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Challenges and new perspectives of developmental cognitive EEG studies

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ABSTRACT

Despite shared procedures with adults, electroencephalography (EEG) in early development presents many specificities that need to be considered for good quality data collection. In this paper, we provide an overview of the most representative early cognitive developmental EEG studies focusing on the specificities of this neuroimaging technique in young participants, such as attrition and artifacts. We also summarize the most representative results in developmental EEG research obtained in the time and time-frequency domains and use more advanced signal processing methods. Finally, we briefly introduce three recent standardized pipelines that will help promote replicability and comparability across experiments and ages. While this paper does not claim to be exhaustive, it aims to give a sufficiently large overview of the challenges and solutions available to conduct robust cognitive developmental EEG studies.

1. Introduction

From a biological perspective, studying early brain development and functioning has substantial theoretical implications because it provides an appropriate level of analysis to understand human cognitive functions (Tinbergen, 1963; MacDougall-Shackleton, 2011; Hladký and Havlíček, 2013). In particular, electro-encephalographic recordings (EEG) applied to developmental research represent an irreplaceable source of knowledge to understand the temporal dynamics of brain activity and, consequently, the timing of cognitive processes in typical and atypical populations. Noteworthy, under specific technical and methodological conditions, EEG can provide reliable spatial information about the neural generators underlying scalp-level activity in infants (Reynolds and Richard, 2005, 2009; Reynolds et al., 2010) and children (Bathelt et al., 2014; Timeo et al., 2019). Further, EEG is an essential tool for studying brain activity in newborns (0 to 1 month old), infants (2 to 24 months old), and very young children (2 to 4 years old) because it presents undeniable advantages compared to other neuroimaging techniques. Compared to magnetic resonance imaging (MRI), EEG is more affordable, more tolerant to movement, more flexible (it can be used while sleeping, sitting, standing, or laying), and less ethically demanding. Nonetheless, collecting good quality EEG data in young participants is conditioned by significant methodological challenges that depend on the experimental contexts and the planned analyses.

The first challenge stands in the limited infants' attentional capabilities that effectively preclude the use of experimental paradigms widely used in preschool and school-aged children. Indeed, infants' visual attention span is limited to a few minutes within the first year of life (Atkinson and Braddick, 2012). A second, not less problematic aspect is the reduced behavioral repertoire that preverbal children can produce. Thus, experimental tasks requiring verbal responses or deliberate motor acts (e.g., pressing a key to select a choice) are impossible for young infants. These issues inevitably reduce the range of possible experimental designs, forcing researchers to select only certain types of stimuli and reduce the number of experimental conditions to maintain a good signal-to-noise ratio (SNR). These two examples are just a tiny part of many challenges experimenters have to deal with when working with infants and EEG.

In addition, data processing should be applied accordingly and adapted to developmental populations. EEG signals can be analyzed using different approaches, thus providing different insights into the human brain's functioning. A first general distinction can be made between time-locked and continuous EEG recordings. Event-related brain potentials (ERPs), the "voltage fluctuations in the ongoing EEG that are time-locked to an event, such as the onset of a stimulus" (Kappenman and Luck, 2011), allow researchers to link brain activities to specific events with precise temporal resolution. More recently, time-frequency (TF) transformations have gained significant interest in the developmental community allowing the study of brain oscillations during rest periods or in response to external events. Furthermore, although TF analyses of continuous EEG recordings were mainly used for clinical purposes (Connell et al., 1989; Hosain et al., 2003; Schumacher et al., 2011) or to describe general states of the brain (de Haan, 2013), they can also be used to study infants brain activity during more ecologically valid situations.

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This article aims to provide an overview of representative EEG studies tapping early cognitive development to help researchers consider each processing step before jumping in. Rather than an exhaustive review of the developmental EEG literature, we report and discuss the main challenges and specificities that any researcher may encounter when conducting an EEG study with young humans. We also provide some practical and methodological guidelines to maximize the success rate in such studies.

