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Towards automatic assessment of atypical early motor development?

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ABSTRACT

Atypical motor development is an early indicator for several neurodevelopmental conditions, including cerebral palsy and Rett Syndrome, prompting early diagnosis and intervention. While not currently part of the diagnostic criteria for other conditions like Autism Spectrum Disorder, the frequent retrospective diagnosis of motor impairments alongside these conditions highlights the necessity of a deeper understanding of the relations between motor and cognitive development. Traditional clinical assessments, while considered the gold standard, rely on movement characteristics discernible to the trained eye of professionals. The emergence of automated technologies, including computer vision and wearable sensors, promises more objective and scalable detections. However, these methods are not without challenges, including concerns over data quality, generalizability, interpretability, and ethics. By reviewing recent advances, we highlight the potential and the challenges of integrating automated detections into research and clinical practice. While we agree that these technologies can revolutionize pediatric care, we believe their use must be tempered with caution and supported by clinical expertise to ensure effective outcomes.

1. Introduction

Early detection of atypical motor development during infancy is important for the screening, diagnosis, and intervention of neurodevelopmental conditions (NDCs) such as cerebral palsy (CP) and Rett Syndrome (Blauw-Hospers and Hadders-Algra, 2005). These conditions can manifest early in life through motor impairments that, if detected in time, can lead to interventions that substantially improve long-term outcomes (Sakzewski et al., 2014; Bowler et al., 2024; Peralta and Cuesta, 2017). Other conditions associated with motor impairment, such as Autistic Spectrum Disorder (ASD), could also benefit from early detection and intervention. Traditional methods of assessing motor development often rely on clinical observation and standardized assessments which are effective but also subjective, labor-intensive, and expensive (Novak et al., 2020).

Consequently, there has been a growing interest in leveraging technology, particularly automated systems, to provide more objective, scalable, and precise evaluations of motor behaviour that can lead to the development of better assessments (Wadhera and Kakkar, 2022; Valentine et al., 2020). Over the last two decades, detailed computer vision methods, such as markerless pose estimation and depth-sensing cameras, powerful machine-learning algorithms, including advanced neural networks to classify atypical movements, and wearable sensor systems, especially those employing miniaturized inertial measurement units and accelerometers, have improved researchers' ability to quantify and detect subtle motor impairments in infants and young children (Ossmy and Adolph, 2020; Redd, 2021; Ossmy et al., 2020). These automated tools have shown promise in detecting subtle abnormalities in motor patterns that might be indicative of neurodevelopmental conditions (Leo et al., 2022; Braito et al., 2018). In particular, depth-enabled computer vision setups and integrated machine-learning systems for interpreting wearable sensor data have emerged as especially promising due to their accuracy, scalability, and potential for continuous, real-time monitoring. Overall, automating the detection process of motor movements offers the possibility of early intervention, thereby addressing some of the limitations of traditional methods (Ni et al., 2023; Chambers et al., 2020; Hashemi et al., 2014; Das et al., 2018; Rad et al., 2018).

However, while these technologies have significant potential benefits, they also come with challenges. Issues such as data quality (i.e., the accuracy and completeness of information collected across various

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settings), generalizability (i.e., the extent to which findings remain valid across different demographic and cultural contexts), and interpretability (i.e., the clarity of how results are derived, which fosters trust among clinicians and stakeholders) remain critical barriers to their widespread adoption (Schmidt et al., 2019; Hadders-Algra, 2021). Moreover, ethical considerations, particularly concerning data privacy and the potential for biases in the data, must be addressed to ensure that these technologies are used responsibly and equitably (Sharma and Giannakos, 2021; Cacciatore et al., 2022; Sullivan et al., 2024).

In this narrative review, we cover key literature on automatic detection tools of atypical motor development during the first two years of life. This review aims to discuss how the current landscape of technologies for infant motor assessment can and should inform future steps in the field, rather than quantifying previous work using effect sizes and inclusion/exclusion criteria. We found quantitative comparisons in this case challenging due to the heterogeneity of the methods, participant populations, and outcome measures across related studies. Thus, our selection of papers was guided by relevance and recency and not exhaustive search criteria. We begin by pointing to traditional approaches to assess atypical early motor development, continue with the latest advances, and elaborate on the advantages and limitations of using automatic tools. Finally, we conclude by discussing future directions for research and clinical practice. Fig. 1 provides a schematic illustration of the connection between different automatic tools and manual detection of atypical infant motor development.

