

The Burden of **Clinical Deterioration** and How One Hospital is Tackling it with **Machine Learning**

SIGNAL 1

Transforming Hospitals with AI.
Clinically validated. Responsibly deployed.



Clinical deterioration is a leading cause of in-hospital mortality and avoidable hospital days

Hospitals care for patients with varying levels of [acuity](#). A patient's acuity level, and how it is expected to change over time, are inputs into virtually every triage and care decision hospital staff make. A key challenge that healthcare providers face is detecting subtle signs of changes in patient acuity - in particular, signs of clinical deterioration.

Clinical deterioration: An unexpected and sometimes tragic outcome

Clinical deterioration is shockingly common. Up to [10%](#) of all patients admitted to a general internal medicine ward will [deteriorate](#) to the point that they require a more intensive level of care or die in-hospital.¹ These events are typically unexpected and lead to [higher mortality rates, longer hospital stays, and increased anxiety](#) for patients and their loved ones,² and can even impact quality of life beyond the hospital stay. Unfortunately, the trends for in-hospital deterioration do not look promising.

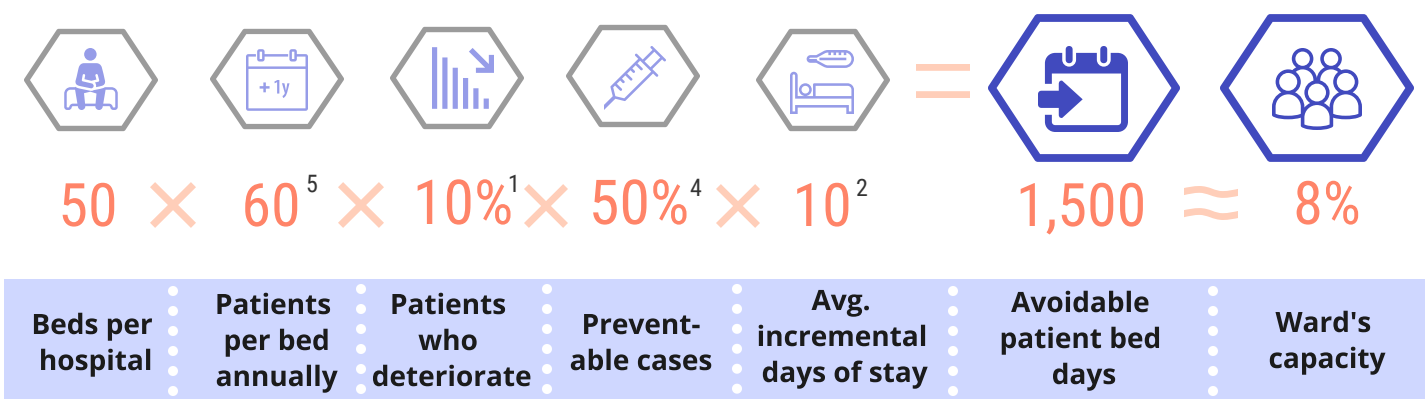
An aging population with increased rates of comorbidities combined with a fatigued, and [understaffed workforce will increasingly challenge administrators to do more with less](#), exacerbating the challenges for clinicians of detecting early signs of deterioration.

The clinical burden of deterioration - a hidden driver of significant avoidable costs and healthcare capacity

A human life is priceless and an unexpected in-hospital deterioration impacts the entire patient, family and provider ecosystem. But there's another cost to these missed events as well - not only do they sometimes lead to tragic consequences but the rapidly deteriorating patients who do survive require an inordinate amount of resources which puts stress on the system as a whole. Studies have shown that patients who deteriorate have significantly longer hospital stays² and cost³ more than 3 times longer - than similar patients who do not deteriorate.

While not all cases can realistically be avoided, a large fraction can. In fact, studies show that up to 50% of adverse events⁴ could be avoided with early detection and intervention. At a time when the top two worries of hospital executives are staffing capacity and inpatient beds to service the surgical backlog, these avoidable patient days loom large in the wake of the pandemic.

What does this mean in terms of lost capacity in a 50 bed internal medicine ward?



Of course, realizing the full addressable capacity would be an enormous undertaking; but preventing even a fraction of these incidents would free up an enormous amount of capacity. This potential capacity savings ignores the other potential benefits of reducing deterioration including lower readmission rates, fewer in-hospital code blues, reduced risk of additional medical malpractice claims^{6,7} and alleviating the stress that emergency responses create for frontline staff.

