

SIGNAL 1

Using machine learning to tackle the burden of clinical deterioration

Executive Summary

Clinical deterioration is difficult for clinicians to predict and is a leading cause of in-hospital mortality and avoidable bed days. Machine learning models can identify patients at high risk of deterioration and serve as an early warning to busy clinicians, enabling them to intervene early and mitigate poor outcomes.

Signal 1's Deterioration Solution is the commercial version of an early warning system, called CHARTWatch, developed at St. Michael's Hospital, part of the Unity Health Toronto network in Canada. The solution is based on a machine learning model that predicts a patient's risk of clinical deterioration and categorizes patients as low, medium or high risk. The delivery of these predictions can be tailored to best fit end users' existing or desired clinical workflows.

Research conducted at St. Michael's Hospital shows that use of their algorithm can generate a 16% improvement in clinicians' ability to predict which patients will clinically deteriorate.¹ Evaluation results indicate that the introduction of the deterioration predictions into their General Internal Medicine unit has resulted in a 26% reduction in the relative risk of death among non-palliative patients.² Based on the impact the tool had in GIM, St. Michael's Hospital expanded use of the solution into their surgical units. In 2024, the tool was adapted and deployed at St. Joseph's Health Centre, a community hospital also part of the Unity Health Toronto system.

Signal 1's Deterioration Solution* identifies patients at risk of clinical deterioration to enable earlier interventions.

* Not yet available for sale. Investigational use only.



A long-recognized challenge: Clinical deterioration is a leading cause of in-hospital mortality and extended hospital stays

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 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.**⁴ These events are often unexpected and lead to higher mortality rates, longer hospital stays, and increased anxiety for patients and their loved ones.⁵

Studies have shown that patients who deteriorate stay in hospital three times longer⁵ and cost significantly more⁶ than similar patients who do not deteriorate. At a time when some of the top worries of hospital executives are a shortage of staff and a shortage of inpatient beds, any source of avoidable patient days looms large.

Clinical deterioration adds stress to an already stretched clinical workforce

Unfortunately, the trends for in-hospital deterioration are unlikely to improve. Hospitals today face an aging population with high comorbidity rates⁷ and an increase in patient acuity as a result of

“A deteriorating patient is one who moves from one clinical state to a worse clinical state which increases their individual risk of morbidity, including organ dysfunction, protracted hospital stay, disability, or death.”³

delayed treatments during the pandemic.⁸ At the same time, many hospitals face staffing shortages and high levels of staff fatigue and burnout.⁹

52%

of nurses said they considered leaving their position due to insufficient staffing and burnout.¹²

Deterioration events can be particularly stressful for frontline nurses, given their important role in identifying early signs of these events.¹⁰ Studies have shown that, when early signs are missed, nurses may internalize a sense of responsibility for the patient's worsening condition¹⁰ and may experience criticism from colleagues, patients, or their families.¹¹ The potential impact this added stress should not be underestimated at a time when 52% of nurses said they considered leaving their position due to insufficient staffing and burnout.¹²

The Opportunity: Using Machine Learning to Identify Deterioration Earlier

Many of the common causes of clinical deterioration (such as sepsis, respiratory failure, and arrhythmias) exhibit early physiological signs - 'fingerprints' that can enable further investigation and interventions if detected early.^{13,14} In fact, research shows that virtually all **clinical deterioration events are preceded by warning signs that occur approximately 6-8 hours in advance.**¹⁵

While frontline staff may recognize signs of deterioration under optimal conditions,¹⁴ the current situation in many hospitals is far from optimal. Patient to staff ratios are high, clinical staff are fatigued and there has been considerable turnover with many highly experienced doctors and nurses choosing to retire after the pandemic. Recognizing subtle changes in a patient's condition that have taken place over multiple days (and potentially multiple transfers of care) or quickly picking up on sudden changes in physiological signs can be extremely challenging in today's hospital environment.¹⁶

