Frequent, Scalable and Global Use of "Intelligent Onesies" to Quantify Newborns' Spontaneous Movements in Natural Settings

Ori Ossmy
Centre for Brain and Cognitive Development
School of Psychological Science
Birkbeck, University of London
London, UK
ori.ossmy@bbk.ac.uk

Hannah Rowan
School of Psychology
University of Sussex
Brighton, UK
H.J.Rowan@sussex.ac.uk

Mohammad Saber Sotoodeh
School of Psychology
University of Sussex
Brighton, UK
S.Sotoodeh@sussex.ac.uk

Jazmine Hall
Centre for Brain and Cognitive Development
School of Psychological Science
Birkbeck, University of London
London, UK
jhall58@student.bbk.ac.uk

Georgina Donati
Department of Psychiatry
Warneford Hospital
University of Oxford
Oxford, UK
georgina.donati@psych.ox.ac.uk

Gillian Forrester
School of Psychology
University of Sussex
Brighton, UK
G.Forrester@sussex.ac.uk

Abstract—**Early identification of atypical neurological function in newborns is essential for the timely detection of cerebral palsy and other neurodevelopmental conditions such as Autistic Spectrum Disorder. Traditionally, assessing infants' spontaneous general movements provides a clinical standard for early detection. Such assessment requires specialized training and periodic in-person observation—conditions that can be difficult to fulfil for many families. Recent technological advances in wearable inertial sensors raise the exciting possibility of an automated, home-based protocol for general movement assessment (GMA) that could increase reach and reduce costs. In this project, we examined the feasibility of testing newborns' spontaneous movements in high frequency and in their natural setting. To that end, we created a wearable "intelligent onesie" equipped with inertial measurement units. The data collections were administered by caregivers and were monitored remotely using secure tunnelling to local Raspberry-Pi devices. We detail the setup and methodological challenges encountered—from shipping the home recording kits to ensuring adequate sensor placement, data syncing, calibration, and retrieval—and how we overcame them. We demonstrate how to collect large-scale and global data that capture newborn spontaneous movements in home environments. We discuss implications for leveraging automated GMA for early intervention pathways and future directions for scalable infant neurodevelopmental screening.**

Keywords—General Movements; Newborns; Wearables; Inertial Sensors; Atypical Motor Development; Infancy;

I. INTRODUCTION

Newborns exhibit rich spontaneous movement patterns that reflect the function of the central nervous system. Over the first weeks and months of life, the developing motor system shows hallmark variability and complexity in infants' general spontaneous movements. Atypicality in these movements may signal an increased risk for neurodevelopmental disorders such as cerebral palsy, Rett syndrome, or global motor delay [1, 2]. Identifying atypical motor activity very early—ideally within the first months of life—can pave the way for prompt therapeutic interventions that may improve long-term neurological outcomes [3].

The General Movements Assessment (GMA) is a clinical framework that focuses on these spontaneous movements, primarily through visual observation of video recordings from the first days and weeks of life. GMA is valued for its high sensitivity to neurological dysfunction, even before overt clinical milestones like rolling, sitting, and crawling become relevant for standard pediatric screening [4]. However, GMA depends on specialized training; experts often need to see multiple structured videos of newborns in calm or awake states, unimpeded by swaddling or excessive caregiver handling. For families in rural areas or those lacking easy access to specialized clinics, scheduling repeated GMA sessions can be difficult and expensive. In addition, capturing the newborn in an ideal behavioral state is challenging, given unpredictable sleep or fussiness cycles.

In recent years, wearable sensor technology has demonstrated efficacy in capturing infant motor activity in an objective manner [5-7]. By integrating accelerometers, gyroscopes, and magnetometers, researchers can obtain high-frequency time-series data that describe movements across multiple limbs. Because GMA focuses on subtle, spontaneous movement features (e.g., movement complexity, variation in amplitude and speed, and fidgety patterns), capturing data at higher sampling rates may be advantageous for automated detection algorithms. Yet, there remain major deployment challenges that hamper the widespread adoption of home-based sensor solutions for GMA—particularly for newborns whose bodies are smaller, more fragile, and require additional considerations for comfort, warmth, and safe positioning.

