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BRIEF REPORT

Learning Health Systems

Beyond prediction: Off-target uses of artificial intelligence-based predictive analytics in a learning health system

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Abstract

Introduction: Artificial-intelligence (AI)-based predictive analytics provide new opportunities to leverage rich sources of continuous data to improve patient care through early warning of the risk of clinical deterioration and improved situational awareness. Part of the success of predictive analytic implementation relies on integration of the analytic within complex clinical workflows. Pharmaceutical interventions have off-target uses where a drug indication has not been formally studied for a different indication but has potential for clinical benefit. An analog has not been described in the context of AI-based predictive analytics, that is, when a predictive analytic has been trained on one outcome of interest but is used for additional applications in clinical practice.

Methods: In this manuscript we present three clinical vignettes describing off-target use of AI-based predictive analytics that evolved organically through real-world practice.

Results: Off-target uses included:real-time feedback about treatment effectiveness, indication of readiness to discharge, and indication of the acuity of a hospital unit.

Conclusion: Such practice fits well with the learning health system goals to continuously integrate data and experience to provide.

KEYWORDS
AI, artificial intelligence, learning health system

1 | INTRODUCTION

Artificial intelligence (AI)-based predictive analytics provide new opportunities to leverage rich sources of continuous data to improve patient care.[1-8] These approaches use machine learning and other modern statistical techniques to provide early warning of events of clinical deterioration such as sepsis, respiratory failure, hemorrhage, and emergent intensive care unit (ICU) transfer.[9-11] While AI-based predictive analytics estimate the risk of specific clinical events, in practice they can be used as a proxy for illness severity, or even as a comprehensive biomarker or physiomarker.[12] For example, after implementation of a display of the risks of urgent unplanned intubation for acute respiratory failure and hemorrhage requiring large transfusion in a surgical/trauma ICU,[10] point-of-care clinicians described

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the clinical utility of using the risk models in ways other than early warning.[13]

Pharmaceutical interventions have off-target uses where a new drug indication has not been formally studied, but has potential for clinical benefit and is still prescribed. An analog has not been described in the context of AI-based predictive analytics, that is, when a predictive analytic has been trained on one outcome of interest but is used for additional applications in clinical practice. In the three cases we present in this manuscript, the AI model was trained on events of clinical deterioration (the model outcomes included events such as: sepsis, emergent intubation, hemorrhage, emergent ICU transfer, etc.).[12,14-16] Since 2015, these models have been implemented as a visual risk analytic in several ICUs and acute care wards. We discuss off-target uses where the score can be used as a proxy for illness severity and point of care clinicians use this information in a variety of ways, beyond just the early warning of imminent deterioration.[12] We specifically discuss clinical off-target uses including: (1) use of the score as a treatment response physiomarker (ie, is my patient responding to the antibiotic regimen appropriately? In other words, is this treatment plan effective for this patient?); (2) an ongoing low risk score indicating relative stability used to assess patient readiness for discharge; (3) assessing all of the patient scores on a unit together to get a sense of overall unit acuity (ie, is there adequate nursing staffing? Which patient is the most acutely ill on the unit? Where should rounding start?). In all of these examples, the AI-derived risk score is used in ways that the model was not originally trained on, yet clinicians have developed off-target uses based on their own role and needs.[13] Additional off-target uses that point of care clinicians described using include: the use of the score to assess for adequate pain and sedation management, determining the need for endotracheal tube suctioning, assessing when the patient is stable enough to get out of bed for a walk or physical therapy, etc.[13,17]

An extreme version of off-target use is a one-size-fits-all approach, that is, a model trained on a specific event as a general tool for deterioration throughout the hospital. Examples include the Rothman Index[18] (trained on death in the next 12 months), eCART[19,20] (trained on cardiac arrest on the wards), and TREWScore[21] (trained on septic shock in the ICU). Note that these are trained models rather than scores such as SIRS, (q)SOFA and (x)EWS that are fashioned by experts. We have argued against this one-size-fits-all approach, favoring the use of predictive models tailored for specific patient populations and target illnesses.[22] Because these models are specific to clinical events and physiologic systems, we suggest that clinicians can use them in ways that have the potential to promote optimal supportive care, responsiveness to therapy, and support overall resource allocation of a unit or hospital.

