CAMBRIDGE
JOURNAL OF
HUMAN
BEHAVIOUR

PSYCHOLOGY

Automating Infant Neurodevelopment Data Processing Methods for Neuroimaging, Social Interactions, and Sleep State Identification

James Bennion[1], Zayna Mian[2], and Romy Sokolow[3]

[1] Magdalene College, University of Cambridge, [2] Trinity College, University of Cambridge
[3] St. John's College, University of Cambridge

Received June 10, 2024
Revision received February 20, 2025
Accepted October 29, 2025

Keywords: infant neurodevelopment, neurodevelopment methods, neuroscience automation, developmental neuroscience, machine learning.

Given the critical importance of neurodevelopment in the first 1000 days of life for later life outcomes, efforts to continuously evaluate and improve methods in infant developmental neuroscience are highly valuable. This paper explores three data processing methods – functional near-infrared spectroscopy (fNIRS) optode registration, parent-child interaction coding, and behavioural sleep state coding – using data collected in the Perinatal Imaging in Partnership with Families (PIPKIN) and Brain Imaging for Global Health (BRIGHT) projects. The three data processing methods share overlapping limitations, including lengthy processing time durations, requirements for expert training and experimenter involvement, and room for subjectivity or human error, which could all be improved by advances in automation. Automated methods include those using machine learning or artificial intelligence, which can increase efficiency, reduce experimenter involvement and subjectivity, and may reveal previously unidentified patterns in the data. Nonetheless, automated methods may not be a perfect solution, with drawbacks including reliance on large, high quality initial training data and the need for expert knowledge at set-up. While the automation of manual data processing methods has high potential, there is still considerable work to be done before this can be fully realized.

INTRODUCTION

Neurodevelopment in the first two years of life is critical, and disruptions can have long-lasting physical, neurological, and cognitive effects (Lloyd-Fox et al., 2016). In recent decades, challenges of measuring infant brain activity have been met by advances in neuroimaging technology such as functional near-infrared spectroscopy (fNIRS; Gervain et al., 2023). Meanwhile, studies have begun to consider the complex interplay of personal and contextual variables necessary for deeper understanding, alongside applying these technologies and principles in Majority World (Draper et al., 2023) or low-to-middle income countries (Blasi et al., 2019), such as the Brain Imaging for Global Health (BRIGHT) study (Lloyd-Fox et al., 2024). Recent innovations in automation, often leveraging artificial intelligence, may have the potential to further improve these methods. This paper discusses the scope for automating neurodevelopment methods as explored in the BRIGHT and Perinatal Imaging in Partnership with Families (PIPKIN) projects, focusing on fNIRS, parent-child interaction, and sleep state coding.

Both BRIGHT and PIPKIN have used fNIRS alongside overlapping measures of contextual variables to investigate neurodevelopment across the first years of life. BRIGHT is a longitudinal study investigating neurodevelopmental trajectories across the first five years of life in the Gambia using fNIRS and EEG and connecting these with contextual variables including parent-child interaction (PCI), sleep, stress, language environment, and numerous measures of resource poverty (Lloyd-Fox et al., 2024). PIPKIN is a longitudinal study from the third trimester to 5 months old, investigating infant neurodevelopment in relation to contextual variables such as PCI, the broader social environment, and numerous measures of resource poverty.

BRIGHT and PIPKIN have used both shared and unique methods and measures, and to explore automation, this paper will focus on three areas where there is high potential for automation: fNIRS headgear placement, parent-child interaction (PCI) behaviours, and sleep state coding. fNIRS (used in both projects) is a non-invasive, infant-friendly neuroimaging method (Lloyd-Fox et al., 2010) which relies on optode registration on the scalp for accurate spatial localization of acquired measurements with underlying neuroanatomy (Lloyd-Fox et al., 2014); however, many optode registration approaches, including 3D digitisers or manual photogrammetry are impractical for use with infants or time-consuming, as discussed further below. Parent-child interactions, characterized by mutual engagement through shared touch and gaze, are critical for infant development as an early form of social communication (Feldman, 2007; Swain et al., 2007). In BRIGHT and PIPKIN, PCI has been video-recorded ready for later offline coding. Manual coding approaches have varied across PIPKIN and BRIGHT, including global ratings of behaviour (e.g. parental sensitivity) and micro-coding of specific behaviours. In PIPKIN, the Datavyu software has been used for manual coding, although this requires time and expertise. Finally, sleep states may be important for healthy development, with deviations reportedly connected to neurodevelopmental disorders (Chen et al., 2022). In BRIGHT, sleep state data was video-recorded and later manually coded, which was lengthy with potentially high subjectivity. For both PCI and sleep-state coding, reliability coding adds further time requirements. In all three methods, automation may improve costs in time, training, and objectivity.

Using fNIRS, PCI, and sleep state coding across BRIGHT and PIPKIN, this paper aims to describe automated methods and evaluate their potential for improving infant neurodevelopment methods.

Functional Near-Infrared Spectroscopy

Functional near-infrared spectroscopy (fNIRS) is a neuroimaging method that measures changes in oxygenated (HbO) and deoxygenated (HbR) haemoglobin levels reflecting increased cerebral blood flow (CBF) to active brain areas (Lloyd-Fox et al., 2010). This is based on differential reflection of near-infrared light caused by the different absorption spectra of HbO and HbR, recorded by source-detector pairs (optodes) on the scalp. High-density diffuse optical tomography (HD-DOT) is an extension of NIRS with a higher number of source-detector pairs with varying separation distances improving spatial resolution and depth information (Zeff et al., 2007). Recently, a flexible wearable HD-DOT system has been developed and validated in adults (Vidal-Rosas et al., 2021) and infants (Frijia et al., 2021). Its practical applications are highlighted by its successful cot-side implementation in a clinical setting to measure functional connectivity in sleeping infants (Uchitel et al., 2023).

fNIRS has several advantages over traditional neuroimaging techniques (e.g. fMRI, EEG) which make it attractive for use with infant populations. These include portability, flexibility, comfortability, reduced constraint, and usability in natural environments. Therefore, fNIRS has been used throughout the BRIGHT (Blasi et al., 2019) and PIPKIN projects, the latter using the LUMO HD-DOT system (Gowerlabs Ltd, UK).

