Movement Behavior in Children using Wearable Biosensors in the Classroom

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Abstract

The earliest milestones of childhood are physical, and motor behavior remains tightly coupled to cognition, arousal, and self-regulation throughout early development. In 4- to 6-year-olds, a sensitive period for prefrontal maturation, how a child moves can carry information about their internal and regulatory state rather than mere physical activity. Yet most of what is known about early childhood movement comes from lab-controlled, discrete-task paradigms, leaving no baseline for how children actually move across a real classroom day or whether that movement reflects the child within it. Here we use a wearable multimodal biosensor to characterize naturalistic motor behavior in 4- to 6-year-olds across structured and unstructured classroom activities, relating IMU-derived movement features to parent-reported affect and self-regulation. We find that movement carries two interleaved signals at once: the amount of movement is structured by activity context, scaling with the freedom an activity affords (lowest in circle time, highest in free play), while the variability of movement is structured by the child, with more variable, abrupt movement tracking higher anxiety, depression, and anger, and smoother movement tracking stronger self-regulation. In contrast to the prevailing view that classroom movement signals distraction or disruption, these results suggest movement functions as a behavioral phenotype—an objective window into children's affective and regulatory states. More broadly, continuously recorded movement may offer a non-invasive way to understand when a child is able to self-regulate and when they struggle. Rather than a behavior to suppress, movement emerges as a functional signal that shifts with both the activity a child is in and the child they are.

Introduction

The earliest milestones of childhood are overwhelmingly physical. A baby's first steps, reaching and grasping, standing and jumping for the first time—these are the developmental markers that parents track most closely, and celebrate loudest, and for good reason. Motor development in early childhood is among the earliest and most reliable indicators that the nervous system is maturing properly. But when children enter school, they are told to sit and be quiet. We have built this assumption that stillness indicates learning, attention, or engagement, but the evidence suggests otherwise. Movement in children is not always random, and it is not merely physical. Children move in ways that reflect their internal states, their level of engagement, their capacity to self-regulate, and their cognitive load in the moment. Movement, in other words, carries a functional signal.

This is particularly true in 4- to 6-year-olds, a sensitive period for prefrontal cortical maturation when the neural circuits that underlie executive function and self-regulation are developing very quickly. Children at this pre-kindergarten age cannot yet properly modulate their own arousal, so the body compensates. When a task gets harder or demands more attention, children may use their bodies to compensate for a cognitive load their still-maturing cortex cannot fully manage. Motor behavior at this age is also less automatic than it will later become, meaning movement patterns are more variable and more likely to reflect underlying cognitive states—and this is exactly the stage when children first enter school and are told to be quiet and sit still.

Because we have been ignoring this signal, or actively suppressing it in the classroom, we have developed incomplete ideas about what movement can mean in a classroom. Children move more during cognitively demanding tasks, because movement can help regulate arousal states that actually support performance and attention (Rapport et al., 2009). Suppressing that movement does not necessarily free up cognitive resources; rather, it can consume them. This signal is individually variable, so the same child moves differently across situations, and different children move differently in the same situation.

We do not yet know what typical movement looks like for 4- to 6-year-olds across a real

school day. Most of what we know comes from lab-controlled studies or discrete controlled tasks. These contexts are internally valid, and a great deal of important work has been done with them, but they are ecologically limited. We have no good baseline for how a 4-year-old moves in the classroom, how much variability is typical, or whether that variability is stable within a child or driven by context. Without this baseline, decisions about children's bodies and behaviors are being made without the context-aware data to support them.

This thesis takes a first step toward that baseline. Using wearable biosensors embedded in a multimodal system, we characterize naturalistic motor behavior in 4- to 6-year-olds across structured and unstructured activities in a simulated classroom day. We organize the work around two central questions. First, can we capture children's movement naturally and continuously in a real classroom? Second, do individual movement patterns across different classroom activities reflect a child's internal and biobehavioral states?

Background

Movement as a functional signal in children

In 4- to 6-year-olds, movement is highly variable and can be directly tied to internal state. Arousal, cognitive load, sensory need, and affect all surface in motor behavior, and in early childhood that relationship is comparatively unfiltered. This is why movement in early childhood has to be measured objectively: the same behavior that looks like distraction may be the visible trace of a regulatory process.

That movement and cognition are coupled rather than separate is well established in developmental work. Fine motor competence in early childhood is treated as a foundational building block of psychological, behavioral, and cognitive development, with early motor skill linked to school readiness and later academic outcomes (Bisi & Stagni, 2025). If motor behavior is entangled with cognitive and regulatory development at this depth, then how a child moves is not incidental to what a child is doing but is part of the same system.

The dominant view in educational contexts treats excessive or dysregulated movement as evidence of disruption, inattention, or behavioral disorder. A more empirically grounded view

treats it as information: movement may be compensatory. In the ADHD literature, children with ADHD show elevated levels of movement during cognitively demanding tasks, and this has been interpreted as a deficit in inhibitory control. On the contrary, movement in such cases may function as a compensatory arousal mechanism. Rapport et al. (2009) show that hyperactive movement increased during tasks requiring sustained attention and working memory and that this movement was associated with better performance on those tasks.

Movement upregulates arousal via the locus coeruleus–norepinephrine (LC–NE) system and dopaminergic pathways, both of which are critically involved in attention and executive control (Sonuga-Barke et al., 2022). In children with ADHD, whose dopaminergic and noradrenergic systems are dysregulated, self-generated movement could serve as a behavioral mechanism for achieving the arousal state necessary for cognitive engagement. But this mechanism is not unique to ADHD. It reflects a general property of the developing nervous system—the coupling of movement to arousal and cognitive engagement—which ADHD simply makes visible. If that coupling is general, then suppressing movement does not necessarily free cognitive resources; it may consume them, impairing the very performance the movement was regulating.

Naturalistic observation and the ecological-validity gap

Most early childhood learning and developmental research relies on lab-controlled, discrete-task paradigms that are internally valid but ecologically limited. No baseline exists for how 4- to 6-year-olds naturally move in a classroom, or how much variability is typical. This introduces a systematic gap. The rehabilitation literature draws an explicit distinction, following the International Classification of Functioning, between capacity and performance. The two can diverge, and capacity measured in the lab need not predict performance in the world (Strohrmann et al., 2013). The same gap appears in developmental psychology, where direct assessments are administered in lab-like environments and reports are only generally informative and untied to specific situations, so that by design both approaches gloss over the moment-to-moment, situational variation that is itself of interest (Eberhart et al., 2024). Naturalistic observation

captures that variation as it occurs, but it is labor-intensive and depends on human coders.

