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REVIEW **Open Access**

Vital signs as biomarkers of early clinical deterioration in pediatric emergency departments: physiology, interpretation, and innovations: a narrative review

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Abstract

Background Early recognition of pediatric deterioration is difficult because age-dependent physiology and compensation mask early shock and safety risks. This narrative review compares vital-sign (VS) biomarkers (heart rate, respiratory rate, blood pressure, oxygen saturation, temperature) with laboratory markers and clinical indicators.

Methods We searched Embase, Pubmed, and guideline repositories to August 2025 for pediatric studies from emergency, inpatient, and critical-care settings. We summarized accuracy, timeliness, and implementation issues, prioritizing cohort and implementation evaluations.

Results Age-adjusted, repeated, and continuous analyses of VS—especially multivariate approaches such as shock index pediatric age-adjusted and heart-rate-characteristics analytics—outperformed single thresholds, often anticipating ICU transfer or sepsis by hours. Laboratory biomarkers provided diagnostic specificity for defined syndromes but were slower and unsuitable for continuous surveillance. Composite scores (e.g., PEWS, ED-PEWS, National PEWS) showed moderate to high discrimination yet performed best when integrated with trends and standardized escalation pathways.

Conclusion VS biomarkers, leveraged as dynamic trends and combined with context, enable earlier, safer detection of pediatric deterioration than static thresholds or isolated laboratory tests. Priorities include validating continuous models beyond NICUs, ensuring equity and calibration across different ages and comorbidities, and testing wearable sensors and EHR-embedded alerts in pragmatic trials that measure timeliness, unintended harms, and patient-centered outcomes.

Clinical trial number Not applicable.

Keywords Pediatrics, Vital signs, Emergency, EHR-embedded alerts, Continuous surveillance, Wearable sensors

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Introduction and physiology

Early recognition of pediatric clinical deterioration is challenging because age-dependent cardiovascular and respiratory physiology can mask early instability and children often compensate until reserves are exhausted [1–4]. Compared with adults, children exhibit higher baseline heart and respiratory rates because smaller hearts eject less blood per beat (lower stroke volume), and mass-specific metabolic demands are greater. Hence, to preserve cardiac output, children compensate with faster heart rates (HR) [5–7]. Increased metabolic activity also drives a higher respiratory rate (RR) to support gas exchange. Smaller, more delicate airways increase vulnerability to obstruction from secretions or foreign bodies, further raising RR requirements [5]. As a child develops, the autonomic nervous system orchestrates the regulation of both the heart and lungs, and its maturation parallels that of these organs [8]. Across childhood into adolescence, HR declines, mirroring the changing metabolic demands and overall physiological maturation [9], while respiratory control becomes more sophisticated, resulting in more efficient ventilatory patterns [10, 11]. Even so, substantial person-to-person variability in cardiopulmonary regulation persists within specific age groups, influenced by genetics and environment [8]. These developmental considerations explain why clinical deterioration in young patients may unfold rapidly once compensatory mechanisms fail. particularly in neonates and infants with immature control systems and limited reserve [12].

These features explain why vital signs (VS) function as practical, continuous biomarkers of early deterioration in pediatric emergency departments (PEDs) and why interpretation must be explicitly age-aware. Accordingly, our aim in this review is to examine how developmental physiology informs the use of age-specific ranges, bedside thresholds, and percentile charts—and how these tools can support timely recognition of risk in frontline care. In this review, “vital signs” refer to HR, RR, systolic blood pressure (SBP) (with mean arterial pressure when available), temperature, and peripheral oxygen saturation (SpO_2) unless otherwise specified.

Age-specific percentile charts derived from large datasets better characterize typical ranges and variability of vital signs (VS) than fixed cutoffs and therefore support more nuanced interpretation. Fleming et al. analyzed data from over 140,000 children to generate centile charts for HR and RR from birth to 18 years, demonstrating the expected age-related decline in both measures [13]. Percentiles allow clinicians to judge how far a measurement deviates from age-expected norms, avoiding the limitations of binary normal/abnormal labels and providing more clinically informative context.

At the bedside, several simple rules are commonly used for children 1–10 years: anticipated HR ≈ 150 − (5 × age in years); minimum SBP ≈ 70 + (2 × age in years) mmHg; and typical RR ranges of 30–60/min in neonates, gradually decreasing through infancy and toddlerhood, and ~ 15–20/min after age 5. Large emergency department datasets, including a Korean study with over 1.5 million VS measurements, reinforce the wide normal variability and support age-specific centile interpretation for pediatric heart and respiratory rates [14] (Table 1).

