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®

Fig. 1. Bedside implementation of the Heart Rate Observer (HeRO) continuous predictive monitoring. The monitor detects various HRCs and transient decelerations that have been shown to accurately depict septicemia in neonates.[8,14] The HeRO model score of 1.52 represents an odds ratio of risk (ie, a score of 2 would represent a 2-fold risk of the neonate becoming septic). (*Courtesy of* Medical Predictive Science Corporation, Charlottesville, VA.)

has been on display in a surgical trauma burn ICU at an academic medical center since 2015.

For continuous predictive analytics monitoring to be useful, point-of-care 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). The Institute of Medicine has defined an LHS as, "a vision of an integrated health system in which progress in science, informatics, and care culture align to generate new knowledge as an ongoing natural by-product of the care experience, and seamlessly refines and delivers best practices for continuous improvement in health and healthcare."[16] Initiation of continuous predictive analytics monitoring in an ICU setting represents an opportunity for iterative evaluation and implementation perspectives that align with an LHS approach.[17]

Continuous predictive analytics monitoring relies on the central premise that the technology and computational models will detect early signs of physiologic adverse events, such as cardiorespiratory instability.[18] To affect health outcomes, these technologies must move from active surveillance of physiologic states, such as cardiorespiratory instability, to enhanced clinician-based assessment and clinical action.[18] The necessary processes needed to move from continuous predictive analytics monitoring surveillance to clinical action in an LHS have not been well-described in the scientific literature.[19–21] Therefore, the purpose of this study was to describe the processes needed to evoke clinical action after initiation of continuous predictive analytics monitoring, or CoMET®, in an LHS. Specifically, the authors sought perceptions from point-of-care clinicians as a part of the overall iterative implementation, evaluation, and optimization of this technology in an ICU setting.

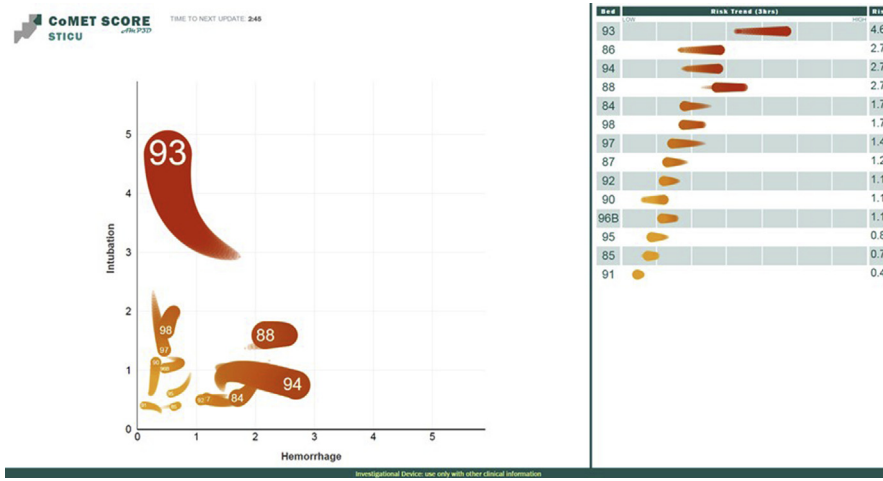

Fig. 2. The original CoMET® display in real-time streaming environment as it appears on a large screen monitor in a unit (dates have been removed). On the left, each patient is represented by a CoMET® with bed number in the head. The x-axis and y-axis show the risk, with respect to average, of emergency intubation or bleeding leading to large transfusion, respectively. Units are increased by fold, so a patient with intubation risk of 1 has average risk for intubation, a patient at 2 has twice the average risk, and so on. The head of the CoMET® represents the current hour, and the tail is 3 hours long. For example, the patient in bed 93 is 5-fold the risk of emergent intubation, up from 3-fold risk 3 hours ago. The right side shows a linearized version of the left plot in which the values are the distance from the origin (coordinates 0,0 on the x-axis and y-axis). In this view, patients are ordered by decreasing risk. The overall rank score of 4.69 represents the combined risk of the intubation and hemorrhage models using the following formula: square root (intubation2 + hemorrhage2). (© 2018 AMP3D Inc.; Charlottesville, VA, USA; with permission. All rights reserved.)