2. Working with young participants: specific issues

This section focuses on some crucial practical challenges allowing researchers to implement EEG studies in developmental populations successfully. We do not claim to provide an exhaustive list of practical issues, but help investigators anticipate and get efficiently through the most specific steps of developmental EEG study. Indeed, compared to studies conducted with adults, developmental studies differ in several ways and rely on specific challenges due to the characteristics of the targeted population that must be considered when designing a developmental EEG experiment.

2.1. Artifacts and attrition

Due to their young age, infants' behaviors are more challenging to control or predict, leading to poor data quality. Artifacts are widespread in infants' EEG studies, especially movement artifacts. The age of the children (from 12 months of age, infants tend to be more active and may try to grab the electrodes), the EEG device (nets tend to move a little compared to caps), the paradigm (visual paradigms tend to encourage head movements), and the experimental setup (children are more likely to move when they are on their parent's lap) can increase the risk of movements during data acquisition (de Haan et al., 2013). The general state of the children is also a key element in obtaining a good SNR: depending on the moment of the day, the quality and duration of sleep during the previous night, the emotional state of the child, the time after feeding time, and external events, the infant can be more or less fussy thus causing movement artifacts. A particularly relevant aspect to consider is the level of vigilance and the sleep stage in which the EEG recording is performed. This aspect is fundamental when collecting data from newborns who spend considerable time sleeping. In human infants, cyclic periods of active and quiet sleep are present after 35 weeks post-conception and can be easily detected by behavioural observation and EEG staging (Mercuri et al., 1995; Pressler et al., 2003). For instance, the neonatal brain is functionally more activated during active sleep, similar to wakefulness. Conversely, cortical activation decreases during quiet sleep (Graven, 2006), suggesting that the sleep stage may significantly impact spontaneous EEG and event-related activity. However, while some evidence supports this claim (Tokioka et al., 1995, Cheour et al., 2002a, Friederici et al., 2002, Friedrich et al., 2004, Suppiej et al., 2010), other studies reported no significant sleep impact (Alho et al., 1990a; Cheour-Lutanen et al., 1996, Martynova et al., 2003; Leppänen et al., 1997; Cheour et al., 1998a). Hence, a definitive consensus on the best sleep stage to collect EEG/ERP activity in newborns and young infants is still unclear. Nevertheless, as a good lab practice, we suggest carefully considering this aspect, reporting, when possible, consistency across sleep stages in EEG frequency band power and distribution or ERP amplitude and latencies.

Overall, the experiment must be well prepared to ensure optimal conditions for electrode application and data acquisition that will minimize artifacts and optimize data quality (Lloyd et al., 2015). It is also essential that the researchers adapt their behavior, tone of voice, and sensitivity to each child (Cotter et al. 2002). In addition, a pleasant and skilled staff should be selected to help the researcher (Cotter et al., 2002). Welcoming young participants to a different room from the experimental booth can facilitate acclimatization (de Haan, 2013, p.19). This room should be pleasant both for parents and children as it can impact the general feeling of the families (see Fig. 1 for an example of a babylab welcoming room). Importantly, a specific space or room should be available for parents to feed the infants or change their diapers (Hoel and Wahl, 2012).

However, some artifacts are inevitable: eye movements, blinks, facial muscle activity, cardiac activity, and respiration are non-cerebral activities that distort the EEG signal. Cardiac activity and respiration are rhythmic and thus have an easily recognizable EEG pattern that can be detected and removed from the signal (Hoehl and Wahl, 2012). While eye movements, blinks, and facial muscle activity can be avoided or strongly decreased in adults under specific instructions as they can control them, this is not the case with infants. Consequently, these artifacts are commonly observed in infants' EEG signals, although more difficult to separate from background EEG activity than in adults (Bell and Wolfe, 2008).

