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Healthcare Wearable Technologies for Primary School Children: Current Devices and Validation Challenges

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Abstract: Wearable health technologies are increasingly being explored for primary school students as part of preventive and personalized pediatric healthcare models. This paper examines current healthcare-oriented wearable devices designed or adapted for children aged 6–12 years, with emphasis on physiological monitoring and inertial measurement unit (IMU)-based motion sensing. Contemporary systems integrate biosensors such as photoplethysmography for heart rate tracking, electrocardiogram modules, respiratory and temperature sensors, pulse oximetry, and continuous glucose monitoring for chronic disease management. IMU sensors, incorporating accelerometers and gyroscopes, enable objective assessment of physical activity, gait, posture, and sleep patterns, supporting early identification of sedentary behavior, motor irregularities, and other health-related indicators. Integration within connected digital health platforms allows longitudinal data analysis and remote supervision. However, challenges remain regarding pediatric-specific validation, measurement accuracy, and data governance. This paper analyzes the clinical potential and limitations of wearable technologies in supporting child health during foundational developmental years.

Keywords: Wearable devices; Primary school students; Digital health; Inertial Measurement Unit; Physical activity monitoring.

1. INTRODUCTION

Current healthcare-oriented wearable technologies [1-3] for primary school students primarily focus on continuous physiological monitoring, behavioral health assessment, and chronic disease management within naturalistic daily environments. These devices range from consumer-grade wrist-worn trackers to medical-grade biosensor systems and emerging smart textile platforms. Although many wearable systems were initially developed for adult populations, increasing attention has been directed toward adapting and validating these technologies for pediatric use, reflecting the broader transition toward preventive, data-driven, and personalized healthcare models. Wrist-worn smartwatches and fitness trackers remain the most widely adopted wearable devices among school-aged children. These devices typically integrate photoplethysmography (PPG) sensors for heart rate monitoring alongside inertial measurement unit (IMU) sensors [4-12], which include accelerometers, gyroscopes, and sometimes magnetometers. IMU sensors play a central role in pediatric health monitoring by capturing fine-grained motion data, including step count, posture, gait characteristics, activity intensity, and sedentary behavior duration. Through multi-axis motion detection, IMUs enable classification of physical activities such as walking, running, jumping, or prolonged sitting, thereby supporting objective assessment of daily energy expenditure. Given the increasing prevalence of childhood obesity and declining physical activity levels, IMU-derived metrics provide valuable longitudinal data for evaluating movement patterns and designing targeted physical activity interventions within school environments.

In addition to general activity tracking, IMU sensors contribute to sleep monitoring by detecting nocturnal movement patterns and estimating sleep duration, sleep onset latency, and wake episodes. Although sleep estimation algorithms may vary in accuracy compared to polysomnography, wearable IMU-based sleep tracking offers scalable, non-invasive monitoring in real-world settings. Sleep quality and duration are strongly associated with cognitive function, emotional regulation, metabolic health, and academic performance in primary school children, making this functionality particularly relevant for preventive pediatric healthcare. With

Beyond wellness tracking, more clinically oriented wearable technologies incorporate advanced biosensors to monitor vital signs continuously. Medical-grade wearable systems may include single-lead electrocardiogram (ECG) modules [13, 14], respiratory rate sensors, skin temperature probes, and pulse oximetry components. These systems are especially relevant for children with chronic conditions such as cardiac arrhythmias, asthma, or autonomic dysfunction. Continuous cardiac rhythm monitoring can support early detection of irregular heart patterns that might not appear during short clinical evaluations. Similarly, respiratory monitoring, sometimes enhanced through motion signals captured by chest-mounted IMUs. These devices can assist in identifying abnormal breathing patterns or early signs of asthma exacerbation.

IMU sensors [15-22] also have specific clinical applications in pediatric motor function assessment. In children with neurodevelopmental conditions, musculoskeletal disorders, or rehabilitation needs, wearable IMUs can quantify gait symmetry, joint movement patterns, balance stability, and fall risk. Compared with traditional observational assessments, IMU-based motion analysis provides objective, high-resolution biomechanical data that can support individualized therapy planning and progress evaluation. This application is particularly relevant in school-aged populations where early identification of motor coordination difficulties may influence long-term functional outcomes. Continuous glucose monitoring (CGM) systems represent another major category of healthcare-oriented wearable technologies for primary school students, particularly for those with type 1 diabetes. These systems use minimally invasive subcutaneous sensors linked to wearable transmitters to provide real-time glucose readings and trend data. While CGMs primarily rely on biochemical sensing rather than motion detection, integration with wearable platforms allows contextualization of glucose fluctuations relative to IMU-detected physical activity levels. Such multimodal integration enhances understanding of activity-related glycemic variability during school hours and supports safer diabetes management. Emerging wearable platforms extend beyond wrist-based devices to include flexible epidermal sensors and smart textiles embedded with physiological and motion-sensing components. These systems aim to improve comfort, compliance, and long-term usability among children. Multimodal designs combining IMU sensors with heart rate, temperature, and environmental sensors enable comprehensive monitoring of physical exertion, thermal stress, and contextual health factors. Although many of these technologies remain in experimental or early commercial stages, they represent the evolution toward integrated pediatric digital health ecosystems.

