Bringing AI to the Point-of-Care: Pragmatic Considerations

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Integrating AI in medicine

• Pragmatic and technical challenges of integrating AI tools in medicine

• Two examples of integrating ML for clinical/operational use
Clinical data (and model building)

- Clinical data is multi-factorial and complex; and expensive!
- Retrieval from clinical data warehouses
- Clinical expertise in identifying data elements
Model implementation (and re-training)

• Model development is important; what to do with a model is even more important

• Translating from retrospective data-based models to live streams

• Who will use the model results? How? Ethical considerations? Model error handling?
AI governance

• Broad guidelines exist, but rules are institution-dependent

• Governance rules rely on value, safety; much of in-house models are research studies
  • Framework/guidelines for implementing models are unclear

• 3rd party tools with specific applications have been implemented
Predicting surgical transfusion risk

Requirements:
- Historical procedure-specific transfusion data
- Decision threshold
- Patient information

Procedure specific
- Planned surgery
  - Procedure-specific transfusion risk

Patient specific
- Demographics
- Lab values
- Comorbidities
  - Personalized transfusion risk

T/S order
Cost savings

Internal validation: $3.28 per patient = $3.5 million
External validation: $2.60 per patient = $42,000
Assuming hospital cost (incl labor, reagents) for T/S ~ $16 (Medicare rate)
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Multi-hospital validation using the MPOG cohort

External model validation with 67 hospitals, ~9 million procedures: evaluate how the model performs overall, at individual hospital levels, differences between hospital types
Predicting surgical duration

“... how much longer is this case going to take ... ?”

York Jiao, MD
Predicting surgical duration

“... how much longer is this case going to take ... ?”
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Procedure Name: INSERTION BILATERAL TISSUE EXPANDER AND PLACEMENT OF BILATERAL ALLODERM (Bilateral); BILATERAL MASTECTOMY SIMPLE SKIN NIPPLE SPARING W/ RECON DR. BRANDT (PROPHYLACTIC) (Bilateral Breast)
Translating prediction models to the point-of-care

Input features  

Prediction results
Translating prediction models to the point-of-care

ABSTRACT

Background: Accurate estimation of surgical transfusion risk is essential for efficient allocation of blood bank resources and for other aspects of anesthesiologists planning. This study hypothesized that a machine learning model incorporating both surgery- and patient-specific variables would supercede the traditional approach that uses only procedure-specific information, allowing for more efficient allocation of perioperative type and screen orders.

Methods: The American College of Surgeons National Surgical Quality Improvement Program Participant Use File was used to train four machine learning models to predict the likelihood of red cell transfusion using surgery-specific and patient-specific variables. A baseline model using only procedure-specific information was created for comparison. The models were trained on surgical encounters that occurred at 772 hospitals in 2016 through 2018. The models were internally validated on surgical cases that occurred at 719 hospitals in 2019. Generalizability of the best performing model was assessed by external validation on surgical cases occurring at a single institution in 2020.
Translating prediction models to the point-of-care

Limitations
• Cognitive compute platform is a “work in progress”
• Significant overhead in setting up the models
• Batch processing relying on real-time data feeds (e.g., vitals) is hard
• Limitations on models that can be implemented
Translating prediction models to the point-of-care
Translating prediction models to the point-of-care

Epic → AlertWatch → Staging Server → Validation and Retraining
Translating prediction models to the point-of-care

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Brad Fritz, MD
Translating prediction models to the point-of-care

Epic → AlertWatch → Staging Server → Validation and Retraining
Challenges of using ACT for implementation

• Data variables limited to what is currently available in the ACT (mostly preoperative and intraoperative only)

• Relies on the AlertWatch infrastructure for processing

• Delivery modes are limited
Other potential solutions
Other potential solutions
Third party tools
• Ambient AI digital scribes
• Chart summarization
• Automated message response/composition (in-basket messages)