While sucking a pacifier can sometimes be compatible with behavioural experiments, tongue movements can induce rhythmic low-frequency EEG activity that is not easily distinguishable from the background EEG (Hoehl and Wahl, 2012; Vanhatalo et al., 2003). Nevertheless, it is worth considering that the potential drawback due to the artifactual EEG activity is usually largely overweighted by the advantage in terms of behavioural compliance, as infants are usually calmed when using the pacifier, resulting in data quality improvement. Further, non-nutritive sucking has no significant impact on EEG data in newborns compared to nutritive sucking (Lehtonen et al., 2016). Cardiac activity should be recorded, and external electrodes should be positioned on the face to detect all these non-cerebral artifacts from the scalp. For example, one generally chooses to place one electrode for ocular artifacts (near the eyes) and one or two for facial muscle movements (on a cheek and near the mouth; Picton et al., 2000). A suitable lab practice is to avoid artifacts by using external control of stimuli and experimental manipulation. Indeed, to minimize data loss, the experimenter can design the experiment so that it can be paused at any time and that some stimuli or sequences of stimuli can be repeated (de Haan, 2013). Although technically challenging, an advanced approach relies on an eye-tracker to allow baby-driven experimental control procedures (Kulke et al., 2017). Eye-tracking systems can be interfaced via software with the EEG amplifier to control the timing and type of experimental conditions based on the child's eye behavior. Importantly, this approach offers accurate online monitoring of artifacts and can lead the child to direct visual attention towards the target stimuli through reinforcement (Maguire et al., 2014). Overall, artifacts affect infants' EEG signals more than adults'. Importantly, these artifacts are often removed from the data, automatically leading to data loss and, thus, a decrease in the SNR. A recent study shows the effects of variability in data editing methods on the quality of infants' visual ERPs (Monroy et al., 2021). Based on 19 EEG datasets collected in 10 m-o infants during an action-perception paradigm, results were clear cut in showing differences between expert editors in (i) the number of participants accepted, (ii) the number of trials accepted, and (iii) the channels marked for interpolation. In this sense, the use of video-EEG to monitor the online child's behavior during the experiment should be implemented (see Fig. 2). This technique allows video synchronization with the EEG via software, making motion artifacts very easy to isolate (e.g., blinks and eye movements, head-turning, sucking, or arm movements) from other environmental artifacts (e.g., electric noise, bad quality channels). In this way, it is possible to adjust online data acquisition quality by providing feedback to the parents or directly to the baby (i.e., an attention-getter picture or sound). This procedure ultimately allows preventing the number of artifacts by monitoring the child's behavior in progress. However, when video-EEG is unavailable, an alternative option is to have a research assistant use a response button to manually insert triggers in the EEG recordings that will help spot artefactual EEG sections (see Partanen et al., 2022).

An alternative option is to correct these artifacts offline using specific signal processing algorithms such as Independent Component Analysis (ICA). The Independent Component Analysis (ICA) source separation method is particularly efficient in correcting artifacts from continuous