In short, in healthcare, quality and cost are linked. Reducing avoidable deaths and deterioration provides hospitals with an opportunity to improve quality while simultaneously reducing costs.

An ML-based risk predictor can enable early detection and intervention to reduce the effects of clinical deterioration

To meaningfully reduce the effects of clinical deterioration, clinicians must be able to identify signs earlier in the process and ensure the proper coordination of care. That is, they must be alerted to the deterioration early enough to provide the right patient with the right care at the right time.

Many of the common causes of clinical deterioration (for example, sepsis, respiratory failure, arrhythmias, etc.) exhibit early physiological signs - 'fingerprints' that can enable further investigation and interventions if detected early.⁴ Clinicians monitor vitals closely but the human brain can only handle processing 7 +/- 2 pieces of information at a time.⁷ With some studies suggesting over a 1000 different patient parameters are required for optimal decision-making⁹ - it is clear why clinicians may not always pick-up non-obvious patterns .

This is where the power of a machine learning-based risk predictor comes in. By studying historical datasets, the machine learning based algorithm is able to uncover subtle relationships between patient data and the onset of deterioration, including relationships that are based on the patient's time-series of data (e.g.: changes in their vital signs) rather than based only on the patient's data at any one point in time)^{10,11,12} The evidence is mounting that machine-learning is superior to alternative approaches when it comes to addressing this problem.¹³

However, there's a lot more to making a machine learning-based solution successful than building a model. Without careful execution, it is simply a prediction and not useful as a clinical decision support tool. There are four key success factors that are critical to ensuring a responsible and impactful risk predictor implementation including:



1. A high performance model tailored to the local population
2. A reliable machine-learning operations tooling system (ML Ops)
3. Deep and ongoing clinical engagement
4. Continuous monitoring to ensure the robustness of the model and consistency of clinician compliance

Key Factors for a Successful Machine Learning Based Risk-Predictor

For a machine learning based risk predictor to create value in a clinical setting, it must deliver on four sets of requirements. These go beyond the mere technical aspects of the predictor and focus on how the system as a whole drives impact.

Model Performance

- The model's ability to **robustly minimize false alarms while capturing as many deteriorating patients as possible**
- For maximal impact, the model must provide **timely** predictions
- The predictor must be correct when **tested on the target population**.
- Predictions must be **equitable** across different subgroups in the population.

Evaluation and Monitoring

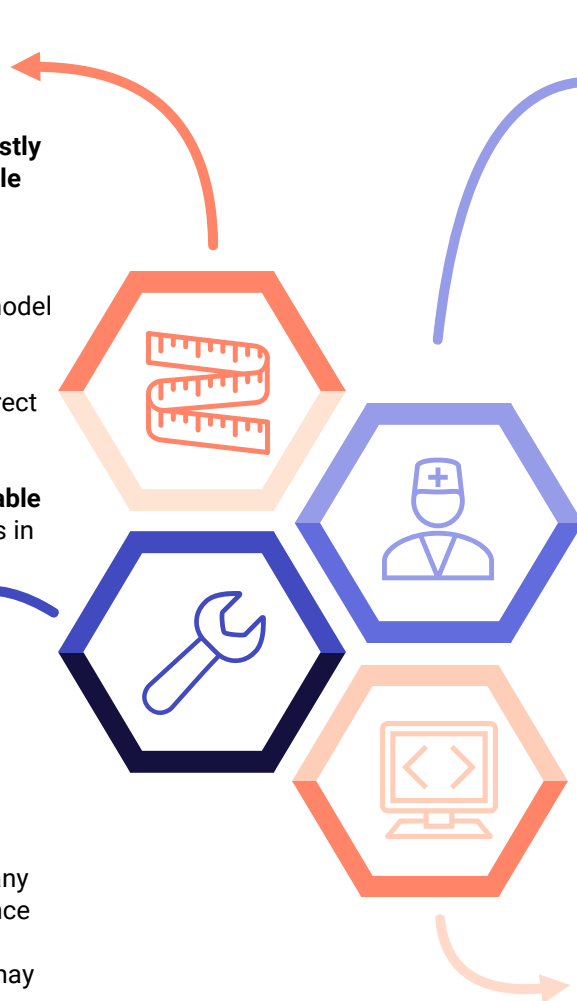
- Active **monitoring** and **auditing** is necessary for detecting and remedying any degradations in performance over time.
- Regular model **upgrades** may be necessary to account, for example, for changes in patient population or clinical routines
- The **impact** of the system must be rigorously measured and communicated back to key stakeholders to maintain support and buy-in.

