Advancing Continuous Predictive Analytics Monitoring

Moving from Implementation to Clinical Action in a Learning Health System

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KEYWORDS

• Predictive analytics monitoring • Implementation science
• Stakeholder driven design • Learning health system • Streaming design

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KEY POINTS

- Continuous predictive analytics monitoring synthesizes data from a variety of inputs into a risk estimate that clinicians can observe in a streaming environment.
- For continuous predictive analytics monitoring to be useful, clinicians must engage with the data in a way that makes sense for their clinical workflow in the context of a learning health system (LHS).
- Clinicians described the processes needed to move to clinical action through the following themes: (1) understand the science behind the algorithm, (2) trust the data inputs, (3) integrate with the electronic medical record, and (4) optimize clinical pathways.
- Larger prospective studies are needed to evaluate the relationship between continuous predictive analytics monitoring and clinical action from the lens of LHS and implementation science perspectives.

INTRODUCTION

Intensive care unit (ICU) patients are at the highest level of acuity where they are vulnerable to potentially catastrophic clinical events or complications during the course of their stay.[1] The financial, societal, and human burdens of intensive care are growing[2] and there has been a steady increase in the amount of data inputs received from patients in the ICU. In the ICU, point-of-care clinicians monitor a diverse array of data inputs to detect early signs of impending clinical demise or improvement.[3] Most information gained from unprocessed cardiorespiratory monitoring (multilead electrocardiogram [ECG], pulse waveform, heart rate, respiratory rate, oxygen saturation) is neither fully used nor stored for later analysis.[4] Continuous predictive analytics monitoring synthesizes data from a variety of inputs into a risk estimate that clinicians can observe in a streaming environment.[4,5] The potential applications for streaming continuous predictive analytics monitoring displays in ICU care settings are extensive.[6]

Continuous predictive analytics monitoring was born in the neonatal ICU (NICU).[5,7–13] In the neonatal setting, investigators found abnormal heart rate characteristics (HRCs) in the hours preceding a clinical diagnosis of sepsis.[5] These HRCs were not obvious in vital sign trends, even to experienced clinicians. Methods were developed and refined to characterize, process, and synthesize data inputs. Computational techniques synthesized these data inputs into a model that produced an estimation of risk, which led to the streaming output of characteristics called the HRCs index (**Fig. 1**).[8,13–15] A large, multicenter randomized controlled trial studied the impact of HRC monitoring on patient outcomes and determined a reduction in mortality among very low birth weight infants who were monitored using the HRC index.[8,14] Patients in the HRC monitoring arm received antibiotics for a longer duration of time and clinicians were able to detect preclinical signs of septicemia hours before overt clinical symptoms.[8,14]

The application of continuous predictive analytics monitoring was then extended to critically ill adults.[3,10,11] The first phase necessitated detection of physiologic signatures of illness (prodromes). Emergent intubation and hemorrhage were chosen as the initial clinical outcomes to demonstrate proof of concept and model validation.[3,10,11] The validated algorithms for early detection of subacute and potentially catastrophic illness were then displayed through a continuous streaming environment, called continuous monitoring of event trajectory (CoMET®) (**Fig. 2**). CoMET®