Within an evolving learning health system, visual AI-based predictive analytics utilize practices based on user-centered design and ongoing stakeholder engagement for successful implementation and adoption. Part of this process includes working with clinicians to have them identify how the analytics can be successfully integrated within their already complex workflow.[17] Here, we present three clinical vignettes describing off-target use of AI-based predictive analytics that evolved organically through real-world practice. Such practice fits well with the learning health system goals to continuously integrate data and experience to provide a holistic view of the patient and to deliver care safely.

1.1 | Brief orientation to AI-based predictive analytics

The CoMET monitoring platform (Nihon Kohden Digital Health Solutions, Irvine, CA) has been in use at the University of Virginia Health System since 2015. It was first used in the surgical/trauma intensive care unit (ICU) and later expanded to the surgical intermediate care unit, medical ICU, Special Pathogens Unit (Covid-19) ICU, coronary care ICU, cardiothoracic surgical ICU, and the acute care ward settings. CoMET uses data from continuous cardiorespiratory monitoring[23] and the EHR. The inputs include signal processing calculations performed on waveforms (continuous chest impedance, electrocardiogram [ECG], and plethysmography) and vital signs (heart rate, respiratory rate, pulse oximetry, non-invasive, and invasive blood pressures) from bedside monitoring; laboratory data from the electronic medical record; patient age; and nurse-entered vital signs. These inputs are used to calculate the fold-increase in the risk of an event of clinical deterioration. These scores are calculated every 15 min and displayed visually.[15,24,25] The models for risk score calculation are multivariable logistic regression expressions adjusted for repeated measures and use a sample and hold strategy for results like laboratory results or nurse-entered vital signs that are not updated at the same frequency. They were trained and tested on clinical deterioration events including sepsis, emergent intubation, emergent ICU transfer, bleeding, and others.[14-16,22,26-28] Unlike one-size-fits-all models, they target specific clinical units and patient populations. The approach of AI-based predictive analytics for early warning is based on the premise that there are often subtle changes that represent signatures of illness, or prodromes, that can be detected hours prior to an adverse clinical event.[10,15]

2 | CLINICAL VIGNETTES DESCRIBING USES OTHER THAN PREDICTION OF FUTURE EVENTS

2.1 | Real-time feedback about treatment effectiveness

A 44-year-old male with diabetes and solid organ transplants developed a mycotic fluid collection around the pancreatic allograft. He developed septic shock requiring admission to the surgical/trauma ICU for vasopressor support and mechanical ventilation with multiple abdominal washouts. He was eventually transferred to the acute care ward where he had an increase in fold-risk of deterioration on both the cardiorespiratory and cardiovascular instability axes (Figure 1). The event specific models for both axes in this unit include risk for sepsis, so an increase on both axes in this