METHODS

Study Design and Sample

This study used a longitudinal qualitative descriptive design using both focus group and individual interviews collected from an academic surgical trauma ICU in central Virginia.[22,23] Participants were recruited through a convenience sampling strategy that included any point-of-care clinician (registered nurse [RN], respiratory therapist, nurse practitioner, attending physician) who worked in the unit and were exposed to CoMET® display monitoring for any period of time. There were no exclusion criteria.

This study included data from 5 focus groups and 14 individual interviews. Invitations to participate were sent through email. Five focus groups were conducted over the course of a year that were audio recorded and included in this analysis. Four of the focus groups had mixed point-of-care clinicians (RN, respiratory therapies, nurse practitioner, or attending physician) and 1 focus group included nurse practitioners and attending physicians. Each focus group ranged from 4 to 6 participants per session and several focus groups included educational content delivered along with semistructured questions to which participants responded. Following the second focus group, feedback was provided to the CoMET® developers and the monitoring platform and visual display were modified. In addition, 7 RNs participated in 2 qualitative individual interviews each, which were conducted about 9 months apart from each other. Observations of unit activity and inpatient rounds were conducted during the study period for context, but were not included as data in this present analysis. Institutional review board approval was obtained before study initiation.

Data Collection and Analysis

Data collection occurred from September 2015 through November 2016. **Table 1** shows relevant timeline associated with data collection. Focus group and individual interviews were conducted using a semistructured interview guide. Questions focused on perceptions of the CoMET® display and use in routine clinical practice. The discussions were audio recorded and transcribed verbatim. Transcripts were then uploaded into a qualitative software management application, Dedoose [Sociocultural Research Consultants (SCRC)].[24] Analytical field notes and observation notes were maintained throughout the data collection time period and were read for context but were not a part of the final data analysis. Data from the 14 individual interviews (n = 7 RNs) and 5 focus groups (n = 26) were included in the final qualitative analysis.

The analytical frame was guided by an open coding strategy applied to the entire data set, followed by an inductive theme development using thematic analysis.[22,23] The text data were analyzed by (1) immersion in the data (ie, reading the transcripts several times for full context), (2) a line-by-line analysis and data reduction in which inductive codes were derived, (3) developing a codebook with newly created code and derived meaning during the coding process, (4) codes were grouped together to form tentative categories and eventual themes.[25] Trustworthiness was addressed in several ways: aspects of the study design were open for review to members of the research team, reflection on prior assumptions and beliefs about the topics discussed, keeping an audit log for analytical decisions, and iterative review of the codes and eventual themes.[26]

RESULTS

Demographic characteristics of the sample were not maintained to protect anonymity because all clinicians were recruited from the same ICU. Several themes and subthemes emerged from the data that described the necessary process to move predictive analytics monitoring from implementation to clinical action. These included

1. Understand the science behind the algorithm (subthemes: first-to-test or lacks standard evidence, and moving to alarm)
2. Trust the data inputs (subtheme: noise).
3. Integrate with the electronic medical record (EMR) (subtheme: treat as vital sign).
4. Optimize clinical pathways (subthemes: reactive to proactive and model refinement).

Sample qualitative exemplars from each theme can be found in **Boxes 1–4**.