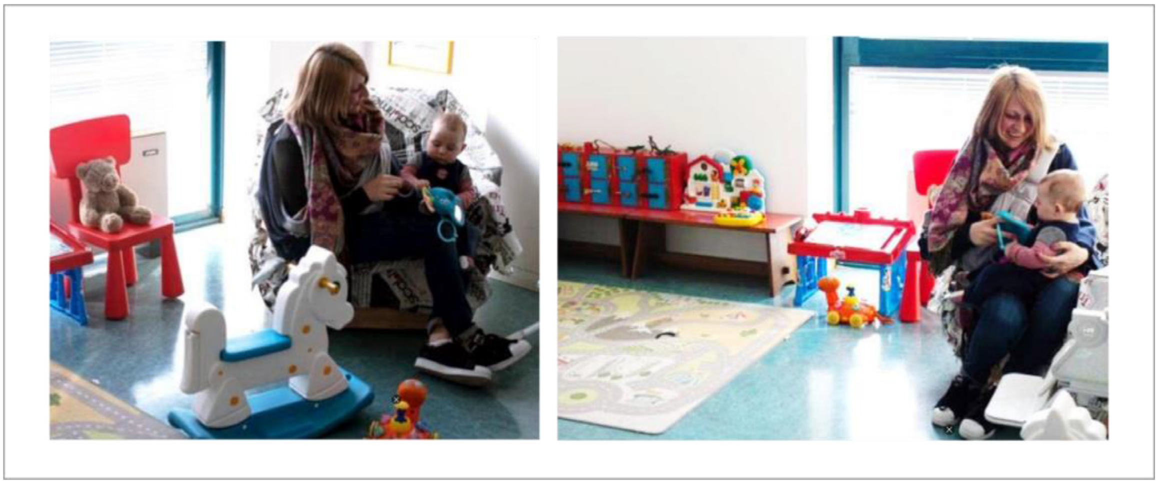

Fig. 1. Example of a waiting room to welcome young infants and their families. Note the presence of child-friendly furniture, toys, and games to habituate the infant before starting the experiment. Courtesy of the Department of Developmental and Social Psychology, University of Padova, Italy.

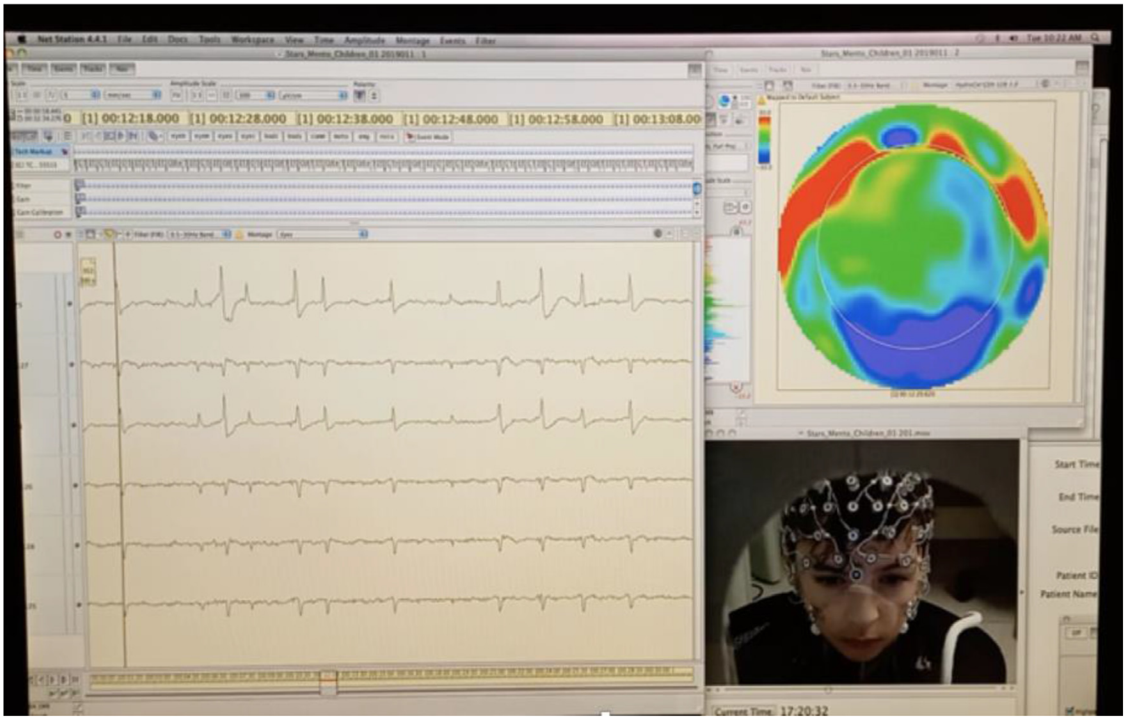

Fig. 2. Snapshot of a video-EEG recording collected in a 5-year-old child while executing a cognitive task. The left panel shows the online EEG recording with a detailed view of the electrodes around the eyes. The top-right panel displays the online topographical spline map, while the bottom-right shows the EEG-synchronized eye behaviour (EGI© system). The EEG recording is taken from a dataset originally published by Timeo, Mento, Fronza, and Farroni, 2018.