The Power of Machine Learning

Machine learning is a type of artificial intelligence that involves training computer algorithms to learn patterns from past data in order to make predictions about future events. For example, machine learning algorithms can be trained on historical data to uncover subtle relationships between physiological data and the onset of deterioration.^{17,18,19} Once those patterns are learned, the algorithm

can be applied to patients in-hospital to make real-time predictions about the patient's risk of clinically deteriorating. In fact, evidence is mounting that machine learning is superior to alternative approaches when it comes to identifying unforeseen clinical events.^{18,19}



A Machine Learning Powered Deterioration Solution

Signal 1's Deterioration Solution is a commercial rebuild of a solution, called CHARTWatch, developed at St. Michael's Hospital, part of the Unity Health Toronto network in Canada (see the Case Study that follows).

The CHARTWatch machine learning model was trained on a large dataset of past patient encounters to identify the subtle changes in physiological data that occur before a deterioration event. When the model is applied to live patient data, it can provide a real-time risk score for each patient. Based on that risk score, patients are categorized as high, medium, or low risk of deterioration. The thresholds for these categories were selected in collaboration with users to optimize safety (i.e., capture most patients who will deteriorate) while minimizing the number of false alerts a clinician will receive.

The result is a model which can predict the risk that a patient will deteriorate during their hospital stay based on a patient's lab results, vital sign measurements, movement through the hospital, and basic demographics.

How these near real-time insights are delivered to busy clinicians can be tailored by hospitals according to the modality and frequency that best fit the existing or desired clinical workflows. Potential workflow integrations include:

- Automated page or text sent to designated clinicians when a patient is first identified as "high risk".
- Direct integration and display in a hospital's clinician information system(s).
- Automated email containing census of all unit patients and their risk group.



CASE STUDY

St. Michael's Hospital in Toronto

CHARTWatch is an early warning system developed at Unity Health Toronto's St. Michael's Hospital by a multidisciplinary partnership of data scientists, clinicians, administrators, and patients who worked together to design and ultimately implement and evaluate the solution.²¹ CHARTWatch has been in use since October 2020.

The General Internal Medicine (GIM) inpatient service at St. Michael's Hospital cares for about 4000 patients each year. Roughly 7% of patients in the GIM service die or require transfer to ICU.²⁰ Using commonly collected data sources, every hour, the CHARTWatch algorithm predicts a patient's risk of deteriorating over the subsequent 48 hours.

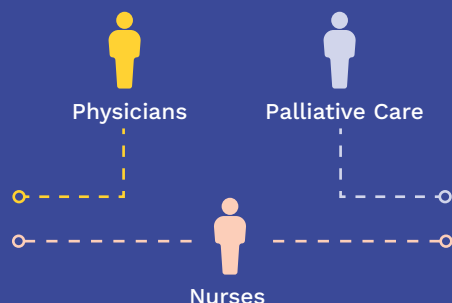
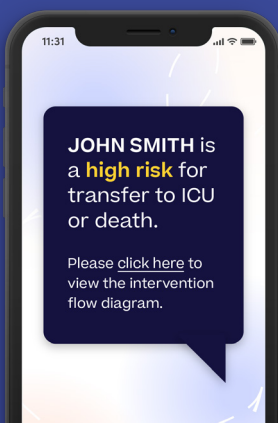
Predictions are delivered to frontline clinicians as part of a multipronged clinical intervention developed by the multidisciplinary team.²⁰

High risk alerts are sent via a paging application to a GIM team phone (typically carried by residents) and the charge nurses' mobile phone. Further, risk classification for the entire unit census is updated daily in the hospital's electronic signout tool and emailed to the charge nurses twice daily to inform bedside nurse assignment. Finally, a daily email that contains information on high risk patients is sent to the palliative care team so that they can connect with the physicians to ask whether a palliative care consultation is warranted.²¹

“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**

Text alert for patients requiring urgent care



Daily patient summary to assist care assignment decisions

GENERATED ON January 20, 2023 1:00pm

Patient Care Summary
All Patients Changed Prediction from March 1, 2023 at 5:00pm