Table 1
Interview structures and Continuous Monitoring of Event Trajectories display timeline

Time	Event
June 2015	CoMET® display monitor mounted in central work station
September 2015	Point-of-care clinician focus group 1
October 2015	Nurse practitioner or attending physician focus group 2
November 2015	Individual interview #1 complete
February 2016	New display features go live based on early focus group feedback
April 2016	Point-of-care clinician focus group 3
December 2016	2 monitors added to front and rear of ICU Individual interview #2 complete

Box 1
Qualitative exemplars of the theme of understanding the science behind the algorithm, and the subthemes of first-to-test or lacks standard evidence, and moving to alarm

It's a bit of a mystery what all those things are, that are being … that are in your algorithm to create that CoMET®. And so it's a mysterious black box (FG1)

[O]ne of my biggest problems was I'd look at it, and then I wouldn't really know what I was actually looking at. There was no handbook to go to. (FG1)

… just being able to see the transparency of what are we looking at. I know that we're talking about—well, we're looking at the vitals, okay. What else are we talking about that's behind this? And then how is it actually presenting back to us? (FG1)

I'm a curious person. I would like to know … for instance what data is going in [to the algorithm], how quickly it's computed, and how delayed is the CoMET® score. What weighs more in this, in the math, I mean, is your oxygen saturation more important than your respiratory rate?, I would like to know that.[6]

For me all I see is two axes and one is hemorrhage and one is intubation. I don't know what data it uses or how frequently it's refreshed or how minute to minute accurate it is.[6]

And just understanding the variables that it takes in and why some outliers can really affect what the CoMET® is doing which I think probably goes back into why … it's not my go to source for information on my patients. (FG2)

[X] told me there was a very big mathematical equation that she didn't even understand, that was coming into play … that weighted certain attributes there. So … I'd love to know how that works, but I know that I wouldn't necessarily understand all the, how each thing gets weighted, … But yes, I would like to … I would like to know more about all of it really.[3]

Nobody really knows what it is and how to access it. I tried to look it up today on the internet. I couldn't find anything about it. I found the company name, but I couldn't find anything about it. (FG1)

You know it seems like when stuff makes it to the bedside it's gone through more rigorous testing. And I think it's more widely accepted. I mean, usually the evidence supports like, using this device or not using this information because it's more risky to insert the device in the first place.[6]

All our patients are monitored of course so we have this real time instant notification with alarms and buzzers and beeps and whistles that tells us exactly when something is going wrong and our brain is already trained to recognize the specific noises that we hear so I feel like we'd hear a respiratory alarm before we'd look and see our CoMET® sway in a certain direction (FG2)

Note: Number corresponds to participant number.
Abbreviation: FG, focus group.

Understand the Science Behind the Algorithm

To fully integrate predictive analytics monitoring capabilities in routine clinical practice, it is necessary for point-of-care clinicians to understand the science behind the algorithm. As 1 clinician described, "I'm a curious person. I would like to know … for instance what is going in [to the algorithm], how quickly it's computed, and how delayed is the CoMET® score. What weighs more in this, in the math, I mean, is your oxygen saturation more important than the respiratory rate? I would like to know that." (Participant #6)

Participants stated that ICU clinicians are so used to understanding how physiologic parameters are calculated that it can be challenging when the calculations underlying the predictive analytics monitoring algorithm are not known. Similarly, it can be frustrating when point-of-care clinicians cannot access data regarding thresholds or

Box 2
Qualitative exemplars of the theme trust the data and the subtheme noise

Sometimes I will see that it's different [meaning the CoMET® score and the general assessment of the patient]. Lots of times, honestly, it's because the data is wrong that's going into the CoMET® score. The data, for some reason, said the pressures were low because the A-line was kinked. Or the respirations were zero when it was not, that kind of thing. The CoMET® is soaring, but [the patient] is actually okay. Then sometimes they are real. They do kind of correlate with it. Sometimes I'll look at a patient and not really be able to put words to what's wrong. Then their CoMET® is higher, wider, whatever.[14]

It is difficult I think sometimes in the ICU to really see if there's been trends because they have been in the hospital for so long or they have blood pressure medications they are on, so with that playing in to account for their heart rate and their blood pressure depending then it is not really giving us an accurate CoMET® score.[13]