A defining feature of modern wearable technologies is their connectivity within broader Internet of Medical Things (IoMT) frameworks [23-25]. Data from IMU sensors and physiological monitors are transmitted via wireless protocols to smartphones or cloud-based platforms, where analytic algorithms process continuous data streams. Machine learning techniques are increasingly applied to IMU-derived motion data to classify activity types, detect anomalies, and identify early indicators of health deterioration. For primary school students, such systems allow remote health supervision and facilitate data-informed clinical decision-making beyond episodic healthcare encounters. Despite these advancements, several challenges remain. The accuracy of IMU-based activity classification and physiological measurements may be influenced by device placement, calibration differences, and variability in pediatric movement patterns. Many commercial wearables are optimized for adult users, and pediatric-specific validation studies are necessary to ensure clinical reliability. Furthermore, continuous collection of motion and physiological data generates large volumes of sensitive health information, requiring stringent data protection measures and compliance with child-specific regulatory frameworks. Together with the advanced technologies [26-36], the wearable devices have high potential to enhance the student's life significantly.

Overall, current healthcare-oriented wearable technologies for primary school students reflect a convergence of biosensing, inertial motion tracking, and digital health integration. IMU sensors serve as foundational components enabling objective quantification of physical activity, sleep behavior, motor development, and rehabilitation progress, while complementary physiological sensors support chronic disease monitoring and preventive health assessment. As pediatric wearable technologies continue to evolve, their clinical value will depend on rigorous validation, child-centered design principles, and careful alignment with pediatric healthcare standards.

2. CURRENT HEALTHCARE-ORIENTED WEARABLE DEVICES FOR CHILDREN AGED 6–12 YEARS

Current healthcare-oriented wearable devices designed or adapted for children aged 6–12 years span a continuum from consumer-grade activity trackers used in preventive health initiatives to clinically regulated systems for chronic disease management. Across these categories, two core technological components dominate: physiological biosensors [37-41] that capture internal biological signals and IMU sensors [42] that quantify movement and biomechanical behavior. Together, these sensing modalities enable continuous, real-world health monitoring during a critical developmental stage. Wrist-worn wearables remain the most prevalent form factor for school-aged children due to their familiarity, comfort, and ease of daily use. In many commercially available child-focused devices, IMU sensors—typically comprising tri-axial accelerometers and gyroscopes—serve as the foundational sensing mechanism. These sensors capture raw motion data that are processed to derive step counts, activity intensity levels, sedentary duration, posture changes, and sleep–wake patterns. In pediatric health contexts, IMU-derived metrics are particularly valuable for assessing physical activity levels associated with cardiometabolic risk, monitoring sedentary behavior linked to obesity, and estimating sleep duration and fragmentation. Beyond basic activity quantification, advanced IMU signal processing enables classification of movement types and extraction of gait-related parameters, supporting objective assessment of motor development and functional mobility. Research-grade accelerometry systems further expand the clinical utility of IMUs in pediatric populations. These devices provide access to high-resolution raw acceleration data, facilitating reproducible analysis and development of pediatric-specific activity intensity thresholds. In rehabilitation and motor assessment contexts, body-worn IMUs placed on the lower limbs or trunk can quantify gait symmetry, stride variability, balance stability, and coordination patterns. Such applications are especially relevant for children with neurodevelopmental disorders, musculoskeletal conditions, or those undergoing physical therapy, as IMU-based metrics offer objective, longitudinal measures of functional progress. In parallel with motion sensing, physiological monitoring wearables provide continuous assessment of vital and condition-specific biomarkers. Wrist-based photoplethysmography (PPG) sensors enable heart rate monitoring, while more advanced devices incorporate electrocardiogram (ECG) modules for rhythm assessment. Adhesive biosensor patches and ambulatory cardiac monitors designed for pediatric tolerability allow multi-day recording of cardiac signals, respiratory rate, skin temperature, and activity context. These systems support early detection of arrhythmias, monitoring of autonomic regulation, and evaluation of cardiorespiratory responses during daily school activities.