Despite these advantages, fNIRS requires methods for registering the position of sources and detectors on the scalp in order to accurately map the origin of acquired measurements to underlying neuroanatomy (Lloyd-Fox et al., 2010). It is possible to use standardised atlases (e.g., 10-20 system, Kabdebon et al., 2014) or generic optode locations obtained from fNIRS system and cap manufacturers, but this risks obscuring individual variations in head anatomy and cap placement, potentially reducing accuracy. For instance, Srinivasan et al. (2024) found that subject-specific optode registration increased spatial accuracy, while more general methods may misattribute neural activity.

Subject-specific optode registration methods include anatomical registration, electromagnetic digitisation, photogrammetry, and video-based solutions. In anatomical optode registration, optodes are manually aligned with individual MRI scans for each participant (Lloyd-Fox et al., 2014). This has high spatial accuracy yet requires structural MRI scans, which may be impractical and time-consuming. In digitisation, a stylus is used to measure the distance of optodes from a reference point and create a unique 3D model (Chiarelli et al., 2015). Although quicker, digitisers can be expensive and require several minutes of stillness from the participant, rendering it impractical in infant populations.

Photogrammetry has been successfully applied to infant populations, including in PIPKIN. In photogrammetry, cameras are used to capture photographs (e.g., Hu et al., 2020) or 3D scans (e.g. Uchitel et al., 2023) which are combined to achieve optode registration. Scans can be created easily and quickly (~1–10 seconds per scan) at a low cost, using equipment as simple as an iPhone (Mazzonetto et al., 2022). In the PIPKIN project, several 3D scans covering all head angles are taken using the scandyPro app for iPhone while the infant wears the HD-DOT headgear. These are then processed in CloudCompare, an open-source software for processing and merging point clouds into meshes. Overlapping scans are manually combined into a single mesh providing full coverage of the cap, optodes, and head landmarks, from which the unique optode positions of each infant can be extracted.

This photogrammetry method has several advantages. Data collection is simple and efficient, requiring minimal training and using inexpensive equipment. It is also relatively resistant to infant movement: photogrammetry is only directly affected by movement when it blurs an initial scan, which can quickly be rectified by re-taking the scan. As such, photogrammetry provides an efficient, inexpensive, and infant-friendly registration method; however, photogrammetry still has important limitations. The quality of the final 3D model depends heavily on the quality of the initial scans, such that missing or poor-quality scans can have large downstream effects. Furthermore, although data collection is simple and fast, processing with CloudCompare is lengthy (30 minutes to 2 hours per scan), requiring considerable training and experimenter involvement. The high degree of experimenter freedom of choice may impact quality and reproducibility. In summary, while photogrammetry has infant-friendly, simple, and quick data collection, it is limited by its lengthy, skilled processing stage and reliance on initial scan quality.

Motivated by these issues, automated video-based approaches utilising machine learning have recently been introduced. For example, Jaffe-Dax et al. (2020) introduced a structure from motion (SfM) algorithm and convolutional neural network (CNN) to reconstruct a 3D model of the optodes on a given participant from a short (20 second) video. This has been validated against a digitiser in adults. Erel et al. (2020) later developed this into STORM-Net (Simple and Timely Optode Registration Method), a more sophisticated set of neural networks which registers optodes by predicting cap orientation from video. It comprises an offline step, in which the network is trained on rendered video data and digitised coordinates for a specific cap, and an online step. In the online step, the experimenter records a short (~5 second) video of the same cap on a participant which is inputted to the network, which outputs rotation parameters, from which subject-specific optode locations can be inferred.

Automation can provide significant advantages in terms of time and required expertise. STORM-Net is relatively movement-resistant, and processing can take under 10 seconds, leading to high infant compatibility. Equipment can be as simple as a smartphone, yet the authors report that it performs as accurately as a 3D digitiser. Data collection requires less training than photogrammetry, as experimenters need only familiarise themselves with the simple and flexible video style required. Perhaps most significantly, STORM-Net does not require any lengthy post-processing, unlike using CloudCompare in photogrammetry. In the broader context of optode registration, it may offer the advantages of subject-specific methods without the reliance on expensive and often impractical MRI data or other lengthy processing.

However, automation still has limitations and is yet to be systematically validated in infants. Although processing is considerably reduced, the initial offline step requires some machine learning knowledge, computing power, and training time (30 minutes with Graphics Processing Unit (GPU), 5 hours without GPU). Further, networks must be individually trained for each cap, while the previous photogrammetry method is universal across caps; however, expert input is only essential during setup so the overall process may still take less time than processing large samples with CloudCompare. Finally, although the authors of STORM-Net report it has been successfully implemented on infants informally (Erel et al., 2020), a systematic evaluation in a large infant sample has not been published, leaving uncertainty as to whether these advantages would be confirmed in practice. Nonetheless, automation could, in theory, advance infant neurodevelopment research by significantly reducing training and processing requirements in optode registration.