I think there is some reservation about the data that's incorporated, because I feel like it's reliant upon us as nurses to validate vital signs and information appropriately. Sometimes it's easy to validate information that could accidently be incorrect. We have somebody that's on a ventilator … from the vent, we get their respiratory rate. However, we had leads on their chest that also has a respiratory rate, and maybe those leads aren't placed appropriately and so we're getting an inflated value of, I don't know, maybe 50. [W]e're reliant on what we know the vent's programmed to do. When we're validating our vital signs, it's can be really easy to click here and validate, versus looking at it intentionally and focused on making sure that it's accurate.[12]

We can choose not to validate that reading [the vital sign]. If we're not careful, almost like alarm fatigue. If you're not careful, you can just automatically validate it not realizing—you know what I mean? Certain things like that can happen and maybe throw off your CoMET® score.[7]

[You'll see] someone's CoMET® score is sky-high, and yet that patient's already intubated, and you're like, "Oh, the respiration rate isn't accurate.[5]

I think that it [the CoMET® model] has a lot of potential. I think the part that's challenging is making sure that the information that they are utilizing to make the calculation is accurate. I think that's always going to be a struggle. I just don't think that—I don't know how you would ever make that accurate, because you can have your leads on, which is measuring an EKG [sic] rhythm, and also a respiration rate that's not accurate. The reason we know an accurate respiration rate is because we can go and look at our ventilator.[5]

I can see where the information could be really good, because you can see if a patient was becoming febrile, they're going become tachycardic. It's just figuring out the accuracy of the information that they're using.[5]

There's sometimes I see it's my patient and I'm like why is their CoMET® score so high? My first instinct is to make sure like the leads are reading accurately (FG2)

Note: Number corresponds to participant number.
Abbreviation: FG, focus group.

cutoffs. Usually when monitoring or clinical decision support devices are deployed at the bedside, they have been rigorously tested through randomized clinical trials and have information on interpretation readily accessible through peer-reviewed manuscripts. Another clinician articulated the challenges associated with being the first to test the monitoring device in the following statement: "[O]ne of my biggest problems was I'd look at it, and then I wouldn't really know what I was looking at. There was no handbook to go to." (Focus group 1)

Because alarms are so ubiquitous with ICU care delivery, several participants noted that it was challenging to keep up with the CoMET® display because there was not an

Box 3
Qualitative exemplars of the theme integrate with electronic medical record and the subtheme treat as vital sign

We open up this document or program for charting. We open up another program for label printing for our blood-work. Then it's a third thing to open up CoMET®. I think that's probably the main barrier. Is that we're all on one screen, and we're opening—there's just multiple programs to open up.[11]

If I want to see their last 24 hours over a timeframe I always pull it up on the computer. But I definitely don't like leave it on the background of the computer all the time. Since we recently just got badge scanners that pretty much allow us to stay logged in in the background I think it might be simpler to pull it up on the screen and have it just open up when we open the computer but the way we logged in and out before you constantly would have to click on it and log back into it.[13]

There's been discussion of trying to incorporate the CoMET® score into our vital signs, so it would be something we were validating every hour as well as into the daily rounds that happen in the morning with the LIPs [licensed independent provider] the nurse, the respiratory therapist and the charge nurse, so it would be incorporated into that daily routine to see if more discussion of it consistently at a specific time it would get more people to pay attention to it throughout the day.[13]

If we were able to incorporate our CoMET® score within our vital signs and something that is, right within Epic would be huge.[9]

I feel maybe if that was CoMET®—if it just got pulled over into our vitals or something like that, it wouldn't just get forgotten about.[8]

I think linking it to Epic would be really helpful because every hour we're required to go in and validate our vital signs so and naturally of course we're required to look like what's their heart rate, what's their blood pressure and that sort of thing and so if we could have just a row in Epic that says their CoMET® score just went from 2, if it was on a scale of twenty, two to twenty or something like that then that would be something to pay attention to. (FG2)

I don't think that there's a way right now to have it pulled in. Our monitors pull in our data, and then we validate that every hour. I don't think that the CoMET® score is attached, so to speak, to Epic. Our last group meeting, we were talking about different ways to try to develop that because we can tailor Epic to do that kind of thing. If it can show up on our desktop, we're trying to find a way to make it show up in Epic. Then we can validate that like we would another vital sign.[10]