Traditional GMA is conducted in a controlled clinical or lab environment, with overhead cameras capturing movements for 3–5-minute segments. For in-home GMA, parents or caregivers must replicate something akin to a mini-lab setup or at least reliably record their newborn in an unencumbered posture [7]. A standard camera arrangement can be prone to poor lighting, partial occlusions, or shaky footage, impacting GMA reliability. Even if high-quality video is attained, an expert must later view and score it manually [7].

The present work addresses challenges in measuring newborns' spontaneous movements by integrating a customized "intelligent onesie," a multi-IMU sensor array, a Raspberry Pi microcomputer for local data handling, and the use of secure tunnelling for remote assistance. We present a novel methodology for a frequent, scalable and global quantification of spontaneous movements in newborns' natural settings. The methodology involves (1) providing caregivers with a well-structured kit that minimizes intimidation and confusion and can be used globally in a large cohort, including families with limited technological literacy; (2) acquiring reliable, high-sample-rate inertial data from each newborn automatically and remotely controlled; and (3) developing a machine-learning pipeline to detect motion patterns that might be relevant for predicting subsequent socio-communication skills.

II. RELATED WORKS

Given the constraints of continuous video monitoring, many scholars have turned to wearable IMUs as an alternative means of tracking infant motor activity [8-10]. Wearable sensors can remotely record rich, quantitative data—including accelerations, angular velocities, and magnetic orientations—thereby reducing or eliminating the need for direct observation [11-13]. By capturing large, high-resolution datasets, these sensor arrays allow researchers to detect posture transitions (e.g., supine to prone), classify different activities (e.g., crawling, rolling, or being carried), and potentially identify nuanced features of spontaneous general movements [1, 11]. Importantly, systematic reviews highlight that IMU-based solutions can achieve comparable reliability to traditional observational methods while also enabling continuous or frequent measurements in home environments and allowing anonymity, which is beneficial for sharing the data with other researchers and support open science [8, 10].

Parallel to the adoption of wearable technology, machine learning has gained prominence for processing and interpreting extensive time-series data generated by IMUs [7, 8, 13]. Supervised classification approaches, trained on brief human-coded video segments, have achieved high accuracies—often exceeding 90%—in classifying postural and locomotor states [1, 7, 11]. By extracting motion features such as speed, amplitude, and variability, algorithms can detect distinct movement signatures relevant to infant development. This approach has proven particularly valuable for identifying transient or low-frequency behaviors, which might be overlooked in short manual observations. Although these algorithms are promising, challenges remain in (i) differentiating subtle variations within each posture type (e.g., being held in different ways), (ii) adapting to atypical movements that differ significantly from normative training data, and (iii) ensuring sufficient generalizability across diverse infant populations and caregiving practices [11].

A promising direction involves multisensory "smart garments" that simplify deployment and reduce user error in IMU placement [7, 12]. By stitching sensors directly into snug-fitting suits, the location and orientation of each IMU remain consistent across recordings, thereby improving classification robustness [6]. Recent examples include the Motility Assessment of Infants with a Jumpsuit (MAIJU) system, which embeds multiple IMUs into a form-fitting garment and streams synchronized data to a smartphone or tablet [14, 15]. Such designs allow minute-by-minute posture tracking and yield a holistic overview of motor activity across longer time frames. Investigators have also introduced frameworks like the Baba Infant Motor Score (BIMS) that integrate these continuous measurements into a standardized metric for motor development [15]. While these wearable suits can drastically reduce the overhead of in-home data collection, further validation is needed for newborns, infants at risk for neurodevelopmental conditions, and varying environmental conditions across different cultures.

Few recent studies highlighted the importance of remote data management to ensure scalability and caregiver convenience [1, 15]. Cloud-based platforms automatically upload sensor data, facilitating near-real-time visualizations that offer researchers immediate insights into data quality and preliminary classification results [15]. This mode of administration has proven especially valuable for large-scale or global studies, as it reduces cost, time, and logistical complications. Nonetheless, user compliance and proper sensor calibration remain nontrivial, challenging the feasibility of specialized materials and built-in calibration checks that can be intuitively followed by caregivers [12].