Wearable Sensors

Wearable movement sensors report movement quantity and movement quality, such as smoothness, variability, and motion coordination (Swain et al., 2023). The regulatory signal lives in movement quality, so understanding how much a child moves, and more importantly how they move, is important. Several devices and tools are able to quantify movement, but they trade off differently against the demands of a classroom. Optical motion capture is accurate but time-consuming and resource-intensive, requiring a dedicated laboratory setup that limits its applicability in natural conditions (Bisi & Stagni, 2025).

Inertial measurement units (IMUs) are sensors that measure and report accelerometer, gyroscope, and magnetometer signals in a way that is robust and practical for assessment in ecological conditions (Bisi & Stagni, 2025; Swain et al., 2023). Specifically when working with children, the wearable fit is crucial. This matters because anything overstimulating could lead to device manipulation or refusal and distort the very signal of interest. A single, low-profile wearable yields less data than a full array but is unobtrusive enough to preserve naturalistic behavior across a long day.

Features extracted from the IMU map onto established movement descriptions. Mean acceleration magnitude has been used to index movement intensity in pediatric sensor work, alongside the variation of that intensity, the smoothness of movement, and the range of angular velocity (Strohrmann et al., 2013); angular velocity and acceleration-based metrics likewise characterize fine motor control and its variability in early childhood (Bisi & Stagni, 2025). The present work summarizes the IMU stream through complementary features in this tradition: the Euclidean Norm Minus One (ENMO) as overall acceleration magnitude (Bai et al., 2016), jerk as the rate of change of acceleration and thus movement intensity (Melendez-Calderon et al., 2021), and angular velocity as rotational rate. This captures how much a child moves, how abruptly, and how they rotate. These come from a multimodal biosensor that also records electrodermal activity, photoplethysmography, and temperature, validated against gold-standard sensors for

inferring psychophysiological state (Montgomery et al., 2024).

As shown in Figure 1, the EmotiBit device provided the primary biometric sensing capabilities.

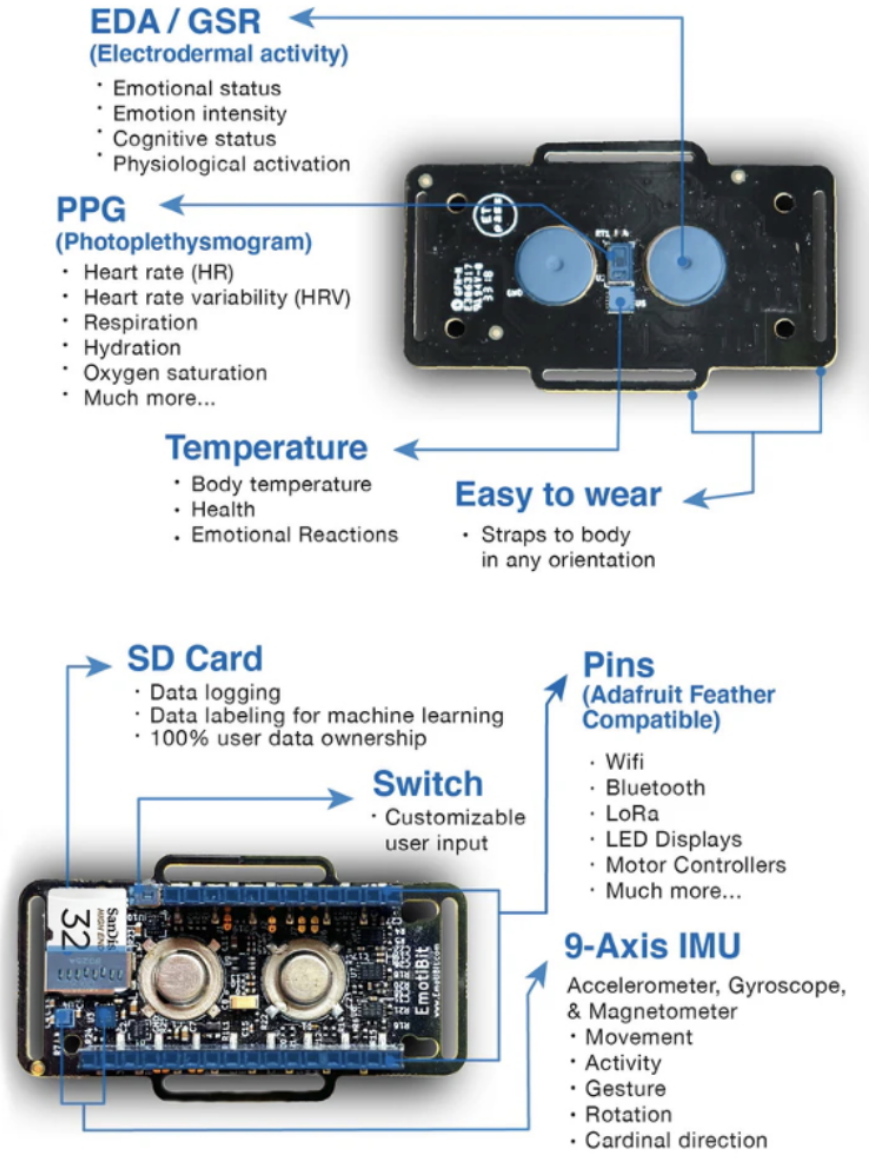


Figure 1

Overview of EmotiBit and its physiological sensing capabilities, adapted from Montgomery et al. (2024).

Method

Human subjects

Written informed consent was obtained from parents prior to participation. On the first day of each camp week, the devices were introduced to the children with simple, age-appropriate explanations emphasizing bodily autonomy, and children were free to decline or remove the device at any point.

Study Design

Data were collected using an embedded multimodal system that captures video, audio, and physiological data from children in a lab-grade setup of a classroom. The classroom is designed to approximate the conditions of a kindergarten classroom running a curriculum delivered by a teacher with a rotating teaching assistant, including activities such as morning songs, read-aloud and circle sessions, thematic lessons, focused movement activities and games, free play, and quiet time. The curriculum was designed to allow naturalistic play with quasi-structured activities so that characteristic developmental and regulatory responses could be elicited without disrupting the natural flow of the classroom. Data were collected for 5 hours per day, 5 days per week, across the camp.

