Trigger Criteria: Big Data

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KEYWORDS

• Rapid response system • Monitoring • Risk prediction • Deterioration

KEY POINTS

- The US health care system is rapidly adopting electronic medical records (EMRs). The capability to analyze a huge amount of clinical data during a care episode will dramatically increase.
- Existing analytical techniques can be applied to enable better prediction of outcomes, which can be applied to the point-of-care decision-making process.
- This change will occur in the near future.
- Aggregate warning systems for imminent death using vital sign abnormalities are now being combined with so-called big data derived from the EMR, offering a great opportunity to detect and respond to the clinical changes that precede clinical deterioration and rapid response team activation.

INTRODUCTION

The US health care system is rapidly adopting electronic medical records (EMRs) and this will dramatically increase the quantity of clinical data available for sophisticated analysis during inpatient and outpatient care. Outpatient information that is becoming routinely available includes notifications of when patients fill their prescriptions and when they use their devices, such as an inhaler for asthma or chronic obstructive pulmonary disease, and noninvasive positive pressure ventilators for obstructive sleep apnea, as well as compliance with follow-up in outpatient clinics. Inpatient data include recent laboratory tests, imaging, vital sign monitoring with continuous electrocardiogram, carbon dioxide monitoring, pulse oximeters, and motion sensors that will monitor respiratory patterns and change in pulse. An integrated approach to analyzing this information creates the opportunity to improve health care quality, distribute resources adequately, and decrease cost. The types and quantity of information

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available and the ability to analyze it in ways that can affect patient management in real time are referred to as big data.

In 2012, big data was described as “large volumes of high velocity, complex and variable data that requires advanced techniques and technologies to enable the capture, storage, distribution, management and analysis of the information.”[1] Existing analytical techniques can be applied to the vast amount of existing patient-related health and medical data to reach a deeper understanding of outcomes, which can be applied to point-of-care management and assist physicians and their patients during the decision-making process and help determine the most appropriate treatment option. Numerous questions can be addressed with big data analytics and the potential benefits include detecting diseases at earlier stages, managing specific individual and population health, and detecting health care fraud more quickly and efficiently.[2] Additionally, the McKinsey Global Institute estimates that big data analytics can generate more than $300 billion in savings in US health care through reduction of waste and inefficiency in clinical operations, research, and development.[3]

There are several opportunities to use big data to improve the quality of health care and decrease health care costs.[4] Some of these uses include

- Identification of high-cost patients
- Identification of patients at risk for readmission
- Triage of resources and estimation of the risk of complications for patients admitted to the hospital
- Early detection of clinical deterioration
- Identification of patients at risk for adverse effects from medications or treatment
- Identification and treatment optimization for diseases affecting multiple organs.

The applications of analysis of big data in health care are not limited to these examples. This is just the beginning of the growing list of benefits of data analysis in health care.

This article describes the potential impact of big data analysis on risk stratification and early detection of serious deterioration, including death. Although the application of big data analysis can affect care for a wide variety of syndromes and treatment modalities, this article focuses on the relationship between the ability to analyze huge data sets to identify and predict deterioration with the occurrence of clinical deterioration requiring a rapid response team (RRT) activation.

BIG DATA IN THE HOSPITAL WARDS

Sudden decompensation leading to cardiac arrest and death occurs uncommonly in hospital wards, affecting only about 1% of patients outside the intensive care unit (ICU). As much as 80% of cardiopulmonary arrests are preceded by prolonged periods of physiologic and clinical instability.[5] These signs may be present up to 24 hours before a serious clinical event requiring intensive interventions.[6] There are 2 approaches to determining when a crisis occurs that can be used as triggers for calling the RRT. The first is the single-parameter system. In this system, any single abnormal vital sign value that is out of bounds is sufficient for the rapid response system (RRS) to be activated. Although single-parameter systems have lower sensitivity and specificity than multiple-parameter and weighted systems, they are very easy to teach and implement. The other approach is to use an aggregate weighted scoring system (AWSS), the most common form of which is the early warning score (EWS) system and its many variants. EWS systems have been developed with the aim of identifying clinical deterioration early, have been recommended by the National Institution of Health and

Clinical Excellence,[7] and are mandated in some countries. In a review by Churpek and colleagues,[8] EWS systems were more accurate than other types of scoring systems for predicting cardiac arrest, mortality, ICU transfer, and a composite outcome. These include the VitalPAC EWS (ViEWS) system (VitalPac manufactured System Healthcare, London, UK) (Table 1), the standardized EWS system (Table 2), the modified EWS (MEWS) system (Table 3), and the cardiac arrest risk triage (CART) score (Table 4). An AWSS allocates points according to the degree of derangement of physiologic variables, which are combined to a composite score. The score is compared with predefined trigger thresholds and are used to direct a graded intervention response, such as increased vital signs monitoring and involvement of a medical emergency team (MET) or more experienced staff.[9]