Despite considerable progression in wearable IMU technology and automated behavioral classification, key challenges persist. Sensor arrays must be refined for newborns' smaller body size and heightened sensitivity to comfort and warmth. Achieving truly global reach demands careful attention to sociocultural contexts, cross-linguistic caregiver instructions, and diverse caregiving practices. Moreover, while existing systems excel at detecting posture and gross motor activities, they are less explored for subtle spontaneous movement patterns integral to GMA constructs, including fidgety and writhing movements in the early postnatal weeks. Addressing these gaps requires continued interdisciplinary collaboration among engineers, developmental psychologists, and clinicians to ensure that wearable systems are safe, accurate, and capable of real-time or near-real-time feedback. Ultimately, refining and validating such solutions could profoundly impact early neurological screening, enabling more timely therapies and potentially reducing the progression of at-risk infants toward established neurodevelopmental diagnoses.

III. EXPERIMENTAL USE CASE: BABYGROW STUDY

Building on recent technological advances, we designed a new workflow for recording newborns' spontaneous movements in their home environment, focusing on four main challenges. First, hardware complexity: while minimal home-recording setups risk insufficient data quality, excessive equipment can overwhelm caregivers—especially during the postpartum period. We address this by providing a streamlined kit (intelligent onesie, cables, chargers, and a preconfigured microcomputer) paired with concise, user-friendly instructions. Second, unpredictable recording times: newborns frequently sleep, and short windows of quiet alertness often arise unexpectedly. Our protocol facilitates flexible data capture, allowing parents to record spontaneous movements whenever feasible. Third, high-frequency data management: sampling at a high frequency (>50Hz) across multiple sensors produces large datasets. To handle these volumes efficiently, we built an integrated system utilizing compression, local caching, and remote uploading with minimal caregiver involvement. Fourth, human-in-the-loop monitoring: although laboratory-based technicians can intervene when sensors shift or cables disconnect, remote studies lack immediate oversight. We therefore provide real-time remote management and troubleshooting, sparing caregivers the burden of technical maintenance. Together, these strategies enable frequent, global, and large-scale deployment of high-quality infant spontaneous movements in their natural home settings.

A. Dataset

Thirty-nine infants (23 boys, 16 girls) were included in this paper as part of the BabyGrow project. We aimed to have caregivers recording their newborns weekly from birth to 34 weeks, yet infants missed sessions due to holidays, illness, moving, and family schedules. We asked caregivers to leave their infants on a yoga mat with the sensors collecting data for up to 20 minutes or as tolerated by the infant.

B. Procedure

Families were provided with a home-setup kit for recording newborns' spontaneous movements in natural settings. The kit contained eight IMUs (MetaMotionRL; Mbientlab; https://mbientlab.com/), a multi-port USB charger hub (Kitbox, 40W, 8-ports), a Raspberry Pi (model 3B+), a touch screen (Elecrow 5-inch, 800×480) for initial configuration, nine USB cables, and several onesies with sewn-in pockets labelled A–H, each corresponding to an IMU. Families also received a yoga mat for standardized positioning, a phone clamp to ensure overhead video capture (for purposes that were part of the overall BabyGrow protocol but are outside the scope of this paper), and detailed printed instructions demonstrating how to calibrate, place, and record.

Prior to each session, parents charged the IMUs for at least one hour, allowing indicator lights to switch from orange to green. Next, they switched on the Raspberry Pi and connected it to the USB hub, triggering IMU lights to turn red upon successful device pairing. Each sensor was then placed horizontally within its designated pocket (the light facing the middle of the infant's body and with the LED-side upwards. The suit was laid flat on the yoga mat for ten seconds of calibration. The infant was dressed in the suit, positioned supine on the mat, and recorded by an overhead phone camera for at least 5 minutes to capture spontaneous movements. Once the baby reached one month of age, parents were asked to extend their recording to 8- to 10-minute sessions to include brief exercises such as supported sitting, tummy time, assisted standing, or spoon grasping (for purposes that were part of the overall BabyGrow protocol but were not used in this paper). These exercises were performed after the initial part of the recording, with the infant remaining as relaxed as possible throughout.

Upon completion, parents removed the infant from the suit and placed the IMUs adjacent to the Raspberry Pi. The Raspberry Pi and the sensors remained powered for up to two hours, ensuring full data transfer. We contacted parents every two weeks by phone or video call to administer a short Vineland developmental survey and assess any technical issues. During these check-ins or via email reminders, parents could adjust or defer sensor/video sessions based on individual circumstances, ensuring that data collection remained flexible yet systematic across the newborn's early months of life.