Methodology

In this narrative review, we conducted a comprehensive literature search across multiple databases, including PubMed, SCOPUS, EMBASE, Web of Science, and the Cochrane Library, up to August 2025. The search strategy incorporated a combination of keywords and MeSH terms related to “vital signs,” “biomarkers,” “clinical deterioration,” “early warning systems,” “pediatric patients,” and “emergency department.” Boolean operators (AND/OR) were used to ensure a broad yet focused retrieval of relevant studies. Studies were selected based on their relevance to the use, interpretation, or innovation of vital signs as indicators of early clinical deterioration in pediatric emergency settings. We included studies examining the physiological basis, predictive value, accuracy, and integration of vital signs (such as HR, RR, blood pressure, oxygen saturation, temperature, and capillary refill time) in clinical assessment tools or monitoring systems. Articles discussing machine learning applications, digital

Table 1 Physiological basis of vital signs in children

Vital Sign Parameter	Underlying Physiology in Pediatrics	Key Influencing Factors
Heart Rate (HR)	Higher baseline HR due to increased metabolic rate and cardiac output demands in children; gradual decrease with age	Fever, anxiety, pain, activity, developmental stage
Respiratory Rate (RR)	Immature respiratory control centers; higher RR to meet oxygen demand in smaller lungs and increased metabolism	Fever, respiratory distress, anxiety, metabolic acidosis
Blood Pressure (BP)	Lower BP in infants due to less vascular resistance; increases with vessel growth and maturation	Pain, anxiety, hydration status, cardiac function
Temperature (Temp)	Thermoregulation immature in infants; body surface area to volume ratio affects heat loss	Infection, environment, activity level, fever
Oxygen Saturation (SpO2)	Efficient oxygen binding in fetal hemoglobin shifts postnatally; high normal saturation range maintained	Respiratory conditions, cardiac defects, ventilation

health innovations, or early warning scores related to pediatric vital sign monitoring were also included.

Clinical epidemiology and burden

Epidemiology of abnormal vital signs in peds

VS monitoring is crucial in EDs to recognize high-risk patients, especially pediatric patients. "Vital signs (VS)" refer to HR, RR, SBP, temperature, and peripheral oxygen saturation [SpO_2] [15, 16]. Emergency physicians are trained to identify abnormal VS, such as tachycardia and hypotension, as they are associated with a higher rate of admission and worse outcomes, including higher risks of ICU admission, hospital admission, in-ED or in-hospital cardiac/respiratory arrest, mortality, prolonged ED/inpatient length of stay, and unplanned 72-hour return ED visits [17]. Therefore, a joint policy by the American College of Emergency Physicians and the Emergency Nurses Association on the care of children in the ED stated that full monitoring of VS in infants and children is mandatory [18]. However, current scoring systems, which incorporate VS, used for identifying high-risk children, are not effective enough as they depend on classifying VS as normal or abnormal, regardless of the variance in confounding factors such as age or type of setting (e.g., pediatric-only vs. mixed EDs, triage level, fever, agitation) [19].

Multiple large cohort studies on pediatric patients confirmed the prevalence of abnormal VS at discharge home from the ED and its association with age, sex, and underlying causes. Ramgopal et al. conducted a retrospective, cross-sectional study using data representing 162.7 million pediatric ED visits. They found at least one abnormal VS in 73% of the children, with a higher frequency of abnormal VS in younger children. Tachycardia, tachypnea, low SBP, and fever were documented in 19.3%, 8.8%, 10.2%, and 11.6% of cases, respectively. HR and RR abnormalities were associated with age, severity of the underlying cause, and outcomes. However, SBP was associated with age only [20]. This is supported by other studies that also showed a higher rate of abnormal VS at discharge in younger children less than 3 years, especially males, and with higher illness severity [15, 21]. (Fig. 1)

Association with patient outcomes

There is sufficient evidence regarding the association between abnormal VS and short-term deterioration, including ICU admission, mortality, and 72-hour return visits [22]. Oxygen saturation and level of consciousness

