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Stanford Healthcare AI Applied Research Team

Nursing Innovation & Informatics

AI and Collaborative Workflows Predict and Prevent Clinical Deterioration

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Learning Objectives

- Discuss how machine learning can drive workflows in hospital settings.
- Apply design principles for electronic health record applications and multidisciplinary workflows to enable key drivers for an improvement project.
- Describe a collaborative approach leveraging artificial intelligence to improve patient outcomes and safety culture.

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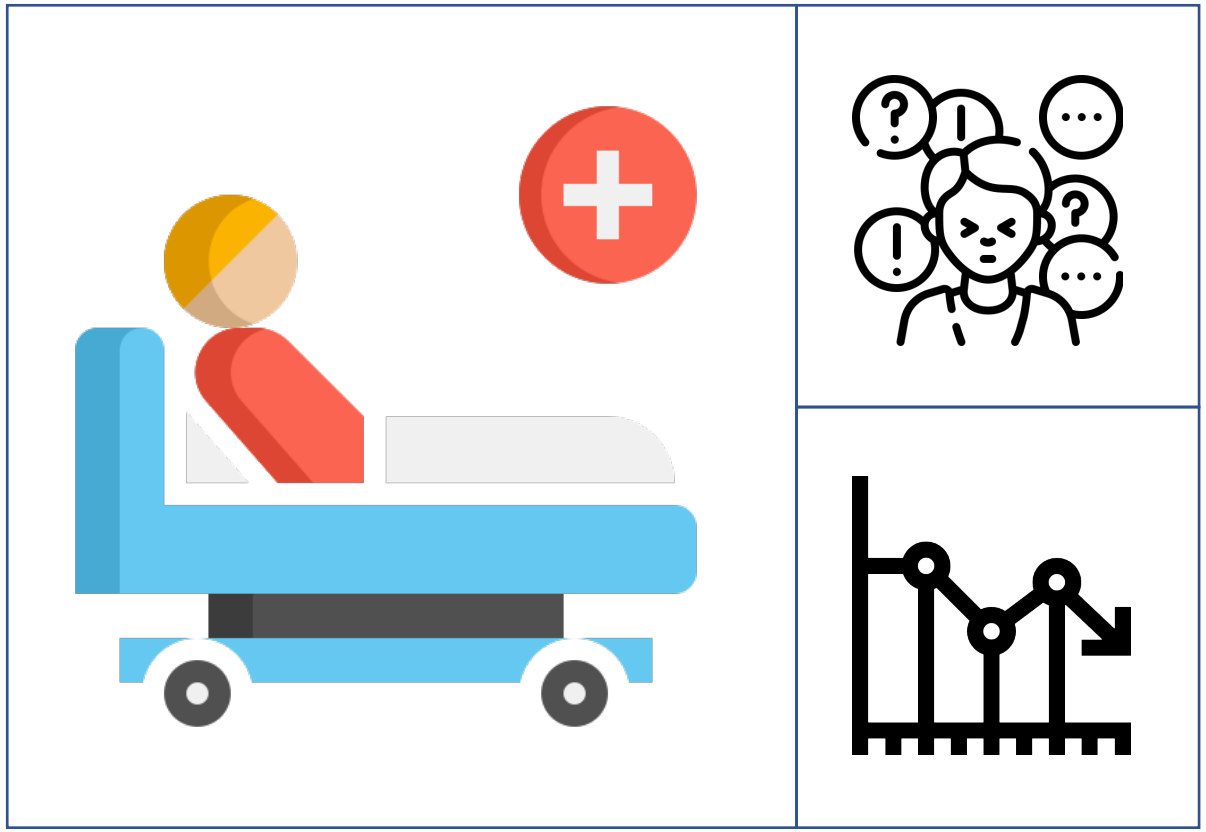
The Problem



- The inpatient care setting is a busy and stressful place
- Patients are cared for by many different clinicians and hundreds of data points are captured every day by devices and care team members
- Often, things are so busy that signs of future clinical deterioration are missed
- As a result, unexpected clinical deterioration occurs - rapid response team activations (RRT), ICU escalations, codes, or death

