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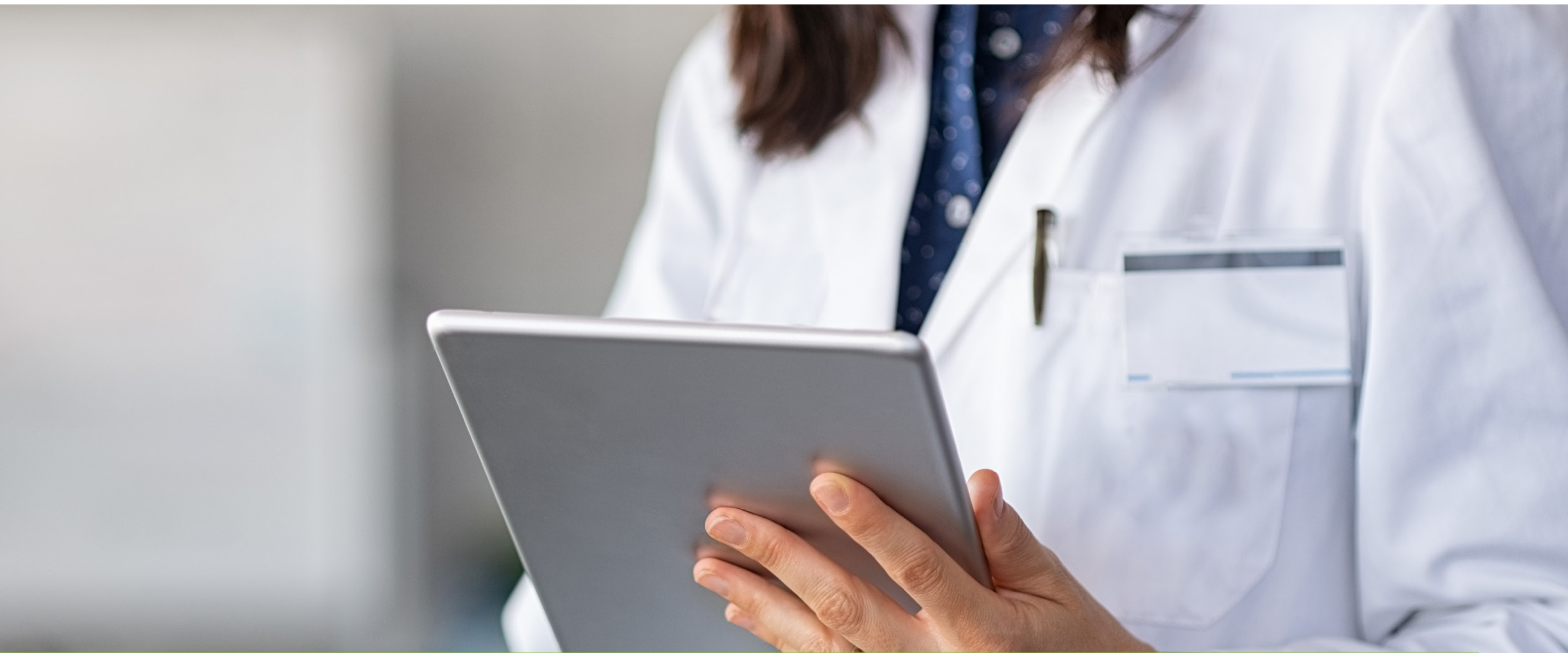

AI-Driven Clinical Surveillance Accurately Identifies Patient Risk and Informs Objective Care Decisions

Research has demonstrated that patients transferred to the ICU from another inpatient unit have higher mortality rates than patients admitted directly to an ICU from the emergency department (ED)[1,2] and that clinical deterioration in a hospital ward is an independent predictor of mortality.[3] There's a corollary finding too, which is that up to 40 percent of ICU patients could be treated at a lower level of care.

Hospital leaders are acutely aware that one of their biggest unmet challenges is optimizing the use of high-intensity care settings to most effectively manage high-risk patients. AI-based risk models are becoming a key tool to support care teams making real-time decisions about patient status and the ideal level of care.