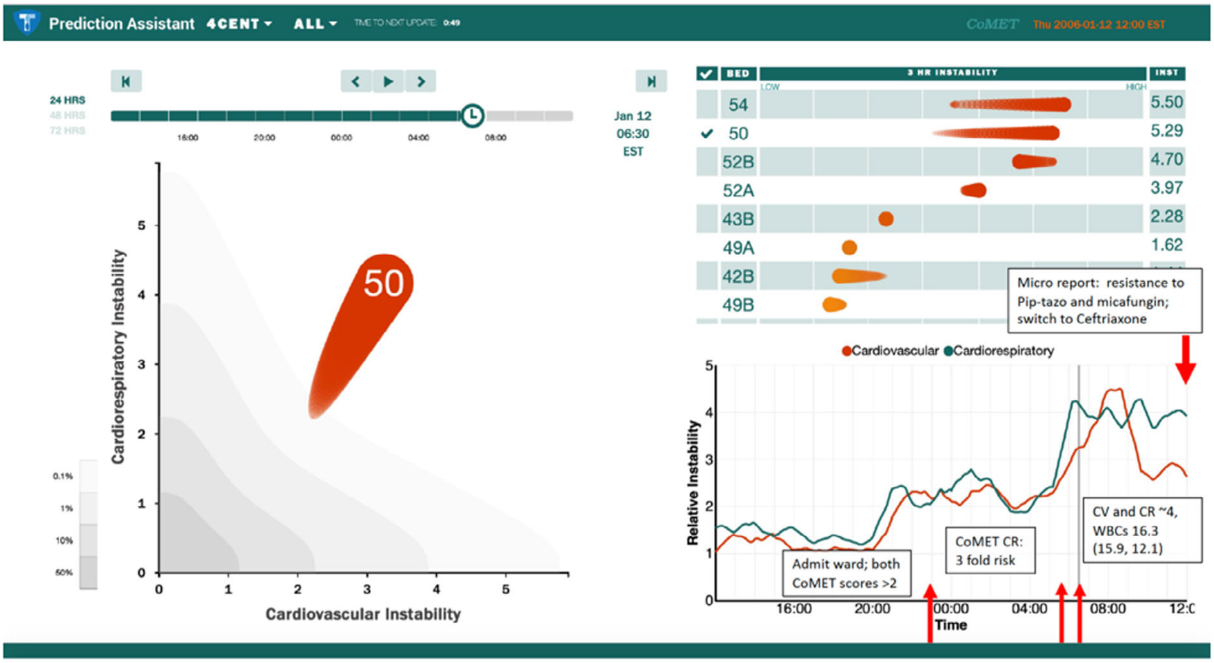

FIGURE 1 Patient with infection in the setting of end-stage renal disease and recent solid organ transplant in whom susceptibility testing indicated resistance to current antibiotic regimen. The head of the CoMET plot indicates the fold-increase in risk and high degree of instability (nearly 4-fold-increased risk of cardiovascular event and 4-fold-increased risk of cardiorespiratory event) over a 3 h period (tail of CoMET to head). The trend window in the bottom right hand corner indicates increasing cardiovascular and cardiorespiratory instability over a period up to 72 h prior. In this and the following figures, the display is of Prediction Assistant: CoMET inside, Premier, Inc., Charlotte, NC

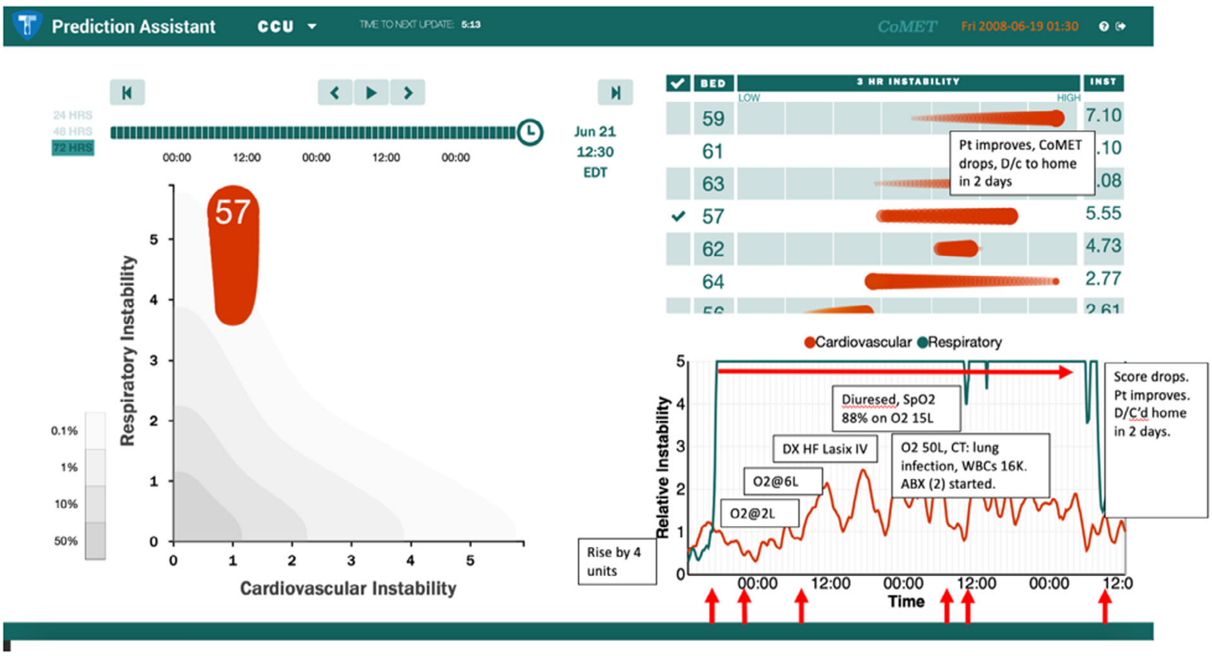

FIGURE 2 This patient remained at nearly a 6-fold increased risk of respiratory decompensation during his admission to the coronary care unit following his surgical complication, despite treatment for working diagnosis of volume overload. Once the appropriate treatment was initiated, the patient's score dropped to 1.5-fold risk and remained low until his successful discharge home