Clinical Engagement

- **Clinical leadership** of the design, development and implementation process is essential
- Predictions must be **embedded** into clinicians' existing workflows and not create additional work.
- Predictions must be **understandable and actionable** to drive desired interventions
- High-touch **education and training** of clinicians are required to drive adoption and usage
- Taking into account the **specific needs of a healthcare organization** (e.g. focusing on risk for ICU transfer) increases the effectiveness of a risk-predictor

MLOps Infrastructure

- System implementation must be done in a **private and secure** infrastructure with enhanced data protection capabilities
- **Data validation & processing** capabilities to **manage messy healthcare data**, including anomaly detection, data profiling, processing functions, etc.
- Full **continuous integration** and deployment capabilities from development to production with traceable and reproducible artifacts for **detailed audit requirements**



Case study: CHARTWatch at St. Michael's Hospital in Toronto

Signal 1's machine learning based risk predictor, CHARTWatch, has been in use at St. Michael's Hospital since October 2020

The General Internal Medicine (GIM) inpatient service at St. Michael's Hospital, an academic health centre in Toronto, Ontario, cares for about 4000 patients each year. Roughly 7% of patients in the GIM service die or require transfer to ICU. In 2017, the hospital began development of CHARTWatch - a machine learning based risk predictor for the GIM service. Using commonly collected data sources, every hour the algorithm predicts a patient's risk of deteriorating over the subsequent 48 hours. Based on their predicted scores, patients are categorized as high, medium or low risk. CHARTWatch sends alerts directly to care providers when it predicts that a patient is at high-risk for deterioration.

Impact of CHARTWatch at St. Michael's Hospital

15%

improvement in clinician's ability to predict deterioration

15-20%

reduction in the in-hospital mortality rate of high-risk patients

9%

9% reduction in length-of-stay for high-risk patients

“

CHARTWatch has become a **valuable tool for daily patient care**, identifying patients at risk of deterioration and **enabling clinicians to intervene earlier.**

Dr. Sharon Straus
Physician-in-Chief,
St. Michael's Hospital

About Signal 1

Signal 1 is a health AI start-up with the mission to transform patient care through responsibly deployed AI. Signal 1 provides hospitals with an end-to-end solution for integrating AI-driven insights into existing hospital workflows. Its first application is a clinically validated real-time automated patient risk predictor called CHARTWatch that has been developed and deployed at St. Michael's Hospital in Toronto, Canada. CHARTWatch helps hospitals improve quality and flow while reducing stress on front-line care providers.

If interested in understanding more about Signal 1's solution, please contact us at: Hello@signal1.ai

The Signal 1 Development and Deployment Process

HOW

Model Design and Co-Development



Alongside a clinical champion, technical team co-designed model specifications to ensure they met **hospital and clinical staff needs** in addition to being **understandable and actionable**. Examples of needs include: number of alerts, and prediction time-window.

Hospital population data was acquired and cycles of development, consultation, and evaluation followed to ensure **robustness, equity** across subgroups, and **high precision/recall**.

1

Silent Deployment and Evaluation

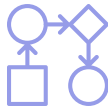
2

Once the model was finalized, the silent deployment phase began to ensure **consistent performance** in a live environment. Model is evaluated

Staff education took place in this phase for a smooth transition and integration.



Deployment and Workflow Integration



Deterioration prediction alerts are being **delivered directly to physicians**, and used to for early intervention in high-risk patients. Insights from the prediction **support clinicians** in ranking patients for rounds and visits through the day.

Charge nurses use the model to assign nurse shifts and aim for a **more equitable assignment** across patient risk-groups.

3

Monitoring

4

Continuous evaluation of clinical model performance and clinical impact takes place.

Any issues with the predictions are dealt with as they arise.



Updates



Model is updated based on **performance criteria**. If a **marginally better model** is developed, or there's a significant **dataset shift** that requires a an updated, the model is updated.

5

Citations

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