2. Traditional assessment approaches to atypical early motor development

Motor development in the first two years of an infant's life has significant implications for their cognitive, social, and emotional well-being (Prechtl, 1986, 1974). During this period, infants develop motor skills necessary for subsequent development in other domains (Bowler et al., 2024; West et al., 2019; Iverson and Wozniak, 2007; Piek et al.,

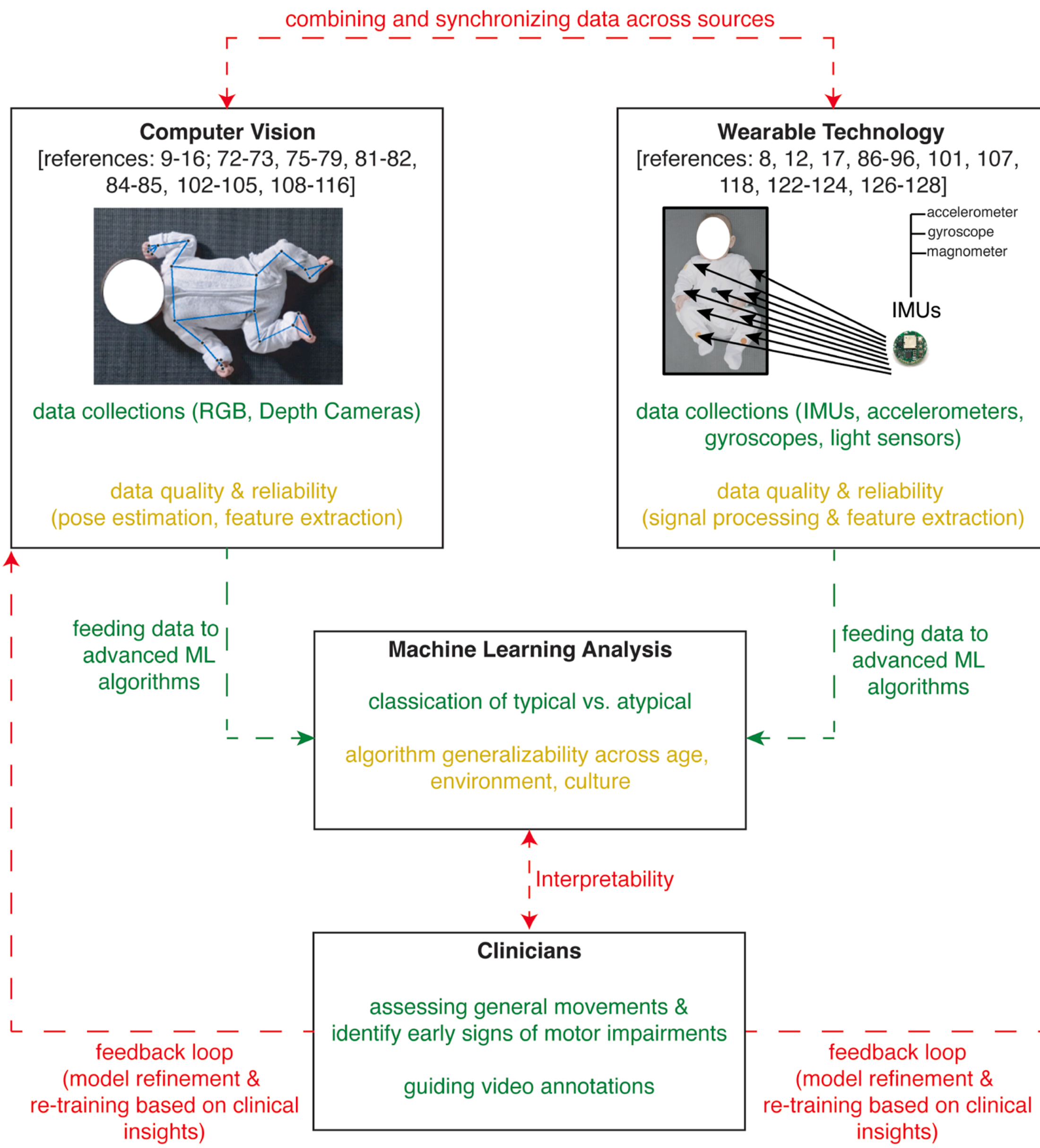

Fig. 1. Schematic illustration of the interplay among computer vision (detection of keypoints based on video; see picture), wearable technology (detection of movements based on intertial sensors which often include accelerometer, gyroscope, and magnometers; see picture), machine learning, and clinical expertise in detecting atypical infant movements. The color-coding highlights the level of research maturity for each component and their interactions: green indicates well-established findings, yellow reflects emerging or limited evidence, and red signifies minimal or no existing research.

2008; Brian, 2021) and abnormalities as delayed milestones or atypical movement patterns can be early indicators of neurodevelopmental conditions (Sakzewski et al., 2014; Bowler et al., 2024; Peralta and Cuesta, 2017; Marschik et al., 2017).