Participants

Across the full study, 43 children aged 4 to 6 years participated over seven weeks, with a new cohort entering at the start of each week. Children participated in a 5 day summer camp approximately 5 hours a day. This thesis analyzed three of those weekly cohorts. The full sample contained 16 children and was used for general movement characterization. Correlation analyses used a subset of 13 children for whom data were available.

Data acquisition

An embedded multimodal system captured synchronized video, audio, and physiological/movement data from the children throughout the curriculum. Visual data in the classroom were collected using six Bolin D412 Dante AV PTZ cameras and four GoPro HERO13

cameras. Cameras were positioned to capture both the full classroom and individual participants' facial expressions. Auditory data were collected with a Shure MXA310 Table Array Microphone placed centrally in the classroom and Rode Wireless GO II lapel microphones worn by participants. Physiological and movement data were collected with EmotiBit biosensors (described below).

All devices were routed through an IGS-6325-8T8S4X Layer 3 switch (PLANET Technology) and synchronized via a Model 5401A Dante Grandmaster Clock using Precision Time Protocol (PTP). Time synchronization is central to the analysis because the regulatory signal of interest depends on aligning a child's movement to the specific activity they were engaged in and, in future work, to their concurrent physiology and video; every device must share a common clock. PTP achieves this by designating a single leader clock as the authoritative time source and continuously disciplining all other devices on the network to it, correcting for transmission delay so that timestamps from different sensors refer to the same instant to within sub-millisecond precision. Activity boundaries within the day were logged using ELAN markers in post-processing as well as a real-time marker script, using a custom Python script with manual keyboard input to produce event markers. Segmentation of the movement data into activities (below) used the alignment between these logged activity timestamps and the EmotiBit recording timeline.

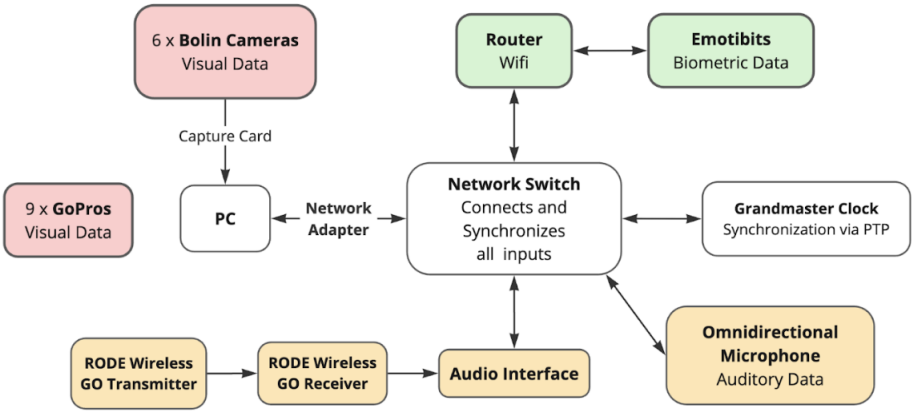


Figure 2

The multimodal embedded data-collection system.

Movement and physiology were recorded with EmotiBit v04a sensors, each powered by an Adafruit HUZZAH32 Feather. The EmotiBit measures electrodermal activity (EDA), photoplethysmography (PPG), temperature, and 9-axis Inertial Measurement Unit (IMU; accelerometer, gyroscope, magnetometer) motion data. These signals have been validated for use in inferring psychophysiological states and sympathetic–parasympathetic balance (Montgomery et al., 2024). Data were recorded to the onboard SD card to ensure no packet loss. Each EmotiBit was encased in a custom 3D-printed thermoplastic polyurethane (TPU) case. TPU was chosen because it is soft and flexible rather than rigid, reducing discomfort during prolonged wear. The case went through several design iterations: it was first fitted to the EmotiBit, then refined to smooth edges and corners, and finally given a velvet-lined border and a velvet band/scrunchy to maximize comfort. The device was worn on the participant's nondominant wrist so that, during seated tasks such as coloring, the recorded motion reflects natural whole-body movement rather than only task-related dominant-hand activity.

Children's social-emotional and self-regulatory functioning was assessed with the PROMIS Early Childhood (PROMIS-EC) Parent Report measures. PROMIS-EC is a bank of parent-reported health measures used to evaluate the physical, mental, and social well-being of

children. Parents respond on behalf of their child, and each instrument yields a single summary score per child per subscale. The measures used here span two domains: emotional distress (Anxiety, Depressive Symptoms, and Anger) and well-being (Positive Affect, Engagement: Curiosity, Engagement: Persistence, Self-Regulation: Flexibility, and Self-Regulation: Frustration Tolerance).

Table 1

Sampling rates of physiological and motion signals recorded by EmotiBit sensors.

Signal	Sampling Rate
IMU	25 Hz
Photoplethysmography (PPG)	100 Hz
Electrodermal Activity (EDA)	15 Hz
Temperature	7.5 Hz

Data Processing

ELAN markers were inputted into the video in post-processing to indicate activity start times. Event marker timestamps were extracted and aligned with the EmotiBit local timestamps. Each child's data were segmented into three activity contexts that appear in the curriculum and differ in their structure and regulatory demands: circle time (structured, instructed, low expected movement), free play (unstructured, uninstructed, high expected movement), and movement (structured, instructed, high expected movement). These three contexts form the within-child comparison used throughout the analysis.

From each activity segment, three movement features were computed from the IMU data:

Euclidean Norm Minus One (ENMO): the mean magnitude of acceleration with gravity removed, ENMO $= \sqrt{x^2 + y^2 + z^2} - 1$, where x, y, and z are the accelerometer axes expressed in gravitational units (g); ENMO is therefore reported in g and indexes total movement (how much the child moved).

Jerk: the rate of change of acceleration over time, $\mathrm{d}a/\mathrm{d}t$, indexing movement intensity / abruptness (how sharply motion changed).

Angular velocity: the rate of change of rotational angle, $\omega = \mathrm{d}\theta/\mathrm{d}t$, computed from the gyroscope and indexing rotation.

Together these give an informative description that is also feasible to extract from a low-profile wrist sensor (cf. Bisi & Stagni, 2025; Strohrmann et al., 2013). For each feature, both the mean and the standard deviation across the segment were computed. In total, six movement features were computed per child per activity.

