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Monitoring Vital Status in PICU: NIRS, Alarm Fatigue, and Predictive Scores

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Abstract

Pediatric intensive care units (PICUs) rely on continuous vital sign assessment to detect early clinical deterioration and guide timely intervention. Traditional monitoring of heart rate (HR), respiratory rate (RR), and peripheral oxygen saturation (SpO_2) remains fundamental, yet single-parameter or intermittent approaches frequently fail to capture the rapid physiological transitions unique to critically ill children. Near-infrared spectroscopy (NIRS) has emerged as a non-invasive adjunct providing real-time regional tissue oxygenation data, while composite scoring systems—including the Pediatric Early Warning Score (PEWS), pediatric Sequential Organ Failure Assessment (pSOFA), and Pediatric Logistic Organ Dysfunction-2 (PELOD-2)—integrate multiple parameters to stratify mortality risk. A pervasive challenge is alarm fatigue, which desensitizes clinical staff and jeopardizes patient safety. Machine learning (ML)-assisted analytics and nurse-led alarm management bundles have demonstrated significant reductions in non-actionable alerts and improved predictive accuracy. This narrative review synthesizes current evidence on PICU monitoring modalities, compares their diagnostic and prognostic performance, evaluates alarm fatigue mitigation strategies, and proposes a framework for multimodal surveillance integrating wearable sensors and AI-driven decision support.

Keywords: *pediatric intensive care, vital signs, near-infrared spectroscopy, alarm fatigue, predictive scoring, hemodynamic monitoring, machine learning*

1. Introduction

Children admitted to the PICU represent one of the most physiologically vulnerable patient populations in medicine. Unlike adults, infants and young children possess higher baseline HR and RR due to elevated mass-specific metabolic demands and lower stroke volumes, and they compensate for hemodynamic instability by raising these parameters until reserves are abruptly exhausted [1]. Early recognition of this compensatory failure is, therefore, both critical and challenging. Studies have confirmed that abnormal vital signs at admission are independently associated with ICU transfer, prolonged length of stay, multi-organ dysfunction, and mortality in the pediatric population [2, 3].

Continuous bedside monitoring of HR, RR, and SpO_2 has been standard PICU practice for decades. However, the explosion of monitoring data—each patient potentially generating thousands of alarms per day—has created an epidemic of alarm fatigue. In a landmark study, up to 90% of PICU alarms were found to be clinically non-actionable, desensitizing nursing staff and delaying responses to genuine emergencies [4]. Simultaneously, advanced non-invasive technologies such as cerebral NIRS and hemodynamic platforms including pulse contour cardiac output (PiCCO) have entered clinical practice, offering richer physiologic insight but raising new questions about integration and interpretability [5, 6].

Composite scoring tools—PEWS, pSOFA, and PELOD-2—translate multiparameter vital sign data into actionable risk scores, but their performance varies substantially across clinical contexts. Recent investigations demonstrate that ML-based vital sign models outperform traditional scoring systems in predicting ICU transfers hours in advance [7]. This review critically evaluates the evidence for established and emerging PICU monitoring tools, with particular focus on NIRS, traditional vital sign surveillance, alarm fatigue, and predictive scoring systems, aiming to provide a clinically actionable synthesis for pediatric intensivists and critical care nurses.

2. Methods

A narrative review was conducted through comprehensive searches of PubMed, EMBASE, SCOPUS, Web of Science, and the Cochrane Library up to April 2026. Search terms combined: pediatric intensive care, vital signs monitoring, near-infrared spectroscopy, NIRS, alarm fatigue, PEWS, pSOFA, PELOD, hemodynamic monitoring, PiCCO, machine learning, clinical deterioration, and cardiac output. Studies were selected based on relevance to PICU monitoring modalities, including randomized controlled trials, cohort studies, systematic reviews, and meta-analyses. Articles focused on neonatal-only populations or adult ICUs without pediatric-relevant data were excluded. Reference lists of included studies were hand-searched to identify additional sources.

