When it Comes to Big Data in Health Care, Size Matters And So Do Variety, Speed and More

Bernoulli Health Chief Analytics Officer John Zaleski, PhD, CAP, CPHIMS, writes on what it takes to enable predictive analytics in health care

What is the promise of predictive analytics in medicine? The promise is in the ability to recognize adverse events or deteriorating patient conditions or behaviors before the actual events, conditions, or behaviors are expressed. More so, early intervention spares the patient from the event and prevents further consequences. These include higher risk of mortality and medical expenses.

The ability to recognize the onset of adverse events is based on observation of the patient and, through experience gained in the practice of medicine, comparing the patient’s state with previous known outcomes to establish a “reading of the tea leaves” on where a patient may be headed in terms of state and onset of deterioration. Much of the information on the patient had historically been captured and managed within a handwritten record. The evolution from paper records and ad-hoc data recording over the past twenty years has formed a more standardized and dense record in terms of the types of data collected. It has also helped to establish the expectations in clinicians that such data will be readily available to them throughout the course of treatment.

With the adoption of electronic health records (EHRs) over the past ten to fifteen years, the challenge of data capture and access to data has diminished. And enhanced is the ability to identify events and establish better patient safety standards for patients. Yet, the notion that all relevant data are captured and maintained in the EHR opposes a belief that discrete data worth capturing can only be found in this medium. The EHR does not capture all necessary information that pertains to short-term patient state changes that, when taken together with other information contained within the EHR, can herald the onset of adverse events.

There is other data needed to round out the state of the patient. That is real-time data that can be continuously captured. Examples include cardiorespiratory properties monitored using physiologic monitors and ancillary therapeutic equipment such as mechanical ventilators, anesthesia machines, and other specialty equipment. Inclusive is equipment used in and around the patient in the high and low-acuity inpatient units. Real-time data obtained through cardiorespiratory monitoring meets the spirit and letter of ‘Big Data’, in terms of volume, variety, velocity, and veracity [1]. High velocity cardiorespiratory information like waveform and alarm-level data are vital for events that may happen when no one is looking. Such events are spikes in heart rate, drops in respirations, and measurements of cardiorespiratory behaviors that are of rather short duration. Typically, these events are shorter than the discrete monitoring interval would capture. For example, if tachycardia or bradycardia occur and are of a sustained duration of fifteen to twenty seconds, such durations may not be captured if discrete heart rate measurements are on one-minute or five-minute intervals. Instead, one might need good luck to capture such events. Similarly, data from multiple sources inclusive of cardiorespiratory monitoring, laboratory, clinical observations, orders, notes, and more make up data variety. Monitored data are by nature of high veracity because, if no errors exist in their capture, they represent as a true, objective measurement of the patient’s cardiorespiratory state.
If captured, these data sources could help to detect patient deterioration. Unfortunately, much of the high velocity data are not reviewed and not captured for population health assessment or predictive analytics.

In his keynote address at the 2017 AAMI conference, Dr. J. Randall Moorman, a professor of medicine, physiology and biomedical engineering at the University of Virginia, stated that information in medical devices, when tapped appropriately, can help doctors and nurses take better care of patients by predicting adverse events. “Detecting the deteriorating patient... is a major goal,” wrote Moorman et al. [2] “Physicians and nurses agree that early warning signs are often present, but are sometimes recognized only in retrospect.”

Furthermore, the limited practice of capturing continuously-monitored data for both in-situ immediate use as well as retrospective assessment means that important patient events can be missed, as noted by Moorman and colleagues: “Continuous physiological monitoring is often available as electrocardiographic (ECG) telemetry, but in current practice is only transiently displayed and then discarded...continuous ECG offers a window into cardiorespiratory dynamics, long known to hold information about the physiological status of the patient.” [2]

More concerning is the challenges of continuous monitoring in the lower acuity settings, such as the postoperative general care unit. Here, monitoring of vital signs can be rather episodic, with vital signs recording at four to six-hour intervals, depending on hospital or unit policies on vital signs capture. It has been estimated, in the case of postsurgical patients, that hypoxemic episodes involving reduced oxyhemoglobin saturations under 90% can be missed in excess of 90% of the time [3].

As has been published in recent years, non-actionable clinical alarms have been a major source of operational distraction in high-acuity settings [4]. Multiple observations and analytics based on multiple sources of data can help offset this problem. The observations and data can help filter out artifact signals that typically invade the high-fidelity data at the core of continuous cardiorespiratory monitoring. “An advantage of models based on physiologic monitoring is that they provide continuously updated estimates of risk within much shorter horizons (the next few hours) based on the most recent measurements,” wrote Moorman and colleagues. [2]

For example, most automated cardiorespiratory data-capture middleware that support medical device integration (MDI) gather and filter data to support EHR documentation. This means that data is typically captured at intervals much less granular than the real-time speed of the medical devices. To achieve real-time clinical surveillance – a more clinically-significant capability – MDI systems should be able to collect all the available data at the highest possible acquisition speed to meet the requirements of various clinical operational settings. As Moorman and colleagues noted, “If you’re in the business of predictive analytics monitoring and you’re not using continuous-monitoring data, you will never be as good as the outfit that does...” [5]
Continuous clinical surveillance solutions that analyze real-time patient data can identify clinically relevant trends, sustained conditions, reoccurrences, and combinatorial indications which may indicate a degraded patient condition based on a clinical cascade prior to triggering the standard limit violation of any individual physiological parameter [6] [7].

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More Information