Clinical observations conducted by experienced professionals take a central role in the assessment of atypical early motor development. In these observations, trained clinicians systematically evaluate various aspects of movement, including movement quality, posture, and the presence of atypical motor patterns (Peralta and Cuesta, 2017; Santos et al., 2001). The observations take place in both structured and unstructured settings to comprehensively capture an infant's motor capabilities across different contexts (Colizzi et al., 2020). The expertise of clinicians in recognizing subtle deviations from typical movement patterns is particularly valuable in identifying early developing conditions such as Rett Syndrome, where symptoms may emerge as early as 2–4 months (Einspieler, 2014; Einspieler et al., 2016).

Central to these movement assessments is the careful observation of spontaneous motor activity. The General Movements Assessment [GMA] (Nunes et al., 2021; Paneth et al., 1997) exemplifies this approach, particularly in identifying conditions such as CP, which affects approximately 2–3 per 1000 live births globally (Paneth et al., 2006). GMA is based on observing and analyzing the infant's general movements (GMs), which are complex, varied, and fluid motor activities without specific external stimulation. GMs are critical indicators of the developing nervous system's integrity (Rakowska et al., 2021). Infants with neurological impairments often display atypical GMs, such as being overly rigid or cramped or exhibiting monotonous or jerky movements. Through expert analysis of video recordings of these spontaneous movements, clinicians identify early signs of motor and neurological impairments long before a formal diagnosis is possible. For instance, infants later diagnosed with CP often exhibit cramped-synchronized or chaotic GMs, while those with conditions such as Angelman syndrome or Prader-Willi syndrome typically present with distinct patterns of hypotonia and reduced movement complexity (Butler et al., 2006; Williams et al., 2006). Yet, although these symptoms may indicate NDCs, infants in most countries typically undergo GMA only if they are born prematurely, have a low birthweight (under 1.5 kg), or experience hypoxia at birth. Consequently, a large proportion of infants at risk for other conditions associated with atypical motor development, such as ASD, may not receive appropriate early screening.

Several standardized assessment tools complement these observational methods, including structured protocols for evaluating motor development. Protocols such as the Peabody Developmental Motor Scales-2 and the Movement Assessment Battery for Children-2, assess specific motor abilities against normative data (Wilson et al., 2018; Liu and Breslin, 2013; Tripathi et al., 2008). These tools evaluate various aspects of motor function, including gross motor skills, fine motor precision, and coordination. Thus, in clinical settings, those protocols provide a framework for systematic evaluation that allows detection of subtle deviations from typical development (Connolly et al., 2006). For example, in Fragile X Syndrome, affecting approximately 1 in 4000 males and 1 in 8000 females, early indicators often include delayed motor milestones and atypical visual attention patterns, detectable through these structured assessments (Crawford et al., 2001).

Parent reports and monitoring tools also supplement direct clinical assessments. The Vineland Adaptive Behavior Scales-3 and the Ages and Stages Questionnaire are the most common methods to provide valuable information about an infant's motor functioning in daily life situations (Viviani and Stucchi, 1992; Paolo et al., 2023; Tveten et al., 2023). Questionnaires rely on caregiver observations and can offer information that may not be apparent during brief clinical evaluations. Moreover, motor milestone checklists remain an essential component of developmental monitoring in primary care settings. Pediatricians routinely monitor the achievement of key motor milestones, such as rolling, sitting, crawling, and walking, as delays in these areas may signal an increased risk for various NDCs (Bowler et al., 2024; Rizzi et al., 2021).

In addition to these tools, cognitive development assessments like the Bayley Scales of Infant and Toddler Development (Bayley, 2006) and the Mullen Scales of Early Learning (Mullen, 1995) also include motor domains integral to track development from a whole-child perspective (Cantor and Osher, 2021; Cantor et al., 2021). These standardized batteries assess fine and gross motor skills alongside cognitive abilities, further supporting that motor development is intrinsically linked to cognitive functioning. Early motor skills—such as grasping, reaching, and coordinating movements—are not isolated milestones but are integral to broader cognitive processes like attention, problem-solving, planning, and spatial awareness. For example, fine motor skills, such as the ability to manipulate objects, support cognitive tasks like sorting, categorizing, and understanding cause-and-effect relationships (Rosenbaum et al., 2012). Gross motor skills, like crawling or walking, allow infants to explore their physical environment and reason about action outcomes (Adolph and Hoch, 2019). Thus, including motor assessments within broader cognitive batteries tests motor delays not only from a physical perspective but also within the context of neurodevelopmental outcomes (Rizzi et al., 2021; Hwarng et al., 2021; Lucas et al., 2016).