In conclusion, automation may advance infant neurodevelopment research methods by providing more time- and cost-efficient methods for NIRS optode registration. Machine learning techniques, including STORM-Net, may replicate advantages of photogrammetry, such as efficient data collection and infant-friendliness, and extend them by further reducing time and expertise in processing. Future work should aim to rigorously evaluate the effectiveness of these methods in large infant samples.

Parent-Child Interactions

Parent-child interactions (PCI), characterised by mutual engagement through shared gaze and touch, are crucial for infant development, serving as the first exposure to social communication (Feldman, 2007; Swain et al., 2007). Key behaviours such as direct gaze and affectionate touch can influence factors such as emotional regulation, secure attachment, and neural development, influencing brain structure and functional connectivity (Feldman, 2007; Ainsworth, 1979). For example, maternal sensitivity during PCI at 6 months has been linked to increased functional connectivity in brain areas involved in emotional regulation and cognition (Ilyka et al., 2021; Rifkin-Graboi et al., 2015). Therefore, identifying dyadic social and motor components that vary in PCI might enable further understanding of how caregiver sensitivity influences socio-emotional and brain development in infants.

Caregiver-infant interaction behaviours have been analysed across both broad domains, such as affect, attention, communication and responsiveness, and more specific domains like affectionate touch and sensitivity (Ilyka et al., 2021). Commonly used tools for measuring these interactions include the Global Rating Scale (Murrey et al., 1996), the Manchester Assessment of Caregiver-Infant Interaction (Wan et al., 2017) and the Emotional Availability Scales (Biringen, 2000), which evaluate different aspects of caregiver responsiveness and engagement. More specific scales, like the Caregiver Infant Touch Scale (Jean & Stack, 2009) and the Mother Infant Touch Scale (Crucianelli et al., 2019), quantify the prevalence and nature of specific touch behaviours. Software like Datavyu is often employed, which allows researchers to code behaviours with high temporal precision. Datavyu also integrates with statistical software like R, allowing for detailed analysis and making it a powerful tool for studying PCI.

At PIPKIN, Datavyu is used to analyse key variables in PCI, specifically focusing on the frequency and duration of mutual engagement, affective touch and affectionate touch. These 5-minute PCI recordings are collected during the one-month home visit and five-month lab visit and analysed using a coding scheme that integrates elements from the Mother-Infant Touch Scale (Crucianelli et al., 2019) and the Caregiver-Infant Touch Scale (Jean & Stack, 2009).This coding scheme allows for researchers to identify instances of affective touch (e.g., gentle, slow, caressing touch) and affectionate touch (e.g., kissing, handholding, playful touch), and includes measures of gaze patterns for both parents and infants (Carnevali et al., 2024). These variables are central to PIPKIN because mutual engagement behaviors, such as direct gaze, are known to activate the social brain network, while affective touch stimulates C-tactile afferents, which are linked to brain areas involved in early social and sensory processing (Farroni et al., 2002; Tuulari et al., 2019; Feldman, 2007). While the current coding scheme effectively captures gaze and touch, there is potential to include additional variables, such as positive and negative affect, to create a more comprehensive understanding of parent-infant interactions.

Manual coding of PCI using Datavyu requires a high level of reliability. In PIPKIN, coders achieved a 96% agreement using the ICI reliability index; however, the process was both lengthy and time-consuming; coding a single 5–7-minute video for parent gaze, infant gaze, affective touch, and affectionate touch often took up to two hours. This challenge is consistent with other studies, where extensive coder training is also required, further increasing the time demands (Brzozowska et al., 2021; Chen et al., 2016). While manual coding has been feasible for some studies in the past, coding longitudinal studies with larger samples may be more challenging. For instance, in the BRIGHT project, around 265 videos to code at multiple timepoints. These factors underscore the need for more efficient coding methods, such as machine learning based computer vision (CV) tools like DeepLabCut, as used in PIPKIN, which can automate some aspects of coding, reducing time and increasing precision. Similar software, such as OpenPose, may offer additional improvements in coding PCI behaviours.

DeepLabCut (DLC) is an AI-driven tool used for markerless pose estimation through machine learning, enabling researchers to track body movements across multiple individuals (Mathis et al., 2018). DLC utilises a pretrained algorithm, allowing researchers to label specific frames and customize body parts of interest (Mathis et al., 2018; Solby et al., 2021). In PIPKIN, DLC was used to track body parts in recorded videos by training on specific points identified using Napari, focusing on key body parts like the nose, mouth, eyes, wrists, and fingers, as well as unique markers such as mutual gaze and affective touch. Labeling frames took around 40 minutes per participant. While the initial training dataset took 3–4 days to process, DLC is later able to evaluate a recording of a 5–7-minute PCI video in about 20 minutes, demonstrating DLC's efficiency compared to manual coding; however, further adjustments, such as identifying outlier frames and expanding the training dataset, are needed to improve accuracy.

Despite some limitations, the preliminary results are promising. In one participant's case, DLC was used to analyse parent-infant interactions at both 1 and 5 months, XY body part features were extracted as a temporal function of behaviours. When the algorithm was trained to estimate the frequency and timing of these behaviours, it achieved an accuracy of approximately 67% compared to Datavyu measures for both samples. Accuracy was higher at 5 months (77%) than at 1 month (68%), likely due to the more consistent lab environment at 5 months, which allowed the DLC algorithm to better learn from the data. Current limitations include the exclusion of certain behaviours from reliability analysis if they occur infrequently or for brief durations. Additionally, continuous motion behaviours like caressing, pose challenges for annotating on a frame-by-frame basis, making them harder to capture accurately with DLC.