Continuous glucose monitoring (CGM) systems represent one of the most clinically established pediatric wearable technologies. Indicated for use in children with type 1 diabetes, these minimally invasive systems continuously measure interstitial glucose levels and transmit data to wearable receivers or mobile applications. Real-time alerts and trend analyses enhance glycemic control during school hours and reduce acute risk events. When integrated with IMU-derived activity data, glucose patterns can be contextualized relative to physical exertion, offering a more comprehensive understanding of activity-related metabolic variability. Emerging wearable platforms increasingly integrate multimodal sensing within compact or textile-based formats. Flexible epidermal sensors and smart garments combine IMUs with heart rate, temperature, or respiratory sensors to improve comfort and long-term compliance in pediatric populations. These systems aim to reduce device intrusiveness while maintaining continuous health surveillance capabilities. Integration within Internet of Medical Things (IoMT) architecture enables wireless data transmission to caregivers or healthcare providers, where cloud-based analytics and machine learning algorithms process longitudinal data streams for anomaly detection and personalized feedback.

Across these device categories, IMU sensors function as the behavioral and biomechanical context layer of pediatric health monitoring, while physiological sensors provide insight into internal biological states. The combined analysis of motion and physiological signals supports early identification of health risks, chronic disease management, and objective evaluation of motor development. However, despite technological progress, challenges remain regarding pediatric-specific calibration, validation of algorithmic outputs, adherence, and secure management of sensitive health data. Ensuring clinical reliability and child-centered design will be essential for responsible integration of wearable technologies into pediatric healthcare frameworks.

Table 1 Categories of Healthcare-Oriented Wearable Devices for Children

Device Category	Primary Sensors	Typical Health Metrics	Clinical / Health Applications	Example Use Context
Child-focused wrist activity trackers	IMU (accelerometer, gyroscope), PPG	Steps, activity intensity, sedentary time, sleep duration, heart rate	Obesity prevention, sleep monitoring, general health promotion	School health programs, preventive monitoring
Research-grade accelerometers	High-resolution IMU	Raw acceleration, gait parameters, activity classification	Pediatric physical activity research, motor assessment	Clinical studies, rehabilitation evaluation
Cardiac & vital sign wearable patches	ECG, PPG, temperature, respiratory sensors, IMU (context)	Heart rhythm, HR variability, respiratory rate, temperature	Arrhythmia detection, autonomic monitoring	Ambulatory pediatric cardiac assessment
Continuous glucose monitoring systems	Subcutaneous glucose sensor	Real-time glucose levels, trends, alerts	Type 1 diabetes management	Daily school-based diabetes care
Multimodal smart textiles / epidermal sensors	IMU + HR + temperature + respiratory sensors	Integrated movement and physiological responses	Long-term monitoring, rehabilitation, stress assessment	Emerging pediatric digital health platforms

3. VALIDATION AND ACCURACY CHALLENGES IN PEDIATRIC WEARABLES

Despite rapid technological advancement, the validation and accuracy of wearable devices in pediatric populations remain significant challenges. Many commercially available wearables were originally developed and calibrated for adult physiology and movement patterns, raising concerns regarding their direct applicability to children aged 6–12 years. Differences in body size, limb proportions, heart rate ranges, gait dynamics, and spontaneous activity behaviors can substantially affect sensor performance and algorithm reliability. As a result, adult-derived models may introduce systematic bias when applied to primary school students.

One major validation challenge involves IMU-based activity classification and energy expenditure estimation. Accelerometer-derived “cut-points” used to define moderate-to-vigorous physical activity (MVPA) are often developed from adult cohorts or older adolescents. However, children exhibit shorter stride lengths, higher cadence, intermittent bursts of movement, and more variable play behaviors. These characteristics complicate intensity classification and may lead to misestimation of physical activity levels. Additionally, device placement (e.g., wrist vs. hip vs. ankle) significantly influences acceleration patterns, making cross-study comparisons difficult and limiting standardization. Validation studies frequently report variability in accuracy depending on placement location, activity type, and epoch length.

Heart rate monitoring via photoplethysmography (PPG) also presents pediatric-specific limitations. Children typically have higher resting and peak heart rates than adults, and smaller wrist circumferences may affect sensor–skin contact quality. Motion artifacts, especially during vigorous play, can degrade PPG signal integrity and lead to inaccurate readings. While resting heart rate measurements are generally reliable, dynamic heart rate tracking during high-intensity or irregular movement is more susceptible to error. In clinical contexts, even small inaccuracies may influence interpretation of exertion levels or autonomic function. Sleep monitoring represents another area of concern. Most wearable sleep algorithms rely heavily on IMU-detected movement and, in some cases, heart rate variability proxies. Compared with polysomnography, the gold standard wearables tend to perform reasonably well in estimating total sleep time but are less accurate in identifying sleep stages or brief awakenings. In pediatric populations, where sleep architecture differs developmentally from adults, these limitations may be amplified. Without pediatric-specific algorithm validation, sleep metrics may overestimate sleep duration or underestimate fragmentation.