Finally, standardized neurological examinations conducted by pediatric neurologists or developmental pediatricians constitute another component in the assessment of atypical infant motor development. These evaluations employ a range of specific tests and observations to assess neuromotor function across multiple domains. The Hammersmith Infant Neurological Examination, for instance, provides a structured approach to evaluating neurological status in infants, assessing posture, cranial nerve function, movements, tone, and reflexes (Romeo et al., 2016; Maitre et al., 2016). Similarly, the Amiel-Tison Neurological Assessment at Term offers a standardised method for evaluating neurological status in both term and preterm infants, with particular attention to muscle tone, primitive reflexes, and postural reactions (Gosselin et al., 2005). These examinations are particularly valuable in differentiating between various conditions that may present with similar motor abnormalities in infancy. For instance, while both CP and genetic disorders may present with delayed motor milestones, the specific pattern of neurological findings can help distinguish between these conditions. The combination of clinical observation, standardised assessment tools, and the examiner's expertise allows for more accurate diagnosis and appropriate targeting of interventions (Noritz et al., 2013; Tamplain et al., 2019).

Nevertheless, despite their widespread use, traditional assessment methods have limitations. The subjectivity inherent in observational assessments can lead to issues in inter-examiner reliability, while the artificial nature of standardised testing environments may not accurately reflect typical motor performance (Bhat et al., 2011). Cultural and linguistic factors can affect the validity of standardised assessments, particularly when these tools have not been adequately validated for diverse populations. Moreover, these motor evaluations are time-intensive, and the requirement for specialized expertise constrains the accessibility and scalability of traditional assessments (Case-Smith, 1992; Heineman and Hadders-Algra, 2008; Mendonça et al., 2016).

The challenges in early movement assessment are also compounded by the overlap of symptoms between different NDCs. For instance, hypotonia may be present in multiple conditions, including Prader-Willi Syndrome, Fragile X Syndrome, and various other genetic disorders, making differential diagnosis challenging based solely on motor assessment (Harris, 2008; McCandless and Cassidy, 2021). Additionally, the limited availability of disorder-specific assessment tools validated for use in the first years of life further complicates early detection efforts (Hadders-Algra, 2021; Rizzi et al., 2021; Walder et al., 2009). Unless an infant is seen in a high-risk clinic for the reasons outlined above, they are unlikely to undergo any motor evaluation beyond the very basic gross motor milestone assessments conducted by parents, general practitioners, or health visitors. This lack of specialized evaluation highlights a critical gap in the early detection process. Relying solely on parental reporting or routine checks often misses subtle motor delays or abnormalities that could be early markers of neurodevelopmental conditions. Moreover, the absence of standardized, early-life motor assessment tools diminishes the chances of identifying atypical motor development that might inform more accurate, earlier interventions.

Current research priorities focus on addressing these limitations with more sensitive, objective, and culturally adaptable evaluation tools. Early recognition remains critical, as a timely intervention during this period of rapid neurodevelopment significantly impacts long-term outcomes. Future directions include the identification of disorder-specific behavioral markers, the creation of standardized assessment protocols for high-risk infants, and the development of more precise evaluation methods specifically designed for the first year of life (Marschik et al., 2017; Hogan et al., 2017; Dimitropoulos et al., 2013). Thus, integrating traditional assessment methods with emerging technologies promises to enhance the early detection of atypical movements, potentially enabling earlier interventions across a spectrum of NDCs. There is also a growing emphasis on developing assessment strategies that can be effectively implemented in community settings, increasing the accessibility of early motor screening for diverse populations (Mendonça et al., 2016; Zwaigenbaum et al., 2015).

3. Advances in automatic detection of atypical infant movement

3.1. Computer vision

Computer vision, a branch of artificial intelligence (AI), enables automatic analysis of visual data from the environment, such as images and videos. In the context of atypical motor development, this technique has emerged as a powerful tool for automatically tracking infant movements and identifying patterns indicative of neurodevelopmental conditions (Leo et al., 2022).

One of the primary applications of computer vision in this context is pose estimation, which involves detecting the position and orientation of an infant's body in an image or video. Pose estimation algorithms identify keypoints of the body, such as joints and limbs, and track their movement over time, which allows the detection of motor patterns and features that are considered abnormal. This approach has been used widely in recent years to research various NDCs, particularly CP and ASD (Chambers et al., 2020; Silva et al., 2021; Hesse et al., 2018). For example, a study by Avcil et al. (2021). used computer vision for upper extremity rehabilitation in children with CP, demonstrating that pose estimation can assist in tracking the progress of therapeutic interventions by analyzing movement changes over time.

Beyond CP, multiple studies on ASD have demonstrated accurate identification of unusual limb movements and postural control consistent with early signs of ASD (Campbell et al., 2019; De Belen et al., 2020), yet there is no standardized screening practice to date. Computer vision was also used to assess fine motor skills in infants at risk of ASD and successfully identified subtle hand gestures and repetitive motions that serve as early markers of the condition (De Belen et al., 2020; Negin et al., 2021). Finally, research has shown that computer vision can effectively capture delayed reaching and grasping movements in infants at risk of ASD compared to low risk of ASD (Dawson et al., 2018).