Table 1. Comparison of PICU Monitoring Modalities

Modality	Type	Key Parameters	AUC / Performance	Advantages	Limitations
Heart Rate (HR)	Non-invasive, continuous	HR (bpm), trend	AUC 0.73 at 12 h [7]	Ubiquitous; real-time	Elevated by pain, fever, anxiety
Respiratory Rate (RR)	Non-invasive, continuous	RR (breaths/min), effort	AUC 0.74 at 12 h [7]	Strongest single predictor	Prone to motion artifact
Pulse Oximetry (SpO_2)	Non-invasive, continuous	SpO_2 (%)	Sensitivity ~85–90% for hypoxia [8]	Gold standard for O_2 sat	Affected by perfusion, skin tone, motion
Cerebral NIRS (rSO_2)	Non-invasive, continuous	rSO_2 (%)	AUC 0.82 multimodal [9]; RR 0.75 mortality (NIRS-only) [5]	Organ-level oxygenation; early hypoperfusion	Superficial cortex only; limited PICU guidelines
BedsidePEWS Score	Composite score	HR, RR, SBP, SpO_2, WOB, AVPU	AUC 0.72 at 12 h [7]	Standardized; widely adopted	Subjective elements; documentation gaps
pSOFA Score	Organ dysfunction score	6 organ systems, age-adjusted	AUC 0.87–0.93 for mortality [10]	Best PICU mortality predictor	Complex; requires lab values

PELOD-2 Score	Organ dysfunction score	Cardiovascular, respiratory, neurologic	AUC 0.74–0.90 [10, 11]	Strong mortality prediction	Resource-intensive; not real-time
ML Vital Sign Model	AI/EHR-based	6 VS + demographics, continuous	AUC 0.78 at 12 h, 0.76 at 24 h [7]	Objective; continuous scoring; outperforms PEWS	"Black box"; requires EHR infrastructure
PiCCO	Minimally invasive, continuous	CO, SVV, PPV, EVLW, GEDV	Superior fluid guidance vs CVP [6]	Real-time hemodynamic optimization	Invasive arterial + central line required
Bedside Echocardiography (TTEcho)	Non-invasive, intermittent	CO, SV, EF, LVOT-VTI	CI accuracy 89.7% vs PiCCO gold standard [12]	No invasive access; shock phenotyping	Snapshot only; operator-dependent

CO: cardiac output; CVP: central venous pressure; EVLW: extravascular lung water; GEDV: global end-diastolic volume; LVOT-VTI: left ventricular outflow tract velocity-time integral; PPV: pulse pressure variation; rSO_2: regional oxygen saturation; SBP: systolic blood pressure; SV: stroke volume; SVV: stroke volume variation; WOB: work of breathing.

3. Results

3.1 Traditional Vital Signs: HR, RR, and SpO_2

Heart rate and respiratory rate emerge consistently as the most predictive individual vital sign parameters for PICU deterioration. In a prospective nine-year cohort of 38,199 pediatric admissions at a tertiary children's hospital, RR achieved an AUC of 0.74 and HR an AUC of 0.73 for predicting ICU transfer within 12 hours—outperforming systolic blood pressure (SBP) and SpO_2 as isolated predictors [7]. Importantly, repeated and continuous measurement of these parameters substantially improves predictive validity compared to single-time-point readings; one prospective study demonstrated that 29.5% of patients deteriorated within 72 hours when abnormal VS were documented on repeated measurement [2].

SpO_2 monitoring via pulse oximetry remains indispensable for detecting hypoxemia in critically ill children. Pediatric-specific challenges—including motion artifact, poor peripheral perfusion, and sensor displacement—can introduce significant measurement error, particularly in neonates and infants [8]. Furthermore, children with cyanotic congenital heart disease require stratified SpO_2 targets rather than the standard normoxia thresholds applied in adult practice, since physiological SpO_2 ranges for these patients may lie between 75% and 90% [3].

Age-adjusted interpretation is paramount. Fleming et al. derived normative HR and RR centile charts from over 140,000 children, demonstrating that fixed cutoffs introduce systematic misclassification [1]. Composite indices that leverage these parameters contextually—such as the Shock Index Pediatric Age-Adjusted (SIPA = HR ÷ SBP), which correlates with increased mortality when exceeding 1.2 in children under 6 years—capture hemodynamic compensation earlier than any single variable in isolation [2].