To further safeguard data integrity and troubleshoot potential issues, PiTunnel (https://www.pitunnel.com/) was used on each Raspberry Pi, affording secure remote access and real-time status monitoring (Fig. 1). Through PiTunnel's web-based interface, a remote team could track resource usage (e.g., CPU, memory, temperature), identify online/offline status, and access logs to confirm successful data transfers. This minimized parental burden for technical issues, as investigators could proactively diagnose

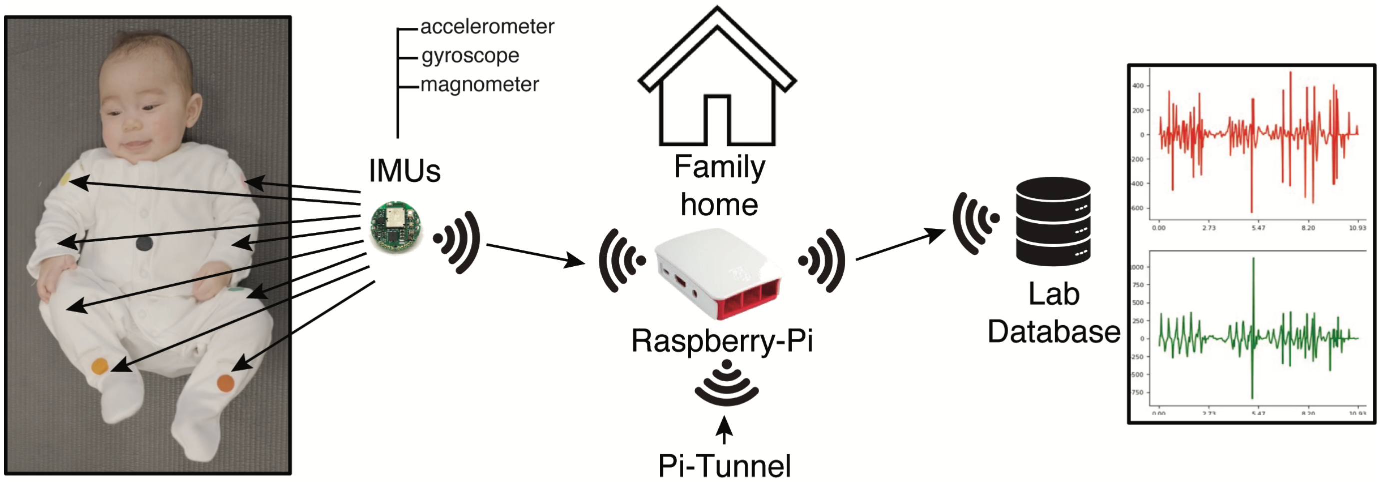

Fig. 1. Schematic illustration of the recording workflow. A Raspberry-PI is located at the family home and communicates with the 8 IMUs located inside the newborn's onesie, each includes an accelerometer, gyroscope and magnetometer. The sensors automatically send data to the Raspberry Pi once it is plugged in and turned on (left panel). There are no other necessary steps by the caregiver. The Raspberry-PI is also controlled via the Pi-Tunnel website and can be accessed worldwide. The Raspberry-PI sent the data at the end of each session to our database (right panel).

connection failures or sensor misconfigurations and offer guidance without requiring in-person visits.

C. Recording System

The IMU-based recording system included multiple hardware and software components to capture, store, and transfer inertial movement data. The IMUs served as primary sensors, each labelled with a unique MAC address and assigned to specific body locations—wrist, ankle, thigh, and upper arm on both body sides). These sensors are encased in water-resistant enclosures and fit into designated pockets on custom-sewn infant onesies. The Raspberry Pi formed the central node for data collection and transmission and communicated with all sensors simultaneously (Fig. 1). To ensure stable and seamless connectivity, one CSR-based BLE USB dongle was plugged into the Pi to stream data from the IMUs and to give an indication for parents that the Pi is turned on (if the dongle's light was on).