EEG (Makeig et al., 1996). Nevertheless, this method requires “the rapid and brief activation of spatially fixed brain regions” (Johnson et al., 2001) for optimal functioning so that it might be more efficient in ERP studies than in continuous EEG recording. Moreover, while ICA may perform best at separating signals after a 1–2 Hz high-pass filter (Winkler et al., 2015), such a filter may also drastically impact several ERP components. Therefore, an alternative two-step procedure might be to apply such a hard filter before ICA decomposition in one dataset, select, save the artifactual ICs, and use them for correcting another dataset with the appropriate filter settings. Although ICA-based artifact correction has traditionally been less used in the infant literature, several studies suggest it works well with participants as young as a few months old (de Haan, 2013, 2002; (Fujioka et al., 2011); Miljković et al., 2010). Fig. 3 illustrates an example of blink-related IC easily recognized and removed from the epoched EEG trace of a four-month-old infant.

Nonetheless, while component-based artifact rejection methods are viable options for high-density EEG recordings as often done with adults, it is still possible that some components may contain activity originating from the brain. Such a situation is highly likely in the case of low-density EEG recordings where the number of sensors is much smaller than the number of brain sources, which may result in activity from multiple brain sources being mixed into a single component. In such a case, rejecting the artefactual IC will likely remove data originating from brain sources as well. Furthermore, the decision about which and how many ICs to reject is not trivial because it is too operator-dependent and thus ultimately arbitrary. The rejection decision should be limited to only those ICs that unambiguously refer to recognizable artifacts such

