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🔔 I Don't Want My Algorithm to Die in a Paper Detecting Deteriorating Patients Early

In this issue of the *Journal*, Pimentel and colleagues (pp. 44–52) report a retrospective evaluation of a new model (Hospital-wide Alerting via Electronic Noticeboard [HAVEN]) for predicting deteriorating ward

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patients using vital signs, laboratory measurements, demographics, and historical diagnostic coding (1). The standard metrics of accuracy are impressive (e.g., a c-statistic of 0.901). Accepting nine false alarms for every one true positive, HAVEN will identify more than 40% of cardiac arrests or unplanned ICU admissions within the preceding 48 hours and provide as much as 12-hour notice for more than 25%. This is twice the rate of the best of the alphabet soup of competitors (NEWS, LAPS-2, eCART, and several friends) (2–4).

But predictive scores with nice acronyms are two-a-penny. So why should we care? Because, reading the report carefully, this is a score that

is built with implementation in mind. The authors state that “HAVEN recalculate(s) a patient’s deterioration risk each time a new variable is recorded” (1).

This is a substantially different challenge to that faced by the poster children of machine learning and artificial intelligence. Successful implementation of machine learning algorithms have largely focused on diagnostic imaging or pathways that do not require updating or real-time feedback loops (5, 6). In these, a digital image is captured, processed, and reported. The timescale follows the rhythm of the clinic visit. The data source is fixed and consistent.

In contrast, acute medicine does not have that luxurious timescale or reliable data source. Ward vital signs change as often as hourly, laboratory values are inconsistently measured, and the technology must update hundreds of patients instantly and simultaneously rather than batch process mammograms overnight.

Building a risk score that supports bedside clinical care for hundreds of patients across an entire hospital is as much about engineering as about machine learning. This requires a different set of trade-offs, and it is, therefore, exciting to see such a score performing well. Three criteria must be met to implement machine learning in such a scenario. These can be neatly mapped to the rapid response system reflex arc (7).

The afferent limb requires that data are digital first. Notably, the authors here have selected those items that are often digital even in hospitals that are only partway along the digital maturity spectrum (8). This suggests a broader impact than a model that depends on natural language processing of notes, current diagnostic information, or drug administrations. Moreover, the afferent limb requires a pipeline that delivers the digital signal to a computational engine near instantaneously. This is not part of the infrastructure provided by most electronic health record systems in which data is typically made available through a reporting data warehouse the following calendar day.

The second stage inserts a machine learning “synapse” before the efferent “effector” limb of the rapid response system. This must rapidly update the risk prediction in a trustworthy and reliable manner. Data entry errors or incomplete results must be managed (indeed the pattern of “missingness” might itself be informative). And “better” models that are computationally expensive must be eschewed for simple, “last one carried forward” median or mode approaches.

The third stage, the efferent limb, then returns this prediction to the bedside clinician in a manner that meets modern medical device engineering quality management standards (9).

Although the paper describes the development of the risk score, it has been done with these stages in mind. And despite the constraints this imposes, the score still performs. The closest similar work is the recent report from Google DeepMind on predicting acute kidney injury (10). They developed a similarly pragmatic data processing pipeline that was also suitable for real-world implementation.

Where work such as this must remain vigilant is in the cultural biases that it cannot help but encode. Unlike digital imaging, the prediction target is clinical, not biological. HAVEN predicts cardiac arrest and unplanned ICU admission. In other words, if intensivists have an age bias (they do) or manifest prognostic pessimism for hematological malignancy, then this will be learned by the model (11). The prediction will then not serve these cohorts well. Such risks are mitigated by interpretable machine learning and by excellent and transparent reporting. Both are present here.

I now cannot wait to see the third stage being implemented and these tools returning predictions to the bedside. Work such as this is a stepping

stone to true translational data science. We are not short of algorithms, but the majority of these end their lives in an academic report. For machine learning to have its promised impact on health care, we need engineering pipelines, and we need pragmatic algorithms. This paper hints at the former and strongly delivers the latter. ■

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