All metrics were then recorded and compiled in a dataframe for each week. Missing values were dropped, and observations during which a child was not wearing the sensor were excluded; all retained data were verified to have been recorded while the child was wearing the device. The dataframes were then run through a statistical analysis and visualization pipeline.

Analysis

To observe associations between the PROMIS-EC subscales and the movement features, Spearman rank correlations were run for each of the three activity contexts. For each activity, every movement feature was correlated with every PROMIS-EC subscale.

To examine how movement evolved over the course of an activity and across the camp, the ENMO signal during circle time was analyzed as a time series rather than collapsed to a single value. For each child, ENMO during circle time was smoothed with a Gaussian kernel to show how movement changed over time.

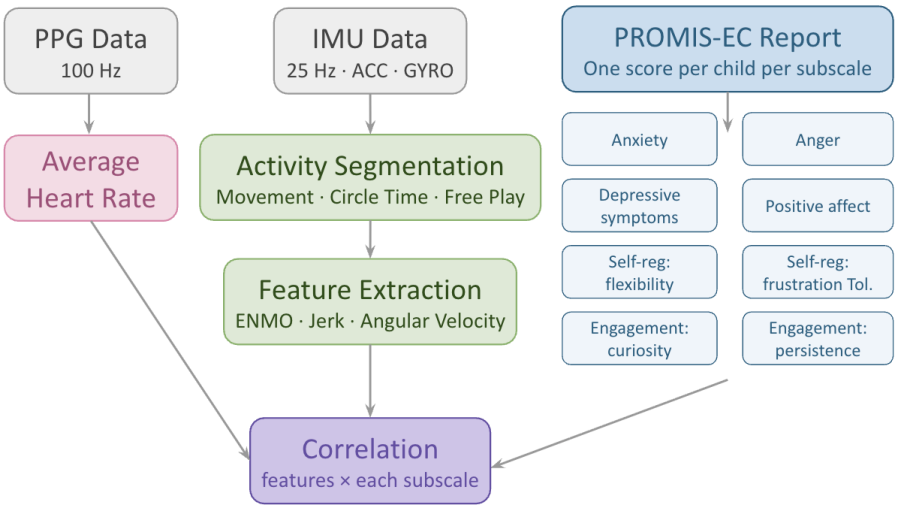


Figure 3

Analysis and processing pipeline for this study.

Results

This section returns to the two questions that motivated this study. First, whether children's movement can be captured naturally and continuously across a classroom day, which is addressed by exploring how recorded IMU movement tracks movement during classroom activity and how it differs between children. Second, whether individual movement patterns across classroom activities reflect a child's internal and biobehavioral states, which is addressed by relating each child's movement features to parent-reported affective and self-regulatory scores.

Movement was characterized for 16 children across three activity contexts (circle time, free play, and a structured movement block), using six IMU-derived features (the mean and standard deviation of ENMO, angular velocity, and jerk). For the subset of 13 children with parent-report data available, these features were then related to eight PROMIS-EC subscales.

Total movement was structured by activity. This is seen in circle time, where we observed the lowest movement for almost every child. This was the case across all three motion metrics. Free play produced the highest movement for the majority of children. Mean ENMO during free play reached around 0.14–0.17 *g* in the most active children (e.g., P02, P03, P12), compared with circle time values near 0.02–0.06 *g* for those same children. This effect was not consistent across

all children: a subset (e.g., P04, P06, P08, P14, P15) moved at comparable levels across all three contexts. In some cases (e.g., P01, P10), the structured movement activity exceeded free play.

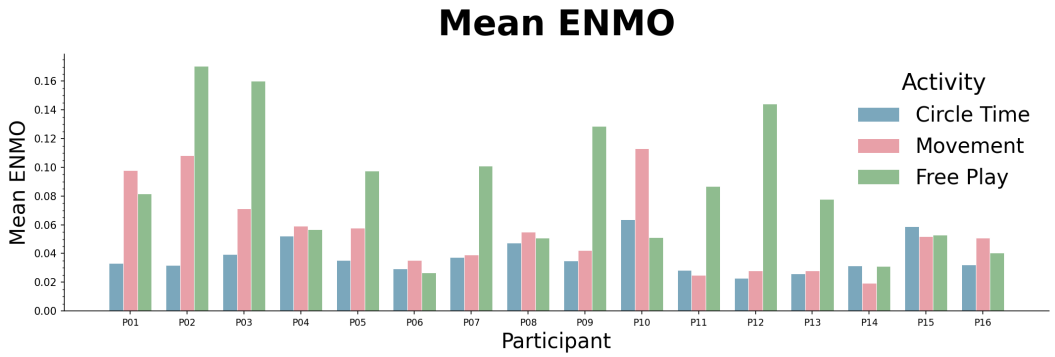


Figure 4

Total movement by activity for each participant across three cohorts and three weeks of camp ($N = 16$). Bars represent the mean ENMO (total movement, in g) during circle time (blue), movement (pink), and free play (green). Movement was consistently lowest in circle time and highest in free play across all three metrics. A subset of children demonstrated equivalent movement in all three conditions.

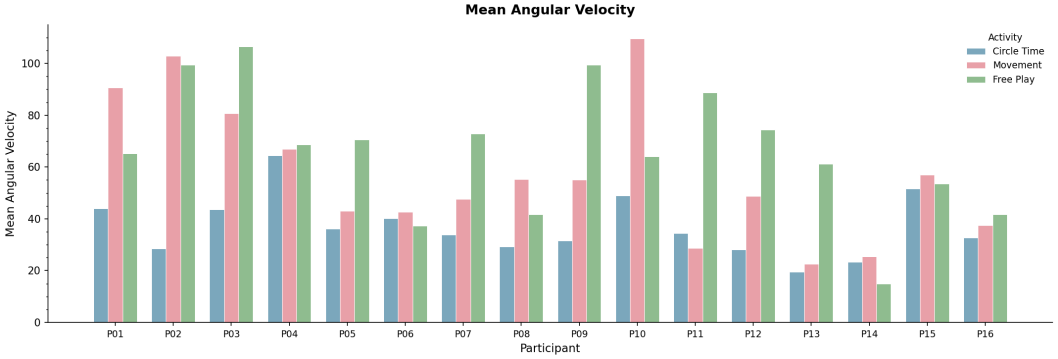


Figure 5

Mean angular velocity (degrees/s) by activity type for each participant ($N = 16$). Across most participants, angular velocity was highest during movement and free play compared with circle time.