The most common physiologic markers included in the AWSS are respiratory rate, oxygen saturation, systolic blood pressure, and temperature. Increased respiratory rate greater than 27 breaths per minute was a strong predictor of cardiopulmonary arrest in a study by Fieselmann and colleagues[10] that explored the vital signs 72 hours before cardiac arrest in 12 nonintensive care internal medicine units. In 2017, Mochizuki and colleagues[11] published a study that showed that an increased respiratory rate in an emergency department was as strong predictor of early clinical deterioration after discharge. Neurologic examination is also included; however, age is not commonly included. Tables 1–3 show commonly used EWS systems.[12–14] They are sensitive and specific for detecting deterioration likely to proceed to death unless there is intervention to reverse the process.

In 2015, a study by Zadravecz and colleagues[15] showed that combining the Glasgow Coma Scale and the Richmond Agitation-Sedation Scale was more accurate than any scale alone or the criteria of alert, responds to voice, responds to pain, and unresponsive (AVPU) in predicting mortality. They proposed that routine tracking of these 2 scales may improve the accuracy of detecting clinical deterioration.

The EWS is not the only system for quantifying high-risk deterioration. There are several scoring scales developed to identify patients at risk for developing clinical decompensation, possible cardiac arrest and death. Some are single-parameter systems, such as the MET criteria reported by Hillman and colleagues.[16] These are the most simple to understand, teach, and implement; therefore, they are commonly used in hospitals even though they are less sensitive and specific than an AWSS, such as the MEWS system. The choice of the scoring system used for each hospital depends on their culture and resources.

Table 1
VitalPAC early warning score

Score	3	2	1	0	1	2	3
Respiratory Rate	<9	—	9–11	11–20	—	21–24	>24
Oxygen Saturation	<92	92–93	94–95	96–100	—	—	—
Supplemental Oxygen	—	—	—	No	—	—	Yes
Heart Rate	—	<41	41–50	51–90	91–110	111–130	>130
Systolic BP	<91	91–100	101–110	111–249	>248	—	—
Temperature	<35.1	—	35.1–36	36.1–38	38.1–39	>39	—
Neurologic	—	—	—	Alert	—	—	Voice
	—	—	—	—	—	—	Pain
	—	—	—	—	—	—	Unresp

Abbreviations: BP, blood pressure; Unresp, unresponsive.

Table 2
Standardized early warning system

Score	3	2	1	0	1	2	3
Respiratory Rate	<8	—	—	9–20	21–30	31–35	>35
Oxygen Saturation	<85	85–89	90–92	>93	—	—	—
Heart Rate	<29	30–39	40–49	50–99	100–109	110–129	>129
Systolic BP	<69	70–79	80–99	100–199	—	>199	—
Temperature	<34	34–34.9	35–35.9	36–37.9	38–38.4	>38.4	—
Neurologic	Unresponsive	Pain	Verbal	Alert	—	—	—

BIG DATA, EVENT PREDICTION, AND EVENT DETECTION

The electronic medical record (EMR) and practical solutions to using it is quickly becoming available. Several researchers have created analytical programs for scanning the EMR to identify those at risk. The methodology used to create these systems vary; however, all access huge databases and use real-time data to generate a highly sensitive and specific risk score. The Worthington Physiologic Scoring System was derived from analysis of admission data, whereas the CART score was designed using logistic regression to detect in-hospital cardiac arrest and was validated for detecting ward-to-ICU transfers. The CART score performed better than the MEWS for detecting cardiac arrest and ICU transfer.[8] Table 4 shows the CART scoring rubric.

The eCART system (Quant HC, Chicago, IL) goes further by using a broader data set. Kang and colleagues[17] designed a prospective black-box validation study, using real-time risk stratification with the eCART that incorporated laboratory information system, bedside patient monitor, and registration data into a scoring database through the integration engine. Patients were stratified as high risk or intermediate risk. The study demonstrated the feasibility of prospective real-time eCART calculation in a general ward and found that it detected 4 times as many cardiac arrests and 50% more ICU transfers compared with the current RRS to activate the RRT. In this study, eCART identified many high-risk patients who were missed by the current RRS using single-parameter triggers and, for those whom the RRT was called, identified those hours earlier.