3.2 Near-Infrared Spectroscopy (NIRS) in PICU

Cerebral NIRS provides continuous, non-invasive assessment of regional tissue oxygen saturation (rSO_2) by exploiting the differential absorption of near-infrared light by oxygenated and deoxygenated hemoglobin. Its anatomical utility in pediatrics is enhanced by the thin cranial vault of infants, which allows greater light penetration to cortical tissue compared with adults [5, 13]. In a systematic review and meta-analysis of 25 randomized trials encompassing 2,606 participants, cerebral NIRS monitoring was associated with a non-significant mortality trend (RR 0.75, 95% CI 0.51–1.10) but demonstrated very low-certainty evidence across neonatal intensive care, cardiac surgery, and neurocritical care contexts, highlighting the need for larger, better-powered trials [5].

The clinical utility of NIRS is most established in the perioperative management of critical congenital heart disease (cCHD). A machine-learning–assisted algorithm integrating cerebral rSO_2 with HR, RR, SpO_2, and invasive mean arterial blood pressure in neonates with cCHD post-cardiac surgery achieved reliable real-time classification of clinical stability versus deterioration in a retrospective dataset of 460 patient admissions [3]. Additionally, cerebral NIRS oximetry demonstrated significant predictive value for severe acute kidney injury (AKI) following pediatric cardiac surgery, with lower perioperative rSO_2 values associated with a substantially higher AKI incidence (AUC 0.82 for the multimodal model), suggesting cross-organ surveillance potential beyond neurological endpoints [9].

Multi-site NIRS—deploying sensors over both frontal lobes simultaneously and optionally over somatic sites such as the kidney or flank—enables a more complete picture of systemic oxygen delivery and regional perfusion mismatch. Bilateral cerebral monitoring is particularly recommended during cardiac surgery given the risk of lateralized perfusion deficits from carotid cannulation or aortic cross-clamping [13]. However, standardized PICU-specific protocols for NIRS-guided intervention thresholds remain largely absent from published guidelines, constituting a major evidence gap [5, 9].

3.3 Composite Scoring Systems: PEWS, pSOFA, and PELOD-2

Among composite scoring tools, pSOFA and PELOD-2 demonstrate superior discrimination for PICU mortality compared to PRISM III and PIM 3. In a single-center study of critically ill children, pSOFA achieved AUC values ranging from 0.87 on Day 1 to 0.93 by Day 28, significantly outperforming PELOD-2 on Day 1 ($p \leq 0.01$) [10]. pSOFA's advantage lies in requiring fewer variables and using parameters that mirror adult SOFA components, facilitating implementation during resource-limited scenarios such as pandemic triage [10].

PEWS, while widely used for early deterioration detection on general wards and in PICU triage, is hampered by subjective scoring elements, inconsistent documentation, and variable performance across centers. A cluster-randomized EPOCH trial across seven countries involving 10,000 pediatric admissions found that BedsidePEWS implementation did not reduce all-cause mortality [7]. Nevertheless, PEWS scores incorporating continuous vital sign trends—rather than intermittent snapshots—show improved discrimination, and the Alder Hey PEWS demonstrated excellent AUC for critical care admission in febrile pediatric cohorts [2].

Machine learning models that integrate the same six objective vital sign parameters used in PEWS—without subjective elements—achieve an AUC of 0.78 at 12 hours and 0.76 at 24 hours ahead of ICU transfer, compared to 0.72 and 0.69 respectively for BedsidePEWS [7]. At a specificity of 90%, the ML model's sensitivity was 53% versus 36% for BedsidePEWS, with a number needed to evaluate of 13 versus 15 patients to detect one deterioration event [7]. These findings underscore that statistical derivation from objective parameters improves both predictive accuracy and operational efficiency.