I don't think it would be [a big deal to document as a vital sign in the EMR] … I'm sure some people are always going to complain and say … "one more thing to document" you know?[3]

Note: Number corresponds to participant number.
Abbreviation: FG, focus group.

alarm, trigger, or threshold associated with the number. The desire for a cut-off or threshold to initiate clinical action represented a prominent subtheme. As stated, "All our patients are monitored of course so we have this real time instant notification with alarms and buzzers and beeps and whistles that tells us exactly when something is going wrong and our brain is already trained to recognize the specific noises that we hear so I feel like we'd hear a respiratory alarm before we'd look and see our CoMET® sway in a certain direction." (Focus group 2)

Moving to an alarm-based system represents a necessary process that incorporates understanding the science in a way that refines continuous predictive analytical scores into appropriate clinical thresholds to respond to. The subtheme of moving to alarm was articulated by several clinicians as a step necessary to later evoke a clinical action.

Box 4
Qualitative exemplars of the theme optimize clinical pathways and the subthemes reactive to proactive and model refinement

That's not our culture yet, to really be referencing the CoMET® score as a part of our report, or as a part of our discussion with one another. It's really just something that we'll look at, and see where our patients fall. I don't know if we're really using it to create interventions yet.[1]

Being able to do something with CoMET® scores, where it's saying, based on these changes this might be what … this might be one pathway. (FG1)

Then I looked at the monitor and it was like, "Oh yeah, the heart rates are a little bit higher than when I thought there were. The pressures have started softening a little bit." I think we did another ABG [arterial blood gas] and I sent off a complete—a CBC [complete blood count] to get the make-up of the blood to see if we had a volume issue with the hemoglobin or hematocrit. We did, so we needed to get some volume.[12]

It's not something titratable, right. There's no drug that is, for lowering your CoMET® score. I think that sometimes what we're doing is we're focusing on numbers and specific numbers that we can treat and alter.[8]

The vital signs are something I can take at the bedside and act pretty instantly on. You know. If somebody's blood pressure is high and I need to bring it down I can see it, I can act on it, I can see it's result instantly. Heart rate, for instance, if … if I know the source then … you know … I'm at the bedside treating the source of the high heart rate, you know, temperature. It's … I guess it's different [CoMET®] in the sense of the immediacy that I can interpret, act, and then also reassess the data.[6]

And then in turn having that active role for the bedside clinician, the LIP [licensed independent provider] will then foster buy-in, and it makes it part of our workflow and makes us attuned to the number. This is the scenario. This is what we were seeing beforehand. This is what you did. This is what we saw afterward. This is the effect that you all had." (FG 2)

[We need to] kind of change our culture from the reactive to a proactive environment.[1]

It would be useful if we were able to take into account interventions that are happening. For example, if a patient already is on a ventilator, their risk for intubation shouldn't necessarily be high. It kind of distorts the people's value that they place in it, because then they see this person who has the largest CoMET® on the board. They're already intubated. Really, looking at that would be nice if they could include interventions. There's almost no way that there would be a streamlined, easy process for that to be implemented in something like this. That would be nice, but would be more so of a dream, I think, than a reality.[1]

Even just like basic having a hemoglobin and hematocrit included into it at least then we'd see are they losing blood, do they need something else, do they need more blood. It would show that and giving the blood products sure we are going to be giving them the volume but their blood pressure would have to improve and then their cardiovascular instability would go down if we were doing that.[13]

The main thing is we're all very interested in having lab values incorporated in it [CoMET®], especially for their risk of hemorrhage, or even if they're able to use ABGs [arterial blood gases] to be looking at their Po_2 [partial pressure of oxygen] and their SATs [saturations] as well on their blood gasses, instead of just looking at what their SATs are on the pulse ox. Because sometimes even the vital signs that are coming up on our monitor aren't necessarily accurate to the patient. Depending on who it is and their blood focus in general.[1]

Note: Number corresponds to participant number.
Abbreviation: FG, focus group.