In the realm of GMA, Silva et al. (2021) reviewed a broad range of recently developed computer-vision systems for automated analysis of GMA and infant fidgety movements. Fidgety refers to tiny movements present within a distinct timeframe (two- to five-month-olds) for all typically developing infants. Most reviewed systems used multiple synchronized cameras to capture infant movements from various angles, combined with advanced pose estimation algorithms to track body landmarks. By applying machine learning techniques to the extracted movement features, researchers automatically classified fidgety movements as typical or atypical with high accuracy at different ages including 100 % accuracy in predicting CP using the mean variability of the centroid of motion from two recordings (Adde et al., 2013), 93 % accuracy using logistic regression on GMA data (Ma et al., 2024), 80 % accuracy in detecting writhing movements using pose-based features (Doroniewicz et al., 2020). 80 % accuracy in predicting expert GMA classification using a smartphone model (Passmore et al., 2024), and 92.7 % sensitivity and 81.6 % specificity in CP prediction with a computer-vision model (Ihlen et al., 2019). These studies demonstrate the potential of automated methods to enhance early CP detection and intervention (for full review, see Silva et al., 2021).

In some studies, the computer-vision algorithms were further supported by advances in hardware. Chambers et al., (2020), for example, developed a system with depth cameras to capture three-dimensional movement data from infants during standardized motor assessments. By applying advanced machine learning algorithms on the video data, they automatically classified infants into high-risk and low-risk categories for CP with remarkable accuracy (~93 % precision). Similarly, Orlandi et al. (2018) introduced a novel markerless motion-tracking system based on RGB-D cameras to analyze spontaneous movements in preterm infants. RGB-D are depth cameras that capture multidimensional movement data, which can be processed using custom computer vision algorithms to extract detailed 3D kinematic information. By comparing the movement patterns of preterm infants to those of full-term infants, the researchers identified differences in movement variability and complexity.

Some researchers went beyond limb movements or posture detection. Sarmiento and Naval used computer vision techniques to analyze facial expressions and body movements in infants at risk for neurodevelopmental conditions (Sarmiento and Naval, 2020). The researchers employed a multi-camera setup to capture high-resolution video data of infants during standardized assessment procedures. Advanced facial recognition algorithms tracked facial landmarks while analyzing limb movements. By integrating these different data streams, the study revealed associations between facial expressions, body movements, and developmental outcomes. This work is an example of the potential of having a holistic computer-vision approach that encompasses both motor and socio-emotional domains.

3.2. Wearable technology

Other technological advancements have introduced objective assessment of motor development. Motion capture technology, wearable sensors, and machine learning algorithms have emerged as promising tools for quantifying atypical motor development (Chen et al., 2016; Airaksinen et al., 2022; Irshad et al., 2020). Wearable technology that relies on inertial measurement units (IMUs) as accelerometers, gyroscopes, and magnetometers, and assess coordination in infants who demonstrate atypical movement patterns (Chen et al., 2016; Machireddy et al., 2017; Fry et al., 2018).

The use of IMUs in this context has been of particular interest. One of the pioneering studies in this field was conducted by Gravem et al. (2012), who used compact wireless accelerometers to assess movement patterns in preterm and full-term infants. The researchers attached the sensors to the wrists and ankles of preterm and full-term infants, enabling continuous monitoring of limb movements. Findings revealed significant differences in movement acceleration between the two groups, particularly in the lower extremities.

Building upon this foundation, Marcroft et al. (2015) explored the feasibility of using miniature accelerometers for long-term movement monitoring in a clinical setting. Their study involved preterm infants, whose limb movements were recorded over a three-day period. The accelerometers, carefully attached to the infants' limbs, provided continuous data on movement frequency and intensity. While the study successfully demonstrated the practicality of using wearable sensors in a neonatal intensive care environment, the authors emphasized the need for larger-scale studies to establish normative data and validate the approach.

Some researchers integrated machine learning techniques with IMU data to further enhance the detection of atypical infant movements. Heinze et al. (2010) tested infants diagnosed with CP and typically developing children with wearable accelerometers to capture spontaneous movements, which were then analyzed using advanced genetic machine-learning algorithms. By processing the rich dataset obtained from the sensors, they distinguished between infants with typical and atypical GMs with an impressive accuracy of 100 % in sensitivity (correct classification of infants with CP) and 83 % in specificity (correct classification of TD infants). In parallel, Airaksinen et al. (2020) introduced an innovative "smart jumpsuit" equipped with multiple accelerometers and gyroscopes. This full-body wearable device was designed to track the movements of infants towards the end of their first year and was demonstrated on infants around 7 months of age (Airaksinen et al., 2022, 2020; Vaaras et al., 2023; Airaksinen et al., 2024). Infants' postures and movements were detected with accuracy comparable to human raters (Pearson $r = 0.9$ with human assessment). This smart jumpsuit represents a significant step towards continuous, objective monitoring of motor development.