For clinically indicated devices such as continuous glucose monitoring (CGM) systems and ambulatory ECG patches, regulatory approval processes ensure baseline safety and performance standards. However, even these systems face practical challenges in pediatric use, including sensor adhesion issues, skin sensitivity, signal dropout during physical activity, and compliance variability. Moreover, real-world accuracy may differ from controlled clinical validation environments, particularly during school-based activities involving sweat, impact, or rapid motion.

Another critical validation issue involves algorithm transparency and generalizability. Many commercial wearable platforms employ proprietary machine learning models that are not openly documented, limiting independent verification of performance in children. When models are trained on adult datasets or non-representative pediatric samples, generalization to diverse populations may be compromised. Factors such as sex, developmental stage, body mass index, and cultural activity patterns can influence motion and physiological signals, potentially introducing demographic bias. Ground-truth acquisition for pediatric validation studies presents additional methodological difficulties. Gold-standard comparisons, such as indirect calorimetry for energy expenditure, polysomnography for sleep, or laboratory-grade motion capture for gait. They are expensive, intrusive, and often impractical in large-scale school-based research. Consequently, sample sizes in pediatric validation studies are frequently small, limiting statistical power and reproducibility.

Data quality is further influenced by adherence and wear-time compliance. Children may remove devices during play, forget to wear them consistently, or adjust placement in ways that affect signal orientation. IMU-based algorithms are sensitive to orientation shifts, and misalignment can degrade classification accuracy. Ensuring consistent wear protocols and designing child-friendly, comfortable devices are essential components of reliable data collection. Finally, ethical and data governance considerations intersect with validation challenges. Continuous monitoring generates high-resolution physiological and behavioral datasets that must be securely stored and appropriately interpreted. False positives, such as erroneous arrhythmia alerts or inaccurate activity flags, which may cause unnecessary anxiety among children, parents, or school staff. Therefore, validation in pediatric wearables must encompass not only technical accuracy but also clinical relevance, usability, and risk–benefit balance.

4. FUTURE TREND

Future healthcare-oriented wearable devices for children aged 6–12 years are expected to advance toward more integrated, accurate, and child-centered systems. A key trend is multimodal sensor fusion, combining IMU-based motion data with physiological signals such as heart rate, respiration, temperature, and glucose levels to provide context-aware health assessment. This integration will improve interpretation of pediatric activity patterns and enhance early detection of health anomalies.

Another important direction is the development of pediatric-specific machine learning models trained on age-appropriate datasets. Personalized and adaptive algorithms will likely replace adult-derived models, improving accuracy in activity classification, sleep estimation, and motor assessment. Advances in flexible electronics and miniaturization will also promote greater comfort, adherence, and long-term usability in school settings. Additionally, wearable systems are expected to become more closely integrated with secure digital health platforms and electronic health records, supporting predictive analytics and preventive care. Ensuring rigorous validation, regulatory oversight, and ethical-by-design implementation will be essential to realizing these innovations responsibly in pediatric healthcare contexts.

5. CONCLUSION

Healthcare-oriented wearable devices for children aged 6–12 years represent a rapidly evolving domain at the intersection of pediatric medicine, sensor technology, and digital health. Current systems incorporate physiological monitoring components—such as heart rate, ECG, respiratory, and glucose sensors—alongside inertial measurement unit (IMU) technologies that quantify physical activity, sleep behavior, gait, and motor function. Together, these sensing modalities enable continuous, real-world health assessment beyond the constraints of episodic clinical visits, supporting preventive care and chronic disease management in school-aged populations.

However, significant validation and accuracy challenges remain. Many wearable devices and embedded algorithms were originally designed for adults, limiting their reliability in children whose physiology and movement patterns differ substantially. Variability in device placement, motion artifacts, limited pediatric-specific datasets, and proprietary algorithm transparency further complicate clinical interpretation. Addressing these challenges requires rigorous pediatric calibration studies, standardized validation protocols, and multidisciplinary collaboration.

With appropriate validation, child-centered design, and strong data governance frameworks, wearable technologies have the potential to enhance pediatric healthcare delivery while supporting healthy development during foundational school years.

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