Currently, the most common method to calculate scores in the AWSS is manual calculation, which can lead to calculation errors. Preprogrammed EMR or handheld device applications decrease errors in calculation but can be time-consuming and redundant to workflow. Ideally, a completed automated system integrated with the EMR and with automatic provider notification (nurse or physician, or even the MET) may be a more accurate and a less redundant way to apply the AWSS in the hospital wards.[9] These scoring systems may be considered small data because they use only a

Table 3
Modified early warning score

Score	3	2	1	0	1	2	3
Respiratory Rate	—	<9	—	9–14	15–20	21–29	>29
Heart Rate	—	<40	41–50	51–100	101–110	111–129	>129
Systolic BP	<70	71–80	81–100	101–199	—	>199	—
Temperature	—	<35	—	35–38.4	—	>38.4	—
Neurologic	—	—	—	Alert	Voice	Pain	Unresp

Table 4
Cardiac arrest risk triage score

Vital Sign	Score
Respiratory Rate, breaths/min	
<21	0
21–23	8
24–25	12
26–29	15
>29	22
Heart Rate, beats/min	
<110	0
110–39	4
>139	13
Diastolic BP, mm Hg	
>49	0
40–49	4
35–39	6
<35	13
Age, years	
<55	0
55–69	4
>69	9

small portion of the data that exist about a patient to create a risk score. So-called big data, in contrast, can access a virtually unbounded data set, including medications, prior hospitalizations, genetic phenotype, age, sex, laboratory and imaging data, social habits, and other indices, such as a frailty index.

There is a significant debate about which approach is better. Single-parameter scores are easier, whereas aggregate weighted scores have better sensitivity and specificity. Mohammed and colleagues[18] showed that, as the EWS increases, the probability of a calculation error goes up, making the EWS system less attractive. However, there are now several options for calculating the EWS in an automated fashion, making the task simpler, faster, and more accurate. Hand-held computer help to improve the accuracy and efficiency of EWS systems in acute hospital care is acceptable to nurses. Hospitals that have fully capable EMRs can incorporate more complex algorithms, including results of laboratory studies. EMR-based detection of impending deterioration outside the ICU is feasible and can reach its maximal potential in integrated health care delivery systems that provide access to outpatient data, such as physician office records, rehabilitation notes, skilled nursing facility visits, and pharmacy records.[19] The potential is still being ascertained; however, many providers are very optimistic about the ability of these analytics not only to predict immediate risk of death but also to facilitate diagnosis of a variety of ailments.

MEDICAL EMERGENCY TEAMS AND RISK STRATIFICATION OF HOSPITALIZED PATIENTS

Identifying the patients at risk for clinical deterioration and impending decompensation is only the first, but important, step. Once the patients are identified, mobilization

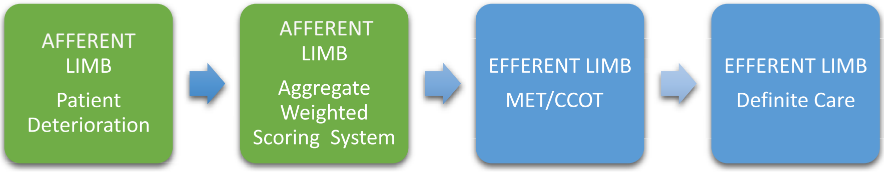

Fig. 1. RRS incorporation afferent and efferent limb. CCOT, critical care outreach team. (*From* DeVita MA, Braithwaite RS, Mahidhara R, et al. Medical Emergency Response Improvement Team (MERIT).Use of medical emergency team responses to reduce hospital cardiopulmonary arrests. Qual Saf Health Care 2004;13(4):251–4; with permission.)

of resources can be activated and deployed, such as METs and critical outreach teams.[20] The transfer to ICU, escalation of care to more monitored settings, or decompensation followed by cardiac arrest may not always be preventable; however, there will be an anticipated transition of care as opposed to emergent care. Fig. 1 shows the integration between the afferent and efferent limbs of a MET.