Hospital researchers have not ignored the challenge of identifying decompensating patients early. Numerous studies have shown that early identification of deteriorating patients in hospital units outside of critical care can improve mortality rates and clinical outcomes—and reduce costs. And risk scores like Modified Early Warning Score (MEWS), eCART, National Early Warning Score (NEWS) and others have been deployed to remove the subjective nature of assessing patient risk. But the work has been primarily focused on identifying abnormal vital signs and deploying rapid response teams (RRT) to inpatient wards, and it has shown varying success.[5,6,7,8] A key factor driving inconsistent results is the lack of an automated advanced early warning system (EWS) that continuously collects patient data and generates objective risk scores in real-time to inform better clinical decision-making.

Recent technology advances make a difference in outcomes. Validated artificial intelligence risk scores already exist that work with

EHRs. These solutions draw on national best practices, local information, and continuously monitored individual patient data to produce timely risk scores and serve as a reliable EWS for specific conditions, such as sepsis and *Clostridioides difficile* infections. Now, innovators are using machine learning models to expand clinical surveillance solutions and improve the specificity of existing scores like MEWS to create an overall patient risk score. Electronic surveillance continuously updates and synthesizes risk factors for, among other things, the five major drivers for adult ICU transfers: respiratory insufficiency/failure, acute myocardial infarction, intracranial hemorrhage or cerebral infarction, percutaneous cardiovascular procedures, and severe sepsis.

Early warning of deterioration also expands the available interventions and allows the care team to respond to worsening condition with a comprehensive plan, and reduce variability in care.

While electronic surveillance is not a panacea, the availability of real-time automated risk scores integrated with the EHR removes some of the subjectivity around assessing the patient status. Early warning of deterioration also expands the available interventions and allows the care team to respond to worsening conditions with a comprehensive plan, and reduce variability in care.

Evidence Mounts for Implementing Next-Generation Solutions

The evidence is strong and getting stronger that there is a very real need for this type of AI-driven EWS. Among the most important research findings:

- Cardoso *et al*. reported that each hour of delay in a patient's admission to the ICU was associated with a 1.5% increase in the risk of death in the ICU and a 1% increase in hospital mortality.[9]
- A study in New York state found that the earlier you notice the patient, the more intervention options you have to decrease the 'intensity of intervention' level of care and the number of comorbidities.[10]
- Sakr *et al*. reported that mortality among critically ill patients was clearly related to the initial evaluation of organ failure and the sequential organ failure (SOFA) score at the time of ICU admission.[11]
- When an 18-hospital system improved its triage practices using risk-scoring models, it reduced ICU admissions of patients identified to be low-risk from 42 percent to 22 percent.[12]

And as noted above, as hospitals have begun implementing a variety of EWSs and interventions, they have realized validated improvements. Scores such as MEWS and NEWS, which provide systematic, objective criteria for clinicians to identify patients at risk, have considerable value. Unfortunately, they also have problematic limits as currently deployed.

For one, because the scores are not automatically updated as lab results and vitals are recorded—rather, nurses manually calculate and assign the scores on their rounds—timely identification of decompensating patients is often delayed. Moreover, these systems are limited by the number of data points they incorporate and their failure, in most cases, to recognize trends over time. Timeline trends are especially crucial and also difficult to account for in manual calculations. In contrast, AI-driven solutions can consider many more data points, account for the complex interaction between different clinical factors, monitor trends over time, and, as more data becomes available, add to their sophisticated understanding of what is putting patients at risk.

Finally, for all the benefits of MEWS or NEWS scores, these systems tend to issue nonspecific alerts that can create alert fatigue, thus undermining the value of decision support. It is time for a new generation of early warning systems to take advantage of the significant advances in AI to improve patient risk identification and interoperability to improve workflow integration.

AI Solutions Will Dramatically Empower Clinical Decision-Making

In the case of sepsis, AI-driven EWSs have already shown their value in improved patient outcomes, decreases in mortality rates and lower costs. A 2020 systematic review and meta-analysis published in *Internal Care Medicine* showed that individual machine learning models could accurately predict sepsis onset ahead of time on retrospective data.[13] Similarly, an article published in *JAMIA* in January 2017 concluded, “A program consisting of change management and electronic surveillance with highly sensitive and specific decision support delivered to the point of care resulted in a significant reduction in deaths from sepsis.”[14] In the latter study, the improved clinical surveillance relied on natural language processing (NLP), a type of AI that enriched the tool’s diagnostic power by incorporating clinician notes into its risk assessment.