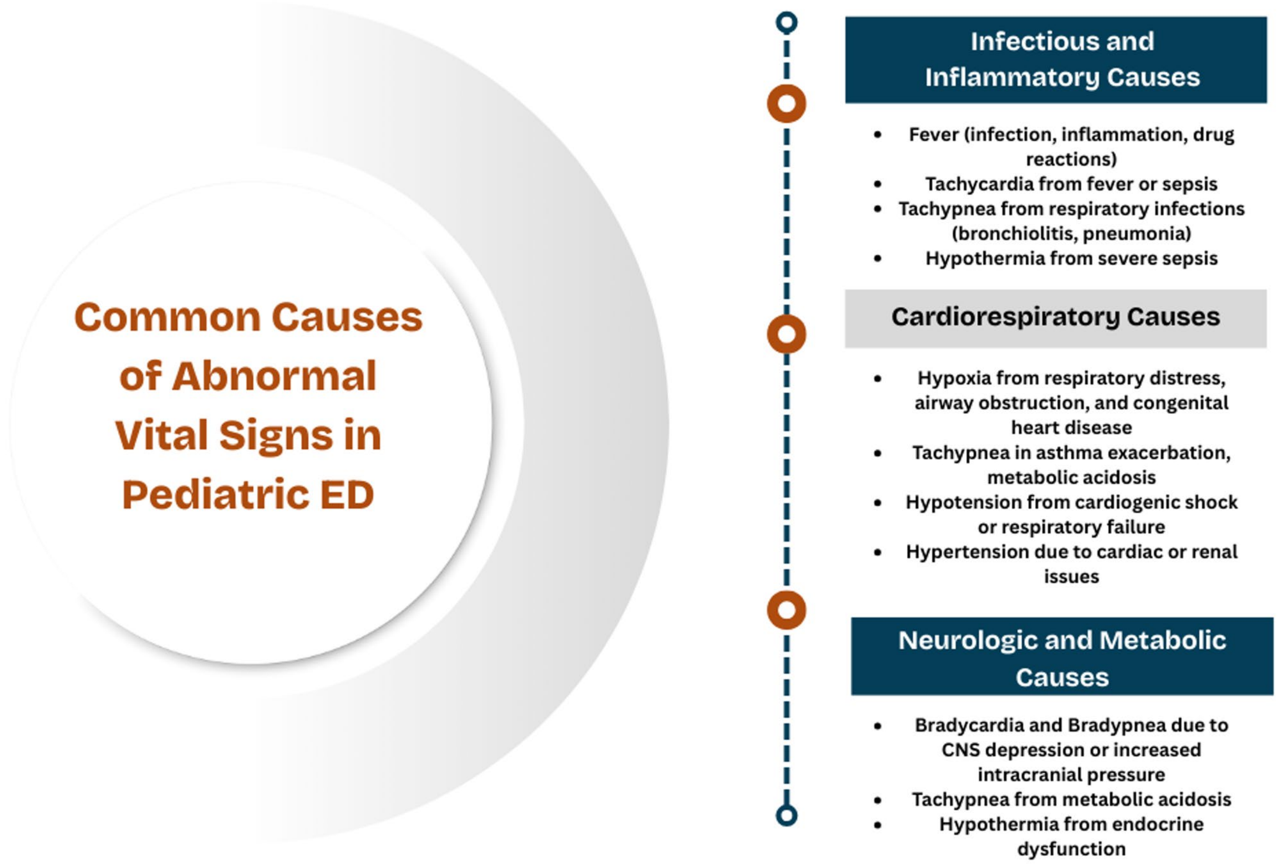


Fig. 1 Common causes of abnormal vital signs in pediatric ED

are associated with mortality. Additionally, HR and the Glasgow Coma Scale (GCS) are associated with ICU admission [22]. Quinten et al. conducted a prospective observational study on 359 patients. They measured VS at regular intervals in the first three hours in the ED. They found that 29.5% of patients deteriorated within 72 h, confirming the association between abnormal VS and clinical deterioration and highlighting the importance of repeated measurement of VS in the ED [22]. Furthermore, Angulik et al. investigated the impact of deterioration associated with abnormal VS on patient outcomes. They conducted a retrospective review on all PICU transfers and arrests and observed longer ICU stays, higher organ dysfunction, and mortality rates associated with delayed ICU transfer due to unrecognized abnormal VS [23].