Trust the Data Inputs

To move across the continuum from implementation of continuous predictive analytics to a resulting clinical action based on a model score, clinicians also articulated they need to trust the data inputs that support the predictive model. Because the clinicians understood that the predictive model was calculated based on the vital sign data they entered and validated in the EMR, the concept of accurate data validation was central to many of the interviews, as described by the following 2 statements.

First statement: "I think there is some reservation about the data that's incorporated, because I feel like it's reliant upon us as nurses to validate vital signs and information appropriately. Sometimes it's easy to validate information that could accidently be incorrect. We have somebody that's on a ventilator … from the vent, we get their respiratory rate. However, we had leads on their chest that also has a respiratory rate, and maybe those leads aren't placed appropriately and so we're getting an inflated value of, I don't know, maybe 50. [W]e're reliant on what we know the vent's programmed to do. When we're validating our vital signs, it's can be really easy to click here and validate, versus looking at it intentionally and focused on making sure that it's accurate." (Participant #12)

Second statement: "We can choose not to validate that reading [the vital sign that is, inaccurate]. If we're not careful, almost like alarm fatigue, you can just automatically validate it not realizing—you know what I mean? Certain things like that can happen and maybe throw off your CoMET® score." (Participant #7)

A subtheme that was critical to this discourse was the noise that skews the predictive model, due to incorrect data inputs. A description of noise is represented by the following excerpt: "I think that it [the CoMET® model] has a lot of potential. I think the part that's challenging is making sure that the information that they are utilizing to make the calculation is accurate. I think that's always going to be a struggle. I just don't think that—I don't know how you would ever make that accurate, because you can have your leads on, which is measuring an EKG [sic] rhythm, and also a respiration rate that's not accurate. The reason we know an accurate respiration rate is because we can go and look at our ventilator." (Participant #5)

The topic of incorrect respiratory leads as a potential problem affecting the model was a pervasive barrier that was noted in almost all of the interviews. It was clear that point-of-care clinicians must trust the data inputs that build the predictive model before fully adopting any subsequent action into routine practice.

Integrate with the Electronic Medical Record

Participants uniformly suggested that integration within the EMR (ie, Epic [Epic Systems, Corporated]) would be a critical component of successful adoption of CoMET®. Some participants noted that it would be advantageous to be able to pull in the data points directly into the flowsheets, just as the EMR is able to do with other vital sign entries. Clinicians described this interface in the following 2 passages.

First statement: "I don't think that there's a way right now to have it pulled in. Our monitors pull in our data, and then we validate that every hour. I don't think that the CoMET® score is attached, so to speak, to Epic. Our last group meeting, we were talking about different ways to try to develop that because we can tailor Epic to do that kind of thing. If it can show up on our desktop, we're trying to find a way to make it show up in Epic. Then we can validate that like we would another vital sign." (Participant #10)

Second statement: "I think linking it to Epic would be really helpful because every hour we're required to go in and validate our vital signs so and naturally of course

we're required to look like what's their heart rate, what's their blood pressure and that sort of thing and so if we could have just a row in Epic that says their CoMET® score just went from two, if it was on a scale of twenty, two to twenty or something like that then that would be something to pay attention to." (Focus group 2)

Related to integration with the EMR is the perception that by doing so clinicians are able to treat the CoMET® score as a vital sign that can be responded to with clinical action. There was strong sentiment that treating CoMET® as a vital sign through integration of the EMR and acknowledgment of the result would lead to more attention to the score as a trend. As stated, "There's been discussion of trying to incorporate the CoMET® score into our vital signs, so it would be something we were validating every hour as well as into the daily rounds that happen in the morning with the LIPs [licensed independent providers], the nurse, the respiratory therapist and the charge nurse, so it would be incorporated into that daily routine to see if more discussion of it consistently at a specific time it would get more people to pay attention to it throughout the day." (Participant #13)

An unintended consequence of integration with the EMR and validation of the CoMET® score as a vital sign could be the increased burden on point-of-care clinicians. Even so, the critical component of acknowledgment and documentation was overwhelmingly described as a necessary component of adoption to move to clinical action.