These focused solutions’ success demonstrates the power and potential of moving forward with those that can produce broader risk scores. A study published in 2019 in the *Journal Of Hospital Medicine* compared the prognostic test accuracy and clinical workloads generated by EWS using multivariable regression or machine learning to aggregate-weighted tools. The study observed a broad assortment of predictor variables including vital signs (heart rate, respiratory rate, blood pressure and venous oxygen saturation), mental state, laboratory data, age and sex. The resulting composite decompensation scoring models “consistently demonstrated superior prognostic performance and generated less workload to identify and treat one true positive case”.[15]

Likewise, a 2020 publication at the Emergency Care Research Institute (ECRI) website, “Identifying and Responding to Clinically Decompensating Patients—Boston Medical Center’s EMR-Based Early Warning” System,[16] found that “the integration of an EWS within the EMR allows for frequent and efficient EWS scoring and rapid clinician response. By automatically calculating updated scores as new vital signs, laboratory results and medication orders are recorded in the EMR, the EWS reflects the patient’s real-time clinical status. The proactive alerting system allows for more rapid clinical intervention. Providers are alerted as soon as changes in objective clinical data occur. A retrospective comparison of pre- and post-intervention samples of clinically decompensating patients showed the following results:

- The time to resuscitative efforts was reduced in the intervention group by 28 minutes ($n = 79$, $p < 0.0001$).
- The time to ICU transfer was reduced by 110 minutes ($n = 79$, $p < 0.0034$).

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- A reduction in mortality was also observed, with the intervention group showing an 8.61% mortality rate compared to the control group's rate of 14.5%.

- A reduction in healthcare resource utilization was reflected by a decrease in the length of hospital stay in the intervention group (11.6 days versus the control group's 14.1 days; n = 79, p <0.0015).

- Although the intervention group experienced an ICU-consult rate of 19%, which was higher than the rate of 5% prior to the intervention, the early and targeted mobilization of resources led to fewer patients being transferred to the ICU, with 25% of patients transferred pre-intervention and 18% of patients transferred post-intervention."

COVID and the Five Primary ICU Transfer Diagnoses

These types of studies are especially important in the current environment, given that the five primary ICU transfer diagnoses for adults are associated with COVID-19, but are also independent drivers of ICU transfer. By aggregating all the elements of patient risk into a generalized risk score and automatically calculating these scores on an ongoing basis, hospitals should be able to reduce care variation in transfer decisions, reduce unnecessary ICU transfers and speed those patients to the ICU who will need intensive care.

By expanding on what is possible today by incorporating additional data sources, more sophisticated analyses and time trends to deliver ever-more reliable alerts in real-time, these tools could be even more of a game-changer. Of course, it's worth remembering that technology is only the essential starting point. Patient care doesn't improve just through the application of technology. Effective change management, as always, is a necessary component in achieving the desired improvements.

Successful models include focused staff education, decompensation rapid-response teams, coordinators, multi-disciplinary quality improvement activities, ongoing performance analysis and executive oversight.

Why Now is the Inflection Point

Optimizing the utilization of ICU resources—through earlier admission when indicated and reducing the transfer of patients who are lower risk—is the next major area of focus for hospitals working to improve outcomes and reduce costs. The value delivered creates a compelling argument for hospitals to adopt AI-driven automated EWSs sooner rather than later.

Improvements in interoperability and AI technology developed in collaboration with clinical experts can automatically generate and deliver trustworthy, actionable risk scores into the EHR, a central monitor or directly to the point of care. Clinical surveillance platforms that offer solutions for multiple clinical programs—including new patient identification and risk algorithms—hold more promise than solutions focused on a single condition because they capture a much wider range of drivers for improving patient care. In addition, they are able to leverage the investment in data integration and enrichment and workflow integration to deliver on many distinct solutions for improving patient care.