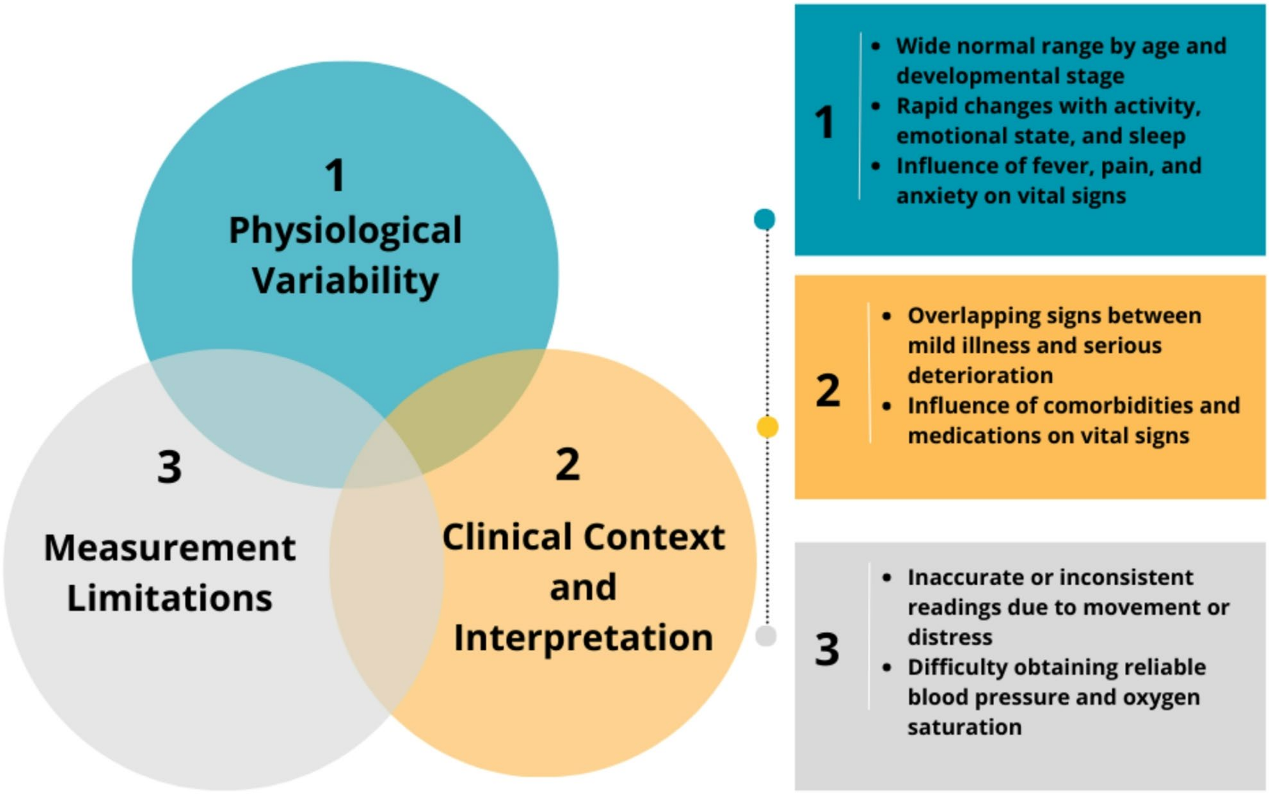
In PED, although abnormal VS at discharge is associated with higher return visits and mortality rates, there is a lack of standard criteria to categorize patients as to be admitted or safe for discharge [16, 24]. Therefore, it is recommended to reassess VS regularly at PED and before discharge to avoid unrecognized cases of deterioration.

Diagnostic challenges and biomarker potential

Limitations of single-time-point vital signs

A single VS measurement can be misleading because children's physiological parameters vary with age and are easily influenced by transient factors. Fear or anxiety can elevate pulse rate and RR, complicating assessment of conditions such as shock [25]. Winter et al. (2017) found that 17% of discharged children had at least one abnormal VS, yet only 0.43% developed serious problems [21]. Using single cutoff points resulted in poor discrimination for adverse outcomes, with AUC values of 0.45–0.59 [21]. Only one case of permanent disability appeared possibly preventable and associated with an abnormal discharge VS, with no preventable deaths. Thus, an isolated abnormal reading is rarely a reliable indicator of serious illness, and reliance on one-time VS can mislead clinicians or delay needed care [21]. (Fig. 2)

Clinical deterioration in hospitalized children frequently goes unrecognized due to inadequate VS documentation and inconsistent responses to abnormal values [26]. PEWS, which rely on periodic VS monitoring, show limited accuracy in predicting deterioration [27]. Their use is hindered by irregular assessments, incomplete recordings, variation in scoring, and uncertainty about escalation thresholds [28]. In a single-center review of PICU emergency transfers, Kowalski et al. (2021)



1
- Wide normal range by age and developmental stage
- Rapid changes with activity, emotional state, and sleep
- Influence of fever, pain, and anxiety on vital signs

2
- Overlapping signs between mild illness and serious deterioration
- Influence of comorbidities and medications on vital signs

3
- Inaccurate or inconsistent readings due to movement or distress
- Difficulty obtaining reliable blood pressure and oxygen saturation