patient suggested increased instability and risk for sepsis. This led clinicians to test the sensitivities of the infective organism, which was resistant to his antibiotic regimen. Following an antibiotic change, the CoMET score fell. The abrupt rise in the score indicated that he was not appropriately responding to his treatment regimen. CoMET identified this treatment issue prior to laboratory notification of culture sensitivity.

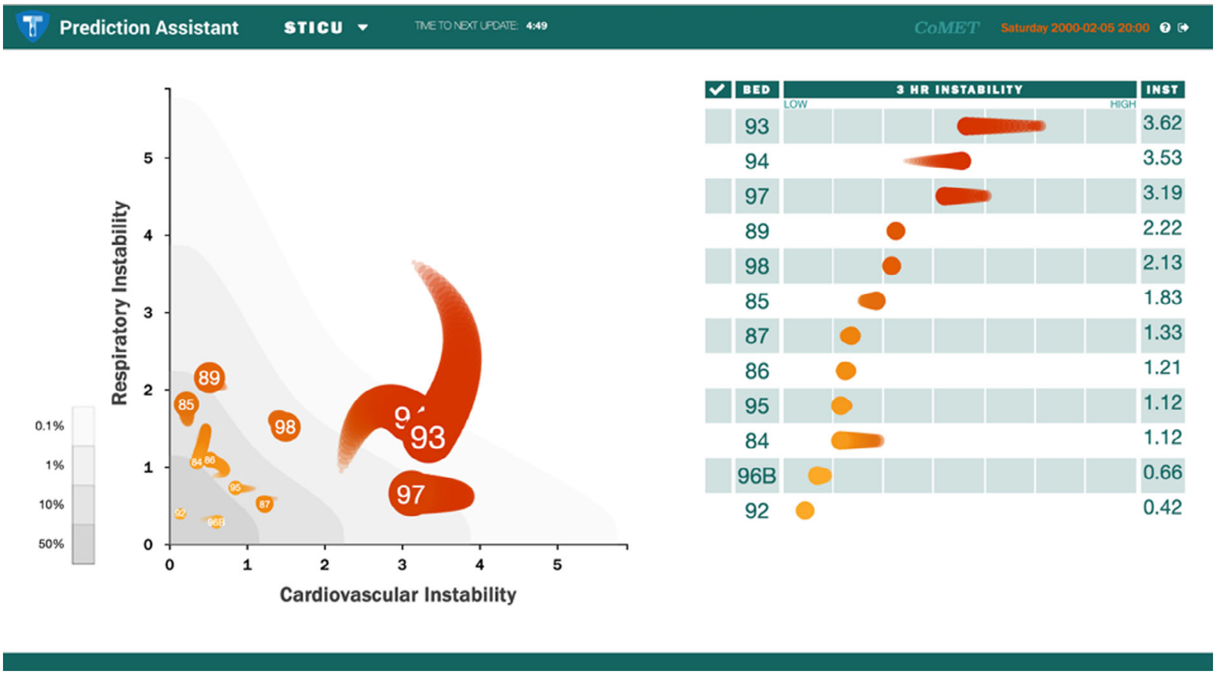

FIGURE 3 Beyond assessing only the individual patient, the entire hospital unit can be viewed to indicate the overall acuity. The top right CoMET panel is used as a "leaderboard" and ranks the overall levels of instability along with a visual indication of greater (Bed 94), lesser (Bed 93), or unchanging (Bed 98) levels of instability

2.2 | Indication of readiness for discharge

A 73-year-old male with atrial fibrillation had implantation of a left atrial appendage occlusion device complicated by cardiac perforation and tamponade. He was admitted to the coronary care unit following pericardiocentesis and placement of a pericardial drain and remained intubated. Throughout the course of his illness, his CoMET score approached a 6-fold increased risk of an adverse cardiorespiratory event (Figure 2). During this time, he had a significant oxygen requirement with no clinical improvement. He was diuresed and given antibiotics after a chest radiograph showed pneumonia. He improved clinically, the CoMET score fell to less than 2, and he was discharged to home 2 days later. Here, the rapid drop in CoMET score indicated that his therapeutic regimen was working well.