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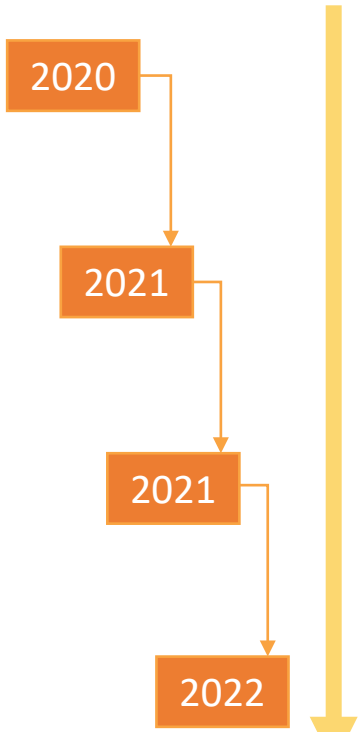
Timeline



- **January 2020**, a multidisciplinary taskforce and project team was assembled to learn more about this problem
- **November 2020**, complete the initial design of an AI-enabled workflow
- **January 2021**, launched an initial pilot of the AI-enabled workflow on a General Medicine unit. Pilot continued through the pandemic
- **May 2021**, pilot expanded to a second General Medicine unit
- **October 2021**, pilot expanded to a third and fourth General Medicine unit
- **November 2021**, pilot expanded to a General Surgery unit
- **March 2022**, pilot results across all units presented to leadership
- **June 2022**, AI-enabled workflow went live across all non-ICU inpatient units

The Team

Representatives from all stakeholder groups in the current work system:

- Bedside Nurses
- Rapid Response Team Nurses
- Attendings
- Residents
- Medical Informatics
- Data Science
- EHR Optimization
- Quality Improvement
- Research

- Secured sponsorship across verticals
- Ensured data science and informatics involvement from the start
- Multidisciplinary to ensure entire process represented

images: Flaticon.com

Current State Analysis – Key Findings

1. Signs of future deterioration not recognized
   - *Why?* Data overload and lack of continuity
   - *Why?* Only able to take into account a subset of the data available and limited ability to see connections that may be precursors to deterioration

2. Sign recognized, but not acted on
   - *Why?* Subjective detection methods leading to disagreement among team members
   - *Why?* No agreed upon process
   - *Why?* Lack of shared mental model for clinical deterioration

- Leverage QI tools such as process mapping and root cause analysis
- Conducted semi-structured interviews to gather pain points and understand the human element

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Key Drivers

The conditions that need to be true in order to solve the problem (*derived from root cause analysis*)

- **Objective** clinical assessment and shared mental model for risk of acute deterioration

- Clinical deterioration **detected early** to allow time for intervention

- Clearly defined and agreed upon workflows **for initial response and follow-up**
- **Role clarity** throughout the process

- Translated root causes into key drivers for success to bridge to intervention design
- Identified AI prediction task articulated in key drivers
- AI is only a fraction of the solution