Fig. 2 Interpretation challenges of vital signs in pediatric patients

Table 2 Vital Sign-based early warning scores for pediatric patients

Scoring System	Vital Sign Components Used	Validation & Clinical Utility
PEWS	HR, RR, WOB/resp. effort, SpO_2 & O_2 therapy, capillary refill/perfusion, mental status (AVPU/behaviour)	Widely studied; predicts deterioration/ICU. Use with trends/clinical judgment—not as a sole ED disposition tool.
ED-PEWS (example of "Modified PEWS")	HR, RR, SpO_2, WOB, AVPU, capillary refill (age-adjusted thresholds)	Strong ED triage discrimination for high-urgency; externally evaluated across settings.
National PEWS (England)	HR, RR, graded resp. distress, SpO_2, O_2 delivery, SBP, cap refill (with standardized escalation)	Nationally standardized; good ED cohort performance; broader cross-setting validation ongoing.
Alder Hey PEWS	HR, RR, SpO_2, WOB, behaviour/neurologic	Excellent discrimination for critical care admission in febrile ED cohorts.
Brighton PEWS	Cardiovascular (HR/perfusion), respiratory (RR/effort/SpO_2), behaviour	Simple, low-resource friendly; predicts deterioration/PICU transfer; cut-offs context-dependent.

reported that over 20% had no PEWS recorded, and among those documented, nearly half underestimated patient risk [28]. Scores were often entered hours before transfer, indicating missed signs of deterioration during the critical pre-escalation period [28]. (Table 2)

Vital sign trends as biomarkers

Because young children have limited physiological reserves and can deteriorate quickly, early recognition of serious illness is critical. Trend-based or continuous VS monitoring offers better insight than one-time measurements [26]. Intermittent checks may miss rapid changes, whereas patterns in rate or stability over time provide a more reliable prediction of serious illness [28, 29].

PEWS systems increasingly incorporate trend data to improve accuracy. For example, the Vitalpac Early Warning Score (ViEWS) assigns weighted scores to VS and averages them over time to track clinical trajectory [26]. Newer technologies automatically track and analyze VS trends. The Deterioration Risk Index (DRI), calculated every 15 min through the EHR, predicts deterioration in hospitalized children [29]. Tools such as the Vitals Risk Index similarly provide early, objective warnings [29]. Machine learning and AI systems now analyze continuous VS in real time to generate risk scores and predict outcomes such as ICU transfer or sepsis [30].

Using trend-based monitoring supports earlier intervention and reduces normalization bias, where clinicians overlook abnormal readings because they appear familiar [26]. These systems help detect subtle changes before critical deterioration occurs [28]. Integrating VS trend analysis into routine ED and ward care can improve early identification of high-risk patients and support more efficient use of limited resources [31]. (Table 3)

Technology and monitoring advances

Continuous monitoring in PEDs

Intermittent VS measurement often every 4 to 8 h has long been standard practice [32], but numerous studies show that this approach can miss important physiological abnormalities that occur between checks. Turan et al. (2019) found that postoperative BP disturbances frequently went undetected between routine measurements, a pattern likely applicable in pediatric settings [33]. Continuous monitoring captures micro-events predictive of deterioration that intermittent sampling often overlooks, as demonstrated by Khanna et al. (2020) and Duus et al. (2018) [34, 35].

Recognizing these limitations, PEDs have increasingly shifted toward continuous VS monitoring, which provides real-time data and allows clinicians to detect subtle changes that may precede deterioration [36, 37]. Bedside monitors remain the foundation of continuous assessment, offering HR, RR, oxygen saturation, BP, and

Table 3 Comparative effectiveness of vital sign biomarkers vs. Other clinical indicators for detecting clinical deterioration in pediatric patients

Biomarker Type	Sensitivity/Specificity	Advantages	Limitations
Vital Sign Biomarkers	Best performance when using continuous, age-adjusted multivariate analyses (HR/RR/SpO_2); heart-rate-characteristics monitoring reduced mortality in very-low-birth-weight neonates in an RCT; prediction in older children improves with continuous/ML models vs. single readings.	Non-invasive, real-time trends enable early detection	Sensor/measurement variability; artifact & alarm burden; intermittent spot checks can miss subtle changes
Laboratory Biomarkers	Moderate diagnostic accuracy overall; in febrile infants, PCT > CRP for invasive bacterial infection at standard cut-offs; performance varies by age/cut-off/setting and is not consistently > 0.9.	Objective; pathology-specific context (e.g., infection); prognostic value in defined syndromes	Invasive; turnaround delays; not suitable for continuous monitoring
Clinical Indicators (Scores/Composite)	Accuracy varies by tool & setting; PEWS associated with ICU admission/deterioration, but insufficient alone for ED disposition	Integrates multiple data sources; supports standardized escalation	Subjective elements; documentation/calculation errors; can lag pure physiologic change

