e29
# Exploring Innovative Methods to Address Postoperative Complications

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</table>

*From Shackford et al.*
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

PRISMA

**Identification**
- Records identified from:
  - Databases (n = 147)
  - Registers (n = 0)

**Screening**
- Records screened (n = 89)
- Reports sought for retrieval (n = 0)
- Reports assessed for eligibility (n = 46)

**Included**
- Studies included in review (n = 36)

**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)

**Records excluded**
- (n = 43)
- Reports not retrieved (n = 0)
- Reports excluded: 10
  - Reason 1 (inadequate setting n = 8)
  - Reason 2 (pediatric population = 2)
Retrospective Studies on ML in Perioperative Care

Perioperative Outcomes Studied

- Neurological
- Respiratory
- Cardiovascular
- VTE
- Mortality
- Acute Kidney Injury
- ICU admission
- Surgical
- Pain
- PONV
- Length of stay
- Sepsis

Most frequently used algorithms

- Gradient Boosting
- Random Forest
- Neural Net
- Support vector
- Bayesian Network
- Logistic Regression
- Deep Learning
- Decision tree
- Super Learner
- Naive Bayes
- Artificial neural
- Oibers

Main outcomes (preoperative/intraoperative) considered in our analysis.
BMJ Open  Using machine learning techniques to develop forecasting algorithms for postoperative complications: protocol for a retrospective study


do: 10.1016/j.bja.2019.07.025
Advance Access Publication Date: 23 September 2019

BJA

Deep-learning model for predicting 30-day postoperative mortality

Bradley A. Fritz1,2, Zicheng Cui2,2, Muhan Zhang2, Yujie He2, Yixin Chen2, Alex Kronzer1, Arbi Ben Abdallah1, Christopher R. King1 and Michael S. Avidan1

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 Kannampallli, Bradley Fritz, Christopher King, Joanna Abraham, Michael Avidan and Chenyang Lu
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

PRISMA

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)

Full text articles assessed for eligibility (n = 96)

Hand-search articles (n = 35)

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)

Studies meeting inclusion criteria (n = 14);
Articles meeting inclusion criteria (n = 15)

Ovid Medline (n = 4715)
Embase (n = 4121)
Scopus (n = 3899)
Clinicaltrials.gov (n = 24)
PubMed (n = 486)

Clinicaltrials.gov (n = 24)
PubMed (n = 486)
Ovid Medline (n = 4715)
Embase (n = 4121)
Scopus (n = 3899)
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
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

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Mean</th>
<th>SD</th>
<th>Total</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schneck</td>
<td>3.35</td>
<td>0.74</td>
<td>25</td>
<td>7.06</td>
</tr>
<tr>
<td>Nassarpapa</td>
<td>3.63</td>
<td>1.18</td>
<td>49</td>
<td>10.13</td>
</tr>
<tr>
<td>Wijbransa</td>
<td>3.44</td>
<td>0.51</td>
<td>31</td>
<td>10.15</td>
</tr>
</tbody>
</table>

**Total** (95% CI): 243

**Heterogeneity**: Tau² = 0.19; Chi² = 20.21; df = 4 (P = 0.0005); I² = 86%

Test for overall effect: Z = 2.15 (P = 0.03)

Test for subgroup differences: Not applicable

### Hypotension as percentage of surgery time

<table>
<thead>
<tr>
<th>Study or Subgroup</th>
<th>Experimental Mean</th>
<th>SD</th>
<th>Total</th>
<th>Weight</th>
<th>Control Mean</th>
<th>SD</th>
<th>Total</th>
<th>Weight</th>
<th>Std. mean difference</th>
<th>Std. mean difference 95% CI</th>
<th>Risk of Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schneck</td>
<td>3.35</td>
<td>0.74</td>
<td>25</td>
<td>7.06</td>
<td>4.57</td>
<td>0.94</td>
<td>24</td>
<td>22.5</td>
<td>-1.13</td>
<td>-1.74 to -0.53</td>
<td>A</td>
</tr>
<tr>
<td>Nassarpapa</td>
<td>3.63</td>
<td>1.18</td>
<td>49</td>
<td>10.13</td>
<td>4.14</td>
<td>0.91</td>
<td>55</td>
<td>48.9</td>
<td>-0.63</td>
<td>-1.24 to 0.42</td>
<td>C</td>
</tr>
<tr>
<td>Wijbransa</td>
<td>3.44</td>
<td>0.51</td>
<td>31</td>
<td>10.15</td>
<td>4.51</td>
<td>0.92</td>
<td>25</td>
<td>25.6</td>
<td>-0.98</td>
<td>-1.51 to -0.46</td>
<td>F</td>
</tr>
</tbody>
</table>