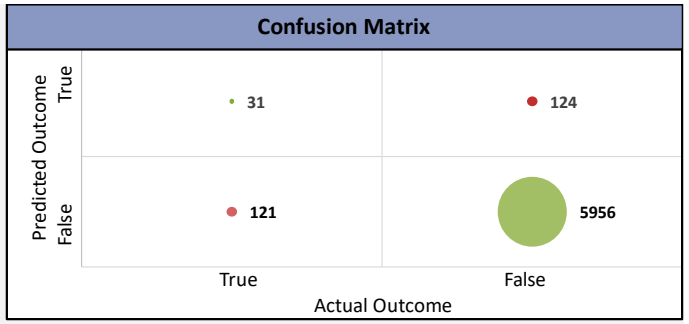
Model Validation

Model Validation : ICU Transfer/RRT/Code

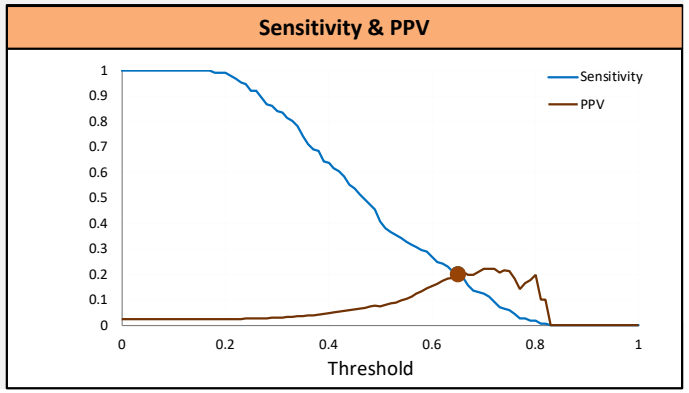
Choose a cutoff threshold. A patient with a risk score above the cutoff threshold is predicted to have a non-PostOp ICU transfer after the first 24 hours of admission.

Cutoff Threshold: 65%

Slide to change threshold for predicted outcome



Performance Measures	
True Positive Rate (Sensitivity): Of the patients with an adverse/mortality event, this is the percentage with scores above the threshold. Higher is better.	20.4%
False Positive Rate (1-Specificity): Of the patients without an adverse/mortality event, this is the percentage with scores above the threshold. Lower is better.	2.0%
Positive Predictive Value: Of the patients with scores above the threshold, this is the percentage who went on to have an adverse/mortality event. Higher is better.	20.0%
Negative Predictive Value: Of the patients with scores below the threshold, this percentage did not have an adverse/mortality event. Higher is better.	98.0%



Optimal sensitivity and positive predictive value (PPV) at a score of 65

When a patient reaches a **score >=65**, there is a **+20% chance of an "event" in 6-18 hours**

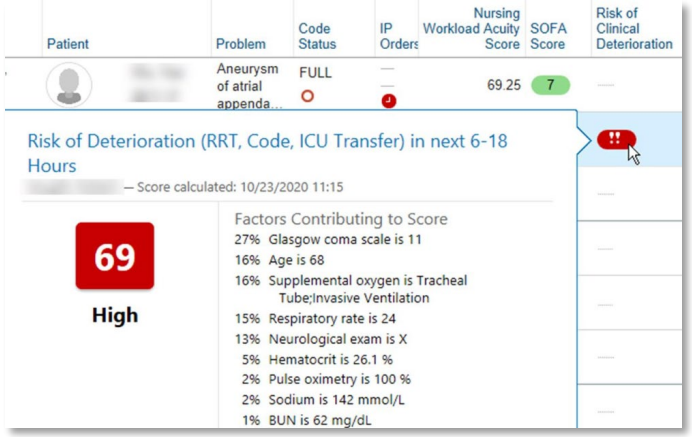
Event = ICU escalation, RRT or Code

- Model validation on the local patient population was paramount (performance change significantly)
- Model validation approach was informed by key drivers & user defined workflow requirements

PPV = Positive Predictive Value

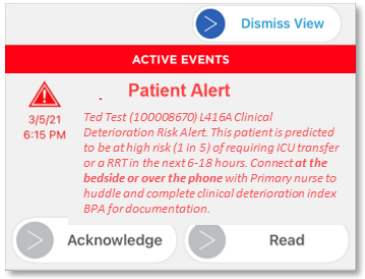
AI-enabled Workflow

Step 1 **Risk of Clinical Deterioration Column Flag** and BPA when patient breeches model threshold (>20% chance of deterioration in 6-18 hours)

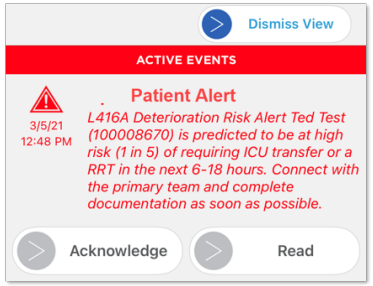


Step 2 **Mobile Alert*** to RN assigned to patient in EHR, Primary Resident/Intern, Cross Cover Resident/Intern

Provider Team Mobile Alert



Nursing Mobile Alert



*Mobile alert only occurs the first time the patient is flagged by the model every 24 hours.

