

EDITOR'S PAGE

Q4 Vital Signs

Can Machine Learning Protect Patients From the Machinery of Modern Medicine?



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While I sleep I have no fear, nor hope, nor trouble, nor glory. God bless the inventor of sleep, the cloak that covers all man's thoughts, the food that cures all hunger, the water that quenches all thirst, the fire that warms the cold, the cold that cools the heart; the common coin, in short, that can purchase all things, the balancing weight that levels the shepherd with the king, and the simple with the wise.

—Miguel de Cervantes (1)

I recently had the opportunity to engage the American health care system as an inpatient. Although I am exceedingly grateful to all of my health care providers (including the well-meaning resident who decided that I required a blood transfusion at 5 AM) for the excellent care that I received in the hospital, I must confess that being awakened for vital signs every 4 h reminded me of the sleep deprivation technique (*tormentum vigilae* [waking torture]) used by the Romans to extract information from their enemies. My inpatient experience evoked a number of memories about being sleep deprived as a resident, which in turn made me curious about the origin of q4 vital signs: surely there must be a logical medical explanation for why we sleep deprive inpatients by waking them up every 4 h.

Although collecting vital signs every 4 h has been practiced in hospitalized patients since 1893, the evidence base that supports the clinical utility of this practice is scant (2,3). A recent systematic review of

the literature concluded that “There are suggestions that vital sign monitoring has become a routine procedure, but little useful information was identified in regard to the optimal frequency of vital sign measurement. It was noted that many of the important issues related to vital sign measurement have not been investigated through research” (4). In contrast to the paucity of evidence that supports the need for frequent vital signs, there is large body of evidence that shows that poor sleep quality in hospitalized patients can lead to impaired immune responses, hypertension, increased pain sensitivity, changes in metabolic and endocrine regulation, and increased delirium (5). Sleep deprivation has also been linked to the post-hospitalization syndrome, which has been implicated as a cause for 30-day readmissions (6). While there are a number of reasons why hospitalized patients are sleep deprived, checking vital signs is the most important factor that contributes to sleep fragmentation (7).

Given that there are multiple reasons for sleep deprivation in hospitalized patients, it is unlikely that there is a simple fix. This statement notwithstanding, the advent of wearable sensors that can monitor vital signs and that can be coupled with either track and trigger systems or with supervised machine learning-based prediction models will likely have a significant impact on how hospitalized patients are monitored in the future. A recent prospective study showed that a modified track and trigger system (Modified Early Warning Score) was able to identify a low-risk subset of patients who had significantly fewer adverse events than high-risk patients, suggesting that the frequency of nighttime vital signs could be reduced for low-risk inpatients (2). The U.S. Food and Drug Administration (FDA) has approved a wireless device (ViSi Mobile, Sotera Wireless, San Diego, California) for monitoring the vital signs of inpatients including

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blood pressure, heart rate, 3- or 5-lead electrocardiograms, functional oxygen saturation, respiratory rate, and skin temperature (8), thereby allowing health care providers to review real-time transmissions of a complete panel of vital signs, regardless of whether the patient is in bed or is ambulatory. Currently the ViSi Mobile device requires interfacing with a track and trigger monitoring system. The FDA has also approved an artificial intelligence-enabled wearable device (Current, Current Health, Edinburgh, Scotland) for inpatients and outpatients that monitors everything except blood pressure (9). The Current also allows health care providers to monitor a patient's vital signs in real time, with the added benefit that their artificial intelligence algorithms may, in the future, be able to predict which patients are more likely to deteriorate clinically in the immediate future. Although the FDA and other regulatory agencies have not established benchmarks for the predictive accuracy of machine learning algorithms, it is noteworthy that a recent study by Google (Menlo Park, California), in which they obtained deidentified data from 216,221 adults, showed that deep learning models were able to predict in-hospital mortality with an area under the receiver operator curve of 0.93 to 0.94 and 30-day unplanned readmission with an area under the receiver operator curve of 0.75 to 0.76. Remarkably, these models outperformed the traditional clinically used predictive models (10).

Q4 NO MORE?

Despite decades of research detailing the deleterious effects of sleep deprivation in hospitalized patients, surprisingly few changes have been made by health care systems to remedy this problem. With the advent of wearable technologies that can reliably monitor vital signs, as well as the advent of machine learning algorithms that can accurately predict clinical events based on data in the electronic health record, there is no reason technically why these types of machine learning algorithms cannot be used to predict real-time clinical events in hospitalized patients based on data from wearable devices. As with any high-tech-low-touch approach, artificial intelligence has the potential to further remove patients from the human connection that they have with their health care providers. The question is whether this is something we should lose sleep over—and if so, how much? As always, we welcome your thoughts about the impact of machine learning on health care, either through social media ([#JACC:BTS](#); [#Q4NoMore](#)) or by e-mail (jaccbts@acc.org).

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