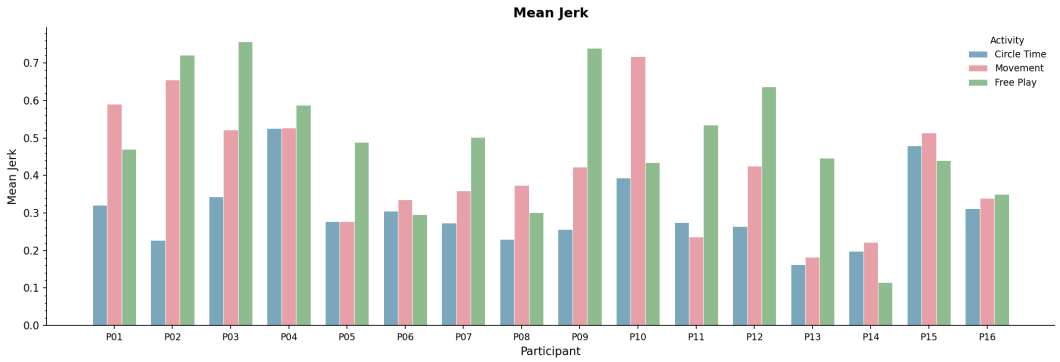


Figure 6

Mean jerk (units/s^3) by activity type for each participant ($N = 16$). Free play and movement activities were generally associated with greater mean jerk than circle time, reflecting more abrupt changes in acceleration.

There was substantial within-child variability in average movement. Mean ENMO spanned roughly a twofold range within a cohort. The within-child error bars were large and themselves varied across children, indicating that children differed not only in their average movement level but in how widely that movement ranged across activities and days. These between-child differences in level and spread were present alongside, and independent of, the context effect described above.

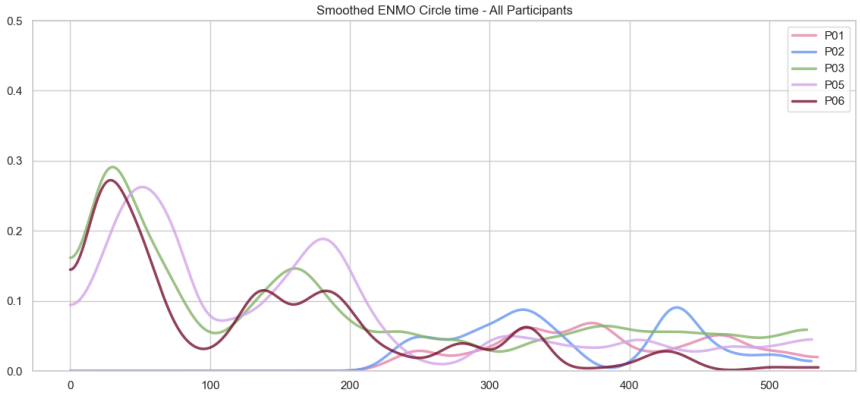


Figure 7

Smoothed ENMO during circle time on Day 1 of camp.

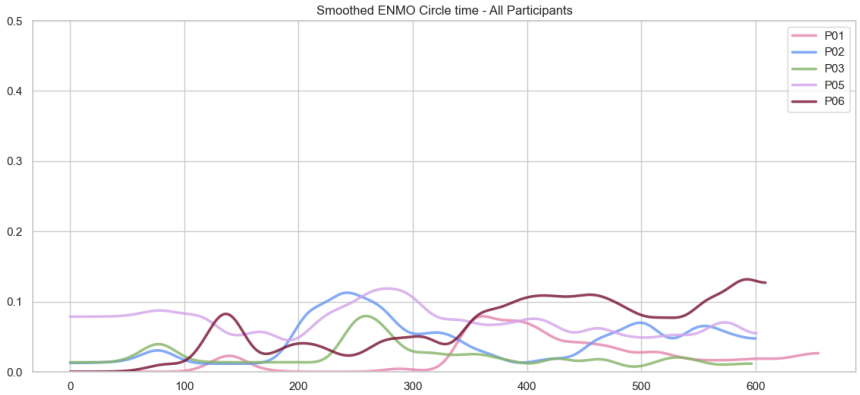
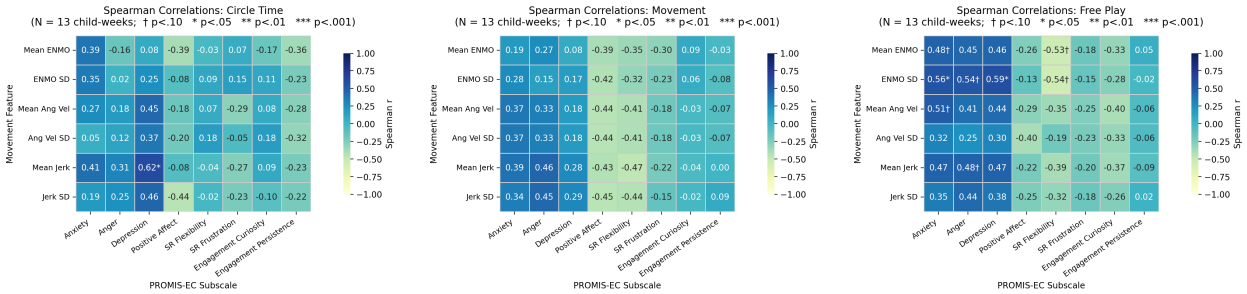


Figure 8

Smoothed ENMO during circle time on Day 5 of camp.

The correlation analyses showed a consistent directional pattern that was strongest in free play. Across contexts, anxiety, depression, and anger were positively associated with movement features, whereas positive affect and self-regulation–flexibility were negatively associated. The clearest associations involved ENMO variability (ENMO standard deviation) during free play. Free-play ENMO SD correlated positively with Anxiety ($r = .56$, $p = .049$), Depression ($r = .59$, $p = .033$), and Anger ($r = .54$, $p = .054$), and negatively with Self-Regulation–Flexibility ($r = -.54$, $p = .057$). Mean ENMO during free play followed the same directions (e.g., Anxiety $r = .48$, SR Flexibility $r = -.53$), as did free-play angular velocity (Anxiety $r = .51$). Children with the lowest free-play ENMO SD (e.g., P14) also had the lowest distress scores, while children with the highest ENMO SD (e.g., P03, P12) had the highest.