Effective EWSs have clearly demonstrated their ability to improve key patient and financial outcomes by giving clinicians the objective patient status information they need to improve decision-making and reduce care variation around transfer decisions. By automating patient risk calculation across the many clinical data points available and integrating alerting into the EHR workflow, AI-based EWSs can drive even more improvement.

Conclusion

In the current environment, with unrelenting pressure on hospital care teams, and floor and ICU capacity stretched beyond capacity, there is a dramatic incentive to adopt AI-driven surveillance technology now. The present moment's crisis will pass, but the value of this technology will continue to help hospitals identify patients at risk for poor outcomes, act early enough to apply the full array of possible interventions and make decisions based on objective criteria far into the future. Because AI-based clinical surveillance opens the door to clinical and financial improvements that extend far beyond the current environment, adopting these technologies is also a wise investment in a much brighter future.

Authors

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Dr. Itay Klaz is responsible for directing clinical efforts toward the development, implementation and support of Wolters Kluwer suite of surveillance software solutions. Dr. Klaz is a clinical informatician, dermatologist and a former military surgeon. He has specialized in the convergence of enterprise-level electronic health records, EHR interoperability, health care data science, clinical governance, patient outreach, risk and value-based care models and provider engagement.

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Sources:

[1] Goldhill DR, Sumner A. Outcome of intensive care patients in a group of British intensive care units. Crit Care Med. 1998;26:1337–45.

[2] Lundberg JS, Perl TM, Wiblin T, et al. Septic shock: an analysis of outcomes for patients with onset on hospital wards versus intensive care units. Crit Care Med. 1998;26:1020–4.

[3] Simchen E, Sprung CL, Galai N, et al. Survival of critically ill patients hospitalized in and out of intensive care. Crit Care Med. 2007;35:449–57.

[4] Solberg, B.C., Dirksen, C.D., Nieman, F.H. et al. Introducing an integrated intermediate care unit improves ICU utilization: a prospective intervention study. *BMC Anesthesiol* 14, 76 (2014). https://doi.org/10.1186/1471-2253-14-76.

[5] Hillman K, Chen J, Cretikos M, et al. Introduction of the medical emergency team (MET) system: a cluster-randomised controlled trial. Lancet. 2005;365:2091.

[6] McGaughey J, Alderdice F, Fowler R, Kapila A, Mayhew A, Moutray M. Outreach and early warning systems (EWS) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards. Cochrane Database Syst Rev. 2007:CD005529.

[7] Priestley G, Watson W, Rashidian A, et al. Introducing critical care outreach: a ward-randomised trial of phased introduction in a general hospital. Intens Care Med. 2004;30:1398–404.

[8] Subbe CP, Williams E, Fligelstone L, Gemmell L. Does earlier detection of critically ill patients on surgical wards lead to better outcomes? Ann R Coll Surg Engl. 2005;87:226–32.

[9] Cardoso LT, Grion CM, Matsuo T, et al. Impact of delayed admission to intensive care units on mortality of critically ill patients: a cohort study. Crit Care 2011; 15:R28.

[10] https://journals.lww.com/ccejournal/fulltext/2020/06000/the_effects_of_early_mobilization_on_patients.2.aspx

[11] Sakr Y, Lobo SM, Moreno RP, et al. Patterns and early evolution of organ failure in the intensive care unit and their relation to outcome. *Crit Care* 2012; 16:R222.

[12] Safavi K, et al. Variation exists in rates of admission to intensive care units for heart failure patients across hospitals in the United States. Circulation, February 2016.

[13] Fleuren, Lucas M et al. "Machine learning for the prediction of sepsis: a systematic review and meta-analysis of diagnostic test"

[14] Manaktala, Sharad. Claypool, Stephen R. *Journal of the American Medical Informatics Association*, Volume 24, Issue 1, January 2017, Pages 88–95.

[15] Linnen DT, et al. Statistical modeling and aggregate-weighted scoring systems in prediction of mortality and ICU transfer: a systematic review. *J Hosp Med.* 2019;14:161–169.

[16] ECRI Institute. Identifying and responding to clinically decompensating patients—Boston Medical Center's EMR-based early warning system. *Health Devices* 2018 May 16.

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