Optimize Clinical Pathways

Clinicians discussed optimization of clinical pathways as a way of describing how the CoMET® score could be turned into a threshold or alarm that would initiate a specific clinical action. One clinician described that the unit was not at the point of adoption yet in the following statement, "That's not our culture yet, to really be referencing the CoMET® score as a part of our report, or as a part of our discussion with one another. It's really just something that we'll look at, and see where our patients fall. I don't know if we're really using it to create interventions yet." (Participant #1)

Another clinician described how she was able to use a rising CoMET® score as a trigger for subsequent clinical action in the following example: "[After noticing a rising CoMET® score] Then I looked at the monitor and it was like, 'Oh yeah, the heart rates are a little bit higher than when I thought there were. The pressures have started softening a little bit.' I think we did another ABG [arterial blood gas] and I sent off a complete—a CBC [complete blood count] to get the make-up of the blood to see if we had a volume issue with the hemoglobin or hematocrit. We did, so we needed to get some volume." (Participant #12)

Because the CoMET® model is predicting an adverse event in the future, many noted that a rising CoMET® score may evoke a different sense of clinical immediacy than a rising heart rate. A clinician described that the clinical response to CoMET® would have to change from a reactive to proactive environment to elicit appropriate action. Several clinicians perceived that allowing for further model refinement could help optimize the clinical response, as described in the following statement: "The main thing is we're all very interested in having lab values incorporated in it [CoMET®], especially for their risk of hemorrhage, or even if they're able to use ABGs [arterial blood gases] to be looking at their P_{O_2} [partial pressure of oxygen] and their SATs [saturations] as well on their blood gasses, instead of just looking at what their SATs are on the pulse ox[imeter]. Because sometimes even the vital signs that are coming up on our monitor aren't necessarily accurate to the patient. Depending on who it is and their blood focus in general." (Participant #1)

None of the point-of-care clinicians expressed that CoMET® was at the point of adoption at which it was amenable to a clinical protocol (ie, if CoMET® reaches X, then do Y, Z); however, several of the participants were interested in refining certain models and determining appropriate CoMET® threshold limits that could elicit specific clinical actions.

Feedback from the first 2 focus groups was used by the CoMET® developers to revise the display (Fig. 3). Handbooks for the CoMET® monitor were distributed to the unit to describe the science behind the algorithm (theme 1), define the filtering used by the platform (theme 3), and provide example cases for proactive use of CoMET® (theme 4). Integration with the EMR was added to CoMET® and risk estimates populate the Epic flowsheet hourly (theme 3).

DISCUSSION

There is a gap in the literature of research focused on implementation of continuous predictive analytics monitoring. Even less known about how to optimize the implementation among a clinician user group that is the first to test the modality in practice.