- Conducted future state process mapping sessions using design thinking methods and human factors to stimulate creativity
- Engaged front-line staff in qualitative model validation to build buy-in and familiarize end users with AI
- Iterated many times on workflow design before and after implementation
- Ensured risk review as well as nursing practice

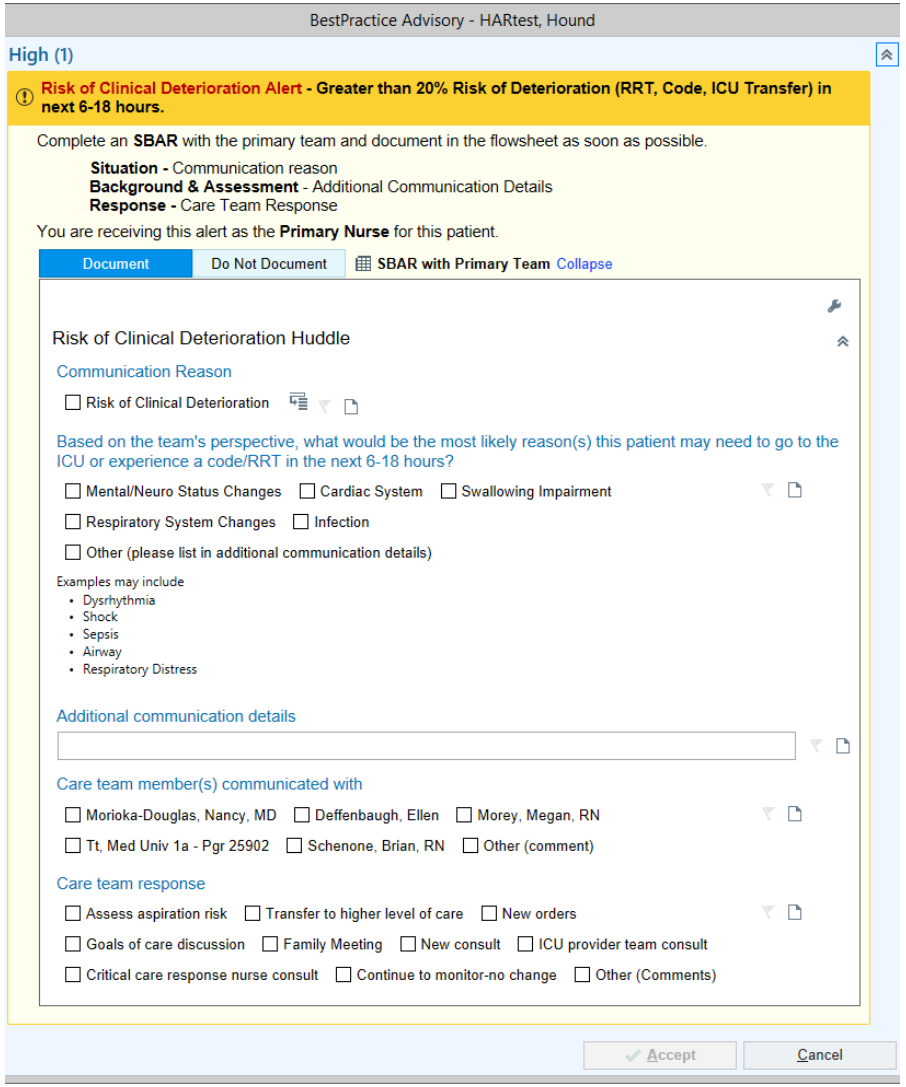
Workflow Design

Step 3 **Primary Nurse** and Charge Nurse connect to assess the patient and **validate alert**