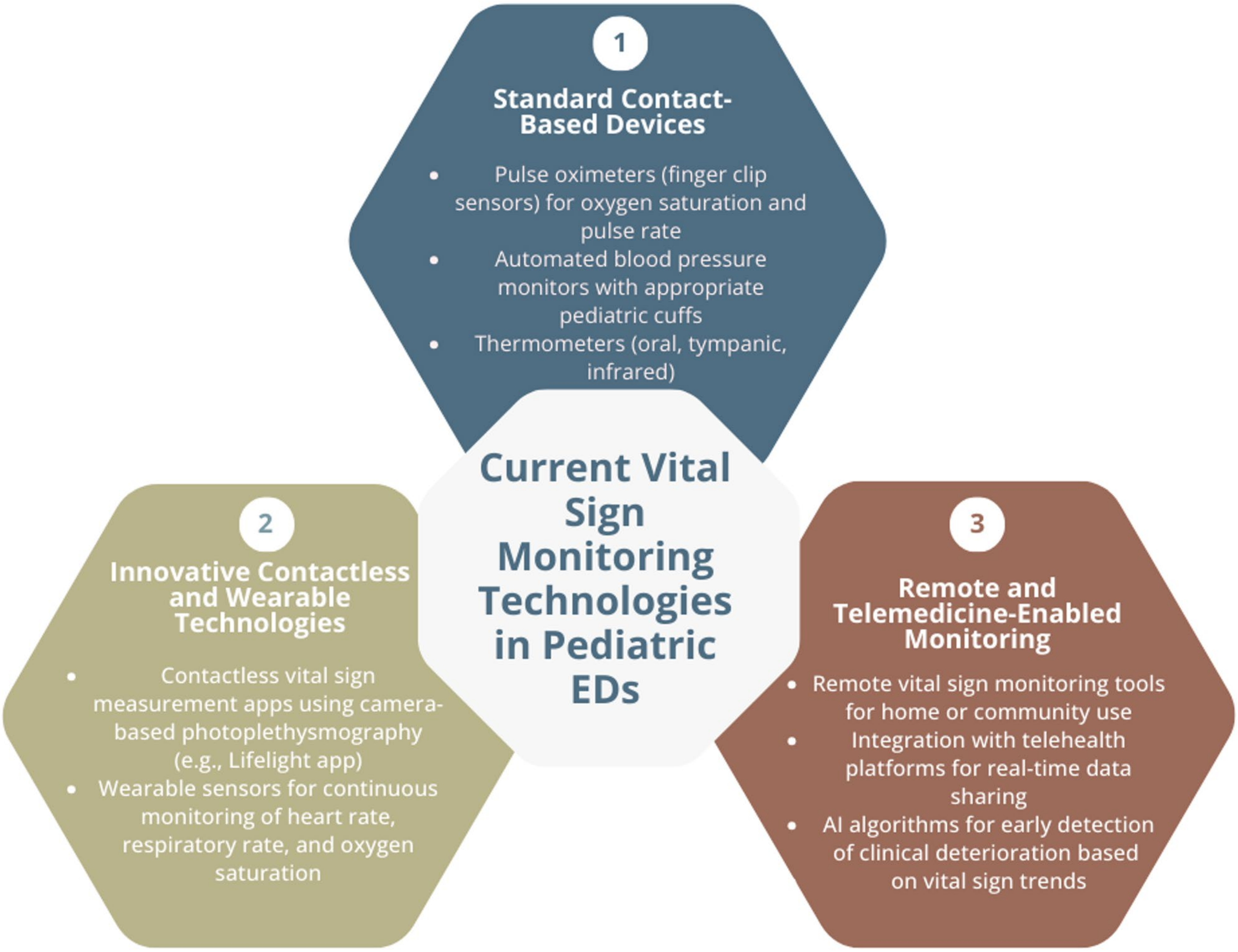


Fig. 3 Current vital sign monitoring technologies in pediatric EDs

temperature displays with threshold-based alarms [32]. However, these systems are limited by their wired design and reduced patient mobility.

Wearable and wireless sensors now address many of these issues. Lightweight, pediatric-specific devices enable continuous monitoring without restricting movement [38]. Garbern et al. (2024) showed that a wearable-enabled mobile system could remotely detect advanced sepsis without laboratory testing or bedside interventions, highlighting the potential for broader surveillance [39]. Still, many wearables are adapted from adult devices, leading to challenges with fit, durability, and sensor displacement; such issues can reduce accuracy or delay diagnosis [40].

Non-contact monitoring technologies are also emerging. Using machine vision, audio analytics, and motion tracking, these systems estimate multiple VS without touching the patient, improving comfort, infection control, and suitability for neonates or scenarios where leads are impractical [41]. Many U.S. PEDs also use portable bedside and transport monitors, with telemetry enabling real-time remote data analysis which is an advantage in overflow or resource-limited settings [42].