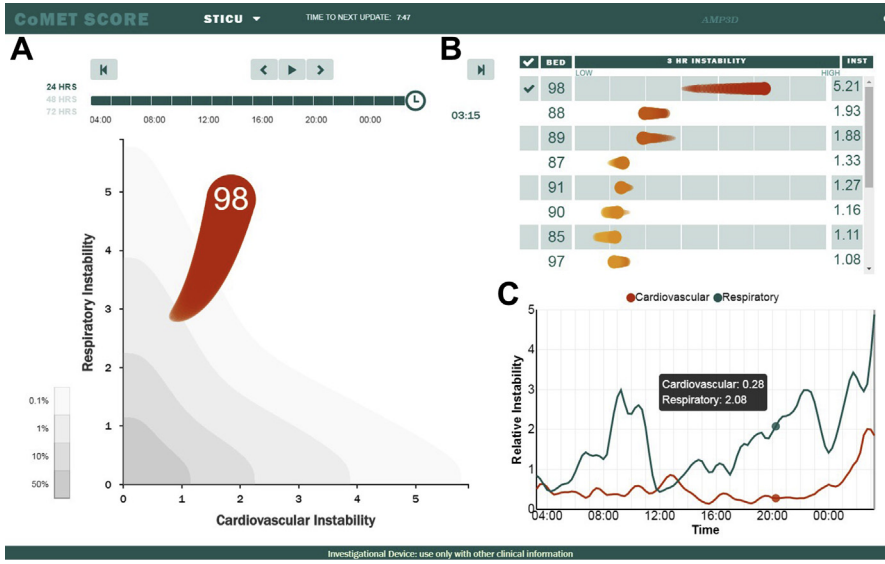

Fig. 3. The CoMET® display with new features based on stakeholder feedback (dates have been removed). On (*B*), the single patient in bed 98 has been selected for closer inspection. Selecting the individual patient brings up (*C*), and all other patients are temporarily removed from (*A*). The axes have been relabeled in terms of system instability. Grayscale contours in the background of (*A*) show percentiles of instability measures, with a legend to the left. The darkest gray represents the 50th percentile, followed by the 10th, and so forth. The current time on the display is 03:15. Play-back tools appear at the top of 3A when the patient is selected, allowing clinicians to review up to 72 hours of monitoring time. Currently, 24 hours is selected and the patient's instability over the preceding 24 hours is shown in the bottom right (*C*) for respiratory (*green*) and cardiovascular (*orange*) systems. Hovering the mouse over the instability lines shows a tooltip with precise values of the instability at that time. As shown in (*B*, *C*), the respiratory instability at 03:15 is currently 5-fold the average; the tooltip shows that the instability increased greater than 2-fold at 20:00 the previous night, 7 hours earlier. The patient was emergently intubated at 04:45.

Point-of-care clinicians in this study articulated that understanding these implementation processes in an LHS are critical steps that are needed before any resulting clinical action. The LHS offers a system of care that allows for exploration of systematic approaches to health delivery based on integrated predictive physiologic data used in a complex clinical milieu.[4] For continuous predictive analytics monitoring to be viewed as a means of clinical decision support, clinicians in this study attested that the processes that are necessary for adoption include understanding the science behind the algorithm, trusting the data, integrating with the EMR, and optimizing clinical pathways.

The process of adoption from implementation to clinical action is even more complex among this user group because they were the first to test the visual streaming display. Although the CoMET® algorithms had been tested and validated,[3,10,11] corresponding clinical thresholds and specific clinical actions are still to be developed. Point-of-care clinicians, particularly nurses and respiratory therapists, are used to alarms, vital sign thresholds, triggers, and clinical protocols as a part of their ICU culture of care.[27–30] Their desires to transform CoMET® through the various processes was articulated as a parallel approach in implementation.

The authors' analysis describes the processes needed before evoking clinical action after initiation of continuous predictive analytics monitoring in an LHS in a surgical trauma ICU located in an academic medical center. This analysis prioritizes the perspectives of the point-of-care clinicians actively working in the environment and allows for tailored iteration based on the specific unit culture of the LHS. Nurses have the opportunity to transform care from reactive to proactive and (1) potentially reduce catastrophic events and complications for their patients and (2) use the data to determine stability and promote nursing care that is patient-centered and beneficial to overall clinical outcomes.

Limitations exist in this study that must be addressed. Because clinicians were all recruited from the same ICU in a single academic medical center and a qualitative methodology was used, results may lack generalizability to other care settings. Additionally, there was a heterogeneity of point-of-care clinicians and experience mix in the sample. Even so, there were several advantages in that the perceptions elicited were from multiple stakeholder groups (RNs, respiratory therapy, nurse practitioner, attending physician). Finally, because this study was longitudinal, the authors were able to account for various levels of exposure to the CoMET® display in the analysis. This study suggests that larger prospective studies with quantitative measures are needed to evaluate the relationship between CoMET® display and clinical action from the lens of LHS and implementation science perspectives.

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