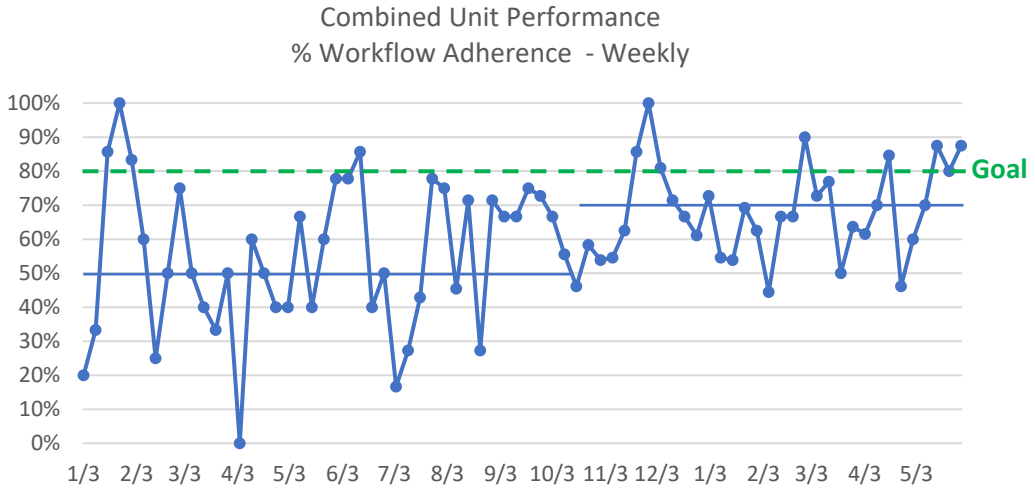
Step 4 **Primary Nurse** and **Provider Team** connect for **SBAR Clinical Deterioration Huddle** in person or on the phone within 2 hours

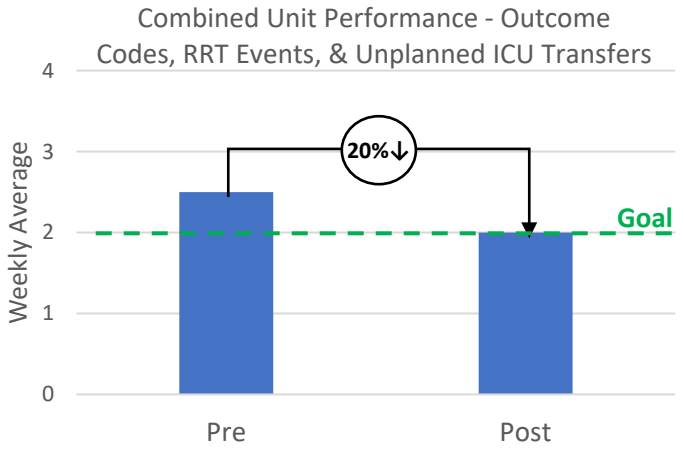
SBAR Clinical Deterioration Huddle:

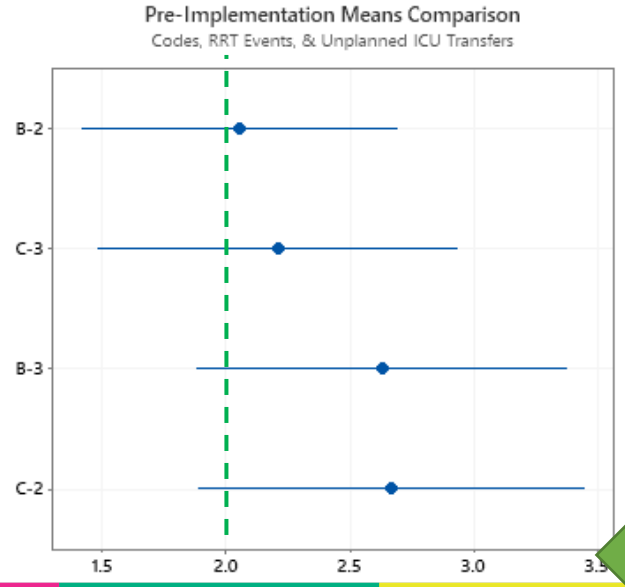
- **S**: Patient at *high* risk of clinical deterioration
- **B/A**: Discuss nursing concerns and likely reason(s) for clinical deterioration
- **R**: Discuss response to risk of clinical deterioration
  - Assess aspiration risk
  - Transfer to higher level of care
  - New orders
  - Goals of care discussion
  - Family meeting
  - New consult
  - ICU provider team consult
  - Critical care response nurse consult
  - Continue to monitor – no change
  - Other (Comments)