Before handing the system to families, we preconfigured the Raspberry Pi by writing the MetaHub operating system image to a 16GB (minimum) microSD card and editing a configuration file to define each sensor's MAC address, sampling rates, and data streams (accelerometer, gyroscope, magnetometer). In the initial use, caregivers paired the Pi with the household's Wi-Fi network via a 5-inch touchscreen interface with basic actions by the caregivers. After the initial use, caregivers could simply plug in the Pi to begin recording. Once powered, the Pi automatically detects and pairs with the pre-labelled IMUs, each recognized by its stored MAC address. When the session ends (i.e., the Pi is unplugged), a set of startup and shutdown scripts handle data transfer, saving local files and uploading them to an encrypted cloud drive at the next power-on (Fig. 1). This design was planned to minimize caregiver burden, allowing robust data collection with no in-person technical support.

D. Machine Learning Analysis

Each IMU was configured to record tri-axial accelerometer (range = ± 2g, resolution = 16 bit) and gyroscope (range = ± 125°/s, resolution = 16 bit) data during spontaneous infant movement sessions at a sampling rate of 25Hz. A dedicated on-board buffer captured raw signals, minimizing packet loss prior to Bluetooth transfer to the Raspberry Pi. Upon receipt, an initial alignment step was performed to ensure consistent timing across all sensor channels, removing any partial or corrupted readings. Data were then trimmed to discard the ten-second calibration span at the start of each recording and truncated to 3-minutes sample of valid data if the session ended prematurely.

The raw accelerometer and gyroscope signals were preprocessed in a dual-stage approach. First, a fourth-order zero-lag Butterworth low-pass filter was applied on each axis (cutoff at 10 Hz for accelerometer data and 5 Hz for gyroscope data) to remove high-frequency noise while preserving essential movement characteristics. Second, signal discontinuities resulting from brief Bluetooth dropouts or sensor malfunctions were linearly interpolated if they spanned fewer than 100 ms; longer gaps triggered the exclusion of that segment.

Periods of inactivity exceeding three consecutive seconds were identified, and movements were segmented accordingly, resulting in discrete "movement bouts." These steps aimed to capture meaningful motor intervals while controlling for variable session lengths and sensor noise levels. From each movement bout, we extracted a suite of kinematic features. These included basic measures (velocity, acceleration) as well as derived metrics (range, symmetry, and signal entropy). Rotational movements (roll, yaw, pitch) were similarly parsed at the bout level, providing characterization of infant spontaneous movement. By representing each bout with a standardized