**Total** (95% CI): 105

**Heterogeneity**: Tau² = 0.00; Chi² = 0.60; df = 2 (P = 0.71); I² = 8%

Test for overall effect: Z = 1.39 (P = 0.0881)

Test for subgroup differences: Not applicable
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
Leveraging ML for Augmenting Postoperative Handoffs
Postoperative Patient Transfers

Operating Room Team

Intensive Care Unit Team

PMID: 18582931; 30722955; 28738985
Postoperative Handoffs

Operating Room (OR) team

Interactive forum for care continuity

Intensive Care Unit (ICU) team

Information Control Responsibility

Questions Concerns
Sentinel Event Alert

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

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.
User-Centered Design (UCD) Approach

1. CONTEXTUAL INQUIRY
2. DESIGN IDEATION
3. PROTOTYPE TESTING AND REFINEMENT
4. INTERVENTION DEVELOPMENT, IMPLEMENTATION AND EVALUATION

END USERS
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
- Simultaneously vent and ETCO2: immediate patient care needs discussion only
- Critical hook-up 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?
- Handout 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 IRM 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

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

1. Handoff Bundle Concept Generation
2. Handoff Bundle Design Ideation
3. Handoff Bundle Prototype Testing and Refinement
4. Handoff Bundle Development, Implementation and Evaluation

Ascertaining Design Requirements for Postoperative Care Transition Interventions

Joanna Abraham, Christopher R King, Alicia Meng

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)
### Information Checklist Requirements

**Core elements**
- Age
- Allergy list
- Preoperative diagnosis
- Duration of anesthesia
- EBL
- Crystalloid given
- Colloid given
- Blood products given
- Antibiotics given
- Neuraxial blockade given (twitches, TOF)
- Opioid analgesics given
- Arterial line present
- Central line present
- Regional block present
- Difficult intubation
- Height, weight, BMI
- Preinduction vital signs
- Average vital signs last 15 min
- Beta blockers given/continued
- Premedication given
- Insulin given
- Reversal medications given or not
- Diuretics given
- ETT size and position

**Flexible elements**
- Intra-op abnormalities
- Opioids
- 30-day mortality
- Method of anesthesia used intra-operatively
- Risk of AKI
- Risk of VTE
- Risk of pneumonitis
- 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

*Red text indicates free-text suggestions from participants to include.*

---

**Proportion of participants**

<table>
<thead>
<tr>
<th>Requirement</th>
<th>0</th>
<th>0.1</th>
<th>0.5</th>
<th>0.8</th>
<th>1</th>
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<tbody>
<tr>
<td>Age</td>
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<td></td>
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<tr>
<td>Allergy list</td>
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<td></td>
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<tr>
<td>Preoperative diagnosis</td>
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<tr>
<td>Scheduled procedure</td>
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<td>Arterial line present</td>
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<td>Insulin given</td>
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<td>Reversal medications given or not</td>
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<tr>
<td>Diuretics given</td>
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<td>ETT size and position</td>
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</tbody>
</table>
Information Checklist Requirements

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

“Some [patient] issues [and complications] don’t fit neatly into the standardized [handoff] structure.” (Anest 5)

“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

“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)

“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)
Information Checklist Requirements

• Risk factors contributing to risks

“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

“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)

“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).