Location	MRN	Patient	Sex/Age	Acuity Prediction	Care Tasks
BA01-01	88945678	TR	M 55	Low Acuity	O2, VSQBH
BA01-02	54223954	GM	F 57	High Acuity	L/Tx2
BA02-01	12004795	BB	F 63	Low Acuity	CAM+
BA02-02	25633014	VD	M 55	Medium Acuity	—
BA03-01	87885032	AW	M 96	Medium Acuity	—
BA03-02	99421003	JJ	M 87	High Acuity	O2
BA04-01	95482203	ED	F 77	Low Acuity	VSQBH, CAM+
BA04-03	93390004	MM	F 47	Low Acuity	—

Model performance

An evaluation performed by St. Michael's found that the CHARTWatch model has a sensitivity of 0.976 for patients marked as high or medium risk - meaning that 97.6% of patients who deteriorated were classified by the model as high or medium risk.²¹ The study also found that alerts generated by the model were perceived as a manageable (median of 2 alerts generated per day for a 84 GIM patients) with good user adherence to the defined workflows in response to alerts.²²

Impact at St. Michael's Hospital

Research from St. Michael's Hospital indicates that CHARTWatch improves clinicians' ability to accurately identify deteriorating patients and has resulted in a reduction in the mortality rate of high-risk patients.

16% improvement in clinician's ability to predict deterioration¹

26% reduction in the in-hospital mortality rate of high-risk patients²

In response to the positive impact, United Health expanded the use of CHARTWatch to St. Michael's surgical units in November 2022 and to a GIM unit at its affiliated community hospital, St. Joseph's Health Centre, in January 2024. There are early indications that it is supporting staff in prioritizing patients, enabling more equitable staff assignment, and improving team communications.²²

“What we're seeing with CHARTWatch is improved teamwork on the unit and improved communication between the nursing and physician teams.”

— Swanee Tobin,

Clinical leader manager, St. Michael's Hospital

“CHARTWatch gives you that added reassurance and validation... It doesn't replace your clinical intelligence, but it definitely helps to enable better patient outcomes.”

— Ruth Mega,

Charge Nurse, St. Michael's Hospital

About Signal 1

Founded in 2022, Signal 1 is building the technology platform to accelerate the AI revolution in healthcare. Signal 1 offers a fully-integrated AI platform built specifically for the healthcare industry. Our Health AI platform provides the technical infrastructure and tools to enable and accelerate a health system's AI program. The platform consists of three components:

1. AI Infrastructure: Secure data pipelines and an award-winning AI engine to easily deploy AI models into production ensuring industry-leading software and machine learning practices.
2. AI Control Center: A single 'pane of glass' to enable management and monitoring of all AI models deployed via the platform.
3. AI App Suite: Library AI applications that address key operational and care management decisions including discharge planning, ED prioritization and unexpected deterioration.

What this means for hospitals we work with:

- Streamlined AI model development and deployment with a faster time-to-value
- Automated model validation and real-time monitoring to ensure models remain accurate and safe to use
- Lower costs of ongoing model management and maintenance
- Up to 10X the output and ROI of existing data science and machine learning teams

To learn more about Signal 1's Deterioration Solution*, please contact us at:

[**hello@signal1.ai**](mailto:hello@signal1.ai)

*Signal 1's Deterioration Solution is currently available for investigational use only.