The use of DLC offers a promising approach for identifying and coding key temporal visual markers in PCI, such as mutual gaze and affective touch, complementing manual coding techniques. DLC has the potential to uncover patterns and trends that may not be visual through manual observation, such as whether touch behaviours precede infant gaze. Machine learning-driven tools like DLC may not only enhance objectivity and efficiency but also generate additional data that would otherwise go undetected with manual coding methods; however, limitations such as the need for a large dataset for accurate video analysis, difficulties in coding continuous motion behaviours, and the system's sensitivity to environmental inconsistencies must be addressed. While machine learning may streamline and even replace certain aspects of manual coding, it is important to question whether they can fully capture the subtle nuances of human behaviour that experienced coders can interpret. Ultimately as machine learning systems continue to evolve, if current limitations are addressed, it is conceivable that they could achieve the accuracy and the contextual understanding needed to replace manual coding entirely.

In conclusion, further evaluation of DLC's accuracy and efficiency in comparison to manual coding methods is necessary. By expanding training on larger datasets and refining methods, AI tools like DLC can enhance the analysis of parent-infant interactions, offering new insights into infants' early socio-emotional development through improved efficiency, accuracy and data quality.

Sleep State Coding

Sleep state coding is a method used to classify an infant's sleep state, typically using behavioural observation, measures of autonomic regulations (e.g., heart rate and respiration), and neurophysiology (Anders, 1971; Horne, 2014; Myers et al., 1997). Ideally, these measures would be combined to increase accuracy. The two major sleep states are quiet sleep (QS) and active sleep (AS). Infants spend more time in active REM sleep than adults. The valid and reliable identification of different sleep states in infants is important. This is because these different sleep cycle stages are associated with unique patterns of brain activity and brain development. QS is important as it promotes experience-dependent synaptic remodelling through synchronised and repetitive neuronal activity (Bik et al., 2022). This sleep state is essential, as by strengthening network connectivity and preserving plasticity, the foundations for later brain maturation are laid. QS also pre-consolidates learning, memory formation, and the maintenance of physiological homeostasis (Ryan et al., 2023). Alternatively, AS stimulates sensorimotor processing brain areas, facilitates neural network maturation and promotes synapse formation (Ryan et al., 2023). AS is strongly correlated with brain growth, thus there is a notable abundance of REM sleep during the critical maturational period of early life (Chen et al., 2022). The connection between sleep stages and development can be used to set targets for developmental interventions and to produce biomarkers to identify infants with impaired or advanced early development (Bik et al., 2022).

Sleep state coding is also important to differentiate the sleep state timings of preterm and full-term infants, as these differences can impact development. Full-term newborns spend two-thirds of their time asleep, and half of this time in REM sleep (Chen et al., 2022); however, preterm newborns spend less time asleep, having more frequent REM episodes but a significantly lower total duration of AS (Ryan et al., 2023). This shorter duration of AS in preterm infants can lead to neurodevelopmental disorders. These include Sudden Infant Death Syndrome (SIDS) where infants experience disturbed periodicity of sleep states and a subsequent failure to rouse during transient events like apnea; childhood onset autism, ADHD, and developmental disabilities relating to executive functions, language, and attention; and adulthood onset REM Sleep Behaviour Disorder (RBD; Chen et al., 2022). Therefore, identifying the different sleep stages is important as having a lower amount of AS in early life, as often seen with preterm infants, can lead to disorders with long term effects seen in adulthood and even terminal syndromes.

In the BRIGHT study, solely the one-month-old session included the infants asleep. During this session, fNIRS data was collected while the infant was exposed to three different sets of auditory stimuli: a social task including auditory social and auditory nonsocial stimuli, a habituation and novelty detection task, and a functional connectivity task. Additionally, the sessions were video recorded. The videos could then be sleep coded. By combining behavioral and hemodynamic data, the study was able to better understand how sleep states potentially modulate cortical responses.

Within the study, the sleep state coding measures were compiled and weighted by Van Der Straaten (2024), in accordance with the Anders Manual (1971) and the Neonatal Behavioural Assessment Scale (NBAS; Brazelton, 1973). The coding features used to classify the sleep states were recorded in fifteen second epochs across the tasks, in accordance with the NBAS. The features that contribute most to aiding classification have a higher weighting. If these features are occluded, their weighting is subtracted from the confidence level. The features used to identify QS (listed in descending order of their weighting) were closed eyes, eyes showing no REM movements, regular breathing, and rapidly suppressed jerky movements which have a delayed onset in response to external stimuli. The features used to identify AS were closed eyes, eyes showing REM movements, irregular breathing, and smoother movements as well as jerky movements. Micro-coding is also used to help classify AS. This is where smaller, less weighted behaviours such as sucking, facial grimaces, vocalisations, and startles are used to provide more detail of the infants' behaviour. These indicate that the infant is in AS. Whilst these micro coding features only have 5% weighting, closed eyes and REMs contribute 25% each to the confidence level. Therefore, the BRIGHT study employs a highly detailed coding method, utilising short classification epochs (i.e., 15 second segments) that necessitates detailed behavioral observation of the infant.

However, whilst comprehensive coding increases the accuracy of determining the sleep state, it suffers from being more time-consuming and laborious, reducing efficiency and potentially leading to more human error. This is especially the case for active sleep which involves more micro coding and can often require thirty minutes of intensive work to code a six-minute video. Behavioural sleep state coding also has a higher level of subjectivity, relying on the judgement of the coder. This reduces reliability, even with interrater training and reliability checks, as there will always be differences between coders.