The structured movement context showed no significant or trend-level correlations. Circle time showed one significant positive correlation, between mean jerk and depressive symptoms ($r = .62$, $p = .025$). This indicates that children with higher depression scores exhibited more abrupt movement during circle time. No other associations were significant or trend-level.



(a) (b) (c)

Figure 9

Spearman correlations between movement features and PROMIS-EC subscales within each activity context: (a) circle time, (b) structured movement, and (c) free play ($N = 13$).

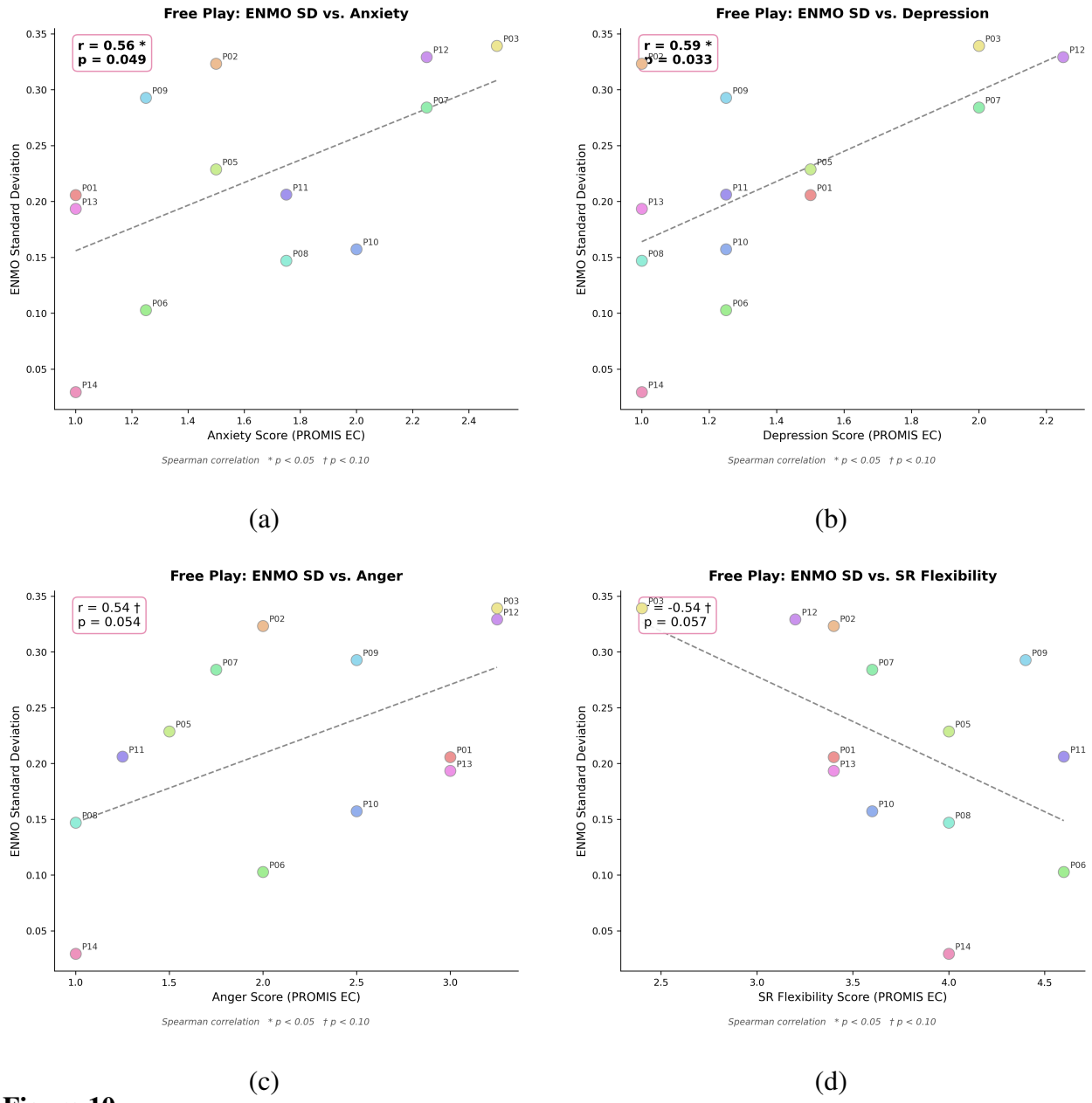
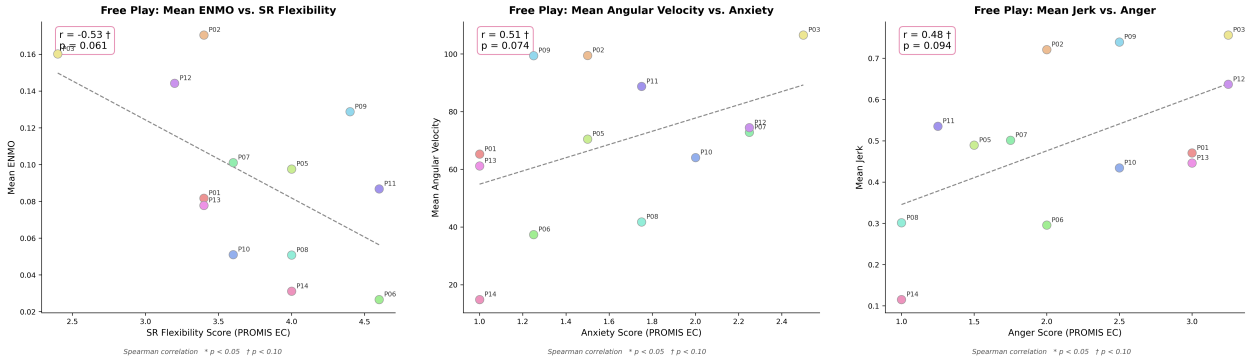


Figure 10

ENMO standard deviation (movement variability) during free play versus parent-reported PROMIS-EC subscales: (a) anxiety, (b) depressive symptoms, (c) anger, and (d) self-regulation–flexibility. Each point is one participant ($N = 13$). Spearman correlations: anxiety $r = .56$, $p = .049$; depression $r = .59$, $p = .033$; anger $r = .54$, $p = .054$; SR flexibility $r = -.54$, $p = .057$. Higher distress is associated with greater movement variability, and higher self-regulation–flexibility with lower variability.



