



Pediatric Intensive Care Units in the Artificial Intelligence Era

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Dear Editor,

Pediatric intensive care units (PICUs) increasingly generate continuous streams of physiologic data. Electrocardiography, pulse oximetry, arterial pressure, capnography, ventilator waveforms, laboratory results, medications, and electronic health records are now complemented by point-of-care ultrasound (POCUS), which provides real-time insight into cardiac, pulmonary, vascular, and hemodynamic status (1, 2). However, these data streams are still largely interpreted in isolation, increasing the cognitive workload for bedside clinicians and potentially delaying recognition of evolving deterioration (3).

Artificial intelligence (AI) could transform this fragmented, multisource information into actionable physiologic intelligence. However, data integration and AI implementation should begin at the bedside rather than with an overly complex autonomous system. Such an intelligent system requires a practical model comprising three sequential steps (4):

- 1) Standardized bedside POCUS acquisition;
- 2) AI-assisted interpretation and quantitative measurements; and
- 3) Integration of these outputs with continuously acquired physiologic data.

Consider, for example, a child with COVID-19 who is progressing toward cardiac and respiratory failure. The intensivist performs a focused cardiac, lung, inflammatory, neurologic, and venous ultrasound examination, while AI provides real-time guidance on image acquisition and quality; assists in assessing lung findings, ventricular function, hematologic and coagulation profiles, and vascular status; and automatically extracts key quantitative parameters. Any potentially related congenital anomaly is

also sought (5). These outputs are then integrated with blood pressure, heart rate, oxygenation status, ventilator variables, urine output, inflammatory markers, lactate, and vasoactive medication data to generate a personalized physiologic and pathologic profile that can be updated through serial reassessment after fluid, vasoactive, ventilatory, or anti-inflammatory interventions (6). Realizing this vision will require clearly defined clinical protocols, competency-based training, systematic image archiving, ongoing quality assurance, and continued clinician oversight. Pediatric-specific validation is essential because age-dependent physiology and anatomy limit direct extrapolation from adult-derived AI models (4).

The goal, therefore, is not another layer of alarms but a bedside cognitive augmentation platform that transforms multimodal data into interpretable, patient-specific information and supports earlier and more precise clinical decision-making.

Footnotes

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