To tackle these limitations, one solution could be to automate this sleep coding. Horbach (2023) has automated the process using convolutional neural networks (CNNs). Their research found that a binary CNN can be used to accurately predict whether eyes are open or closed in 96.3% of cases. A binary 3D CNN was also used to identify REMs 74.5% of the time. In the study, wakefulness, QS, and AS were accurately classified 92.2% of the time (Horbach, 2023). One drawback of this study was that the participating preterm infants produced limited datasets needed to train classifiers, with only eye movements contributing to classification. This was due to privacy concerns and low data quality from the preterm infants often being heavily occluded by NICU equipment. The BRIGHT sample, and other studies using full term infants, do not encounter these restrictions, so bodily movements and facial landmarks can be used as well as recordings of the eyes to increase accuracy.

However, in both the case of manual and automated sleep state coding using preterm and full-term infants, it is important to note that they heavily rely on the quality of the data. When training CNNs, any dim lighting, poorly positioned infants, or tightly swaddled infants with restricted movements can reduce the confidence level. As mentioned before, the eyes are heavily weighted in classification. If the video does not have a clear image of the eyes, confidence is immediately reduced by half. Therefore, it is important to be conscious of the behavioural measures required for later processing when collecting the data, in both manual and automated sleep state coding.

In conclusion, whilst the conventional manual method of sleep state coding is comprehensive, in its use of many behavioural measures and short epochs, automating the process allows for greater efficiency and reduced subjectivity; however, initial data quality at collection must still be prioritised, as high-quality videos are needed for sufficient training of CNNs.

DISCUSSION

This paper evaluates existing methods in infant neurodevelopment research, specifically focusing on fNIRS, PCI and sleep state coding, and emphasises the potential benefits of a transition towards automation. Across these methods, several key themes emerge, such as the potential confounds in manual coding methods, the time and labour-intensive nature of these techniques, and the need for data optimization through automation, particularly AI driven machine learning software. A brief outlook on the practicalities of implementing such automation is also provided.

Manual coding schemes across fNIRS, PCI and sleep state coding are notably time-consuming, vulnerable to subjectivity and prone to inaccuracies. For example, fNIRS pre-processing, especially through photogrammetry can take up to 2 hours using software like CloudCompare to generate a head mesh. Similarly, PCI and sleep state coding processes are time-intensive, with PCI requiring hours to code, while sleep state coding, particularly for active sleep (AS) in infants, often necessitates detailed microcoding. Additionally, while reliability testing is more established for PCI and sleep state coding, manual methods still allow for subjective interpretation, and coder training can be time-consuming, demonstrated by the use of Cloud Compare for photogrammetry training with fNIRS. Alongside the coding methods themselves, data quality also presents a significant challenge. Photogrammetry components rely heavily on scan quality, and for PCI and sleep state coding, video quality, particularly the visibility of key features, like the eyes, is paramount. These challenges in data collection and analysis underscore the need to shift towards automated methods to enhance the accuracy and efficiency of infant neurodevelopment research.

Automated methods for fNIRS (e.g., STORM-Net), PCI (DeepLabCut), and sleep state coding (CNN-based approaches) offer significant advantages. Both STORM-net and automated sleep state coding leverage convolutional neural networks (CNNs), while DeepLabCut employs deep neural networks to drive machine learning (Horbach, 2023; Erel et al., 2020; Mathis et al., 2018). These tools reduce experimenter subjectivity and improve efficiency, as demonstrated in sleep state coding, where CNNs can accurately identify REM sleep and AS (Horbach, 2023). Crucially, AI tools such as DeepLabCut have the potential to uncover patterns in parent-infant interactions that may be undetectable with manual coding alone. Given the success of AI tools in monitoring child development, such as predicting developmental disorders and language delays, there is a clear need to incorporate automation and AI-based technologies into infant neurodevelopmental research (Reinhart et al., 2024; Aylward et al., 2023).

Automation through AI offers promising solutions to enhance existing coding mechanisms, especially in data-intensive projects like PIPKIN; however, these approaches are not without challenges. AI-based machine learning technologies, such as DLC and STORM-net, require substantial expertise and time for setup and training. While the initial investment in training yields faster video analysis later, there is also a need to expand training datasets to improve the accuracy of the analysis, as demonstrated in the PIPKIN project with DLC for PCI analysis. Video quality also remains a critical factor, as seen with DLC, where the algorithm performed better with the 5-month sample due to consistent lab setting and better-quality data. Although larger training datasets may allow AI to handle lower-quality videos more effectively, both STORM-net and DLC perform best with high-quality video data. In a global context, projects like BRIGHT highlight another limitation- many AI-based tools require significant computing power, which can prove disadvantageous in regions with limited access to technology.

Despite the limitations mentioned, incorporating automation can significantly enhance current methods by increasing efficiency, accuracy and the scope of analysis, while advancing infant neurodevelopment research. The interconnectedness of techniques like fNIRS, PCI and sleep state coding underscores the need for such improvements; however, before these technologies can be fully incorporated into large-scale studies, future research should prioritise refining and validating existing automated tools. For instance, while STORM-Net is a promising avenue for automated spatial localization in fNIRS, it still needs quantitative validation in infant populations to ensure reliability. Likewise, although DLC is widely used for motion tracking, further optimization may be necessary for analysing complex PCI, particularly subtle forms of caressing touch and gaze-touch coordination, which are more challenging to label frame-by-frame.