Box 1
Clinical criteria for activating the medical emergency team

Respiration

- Rate less than 8 or greater than 36
- New onset of difficulty breathing
- New pulse oximeter reading less than 85% for more than 5 minutes (unless patient known to have chronic hypoxemia)

Heart rate

- Less than 40 or greater than 140 with symptoms
- Any greater than 160

Blood pressure

- Less than 80 or greater than 200 systolic blood pressure with symptoms
- Greater than 110 diastolic blood pressure with symptoms

Acute neurologic changes

- Acute loss of consciousness
- New onset lethargy or Narcan use without immediate response
- Seizure (outside of seizure monitor unit)
- Sudden loss of movement (or weakness) of face, arm, or leg

Other

- Chest pain, unresponsive to nitroglycerine or doctor unavailable
- Color change (of patient or extremity): pale, dusky gray, or blue
- Unexplained agitation more than 10 minutes
- Suicide attempt
- Uncontrolled bleeding

Data from Huh JW, Lim CM, Koh Y, et al. Activation of a medical emergency team using an electronic medical recording-based screening system*. Crit Care Med 2014;42(4):801–8.

A review by McNeill and Bryden,[21] published in *Resuscitation* in 2013, presented strong evidence that a MET improved hospital mortality, reduced unplanned ICU admissions, and reduced cardiac arrests. The AWSS also improved hospital survival and reduced both unplanned ICU admissions and cardiac arrest rates.

An AWSS triggering activation of a MET offers added benefits to the hospitalized patient with impending clinical decline.[21] Adopting an early AWSS may decrease the delay in the activation of a MET, which is a strong predictor of mortality.[22,23]

The clinical criteria for activating a MET offers a list of clinical changes as signs of clinical deterioration that will prompt MET activation (**Box 1**). In 2014, a randomized study by Kollef and colleagues[24] showed that real-time alerts triggered by early warning system and sent to the RRT before MET criteria was met did not reduce ICU transfers, hospital mortality, and/or the need for subsequent long-term care; however, length of stay in the hospital was modestly reduced. A modified MET was studied by Huh and colleagues,[25] which they used as a triggering tool for MET activation, that included screening criteria from the EMR (**Box 2**). The afferent limb and the activation of a MET could be triggered by EMR-based screening or by a call from a bedside medical team. The efferent limb included physicians, nurses, and respiratory therapists who were responsible for providing early goal-directed therapy for shock, respiratory care (eg, advanced airway management), and cardiopulmonary

Box 2
Triggering tool for medical emergency activation team

Screening criteria from EMR
- Systolic mean blood pressure less than 60 mm Hg or systolic blood pressure less than 90 mm Hg
- Respiratory distress (rate >25 or <8 breaths per minute)
- Unexplained pulse rate greater than 130 beats per minute or pulse rate less than 50 beats per minute
- Unexplained metabolic acidosis (pH <7.3) or lactate greater than 2 mmol per liter
- $Paco_2$ greater than 50 mm Hg or Pao_2 less than 55 mm Hg
- Glucose less than 2.8 mmol per liter
- Sudden mental status changes or unexplained agitation
- Applying oxygen nasal prong greater than 3 L, or Venturi mask greater than 30%
- Unexplained seizures
- Chest pain
- Upper airway obstruction sign: stridor

Calling criteria

Airway
- Threatened
- Stridor

Breathing
- Respiratory rate less than 6 breaths per minute
- Respiratory rate greater than 30 breaths per minute
- SpO_2 less than 90% on Venturi mask 40% or oxygen 12 L per minute

Circulation
- Pulse rate less than 40 beats per minute
- Pulse rate greater than 140 beats per minute
- Systolic blood pressure less than 90 mm Hg

Neurology
- Sudden mental change
- Seizure

Others
- Bedside nurse's concern about overall deterioration

Cardiopulmonary resuscitation code blue

resuscitation. The EMR-triggered group had lower ICU admissions than the call-triggered group.

There is significant variability in the availability of data, the EMR, and resources in each hospital system. Adopting an early warning system and integrating this with the EMR with real-time communication to a fully staffed MET may be the ultimate goal to decrease the number of cases with acute decompensation that occur in the inpatient wards. Further studies and description of the requirements are needed.

SUMMARY

Aggregate warning systems, in combination with big data derived from the EMR, offers a great opportunity to detect clinical changes that precede a MET activation. Further studies are needed to determine if this will decrease the number of transfers to the ICU and cardiac arrests on the floors, as well as improve outcomes. Data interpretation depends significantly on the EMR available in each hospital and the resources available at each site. This variability affects both the afferent and the efferent limbs of the medical emergency systems.

Real-time big data analytics have the potential to transform the way health care providers use technologies to gain insight from clinical and other data repositories and make informed decisions.[2] In the future, the authors expect the use of big data analytics, including an AWSS, will allow providers to predict that a patient will meet clinical criteria to activate MET and enable intervention before the critical moment happens. More research is needed to determine if this early identification will affect patient clinical outcomes, including cardiac arrest, transfer to the ICU, length of stay, morbidity, and mortality.

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