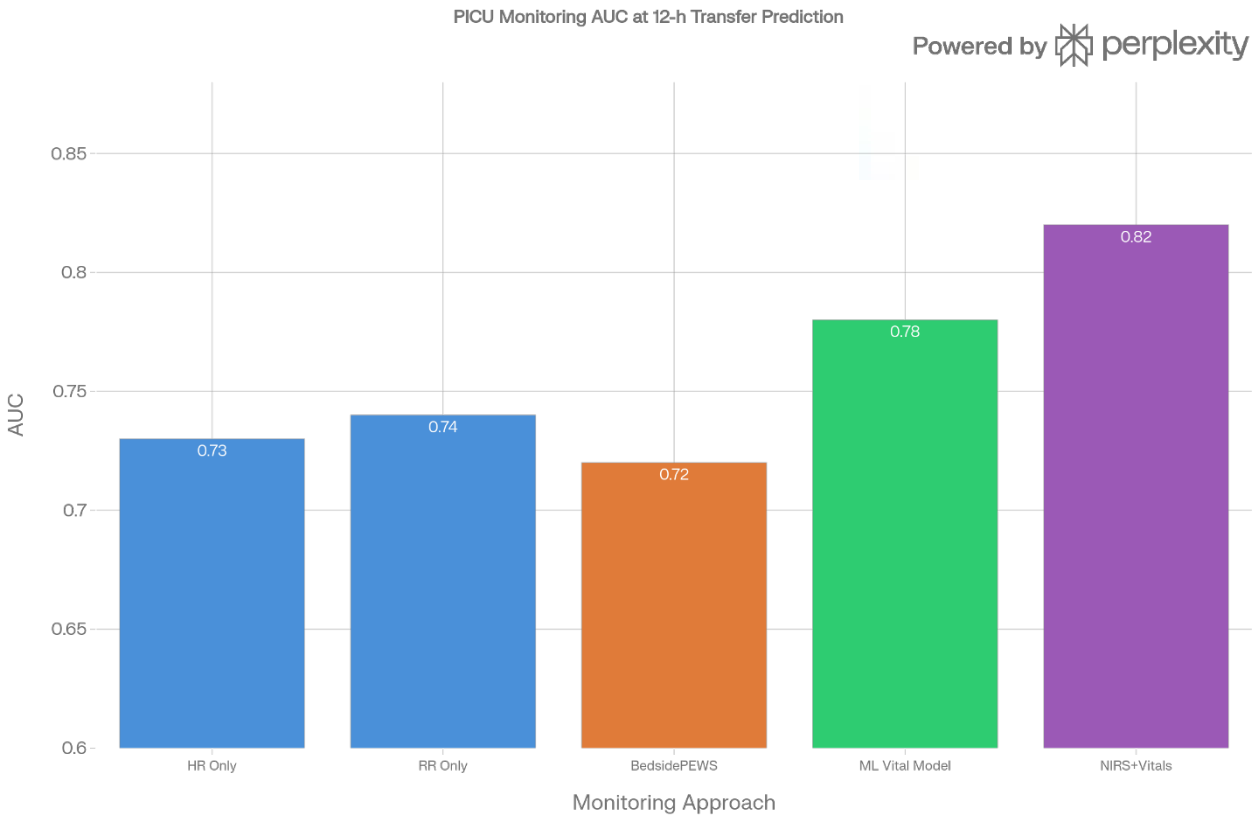

Figure 1. Predictive AUC at 12-Hour PICU Transfer Horizon by Monitoring Approach. NIRS+Vitals multimodal achieves highest discrimination (AUC 0.82). Sources: Mayampurath et al. 2020 [7]; Flechet et al. 2019 [9].

3.4 Alarm Fatigue: Burden and Mitigation

Alarm fatigue represents one of the most critical patient safety threats in contemporary PICU practice. Studies consistently report that 80–90% of physiological monitor alarms in the PICU are clinically non-actionable—attributable to artifact, self-resolving transients, or inappropriate threshold settings [4, 14]. This chronic noise desensitizes nursing staff, increases response latency to genuine alarms, and imposes psychological strain that compounds with high patient acuity workloads [14]. The Joint Commission has listed alarm safety among its National Patient Safety Goals since 2014, yet the problem persists across institution types and healthcare systems.

A nurse-led intervention study transferring alarm threshold-setting authority from physicians to nursing staff—supported by structured training—reported that 90% of PICU nurses demonstrated increased confidence in alarm management, with measurable reductions in non-actionable alarm rates [4]. Implementation of the CEASE bundle (Customize, Evaluate, Adjust, Situate, Educate) in a PICU pilot achieved a 44.17% reduction in physiological alarms during the pilot period, with families reporting fewer complaints about alarm noise [15]. These findings suggest that organizational and educational interventions, rather than technology alone, are essential for sustainable alarm fatigue mitigation.