• Modifiable patient risks and suggestions for mitigating risks
UCD Step 3

1. Handoff Bundle Concept Generation
2. Handoff Bundle Ideation
3. Handoff Bundle Prototype Testing and Refinement
4. Handoff Bundle Development, Implementation and Evaluation

OR-ICU Handoff Bundle Users

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

Bing Xue, MS; Dingsin Li, MD; Chenyang Lu, PhD; Christopher R. King, MD, PhD; Troy Wildes, MD; Michael S. Avidan, MBChB; Thanass Karampeli, 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 11,188 operations at a large academic medical center.

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 11,188 operations at a large academic medical center, several machine learning models correctly predicted postoperative complications related to pneumonia, acute kidney injury, deep vein thrombosis, delirium, and pulmonary embolism, whereas a machine learning model combining preoperative and intraoperative data was particularly strong. The models were able to identify increased postoperative complication risks among patients with preoperative risks of pneumonia, acute kidney injury, deep vein thrombosis, delirium, and pulmonary embolism.

Implications. These findings suggest that machine learning models can improve operational management and planning for postoperative care in surgical patients.
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
ML Risk: Visualization Format

- Tables and graphs to display risk predictions

<table>
<thead>
<tr>
<th>Postop Complications</th>
<th>Predicted likelihood risk for complication</th>
<th>Accuracy of prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>AKI</td>
<td>13</td>
<td>78</td>
</tr>
<tr>
<td>Delirium</td>
<td>49</td>
<td>66</td>
</tr>
<tr>
<td>DVT</td>
<td>4</td>
<td>92</td>
</tr>
<tr>
<td>Pulmonary embolism</td>
<td>6</td>
<td>97</td>
</tr>
<tr>
<td>Pneumonia</td>
<td>10</td>
<td>92</td>
</tr>
</tbody>
</table>

- 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

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

• 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)

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</table>
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 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

1. Handoff bundle concept generation
2. Handoff bundle design ideation
3. Handoff bundle prototype testing and refinement
4. Handoff bundle development, implementation and evaluation

OR-ICU Handoff Bundle Users
ML-Augmented Handoff Model

**Telemedicine-augmented handoff process**

1. **Direct access via FHIR link**
2. **OR team**
   - Critical hookups
   - Team introductions
3. **Circulating nurse**
4. **Anesthesiology representative**
5a. **5a**
   - Patient introduction, diagnosis, allergies, PMH/PSH, procedure, questions
5b. **5b**
   - CORE: Vitals, baseline condition, expected postoperative course and orders, access, anesthesia, physiological parameters, goals, pain management, medications, questions and concerns
   - FLEXIBLE: Airway, inputs and outputs, blood, plan for extubation, respiratory support, complications, recommendations (vital sign goals), special precautions and considerations
6. **eOR clinician**
   - eOR monitoring and identification of intraoperative risks and risk mitigation strategies
7. **eICU clinician**
   - eICU monitoring and identification of anticipatory management plans for postoperative risks and risk mitigation strategies
8. **ICU team**

**BEDSIDE TEAM**

**ML-augmented handoff report**

**ECHO (EnhanCed HandOffs)**

**UCD STEP**

1. 2. 3. 4.
Dynamic risk assessment based on real time feeds from the machine-learning algorithms.
Epic Intraoperative and Postoperative CDSS

Epic Intraoperative CDSS

Brad Fritz, MD

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

1. Choosing the right problems
   - clinical relevance?
   - appropriate data?
   - collaborators?
   - definition of success?

2. Developing a useful solution
   - data provenance?
   - ground truth?

3. Rigorous evaluation and thoughtful reporting
   - model use?
   - sensible predictions?
   - shared model/code?
   - failure modes?

4. Considering the ethical implications
   - ethicist engagement?
   - bias correction?

5. Deploying responsibly
   - prospective performance?
   - clinical trial?
   - safety monitoring?

6. Making it to market
   - medical device?
   - model updates?

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

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

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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 development and implementation phases. With all the hype, the challenges of AI adoption in healthcare are coming into focus. Regulation, data quality, privacy, and interoperability are some of the most cited challenges. Yet, when senior leaders are asked what factors most often
Call to Action:
Human-centered AI: Aligning AI systems with human intent
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