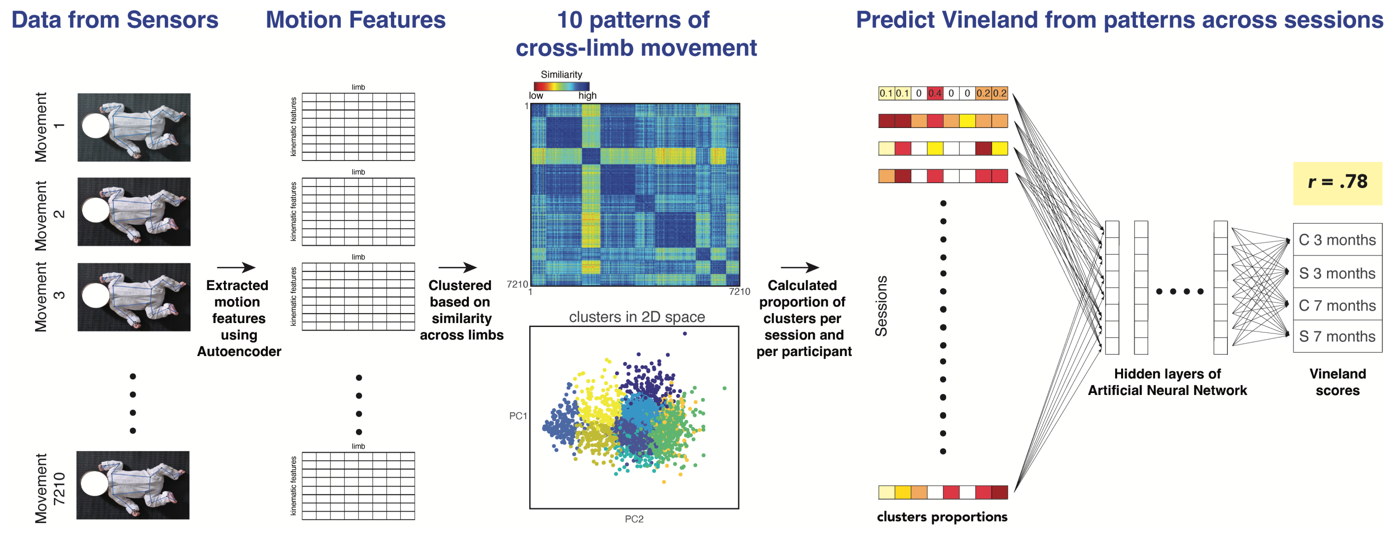

Fig. 2. Evaluating quality of spontaneous movement data from IMUs. The machine-learning-based analysis focused on predicting infants' socio-communication skills (measured using the Vineland test at 3- and 7-months) based on kinematic measures from the intelligent onesies. We first extracted motion features from the sensors using autoencoder (based on velocity, acceleration, range, symmetry and entropy, and rotational movements from the sensors as roll, yaw and pitch). We then clustered all the movements across all sessions and all participants and found 10 patterns of movement across all limbs. Next, we calculated the probability of having a specific pattern in each of the sessions and this was our input to an Artificial Neural Network (ANN). The ANN predicted 4 values – communication skills at 3 months, social skills at 3-months, communication skills at 7 months, and social skills at 7 months. This prediction significantly correlated with infants' real values.

set of features, the data were made analytically tractable for subsequent pattern analysis (Fig. 2).

Then, we used a stacked autoencoder architecture to extract latent representations from the feature sets (Fig. 2). Specifically, the autoencoder consisted of a series of fully connected encoding layers followed by a symmetric decoding stack, aiming to learn a low-dimensional embedding that retained the most discriminative elements of the motor behavior data. Once trained via backpropagation to minimize reconstruction error, the encoder section was used to project the original feature vectors into a compressed feature representation for identifying movement patterns.

We then calculated similarity between each pair of movement bouts across all infants and session based on their compressed feature representations using Euclidean distance (see similarity matrix in Fig. 2, central panel), yielding a similarity matrix where the value of each cell reflects the degree to which the pair of movement bouts were similar. Thus, the similarity matrix encapsulates essential information about infants' spontaneous movements, which allowed us to cluster them based on their similarity. To that end, we used a density-based cluster analysis that makes no assumptions about the number of clusters. If movement bouts sort into more than one cluster, that would provide evidence for distinct spontaneous movement patterns recorded by the sensors. As shown in Fig. 2, the cluster distributions were then consolidated into input vectors for a feed-forward artificial neural network with the Vineland scores at 3 and 6 months serving as the training targets (outputs). Finally, we correlated the predicted values from the neural network to infants' real Vineland score as a measure of how well the spontaneous movements predict socio-communication skills at a later age.

IV. EVALUATION

The evaluation of our workflow encompassed caregiver engagement and feasibility, sensor data reliability, and predictive validity of the machine-learning analysis.

A. Caregiver Engagement and Feasibility

A total of 54 families were enrolled, with instructions to conduct home recordings routinely over eight months. While most parents voiced enthusiasm about tracking their infants' early movements, 15 families (28%) sent no sensor data. Of those who did not send data, 53%% of families reported apprehension when opening the equipment kit and attempting to set it up, while 60% cited the time needed to set up the sensor sessions, along with the demands of a newborn. These parents cited both the volume of supplied components and the time-intensive setup: for instance, sensors typically required a multi-hour charging process before calibration. Moreover, the need to physically attach a touchscreen to the Raspberry Pi and manually connect it to home Wi-Fi led several participants, notably those less comfortable with electronics, to abandon the procedure. Of the remaining 39 families who sent some data, seven families (13%) attempted only a few sessions before ceasing participation. In many of these instances, parents indicated that the logistical demands of sensor setup and calibration conflicted with the unpredictable nature of infant routines. The emotional stress of the early postnatal period—particularly for first-time parents—further exacerbated their reluctance to continue. In addition, of the families who withdrew from the study before sending data, 20% (3) families withdrew due to family illness or bereavement and another 20% (3) families simply stopped responding to the research team without giving a reason.