4. Advantages

Automated systems offer several significant advantages over traditional methods of detecting atypical early motor development, particularly in terms of objectivity, scalability, and continuous monitoring capabilities.

4.1. Objectivity and scalability

One of the primary benefits of automated systems is their ability to provide objective assessments of motor function, thus reducing the inherent risk of observer bias. This objectivity is important, especially when dealing with early motor development, where subtle movements can be missed or interpreted differently by human observers (Kepenek-Varol et al., 2016; Fjørtoft et al., 2009). Moreover, automated systems can process vast amounts of data with consistent accuracy, enabling the detection of patterns and anomalies that might elude even experienced clinicians. For instance, a study by Kanemaru et al., (2014) demonstrated that automated analysis of GMs using accelerometers could identify infants at risk for CP with high sensitivity and specificity, outperforming traditional observational methods.

Such achievement is attainable due to the scalability of automated assessment tools which can handle large amounts of data. Traditional methods of assessing motor development require extensive training and can be time-consuming. As Einspieler et al. (2016) point out, GMA is effective, but it is not easily scalable due to the need for expert clinicians who are trained in interpreting infant movements. Automated tools mitigate this limitation by being deployed on a larger scale, allowing for more widespread screening of populations, even in low-resource settings where access to specialized care is limited. This scalability supports the expansion of early detection programs, particularly in underserved communities, as it enables more infants to be assessed without the need for constant clinical oversight (Gao et al., 2019; Groos et al., 2022; Sapiro et al., 2019).

4.2. Continuous monitoring

The ability of automated tools to provide continuous monitoring is a big step forward in assessing motor development. Traditional methods often rely on periodic assessments, which may miss critical periods of motor development or subtle changes over time (Braito et al., 2018). Numerous studies over the past decade have highlighted the potential to mitigate scaling errors in atypical development by collecting data over extended periods and at high frequency (for reviews: Rahman et al., 2022; Gargot et al., 2022; Ribas et al., 2023). By using automatic technology for frequent measurements, researchers can better track developmental trends, which are often mischaracterized when using infrequent assessments. For example, low-frequency measurements can give the impression of distinct developmental stages, despite the reality that development is a continuous process. In contrast, high-frequency data collection allows measurements of how motor skills are acquired on a minute-by-minute basis. Achieving this level of detail in movement analysis is challenging with traditional observational methods alone.

One example comes from Smith et al. (2015) who used a network of wearable sensors to continuously monitor full-body movements of infants in their home environment. Their study, conducted over a five-month period, revealed not only how movement patterns evolved across developmental milestones but also how these patterns fluctuated on a day-to-day basis, challenging the assumption that motor development follows a linear trajectory—even in low-risk children. The continuous nature of their monitoring allowed for the detection of transient movement patterns that might have been missed in shorter observation periods.

5. Limitations and ethical considerations

Despite these promising advancements, automatic detection technologies face several limitations that must be addressed to ensure their effective application in clinical settings (See Fig. 1).

5.1. Quality and reliability

One of the most pressing challenges lies in ensuring the quality and reliability of the data upon which these systems rely. Automated detection tools are highly sensitive to the conditions under which the data is captured. Various factors such as lighting conditions, camera angles (in the case of computer vision) and sensor placement (in the case of wearables) can substantially impact the accuracy of the captured data and, consequently, the predictions made by the system.

Poor-quality video data can lead to inaccurate interpretations of motor behavior (Daliri et al., 2023). Varying illuminations have been shown to corrupt image segmentation and movement detection (Tung et al., 2019; Fu et al., 2017). A few researchers showed that these effects on detection can be improved using light-adaptive algorithms (Hu et al., 2024), shadow elimination, and noise reduction (Sridevi and Meenakshi, 2020; Li and Hu, 2010). Camera placement also affects detection, as demonstrated by experiments using ceiling and wall-mounted sensors (Yun and Lee, 2014). Different sensing technologies have been explored, including pyroelectric infrared sensors (Yun and Lee, 2014), depth cameras (Ranganathan, 2020), and visible light sensing (Deprez et al., 2020).

Similarly, the benefits of wearable technology's objectivity and scalability are tempered by the need for careful calibration and standardized sensor placement protocols, which are essential for ensuring reliable data collection, particularly in naturalistic settings. Even minor measurement drift, external interferences, and incorrect positioning (known from the adult and patient literature; Wong, 2015; Suzuki et al., 2017) can significantly compromise data quality, potentially obscuring indicators of atypical development.