(a) (b) (c)

Figure 11

Free-play associations between movement features and PROMIS-EC subscales: (a) mean ENMO versus self-regulation–flexibility ($r = -.53,\ p = .061$), (b) mean angular velocity versus anxiety ($r = .51,\ p = .074$), and (c) mean jerk versus anger ($r = .48,\ p = .094$). Higher distress is associated with faster, more intense movement, and higher self-regulation with lower movement intensity.

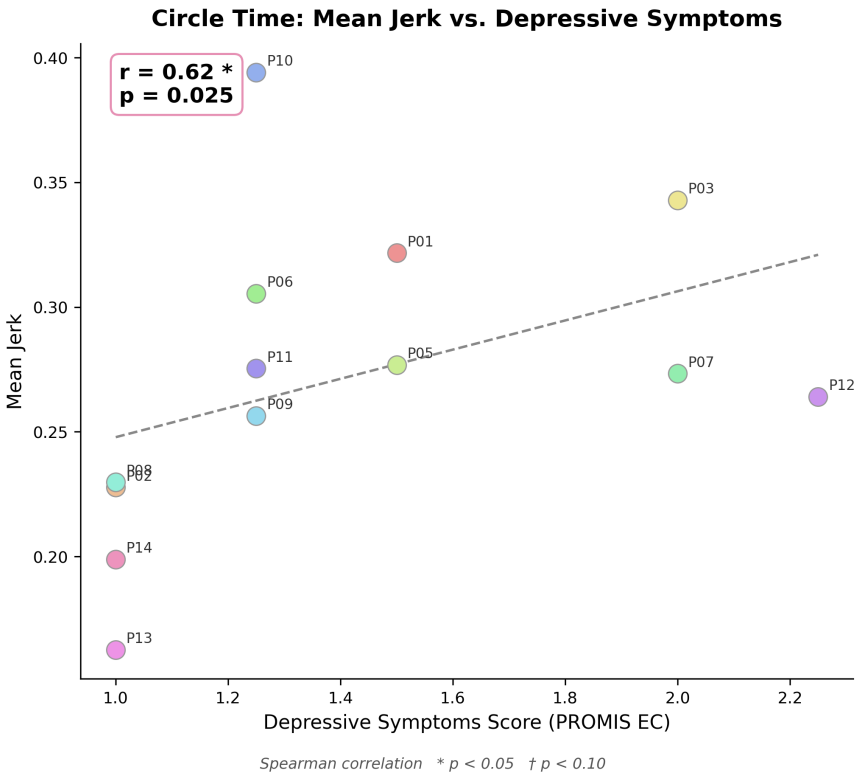


Figure 12

Mean jerk during circle time versus parent-reported PROMIS-EC depressive symptoms ($r = .62$, $p = .025$). Children with higher depression scores produced more abrupt, less smooth movement during structured group activity.

Discussion

This thesis examined whether children's movement can be measured naturally across a classroom day, and whether it reflects characteristics of the child who is moving. Using the EmotiBit biosensor in a naturalistic classroom setting, movement was recorded continuously across a range of classroom activities and contexts. The amount of movement was strongly shaped by the activity itself for the majority of children: movement was lowest during circle time and highest during free play, a pattern that was consistent across ENMO, angular velocity, and jerk measures. For a subset of children, however, movement was roughly equivalent across all three contexts, which indicates individual variability in movement patterns. This raises the possibility that a second profile, one in which movement is less tied to the demands of the activity,

may emerge with a larger sample.

In contrast, variability in movement was shaped by the individual child and was associated with parent-reported affect and self-regulation. Greater movement variability during free play was linked to higher levels of anxiety, depression, and anger, as well as lower self-regulatory flexibility. More abrupt movement during circle time was associated with depressive symptoms. These findings suggest that movement in early childhood classrooms is neither random nor uniform; instead, it reflects both the structure of the environment and characteristics of the child.

Situating these findings within a broader context, a picture emerges in which children's movement is organized along two distinct dimensions. The first reflects the environment and determines how much movement an activity permits. The second reflects the child and captures how the child moves within those environmental constraints. While the first dimension is expected, the second is more subtle and potentially more informative. It suggests that continuously recorded movement signals may provide an objective window into children's affective and self-regulatory states, linking everyday behavior to underlying biobehavioral processes.

These individual movement findings demonstrate how movement patterns in children can function less like noise and more like behavioral phenotypes. They differed between children: free-play movement variability ranged widely, from children at the low end (e.g., P14, who also had the lowest distress scores) to those at the high end (e.g., P03 and P12, who had the highest). We saw the same pattern across all three cohorts. These patterns differed between children and recurred across cohorts; most notably, they correlated systematically with parent-reported scores collected entirely separately from the movement data. The phenotypes also surfaced differently across contexts rather than identically everywhere, which is informative in itself. Some children's regulatory signatures were legible in some settings and muted in others. This pattern is consistent with the broader perspective that quality of movement carries regulatory information and that movement variability in early childhood can reflect meaningful individual differences rather than mere immaturity (Bisi & Stagni, 2025).

Movement is grounded in the coupling of motor and regulatory systems, which are linked at the level of neural architecture. The somatocognitive action network describes the integration of primary motor cortex with regions that govern arousal and autonomic control (Gordon et al., 2023). Self-generated movement, in turn, upregulates arousal through the systems that support attention and executive function (Rapport et al., 2009). Against this backdrop, a child whose affective and regulatory state surfaces in how variably or abruptly they move is exactly what one would expect: heightened distress expressed as more variable, less settled movement, and stronger self-regulation expressed as smoother, steadier movement.

In this study, the movement signal was clearest in free play and weaker under structure. Externally imposed structure may constrain movement and compress differences between children, whereas unstructured, uninstructed activity gives regulation room to breathe. This is reflected in other naturalistic work showing that children's self-regulation is more fully expressed in unstructured, uninstructed activities than in structured, instructed ones, and that individual differences are more visible when the environment permits it (Eberhart et al., 2024). It also reflects the capacity–performance distinction from the rehabilitation literature: what a child can do in a constrained task may not predict what they do in the freedom of real activity, and the regulatory signal lives in the latter (Strohrmann et al., 2013).