Growing evidence supports continuous monitoring's clinical benefits. Bonafide et al. (2015) showed it shortens time to detect respiratory arrest, expediting life-saving interventions [43]. Khanna et al. (2025) found that many complications evolve gradually, underscoring the importance of uninterrupted surveillance [44]. A meta-analysis by Areia et al. (2021) reported fewer ICU admissions and rapid response activations with continuous wearable monitoring, demonstrating broader improvements in patient safety and resource use [45]. (Fig. 3)

Integrating AI and predictive analytics

Continuous VS monitoring in PEDs generates large volumes of complex data, requiring advanced analytic tools. Artificial intelligence (AI) and machine learning (ML) can transform raw physiologic and EHR data into actionable predictions that support clinical decision-making [46, 47]. ML models identify patterns within high-dimensional datasets and, although not self-updating in real time, are periodically retrained under established governance systems [46].

AI and ML have shown strong potential in predicting pediatric deterioration and sepsis. Spaeder et al. (2019) demonstrated that age-adjusted ML models could identify sepsis up to 24 h before clinical diagnosis [47]. The AiSEPTRON study (2025) similarly found that ML-based tools outperformed traditional scoring systems for early sepsis recognition in PEDs [48]. The TREWs system, implemented across multiple centers, has been associated with reductions in sepsis-related mortality and organ failure by providing early alerts that prompt timely intervention [49].

Given the wide physiological variability in children, ML's ability to learn from large, diverse datasets is especially valuable. These models can accommodate age-dependent differences and provide more individualized risk assessments, addressing limitations of one-size-fits-all clinical approaches [46].

Prognostic indicators and scoring systems

Vital signs in pediatric early warning scores (PEWS)

PEWS systems are widely used in EDs to assess VS and consciousness, helping clinicians recognize early deterioration [50]. However, scores are often documented hours before critical events and can underestimate severity [28]. Abnormal VS at discharge are also associated with higher revisit rates, suggesting that static cutoffs within PEWS may not fully capture illness trajectory [15].

Newer tools such as the Pediatric Age-Adjusted Shock Index improve mortality prediction, while continuous monitoring methods like pulse oximetry detect hypoxemia early, though they may contribute to alarm fatigue [43]. Machine-learning approaches now analyze multiple VS streams to provide early deterioration predictions, potentially outperforming traditional scores [51]. Despite these advancements, PEWS remains valuable for its simplicity and ability to support bedside decision-making and team communication. Enhancing PEWS with trend-based VS, shock indices, and automated monitoring data may improve ED care.

Composite vital sign indices

Composite indices are gaining interest for their ability to integrate physiologic information. The Shock Index Pediatric Age-Adjusted (SIPA), calculated as HR ÷ SBP, identifies high-risk patients when values exceed 1.2 in children under 6 years or 1.0 in older children, correlating with increased mortality and ICU need [52]. SIPA detects compensated shock earlier than isolated VS.

Respiratory indices are also important. The Rate-Oxygenation (ROX) index ($SpO_2/FiO_2 \div RR$), though originally for adults, shows emerging pediatric utility particularly for bronchiolitis and pneumonia when adjusted for age [53]. Machine-learning models that analyze VS patterns further enhance early risk detection [51]. Used alongside PEWS, these tools help create a more accurate, physiology-based assessment of deterioration in pediatric emergency care.

Guidelines, equity, and future directions

Current pediatric emergency guidelines including APLS, PALS, and NICE identify hypotension using age-adjusted SBP thresholds [25, 50]. Although these cutoffs are well supported, adding parameters such as HR and RR may improve prognostic accuracy [54]. There is still no universal consensus on defining tachycardia or tachypnea at discharge, and abnormal HR or RR is common despite limited guidance for decision-making in this setting [21].

Tachycardia reflects both shock status and stroke volume, while tachypnea is well established in predicting pneumonia severity and other emergencies [55]. Children discharged with tachycardia or abnormal RR are more likely to return to the ED, experience adverse outcomes, and require interventions such as supplemental oxygen, respiratory medications, or IV access [24].

Although incorporating HR and RR could support safer discharge decisions, several challenges remain. Tachycardia and tachypnea may be influenced by pain, fever, dehydration, or anxiety [56]. Both vary over short intervals, and circadian changes can shift HR substantially without affecting outcomes [57]. These limitations become especially relevant in children who appear clinically stable but have abnormal VS just outside normal thresholds. This group is at risk because deviations may be misinterpreted as benign or transient [20]. Establishing a clear definition for this intermediate-risk category could improve discharge planning, follow-up, and consistency across healthcare settings, and supports the need to integrate this group into pediatric emergency guidelines.