AI-enabled smart alarm systems represent the technological frontier of alarm management. By analyzing continuous physiologic waveforms in real time, these systems distinguish artifact-driven alerts from true physiological events with significantly greater accuracy than threshold-based alarms. The LSTM-based AI framework evaluated in NICU settings achieved an F1-score of 91.3% for anomaly detection, with sub-second latency, offering a practical pathway to dramatically reducing alarm burden while maintaining safety [16]. Transparent decision support incorporating SHAP-based feature attribution further addresses clinician trust concerns with 'black box' AI [16].

4. Discussion

The evidence synthesized in this review demonstrates that no single monitoring modality is sufficient for comprehensive vital status assessment in the PICU. Traditional vital signs—HR and RR in particular—retain primacy as real-time, continuous biomarkers that capture compensatory physiology earlier than blood pressure changes and more reliably than SpO_2 in well-compensated states [1, 2, 7]. The critical insight that trend-based, continuous, and age-adjusted interpretation substantially outperforms single-point measurement has direct implications for how PICU monitoring systems should be designed and staffed [2, 7].

NIRS occupies an increasingly important adjunctive role, particularly for post-cardiac surgery patients and infants with cCHD, where standard oxygenation targets do not apply and organ-level perfusion data can guide individualized resuscitation [3, 5, 9]. The multimodal integration of NIRS with hemodynamic parameters—as demonstrated by the cCHD algorithm achieving AUC 0.82 for deterioration detection—offers a template for comprehensive surveillance that transcends the limitations of any individual parameter [3, 9]. The current absence of PICU-specific NIRS intervention guidelines represents a major translational gap that future randomized trials must address, prioritizing clinically meaningful endpoints such as neurodevelopmental outcomes and organ dysfunction rather than surrogate physiologic targets [5].

Composite scores such as pSOFA are superior to PEWS for mortality stratification in established PICU illness but are inherently retrospective and resource-intensive, making them poorly suited for real-time deterioration detection [10, 11]. The PEWS, despite its limitations, retains clinical value as a communication and escalation tool when embedded within standardized rapid-response pathways. Its integration with ML-derived continuous risk scores—calculated automatically from EHR data—represents the most pragmatic path forward, leveraging the interpretability of PEWS for human communication while using ML precision for algorithmic surveillance [7, 2].

The alarm fatigue crisis demands a coordinated response spanning technological, organizational, and educational domains. While smart AI-driven alarm systems offer promising false-positive reduction [16], institutional culture and nursing empowerment are equally critical determinants of successful implementation [4, 15]. Multimodal surveillance architectures that integrate bedside monitors, NIRS sensors, wearable devices, and EHR-based ML analytics through unified visualization platforms will require robust interoperability standards, data governance frameworks, and frontline training to translate technical capability into improved patient outcomes [3, 6, 16].

The generalizability of current evidence is constrained by several factors. Most ML model validations originate from single academic centers in high-income countries, limiting applicability to resource-constrained settings where PICU monitoring infrastructure may be minimal [1, 2]. Equity considerations are particularly pressing given that only approximately 50% of pediatric ED encounters have a complete set of documented vital signs globally, and abnormal vital signs in discharge settings are disproportionately missed in low-resource environments [2]. Future research should prioritize multicenter validation of continuous monitoring and ML models across diverse age strata, PICU diagnoses, and healthcare resource contexts, with attention to unintended harms from algorithmic surveillance including alert burden redistribution and automation bias [1, 7].

5. Conclusion

Vital status monitoring in the PICU is undergoing a transformative evolution driven by continuous sensor miniaturization, non-invasive tissue oxygenation technology, and AI-driven analytics. The convergence of traditional vital sign surveillance—anchored by the predictive power of RR and HR—with NIRS-based organ oxygenation data and ML-assisted scoring systems offers a pathway toward earlier, more accurate, and truly personalized deterioration detection in critically ill children. Alarm fatigue, long an underestimated obstacle to monitoring efficacy, can now be substantially addressed through nurse-led empowerment programs, bundled alarm management strategies, and intelligent AI-driven filtering. The field stands at an inflection point: implementing these tools in an integrated, evidence-based, and equitable manner will determine whether the next generation of PICU monitoring translates into measurable reductions in pediatric critical care morbidity and mortality worldwide.

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