Nevertheless, 39 families sent data and 17 families (31% of those originally recruited) successfully completed the protocol. Compared to those who did not maintain participation, these committed parents tended to exhibit higher organizational skills, greater curiosity about infant developmental processes, and more confidence in handling technology. A subset of these families even reported enjoying the recordings, characterizing it as a structured way to engage with their newborn's day-to-day changes. Several caregivers highlighted that the video demonstrations and phone-call assistance were instrumental in easing anxieties about equipment use. The need for the infant to be calm and comfortable on a mat also significantly influenced compliance: parents whose babies tolerated independent lying were more likely to gather data at the requested frequency, whereas parents with more easily agitated infants found the protocol especially challenging.

B. Sensor Data Reliability

Across 39 families, a total of 429 home-recording sessions were initiated (M =11.00, SD=10.07 per family); 57.6% yielded comprehensive sensor coverage—247 sessions with full recording from all 8 sensors and 182 sessions with partial recording. The most common error mode involved transient Bluetooth dropouts from one or more IMUs, typically lasting under 100 ms. These disruptions were compensated for via linear interpolation, but when such disruptions became frequent in a single session—occurring, for instance, every few seconds—interpolation was no longer feasible.

Throughout the study, data quality underwent periodic manual verification, consisting of spot-checks for sensor sync mismatches, time-stamped alignment with video recordings, and consistent IMU orientation. These checks revealed occasional calibration missteps, often traced to rushed or incomplete instructions. However, once we identified these issues via the PiTunnel logs and reached out to families, rectifications were readily made in subsequent sessions, emphasizing the importance of near-real-time feedback loops.

Technical home environments also impacted sensor reliability. Slow internet speeds or routers placed far from the infant's recording room exacerbated the risk of incomplete uploads. Few caregivers reported having to move their Pi setup to different rooms or switch to mobile phone hotspots. The majority of data loss cases occurred within the first three sessions; once families adapted to a routine involving predictable charging, calibration, and Pi placement, dropout rates decreased significantly.

C. Machine Learning Outcomes

The recorded sessions underwent a multi-phase analysis pipeline designed to capture both the overall character of infant spontaneous movements and cluster-level distinctions in motor patterns. First, 7210 discrete "movement bouts" were isolated from raw sensor signals, then mapped into low-dimensional embeddings via the stacked autoencoder. The density-based clustering algorithm identified 10 patterns of movement. The feed-forward neural network trained on these data showed a mean correlation of $r = .78$, $p < .01$ between the network prediction and infants' real Vineland scores across the social and communication domains and both ages.

V. SUMMARY AND FUTURE WORK

This study puts forward a new scalable and global home-based workflow for frequent infant movement assessments using an "intelligent onesie" equipped with wearable sensors and supported by remote data transfer and monitoring. By collecting fine-grained kinematic data and employing a robust machine-learning pipeline, we showcased how caregiver-led recordings can yield predictive insights into infants' early developmental trajectories. The resulting framework extends beyond purely technological advances, representing a shift in how researchers may observe and interpret spontaneous motor behavior outside traditional clinical or laboratory settings.

Despite promising results, our findings highlight several key challenges that must be addressed if such methods are to scale further effectively. Attritions point to the delicate balance between hardware sophistication and caregiver burden, highlighting the need for more user-friendly interfaces and clearer setup guidelines. Additionally, intermittent sensor dropouts and suboptimal connectivity restricted both the consistency of data capture and real-time remote monitoring. In future work, streamlining the charging and calibration process, improving connectivity solutions, and broadening technical support will be essential to sustain engagement and ensure data integrity at scale.

Moving forward, our analytic framework can be expanded to incorporate multiple complementary data modalities—ranging from annotated behavioral videos to computational vision outputs and standardized developmental assessments. By converging these independent streams in a unified modeling approach, researchers may uncover deeper connections between motor functions and socio-cognitive milestones [7]. This push toward richer, multifaceted datasets stands to yield sharper characterizations of typical and atypical movement patterns.

Beyond infancy, there exists significant potential for applying these wearable technologies and analytic pipelines to later developmental stages. More advanced neural network architectures, for example, can delve into how complex, emerging sensorimotor patterns evolve over time or differ in specific neurodevelopmental disorders. Researchers might also build on these methods to explore domain-general questions such as how manipulative play shapes child learning, or to develop noninvasive screening procedures for broader cognitive and motor skill assessments. By refining sensor configurations, solidifying remote management, and fostering the integration of large-scale data streams, we can expand the scientific understanding of infant development on a global scale.

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