5.2. Generalization

Another limitation is the generalizability of the algorithms used in these automated systems. Machine learning models are typically trained on specific datasets, which may not fully represent the broader population. Many datasets used for training these models are drawn from infants in high-income countries, where environmental and cultural factors significantly differ from those in low-income settings. This discrepancy can limit the generalizability of the algorithms, making them less effective when applied to diverse populations. An algorithm trained on data from infants in urban environments may fail to account for the variations in motor development seen in rural or resource-limited settings. The lack of diverse training data could also introduce biases into the system, leading to skewed predictions that disproportionately affect certain demographic groups.

Furthermore, the majority of computer vision algorithms used in infant movement analysis are based on models originally developed for adult movement recognition. This presents significant challenges as infant movements differ substantially from adult movements in terms of speed, coordination, and variability. Indeed, Chambers et al. (2020) observed that standard pose estimation algorithms, which were primarily designed for adult bodies, often struggle to accurately track the rapid and unpredictable movements characteristic of infants. For example, Microsoft Kinect SDK skeleton tracking, random ferns body-part classifiers, or CNN-based 2D pose estimators fail to detect or localize limbs accurately when infants lie on their backs, have shorter limb proportions, or exhibit self-occlusions (e.g., grabbing feet; Hesse et al., 2018). Kinect's SDK often cannot track small supine infants, random ferns mislabel body parts due to unseen poses in adult-focused training sets, and CNN-based estimators mix up limbs when hands and feet overlap. These issues result in large joint errors, swapped limbs, or complete tracking failures for infant data (Hesse et al., 2018).

This discrepancy between the adult and infant movement detections can lead to errors in movement detection and classification. The need for specialized algorithms that account for the distinct biomechanical properties of infant bodies and the developmental stages of motor control. Algorithms specifically tailored to infant movement patterns may achieve significantly higher accuracy in detecting subtle motor abnormalities compared to those adapted from adult models.

Moreover, the reliance on adult-based algorithms may inadvertently introduce age-related biases into the assessment process. The fundamental differences in movement quality between infants and adults necessitate a ground-up approach to algorithm development for infant movement analysis. Such an approach involves not only adapting existing computer vision techniques but also developing novel approaches that are inherently suited to the unique challenges of infant movement recognition.

5.3. Interpretability

Interpretability remains the substantial challenge in adopting machine-learning-based tools, which often function as "black boxes," producing predictions without offering clear explanations for how those predictions were derived. Moreover, interpreting neurological examination findings in infants requires significant clinical experience and expertise, as the manifestation of neurological signs can be subtle and variable in early development.

This lack of interpretability can be a significant barrier to the clinical adoption of these technologies, as clinicians may be hesitant to rely on a system whose decision-making process is opaque. Without a clear understanding of how an algorithm arrives at its predictions, it becomes difficult for healthcare professionals to evaluate the accuracy and reliability of the system's outputs. This issue of interpretability is especially critical in a clinical setting because erroneous predictions can have significant consequences for a child's developmental trajectory. Therefore, enhancing the transparency and interpretability of automatic tools is important for building clinician trust and ensuring these systems can be effectively integrated into healthcare practices.

5.4. Ethics

Finally, the reliance on large datasets of infant motor behavior raises important ethical considerations about data privacy and consent. Researchers stress that collecting and storing sensitive data, particularly when involving vulnerable populations such as infants, must adhere to strict privacy and security standards (Castellani et al., 2023). Ensuring that families provide informed consent, and that the data is anonymized and securely stored is essential to protect the privacy and rights of the participants.

Distinct ethical challenges emerge for different technological approaches. While both computer vision and wearable technologies raise privacy issues, they require different ethical considerations. Computer-vision systems, which rely on video recordings, pose privacy challenges due to the identifiable nature of visual data. Video recordings of infants may inadvertently capture sensitive information about the home environment or family members, raising concerns about data security and potential misuse.

In contrast, wearable technologies like IMUs generally collect less identifiable data, primarily focusing on movement patterns and accelerations. However, these devices can still capture sensitive information about an infant's daily routines and behaviors. The continuous nature of data collection from wearable devices also raises questions about the extent of monitoring and the potential for over-surveillance of infant activities.

Furthermore, the ethical implications of data ownership and control differ between these approaches. With wearable technologies, data is typically stored locally or transmitted directly to secure servers, potentially offering greater control over data access and distribution. In contrast, video data from computer vision systems may be more challenging to manage securely, particularly if cloud-based processing is involved.

Practical issues such as the cost and accessibility of these technologies must also be considered, and the widespread adoption of automatic detection tools may be hindered by the high costs associated with developing and maintaining these systems. For example, advanced wearable motion tracking systems and high-quality video analysis tools can be prohibitively expensive for many healthcare providers, particularly in low-resource settings. Additionally, the need for specialized equipment to operate these systems may limit their accessibility, further widening the gap in healthcare access between high-income and low-income regions.