2.3 | Indication of the acuity of a hospital unit

All of the CoMET scores of patients within a hospital unit can be viewed simultaneously to indicate the overall acuity of the unit (Figure 3). Unlike other acuity scores that are infrequently updated in real-time, only calculated once, or are otherwise static, AI-based predictive analytics can be updated in real-time. This feature allows evaluation of resource utilization and nursing assignments as the overall stability level within the unit changes. Different users will have different perspectives and uses for this unit interface—for instance, a physician might use the leaderboard to determine where to begin bedside rounds for the day, a charge nurse may use it to make appropriate nursing assignments or to anticipate staffing needs for the next shift, and an individual nurse may use it to offer help or check in on their fellow nurse assigned to a less stable patient.

3 | CONCLUSION

As the *Institute of Medicine* report entitled "Digital Infrastructure for the Learning Health System" suggests, predictive analytics, risk predictions, and use of AI in healthcare are central to the future healthcare delivery.[29] Clinicians at the point of care must engage with risk estimates in a way that integrates within their already complex workflow. This is fundamental in the learning health system where informatics and care culture align for continuous improvement.[13,25,30-32]

Off-target uses for AI-based predictive analytics can address multiple goals. A global estimate of the changing severity of illness can direct the conversations of clinicians, patients, and families, give feedback on the success of therapies, and add to discharge decisions. They allow clinicians and health systems to imagine the various ways analytics can be incorporated within a learning health system at the bedside and prioritizes the bedside clinicians' needs and priorities, which often reflect patient and family concerns. Understanding that visual AI-based predictive analytics can serve as a continuously updated measure of severity of illness, or treatment response physiomarker allows for their use beyond early warning of potential future events. For example, as we show here, these analytics can assess the effectiveness of treatment regimens or the relative stability of a patient who may be ready for discharge.[12,26,33] The many potential uses at the hospital unit or health system level have implications for resource allocation in situations of scarcity such as during the Covid-19 pandemic, although it is critical to be mindful of the potential for alert fatigue for bedside clinicians.[25,34]

The education of users can incorporate these ideas in a way that does not detract from the original intention of the AI-based predictive analytic to provide early warning of events of clinical deterioration. Most of the current educational considerations of AI-based predictive analytics for clinical deterioration within a learning health system focus on the use of situational awareness as a means of incorporating these scores into the continuous monitoring paradigm and moving the clinical stance from reactive to proactive.[13,17] Education and implementation can be diversified and tailored based on the user group and their identified use for the analytics in the context of their specific workflows and patient populations.[17] These types of clinician-centered perspectives can add to the successful implementation and long-term adoption of AI-based predictive analytics within learning health systems. In the three cases presented here, the visual AI-based predictive analytic displays were in use, and we learned of the off-target uses because of feedback elicitation and stakeholder engagement following implementation.[17]

Model end-users, such as bedside clinicians, are rarely consulted during the model development stage to offer suggestions on model outcomes that would be useful for their workflow to improve patient care delivery. We view this as a missed opportunity. In this case series, we demonstrate how visual AI-based predictive analytics that were trained on events of clinical deterioration can be used in off-target ways when the score represents underlying physiological stability.[12,35] It is not feasible to develop and train AI-based models on every possible event or model outcome that clinicians may view as useful, but it is incredibly important to elicit feedback following implementation on how clinicians have incorporated the model output into their workflows.[13] It is critical to collect long-term data on uses, clinical actions, and quality outcomes within a learning health system cycle feedback to determine if further study or additional validations are needed due to data reasons (data drift, missingness). Further, it is imperative to compare model outputs and clinical outcomes associated with various sub-groups to formally assess for the risk of bias in model development and implementation.[36,37]

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Photos of CoMET used with permission from AMP3D, a Nihon Kohden Company, and Premier, Inc., which markets it as Prediction Assistant: CoMET inside.

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CONFLICT OF INTEREST

Dr. Clark and Ms. Moorman disclose a conflict of interest. They are both employees of Nihon Kohden Digital Health Solutions.

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