Enhancing automation in fNIRS, PCI, and sleep state coding may have implications beyond improving individual methods; it can accelerate integrative research offering deeper insights into neurodevelopment. For instance, early PCI has been associated with later functional connectivity derived through analysis of both fNIRS and PCI (Ilyka et al., 2021). Therefore, future studies could integrate these methods, such as hyperscanning, where both parents and infants wear fNIRS during PCI, enabling investigation of how brain-behaviour interactions contribute to socio-cognitive development (Alonso et al., 2024). Automating aspects of this research, for example, using STORM-Net for efficient fNIRS localization or DLC to analyse PCI videos, could streamline processing, enhance reproducibility, and uncover patterns potentially overlooked by manual coding. Additionally, machine learning could be leveraged to identify cross-modal relationships between brain and behavioural data, offering insights beyond analysing measures in isolation. For example, deep learning algorithms could integrate functional connectivity from fNIRS with PCI gaze and touch patterns to identify predictive markers of developmental trajectories. Furthermore, given evidence that sleep-states influence fNIRS signals (Dang-Vu, 2010), future studies should explore automated sleep-state classification alongside fNIRS and PCI measures, to advance a more holistic understanding of neurodevelopment. Ultimately, advancing automation could not only improve individual methods but also facilitate interdisciplinary research to capture the complexity of early brain-behaviour interactions.

CONCLUSION

Infant neurodevelopmental research uses manual methods that can be improved with the use of automation. Within fNIRS, STORM-Net addresses the need for infant-friendly yet efficient optode registration with minimal training and simple collection of high-quality data (Erel et al., 2020). In PCI coding, the automated DeepLabCut can complement the manual Datavyu (Mathis et al., 2018). Sleep state coding could replace manual coding with CNNs (Horbach, 2023). Automation is not only more efficient by avoiding laborious manual coding, but may also improve objectivity and reliability, reducing the need for time-consuming interrater training and reliability checks. Automation may also reduce human error and improve our ability to detect patterns. Therefore, the cost of greater resource inputs for setup and training may be justified; however, output remains dependent on initial data quality even using automated methods, necessitating prioritisation of training in data collection. For more nuanced coding, complete automation may be unrealistic, for instance given the relative complexity of PCI versus sleep state coding. Whilst research into automating other infant neurodevelopment methods should be developed, it is important to attend to the feasibility of automation more broadly. To avoid being constrained to a Minority World perspective, future research must consider the suitability of automation in Majority World contexts with limited technologies.

Article references

Alonso, A., McDorman, S. A., & Romeo, R. R. (2024). How parent–child braintobrain synchrony can inform the study of child development. Child Development Perspectives, 18(1), 26–35. https://doi.org/10.1111/cdep.12494

Anders, T. F., Emde, R. N., & Parmelee, A. H. (1971). A Manual of standardized terminology, techniques and criteria for scoring of states of sleep and wakefulness in newborn infants. UCLA Brain Information Service/BRI Publications Office, NINDS Neurological Information Network.

Aslin, R. N., Shukla, M., & Emberson, L. L. (2015). Hemodynamic correlates of cognition in human infants. Annual Review of Psychology, 66, 349–379. https://doi.org/10.1146/annurev-psych-010213-115108

Aylward, B. S., Abbas, H., Taraman, S., Salomon, C., Gal-Szabo, D., Kraft, C., Ehwerhemuepha, L., Chang, A., & Wall, D. P. (2023). An introduction to artificial intelligence in developmental and behavioral pediatrics. Journal of Developmental and Behavioral Pediatrics, 44(2), e126–e134. https://doi.org/10.1097/DBP.0000000000001149

Bik, A., Sam, C., De Groot, E. R., Visser, S. S., Wang, X., Tataranno, M. L., Benders, M. J., Van Den Hoogen, A., & Dudink, J. (2022). A scoping review of behavioral sleep stage classification methods for preterm infants. Sleep Medicine, 90, 74–82. https://doi.org/10.1016/j.sleep.2022.01.006

Biringen, Z. (2000). Emotional availability: Conceptualization and research findings. American Journal of Orthopsychiatry, 70(1), 104–114. https://doi.org/10.1037/h0087711

Blasi, A., Lloyd-Fox, S., Katus, L., & Elwell, C. E. (2019). fNIRS for tracking brain development in the context of global health projects. Photonics, 6(3). MDPI AG. https://doi.org/10.3390/photonics6030089

Brazelton, T. B., M. D., Spastics International Medical Publications, Freedman, D. G., Horowitz, F. D., Koslowski, B., Ricciuti, H., Robey, J. S., Sameroff, A., & Tronick, E. (1973). Neonatal Behavioral Assessment Scale. Spastics International Medical Publications. https://nidcap.org/wp-content/uploads/2013/12/Brazelton-1973-BNBAS.pdf

Brzozowska, A., Longo, M. R., Mareschal, D., Wiesemann, F., & Gliga, T. (2021). Capturing touch in parent–infant interaction: A comparison of methods. Infancy, 26(3), 494–514. https://doi.org/10.1111/infa.12394

Carnevali, L., Blanco, B., Ilyka, D., Rozhko, M., Weiss, S.M., Clackson, K., Greenhalgh, I., Lee, K., Farroni, T., Johnson, M.H., & Lloyd-Fox, S. (2024, July 9). Bridging social ties to brain wires: A longitudinal approach to neonatal task-free functional connectivity and early interactions. The International Congress of Infant Studies, ICIS, Glasgow, Scotland.