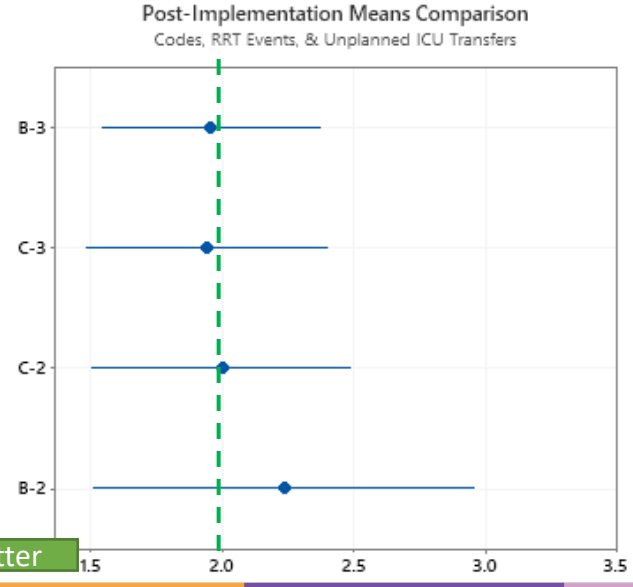


Pilot Results









Less is better

- Trending at **70% workflow adherence**; ongoing efforts to increase to 80%
- Met our outcome goal of a **20% reduction** in clinical deterioration events

Pilot Results – Provider Feedback

In a survey of nursing staff (52 nurses, 30 responded; 57%):

- **96.5%** reported that they felt the **workflow was adding value to patient care**
- **89.6%** indicated that the tool **changes the way they care for their patients**:
  - Charge nurses in the survey reported **alternating patient assignments** or ratios in **anticipation of clinical changes** with the flagging patient, and bedside nurses reported they **rounded more frequently** and/or completed a more **in-depth patient assessment** on their patients who were flagging

In a survey among 19 medicine residents participating in the pilot:

- **50%** indicated that they **take action on the alerts** by calling the bedside nurse to huddle, messaging the bedside nurse, or going to the bedside to huddle with the nurse
- **50%** indicated that no personal action is taken on the alert; however, **64%** said that after receiving an alert, the **bedside nurse also reached out to them to discuss the patient's status**
- When asked about challenges to workflow adherence, 30% of physicians indicated that when they received the alert, they had recently assessed the patient, and, therefore, further action seemed redundant

Lessons Learned

- Collaborative team – relationships are paramount
- Empowering bedside nurse’s and primary provider teams
- Managing frequency of alerts is key
- Alert delivery mechanism – lock out periods
- Action clearly defined – check-list structured huddle
- Keep an eye out for unanticipated use and misuse
- Building trust in the tool early on
- Cautionary tale > the AI tool does not replace clinical judgement

Key Takeaways

- Artificial intelligence (AI) is not the end product, but rather an enabling function in the form of machine-learning (ML) generated predictions that power a broader set of digital applications, workflows, and human teams (i.e., an AI-enabled system)

- The AI-enabled system must be designed and implemented in a manner that is user centered and driven by pragmatic needs and challenges

- Empowering nurses and other front-line providers with AI tools enhances collaboration and a culture of safety

Questions?

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