Implementation considerations

Despite these promising applications, the integration of AI and ML into PED clinical workflows faces substantial obstacles. One prominent issue is the "black box" nature of many ML algorithms, which lack transparency in how predictions are generated, undermining clinician trust and limiting adoption [58]. As Cutillo et al. (2020) emphasized, ideal ML models in healthcare must prioritize explainability, reliability, and fairness to gain clinician acceptance [59]. Alarm fatigue remains a significant concern, as some AI-enabled monitoring systems produce a high frequency of false-positive alerts, potentially desensitizing healthcare providers to critical alarms [60, 61]. Technical challenges include insufficient hospital infrastructure for real-time wireless data transmission and aggregation, complicating integration of AI tools into existing electronic medical record systems [32, 62]. Furthermore, implementing AI requires significant workflow adaptations, staff training, and cultural shifts within clinical teams, which can meet resistance and slow uptake [63].

Ethical considerations are paramount. AI algorithms can inadvertently perpetuate or amplify biases present in training data, risking unequal care delivery among demographic groups [64]. Ensuring data privacy and compliance with regulatory standards adds further complexity [65]. Transparency regarding how patient data is used and how predictions are made is essential to maintain public trust and meet legal requirements [66].

To overcome these challenges, multidisciplinary collaboration among clinicians, data scientists, engineers, and ethicists is crucial. Strategies include developing interpretable ML models, refining alarm algorithms to reduce false positives, enhancing data infrastructure, and providing comprehensive education and support to clinical staff. Regulatory frameworks must evolve to guide the safe and ethical deployment of AI in pediatric care.

Future research and equity considerations

Over the past two decades, PED guidelines have been restructured to better use existing services and technological advances. Despite this progress, large-scale studies and continuous data collection remain essential to refine current VS thresholds into data-driven cut-points rather than generic norms [67]. Multicenter research across diverse settings is especially important to evaluate and apply these modifications in both high- and low-resource environments.

VS documentation remains inconsistent; only about 50% of pediatric ED encounters have a complete set of measurements, and abnormal vitals are associated with increased transfers or admissions [68]. Emergency care in low- and middle-income countries (LMICs) faces additional constraints, including limited resources, workforce shortages, and barriers to timely intervention. These settings require simple, evidence-based VS indices, durable low-cost monitoring tools, and workforce development that reduces financial and geographic barriers to critical care. Expanding affordable monitoring systems, bedside biomarkers, and emerging technologies can also strengthen equity [38].

However, technology alone cannot ensure equitable improvement. Effective implementation requires tailored training strategies and workflow adjustments. Without concurrent investment in staff education, the impact of PEWS or enhanced monitoring remains limited. Training should include operation of monitoring equipment, pediatric-specific index interpretation, early deterioration recognition, and escalation protocols aligned with available resources. Many LMIC frontline clinicians lack formal pediatric emergency training and rely heavily on experience. Programs such as APLS and WHO's ETAT have demonstrated improvements in triage accuracy and patient outcomes, but expanded digital and simulation-based training may provide more consistent, scalable support.

Conclusion

Vital signs remain essential for early detection of pediatric deterioration, especially in emergency settings. Advances in wearable and non-contact monitoring, combined with AI and EHR integration, are transforming how VS data is collected and interpreted, offering improved predictive accuracy and earlier recognition of risk. Successful adoption of these tools, however, requires attention to data transparency, clinician trust, workflow integration, and equitable access across healthcare systems. Future research should focus on large, multicenter validation of continuous monitoring models across diverse age groups and resource settings, with attention to calibration, usability, and unintended harms. Strengthening training and infrastructure will be critical to ensuring that innovations in VS surveillance translate into safe, equitable improvements in pediatric emergency care.

Abbreviations

VS	Vital Signs
ED	Emergency Department
PED	Pediatric Emergency Department
ICU	Intensive Care Unit
PEWS	Pediatric Early Warning Score
ED	PEWS-Emergency Department Pediatric Early Warning Score
SBP	Systolic Blood Pressure
HR	Heart Rate
SVR	Systemic Vascular Resistance
PVR	Pulmonary Vascular Resistance
GCS	Glasgow Coma Scale
AUC	Area Under the Curve
DRI	Deterioration Risk Index
ViEWS	Vitalpac Early Warning Score
AI	Artificial Intelligence
ML	Machine Learning
EHR	Electronic Health Record
SIPA	Shock Index Pediatric Age-Adjusted
ROX	Respiratory Rate-Oxygenation Index
APLS	Advanced Pediatric Life Support
PALS	Pediatric Advanced Life Support
NICE	National Institute for Health and Care Excellence
LMIC	Low and Middle-Income Countries
ETAT	Emergency Triage Assessment and Treatment
NICU	Neonatal Intensive Care Unit
RR	Respiratory Rate

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Author contributions

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Declarations

Ethics approval

We declare that the work presented in this manuscript is original and has not been submitted, in whole or in part, for publication elsewhere. All authors have contributed significantly to the conception, design, execution, and interpretation of the work.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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