Chen, Q., Li, H., Abu-Zhaya, R., Seidl, A., Zhu, F., & Delp, E. J. (2016). Touch event recognition for human interaction. Electronic Imaging, 28, 1–6. https://doi.org/10.2352/ISSN.2470-1173.2016.11.IMAWM-465

Chen, H., Gao, J., Chen, Y., Xie, J., Xie, Y., Spruyt, K., Lin, J., Shao, Y., & Hou, Y. (2022). Rapid eye movement sleep during early life: A comprehensive narrative review. International Journal of Environmental Research and Public Health, 19(20), 13101. https://doi.org/10.3390/ijerph192013101

Chiarelli, A. M., Maclin, E. L., Low, K. A., Fabiani, M., & Gratton, G. (2015). Comparison of procedures for co-registering scalp-recording locations to anatomical magnetic resonance images. Journal of Biomedical Optics, 20(1), 016009. https://doi.org/10.1117/1.JBO.20.1.016009

Crucianelli, L., Wheatley, L., Filippetti, M. L., Kirk, E., Jenkinson, P., & Fotopoulou, A. (2019). The mindedness of maternal touch: An investigation of maternal mind-mindedness and mother-infant touch interactions. Developmental Cognitive Neuroscience, 35, 47–56. https://doi.org/10.1016/j.dcn.2018.01.010

Dang-Vu, T. T., Schabus, M., Desseilles, M., Sterpenich, V., Bonjean, M., & Maquet, P. (2010). Functional neuroimaging insights into the physiology of human sleep. Sleep, 33(12), 1589–1603. https://doi.org/10.1093/sleep/33.12.1589

Draper, C. E., Barnett, L. M., Cook, C. J., Cuartas, J. A., Howard, S. J., McCoy, D. C., Merkley, R., Molano, A., Maldonado-Carreño, C., Obradović, J., Scerif, G., Valentini, N. C., Venetsanou, F., & Yousafzai, A. K. (2023). Publishing child development research from around the world: An unfair playing field resulting in most of the world's child population under-represented in research. Infant and Child Development, 32(6), e2375. https://doi.org/10.1002/icd.2375

Erel, Y., Jaffe-Dax, S., Yeshurun, Y., & Bermano, A. H. (2020). STORM-Net: Simple and timely optode registration method for functional near-infrared spectroscopy (fNIRS). https://doi.org/10.1101/2020.12.29.424683

Frijia, E. M., Billing, A., Lloyd-Fox, S., Vidal Rosas, E., Collins-Jones, L., Crespo-Llado, M. M., Amadó, M. P., Austin, T., Edwards, A., Dunne, L., Smith, G., Nixon-Hill, R., Powell, S., Everdell, N. L., & Cooper, R. J. (2021). Functional imaging of the developing brain with wearable high-density diffuse optical tomography: A new benchmark for infant neuroimaging outside the scanner environment. NeuroImage, 225. https://doi.org/10.1016/j.neuroimage.2020.117490

Gervain, J., Mehler, J., Werker, J. F., Nelson, C. A., Csibra, G., Lloyd-Fox, S., Shukla, M., & Aslin, R. N. (2011). Near-infrared spectroscopy: A report from the McDonnell infant methodology consortium. Developmental Cognitive Neuroscience, 1(1), 22–46. https://doi.org/10.1016/j.dcn.2010.07.004

Gervain, J., Minagawa, Y., Emberson, L., & Lloyd-Fox, S. (2023). Using functional near-infrared spectroscopy to study the early developing brain: Future directions and new challenges. Neurophotonics, 10(02). https://doi.org/10.1117/1.nph.10.2.023519

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world?. The Behavioral and Brain Sciences, 33(2-3), 61–135. https://doi.org/10.1017/S0140525X0999152X

Horbach, R. (2023). Automatic sleep assessment from eye cues in videos of strongly occluded preterm infants. https://studenttheses.uu.nl/handle/20.500.12932/44260

Horne, R. S. (2014). Cardio-respiratory control during sleep in infancy. Paediatric Respiratory Reviews, 15, 163–169.

Hu, X.-S., Wagley, N., Rioboo, A. T., DaSilva, A. F., & Kovelman, I. (2020). Photogrammetry-based stereoscopic optode registration method for functional near-infrared spectroscopy. Journal of Biomedical Optics, 25(09). https://doi.org/10.1117/1.jbo.25.9.095001

Ilyka, D., Johnson, M. H., & Lloyd-Fox, S. (2021). Infant social interactions and brain development: A systematic review. Neuroscience and Biobehavioral Reviews, 130, 448–469. https://doi.org/10.1016/j.neubiorev.2021.09.001

Jaffe-Dax, S., Bermano, A. H., Erel, Y., & Emberson, L. L. (2020). Video-based motion-resilient reconstruction of three-dimensional position for functional near-infrared spectroscopy and electroencephalography head-mounted probes. Neurophotonics, 7(03), 1. https://doi.org/10.1117/1.nph.7.3.035001

Jean, A. D. L., & Stack, D. M. (2009). Functions of maternal touch and infants' affect during face-to-face interactions: New directions for the still-face. Infant Behavior and Development, 32(1), 123–128. https://doi.org/10.1016/j.infbeh.2008.09.008

Kabdebon, C., Leroy, F., Simmonet, H., Perrot, M., Dubois, J., & Dehaene-Lambertz, G. (2014). Anatomical correlations of the international 10-20 sensor placement system in infants. NeuroImage, 99, 342–356. https://doi.org/10.1016/j.neuroimage.2014.05.046

Lloyd-Fox, S., Blasi, A., & Elwell, C. E. (2010). Illuminating the developing brain: The past, present and future of functional near infrared spectroscopy. Neuroscience and Biobehavioral Reviews, 34(3), 269–284. https://doi.org/10.1016/j.neubiorev.2009.07.008

Lloyd-Fox, S., Richards, J. E., Blasi, A., Murphy, D. G. M., Elwell, C. E., & Johnson, M. H. (2014). Coregistering functional near-infrared spectroscopy with underlying cortical areas in infants. Neurophotonics, 1(2), 025006. https://doi.org/10.1117/1.nph.1.2.025006