References

1. Verma AA, Pou-Prom C, McCoy LG, Murray J, Nestor B, Bell S, Mourad O, Fralick M, Friedrich J, Ghassemi M, Mamdani M. Developing and Validating a Prediction Model For Death or Critical Illness in Hospitalized Adults, an Opportunity for Human-Computer Collaboration. *Crit Care Explor.* 2023 May 1;5(5):e0897. doi: 10.1097/CCE.0000000000000897. PMID: 37151895; PMCID: PMC10155889.
2. Verma AA, Stukel TA, Colacci M, Bell S, Ailon J, Friedrich JO, Murray J, Kuzulugil S, Yang Z, Lee Y, Pou-Prom C. Clinical evaluation of a machine learning-based early warning system for patient deterioration. *CMAJ.* 2024 Sep 16;196(30):E1027-37.
3. Jones D, et al. Defining clinical deterioration. *Resuscitation* 2013; 84(8):1029-34.
4. Verma, A. A. et al. Patient characteristics, resource use and outcomes associated with general internal medicine hospital care: the General Medicine Inpatient Initiative (GEMINI) retrospective cohort study. *Canadian Medical Association Open Access Journal* 2017; 5, E842-E849.
5. Escobar, G. J. et al. Intra-hospital transfers to a higher level of care: contribution to total hospital and intensive care unit (ICU) mortality and length of stay (LOS). *Journal of hospital medicine* 2011; 6: 74-80
6. Curtis, K. et al. Treatments costs associated with inpatient clinical deterioration. *Resuscitation* 2021; 166: 49-54.
7. Ruiz M et al. Multi-Morbidity in Hospitalised Older Patients: Who Are the Complex Elderly? *PLoS One* 2015;10(12):e0145372.
8. Statistics Canada. Adults in Canada delayed seeking health care during the first year of the pandemic. 2022. (Available at <https://www.statcan.gc.ca/o1/en/plus/735-adults-canada-delayed-seeking-health-care-during-first-year-pandemic>)
9. Veenema, T. et al. The COVID-19 Nursing Workforce Crisis: Implications for National Health Security. *Health Security.* 2022; 20:3, 264-269.
10. Dresser, S. et al. Frontline Nurses' clinical judgement in recognizing, understanding, and responding to patient deterioration: A qualitative study, *International Journal of Nursing Studies* 2023; 139: 104436.
11. Massey D. et al. What factors influence ward nurses' recognition of and response to patient deterioration? An integrative review of the literature. *Nurs Open* 2016; ;4(1):6-23.
12. American Nurses Foundation. Pulse on the Nation's Nurses Survey Series: COVID-19 Two-Year Impact Assessment Survey. 2022. (Available at <https://www.nursingworld.org/~4a2260/contentassets/872ebb13c63f44f6b11a1bd0c74907c9/covid-19-two-year-impact-assessment-written-report-final.pdf>)
13. Vincent JL, et al. Improving detection of patient deterioration in the general hospital ward environment. *Eur J Anaesthesiol.* 2018;35(5):325-333.
14. Padilla RM and Mayo AM. Clinical deterioration: A concept analysis. *J Clin Nurs.* 2018;27(7-8):1360-1368.
15. Rose MA et al. Utilization of electronic modified early warning score to engage rapid response team early in clinical deterioration. *J Nurses Prof Dev* 2015 31(3): E1-7.
16. Smith, D. et al. Barriers and enablers of recognition and response to deteriorating patients in the acute hospital setting: A theory-driven interview study using the Theoretical Domains Framework. *J Adv Nurs* 2021; 77: 2831- 2844.
17. Sendak, M. P. et al. Real-world integration of a sepsis deep learning technology into routine clinical care: implementation study. *JMIR medical informatics* 2020; 8: e15182
18. Malycha J, et al. Artificial intelligence and clinical deterioration. *Curr Opin Crit Care* 2022;28(3):315-321.
19. Veldhuis, L. et al. Artificial Intelligence for the Prediction of In-Hospital Clinical Deterioration: A Systematic Review. *Critical Care Explorations* 2022; 4(9):e0744.
20. Verma AA, et al. Implementing machine learning in medicine. *CMAJ* 2021;193(34):E1351-E1357.
21. Pou-Prom C, et al. From compute to care: Lessons learned from deploying an early warning system into clinical practice. *Front Digit Health* 2022; 5(4): 932123.
22. Cox, Robyn. AI-Powered tool on surgical unit to improve patient care. *Hospital News.* [Available at <https://hospitalnews.com/ai-powered-tool-on-surgical-unit-to-improve-patient-care/>]