At a system level, the approach itself proved valuable. The multimodal embedded system achieved millisecond precision and synchronized recordings across all three data streams. At the same time, the study revealed some practical limitations that come with naturalistic data from young children. Although we prioritized children's bodily autonomy and explained the devices to them, some children became more aware of the sensors and occasionally fidgeted with them. The data quality was not always consistent because of motion artifact, which was expected for a pilot study with child participants. Observations in which a child did not wear the sensor properly, or at all, were excluded; we consider these design constraints.

Children's phenotypes are dynamic, context-dependent, and highly variable across individuals. A method that preserves variability across time and context is more useful for

understanding children than a single snapshot or discrete measure. The central challenge is to build a system that is unobtrusive and robust enough to capture behavior throughout a child's everyday activities, and meeting that challenge was part of this thesis's contribution. A personalized approach to early childhood education could identify the situations in which a child is able to self-regulate effectively and the situations in which they struggle. That information could then be used to better support the child rather than suppress their movement. In this way, movement can become a source of diagnostic information that helps guide how environments and activities are designed around individual needs.

Limitations

The sample size was small and the analyses conducted were exploratory. Several observed associations were only trend-level and did not reach statistical significance, and therefore should be viewed as testable hypotheses rather than confirmed findings. Movement was measured using a single sensor worn on the wrist. This inevitably captures only a subset of whole-body movement and provides less information than a multi-sensor approach. However, this reflects a deliberate tradeoff between measurement completeness and ecological validity. By prioritizing an unobtrusive and feasible setup, behavior could be recorded continuously in a naturalistic classroom setting, especially with young children.

Future Directions

A clear next step would be to integrate other streams from the biosensor. Electrodermal activity (EDA), photoplethysmography (PPG), and skin temperature provide complementary information about physiological arousal and behavior. A further step would be to explore and validate additional movement metrics. For example, mean amplitude deviation (MAD) has been proposed as an alternative measure of movement variability and intensity that does not require gravity subtraction and may be less susceptible to floor effects than ENMO-derived metrics (Bakrania et al., 2016). Future studies should test whether the same patterns emerge using alternative measures of movement.

We hope to move beyond describing movement phenotypes toward using them to support

individual children. If movement patterns can reliably predict affect and internal states, then they may eventually help us explain contexts in which a child may thrive or struggle.

Understanding young children is difficult, and no single task or moment can capture it. This thesis shows that movement, measured continuously and in context, is a direct and underused way to see a child whole. Movement is not a behavior to suppress or quiet but a functional signal, one that shifts with both the activity a child is in and the child they are. A child's movement carries us past surface snapshots toward a fuller picture of how children regulate, move, and learn.

References

Bai, J., Di, C., Xiao, L., Evenson, K. R., LaCroix, A. Z., Crainiceanu, C. M., & Buchner, D. M. (2016). An activity index for raw accelerometry data and its comparison with other activity metrics. *PLOS ONE*, *11*(8), Article e0160644. https://doi.org/10.1371/journal.pone.0160644

Bakrania, K., Yates, T., Rowlands, A. V., Esliger, D. W., Bunnewell, S., Sanders, J., Davies, M., Khunti, K., & Edwardson, C. L. (2016). Intensity thresholds on raw acceleration data: Euclidean norm minus one (ENMO) and mean amplitude deviation (MAD) approaches. *PLOS ONE*, *11*(10), Article e0164045. https://doi.org/10.1371/journal.pone.0164045

Bisi, M. C., & Stagni, R. (2025). IMU-based linear and nonlinear metrics for the characterization of fine motor development in early childhood. *Gait & Posture*, *122*, 130–136. https://doi.org/10.1016/j.gaitpost.2025.06.025

Eberhart, J., Bryce, D., & Baker, S. T. (2024). Staying self-regulated in the classroom: The role of children's executive functions and situational factors. *British Journal of Educational Psychology*, *94*(3), 995–1010. https://doi.org/10.1111/bjep.12700

Gordon, E. M., Chauvin, R. J., Van, A. N., Rajesh, A., Nielsen, A., Newbold, D. J., Lynch, C. J., Seider, N. A., Krimmel, S. R., Scheidter, K. M., Monk, J., Miller, R. L., Metoki, A., Montez, D. F., Zheng, A., Elbau, I., Madison, T., Nishino, T., Myers, M. J., et al. (2023). A somato-cognitive action network alternates with effector regions in motor cortex. *Nature*, *617*(7960), 351–359. https://doi.org/10.1038/s41586-023-05964-2

Melendez-Calderon, A., Shirota, C., & Balasubramanian, S. (2021). Estimating movement smoothness from inertial measurement units. *Frontiers in Bioengineering and Biotechnology*, *8*, Article 558771. https://doi.org/10.3389/fbioe.2020.558771

Montgomery, S. M., Nair, N., Chen, P., & Dikker, S. (2024). Validating EmotiBit, an open-source multi-modal sensor for capturing research-grade physiological signals from anywhere on the body. *Measurement: Sensors*, *32*, Article 101075. https://doi.org/10.1016/j.measen.2024.101075

Rapport, M. D., Kofler, M. J., Alderson, R. M., Timko, T. M., & DuPaul, G. J. (2009). Variability of attention processes in ADHD: Observations from the classroom. *Journal of Attention Disorders*, *12*(6), 563–573. https://doi.org/10.1177/1087054708322990

Sonuga-Barke, E. J. S., Becker, S. P., Bölte, S., Castellanos, F. X., Franke, B., Newcorn, J. H., Nigg, J. T., Rohde, L. A., & Simonoff, E. (2022). Annual Research Review: Perspectives on progress in ADHD science-from characterisation to cause. *Journal of Child Psychology and Psychiatry*, *64*(4), 506–532. https://doi.org/10.1111/jcpp.13696

Strohrmann, C., Labruyère, R., Gerber, C. N., van Hedel, H. J., Arnrich, B., & Tröster, G. (2013). Monitoring motor capacity changes of children during rehabilitation using body-worn sensors. *Journal of NeuroEngineering and Rehabilitation*, *10*, Article 83. https://doi.org/10.1186/1743-0003-10-83

Swain, T. A., McNarry, M. A., Runacres, A. W. H., & Mackintosh, K. A. (2023). The role of multi-sensor measurement in the assessment of movement quality: A systematic review. *Sports Medicine*, *53*(12), 2477–2504. https://doi.org/10.1007/s40279-023-01905-1