Lloyd-Fox, S., Begus, K., Halliday, D., Pirazzoli, L., Blasi, A., Papademetriou, M., Darboe, M. K., Prentice, A. M., Johnson, M.H., Moore, S. E., & Elwell, C. E. (2017). Cortical specialisation to social stimuli from the first days to the second year of life: A rural Gambian cohort. Developmental Cognitive Neuroscience, 25, 92 104. https://doi.org/10.1016/j.dcn.2016.11.005

Lloyd-Fox, S., McCann, S., Milosavljevic, B., et al. (2024). The Brain Imaging for Global Health (BRIGHT) Project: Longitudinal cohort study protocol [version 2; peer review: 1 approved, 1 approved with reservations]. Gates Open Research, 7(126). https://doi.org/10.12688/gatesopenres.14795.2

Mathis, A., Mamidanna, P., Cury, K. M., Abe, T., Murthy, V. N., Mathis, M. W., & Bethge, M. (2018). DeepLabCut: Markerless pose estimation of user-defined body parts with deep learning. Nature Neuroscience, 21(9), 1281–1289. https://doi.org/10.1038/s41593-018-0209-y

Mazzonetto, I., Castellaro, M., Cooper, R. J., & Brigadoi, S. (2022). Smartphone-based photogrammetry provides improved localization and registration of scalp-mounted neuroimaging sensors. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-14458-6

Murray, L., Fiori-Cowley, A., Hooper, R., & Cooper, P. (1996). The impact of postnatal depression and associated adversity on early mother-infant interactions and later infant outcome. Child Development, 67(5), 2512–2526.

Myers, M. M., Fifer, W. P., Grose-Fifer, J., Sahni, R., Stark, R. I., & Schulze, K. F. (1997). A novel quantitative measure of Tracé-alternant EEG activity and its association with sleep states of preterm infants. Developmental Psychobiology, 31, 167–174.

Reinhart, L., Bischops, A. C., Kerth, J.-L., Hagemeister, M., Heinrichs, B., Eickhoff, S. B., Dukart, J., Konrad, K., Mayatepek, E., & Meissner, T. (2024). Artificial intelligence in child development monitoring: A systematic review on usage, outcomes and acceptance. Intelligence-Based Medicine, 9, 100134. https://doi.org/10.1016/j.ibmed.2024.100134

Ryan, M. A. J., Mathieson, S. R., Livingstone, V., O'Sullivan, M. P., Dempsey, E. M., & Boylan, G. B. (2022). Sleep state organisation of moderate to late preterm infants in the neonatal unit. Pediatric Research, 93(3), 595–603. https://doi.org/10.1038/s41390-022-02319-x

Solby, H., Radovanovic, M., & Sommerville, J. A. (2021). A new look at infant problem-solving: Using DeepLabCut to investigate exploratory problem-solving approaches. Frontiers in Psychology, 12, 705108. https://doi.org/10.3389/fpsyg.2021.705108

Srinivasan, S., Acharya, D., Butters, E., Collins-Jones, L., Mancini, F., & Bale, G. (2024). Subject-specific information enhances spatial accuracy of high-density diffuse optical tomography. Frontiers in Neuroergonomics, 5. https://doi.org/10.3389/fnrgo.2024.1283290

Swain, J. E., Lorberbaum, J. P., Kose, S., & Strathearn, L. (2007). Brain basis of early parent–infant interactions: Psychology, physiology, and in vivo functional neuroimaging studies. Journal of Child Psychology and Psychiatry, 48(3–4), 262–287. https://doi.org/10.1111/j.1469-7610.2007.01731.x

Tuulari, J. J., Scheinin, N. M., Lehtola, S., Merisaari, H., Saunavaara, J., Parkkola, R., Sehlstedt, I., Karlsson, L., Karlsson, H., & Björnsdotter, M. (2019). Neural correlates of gentle skin stroking in early infancy. Developmental Cognitive Neuroscience, 35, 36–41. https://doi.org/10.1016/j.dcn.2017.10.004

Uchitel, J., Blanco, B., Collins-Jones, L., Edwards, A., Porter, E., Pammenter, K., Hebden, J., Cooper, R. J., & Austin, T. (2023). Cot-side imaging of functional connectivity in the developing brain during sleep using wearable high-density diffuse optical tomography. NeuroImage, 265. https://doi.org/10.1016/j.neuroimage.2022.119784

Van der Straaten, M. (2024). Exploring Sleep State Modulation of Habituation and Novelty Responses in One-Month-Old Gambian Infants: fNIRS and Heart Rate Analysis from the BRIGHT Study [Minor Research Report, University of Utrecht].

Vidal-Rosas, E. E., Zhao, H., Nixon-Hill, R. W., Smith, G., Dunne, L., Powell, S., Cooper, R. J., & Everdell, N. L. (2021). Evaluating a new generation of wearable high-density diffuse optical tomography technology via retinotopic mapping of the adult visual cortex. Neurophotonics, 8(02). https://doi.org/10.1117/1.NPh.8.2.025002

Wan, M. W., Brooks, A., Green, J., Abel, K., & Elmadih, A. (2017). Psychometrics and validation of a brief rating measure of parent-infant interaction: Manchester assessment of caregiver–infant interaction. International Journal of Behavioral Development, 41(4), 542–549. https://doi.org/10.1177/0165025416631835

Zeff, B. W., White, B. R., Dehghani, H., Schlaggar, B. L., & Culver, J. P. (2007). Retinotopic mapping of adult human visual cortex with high-density diffuse optical tomography. Proceedings of the National Academy of Sciences, 104(29). https://doi.org/10.1073/pnas.0611266104