6. Future directions and conclusion

The field of automated detection of atypical infant movements is at a point when it is ready to transform early identification and intervention for neurodevelopmental conditions. As we look ahead, several key directions emerge to address current limitations and maximize the potential of these technologies (Fig. 1).

A primary focus for future research lies in developing longitudinal, high-frequency data collection protocols. The quick changes in infant movements necessitate continuous, long-term monitoring to capture the full spectrum of motor behaviors. We agree with Marschik et al. (2017) that single-point assessments may miss crucial developmental windows. Future studies should aim to track infants from birth through the first two years of life, with frequent, regular assessments. This approach would provide a more comprehensive picture of developmental trajectories in motor skills and enable the detection of subtle deviations indicative of emerging neurodevelopmental conditions. The success of such longitudinal studies hinges on integrating clinical expertise with automated systems. Whilst machine learning algorithms offer powerful analytical capabilities, they must be guided by clinicians. This synergy should be prioritized in future research, bringing together pediatric neurologists, developmental psychologists, and machine learning experts. We argue that clinicians should be integral at every stage of the automated assessment pipeline. Specifically, clinicians should support the work of algorithm developers by (1) guiding the annotation of the training data by identifying and labeling critical movement features or atypical patterns; (2) validating algorithm outputs during its development through clinical evaluations and standardized assessments, ensuring that automated detections align with established diagnostic criteria; and (3) interpreting and contextualize model predictions in real-world clinical settings, advising on treatment decisions, interventions, and follow-up plans based on each infant's unique developmental profile.

In this context, a stronger bioengineering perspective is essential for guiding the design and standardization of sensor-based technology. Recent advancements in wearable and sensors have revolutionized the monitoring of biophysical and biochemical parameters in healthcare (Suo et al., 2024; Yogev et al., 2023), enabling real-time data collection across physical activity, vital signs, and even environmental cues (Chen et al., 2012). Integrating multi-sensor approaches in future research—incorporating movement data alongside physiological, contextual, and environmental measurements—could significantly broaden our understanding of infant motor behavior (Williams et al., 2020; Chen et al., 2007).

Another important future direction concerns the challenge of generalizability by examining how demographic, cultural, and environmental factors influence infant motor development. Variations in infant-caring practices—such as swaddling, carrying methods, and available physical spaces—can shape movement experiences. Likewise, different cultural expectations for early motor milestones may alter parent-child interactions and thus modulate infants' behaviors. Automated tools that have been often trained on infants from high-income or specific cultural backgrounds may fail to capture these variations, leading to biased outcomes. Expanding data collection efforts to include diverse populations and movement contexts will be crucial for creating robust algorithms that can accurately identify atypical motor development across all communities. These steps will help ensure equitable access to early detection and will minimize the risk that certain populations are overlooked or mischaracterized by existing technologies.

Moreover, while previous infancy research has used audio recorders, accelerometers, and cameras to capture everyday behaviors during the first years of life (de Barbaro and Fausey, 2022), there has been limited use of embodied sensors in everyday objects. However, few researchers have examined the possibility of using sensor-equipped toys to assess spatial cognition (Campolo et al., 2011, 2012) and the feasibility of collecting rich motor data from infants using this technology (Kuo et al., 2022). Yet, this approach has not been systematically used for automated early detection of atypical development, and it still requires adaptation and validation before it can achieve continuous, high-frequency monitoring for detecting subtle, early signs of atypical motor development. Future research should further refine these approaches for more sensitive and scalable early detection in naturalistic settings.

Integrating multiple data modalities presents another promising avenue. Combining data from wearable sensors, computer vision systems, and traditional clinical assessments could provide a more holistic view of infant development. Such an approach will also address issues in generalizability, as it will focus on developing and validating algorithms using diverse, representative datasets encompassing a wide range of ethnic, socioeconomic, and cultural backgrounds.

Finally, as these technologies become more prevalent, developing a robust framework for data privacy, consent, and equitable access is necessary. Researchers and engineers should work closely with ethicists, policymakers, and community stakeholders to ensure responsible development and deployment.

In conclusion, we believe that the future of automated detection of atypical infant movements lies in integrating longitudinal, high-frequency data collection with expert clinical knowledge. Embracing interdisciplinary collaboration, addressing current limitations, and maintaining a strong ethical foundation will fulfil the potential of these technologies in improving long-term outcomes for children at risk.

CRediT authorship contribution statement

Ossmy Ori: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Forrester Gillian:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Sotoodeh Saber:** Writing – review & editing, Methodology, Investigation. **Kaur Aman:** Investigation. **Donati Georgina:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

No data was used for the research described in the article.

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