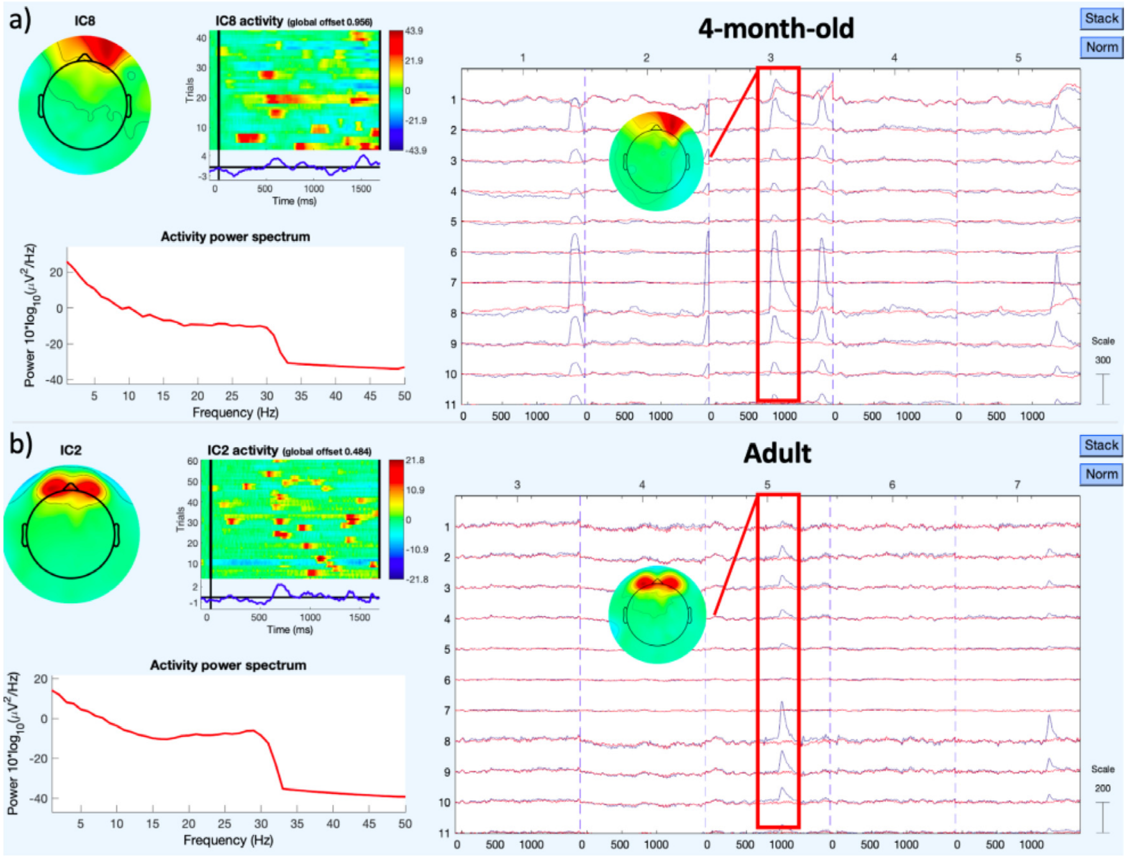

Fig. 3. Independent Component Analysis. The picture shows the details of a blink-related IC in a 4-month-old infant (a) and an adult (b) extracted from a High-Density EEG dataset (128 channels; EGI system) by using the EEGlab toolbox. The left part of the picture shows the spectral, temporal, and spatial properties of the IC. The right part displays the EEG recording with a detailed view of the electrodes around the eyes. The blue and red lines depict the EEG signal with and without the IC. Note that the rejection of this IC reliably rules out the eye-blink artifactual noise without losing much EEG signal in both the adult and infant recording. (The EEG recordings are taken from a dataset originally published by Mento and Valenza, 2016).

as blinks, heartbeat, or network noise. Although this appears relatively straightforward in the case of adults, it is not always possible to easily detect artifactual ICs in infants' EEG data.

Interestingly, the wavelet-ICA (w-ICA) is a two-step ICA implemented in the recent toolboxes developed for infants' EEG data that may be particularly relevant as it increases component separation efficiency and decreases data loss when removing artifacts (Azzerboni et al., 2005; Mammone et al., 2012). Moreover, a common problem of the ICA methods is that classical algorithms used with adults usually require long datasets for optimal functioning, whereas infants' recordings are generally shorter. Blind Source Separation (BSS) algorithms are very efficient in separating cerebral from extra-cerebral sources (Romo-Vázquez et al., 2012). However, the final result mainly depends on the type and number of artifacts and the choice of the BSS algorithm (Fitzgibbon et al., 2007). A combination of different algorithms seems to be the most powerful solution for artifact separation, as Romo-Vázquez et al. (2012) pointed out. However, data loss (and attrition) is inevitable when considering artifacts and other uncontrollable events inherent to developmental studies.

Studies involving human beings necessarily imply attrition, especially when they are very young. Data loss can be due to inter- or intra-individual differences, experimental characteristics, technical issues during data acquisition, interruption of data recording upon participant's request, or any other measure-related issue. By reducing the sample size and decreasing statistical power, attrition can "threaten the internal validity of experimental studies" (Ribisl et al., 1996). Attrition rates in infants' studies are usually higher than in adults and negatively impact data reliability. Although attrition during EEG acquisition tends to show an inverted u-shaped pattern through development (Bell and Cuevas, 2012), the factors that may increase data loss in developmental studies are not fully known. In a meta-analysis investigating attrition rate in infant ERP studies, Stets et al. (2012) found that the nature of the stimuli was the main influential factor for attrition, but that age was not. Remarkably, studies involving visual stimuli showed the highest attrition rates. However, the attrition rate may also depend on the paradigm and the age of participants (de Haan, 2013). These contradictory results reflect the lack of knowledge about the attrition rate in infants' EEG studies.

Nevertheless, attrition can be overcome by recruiting larger samples of participants, choosing adequate experimental settings, implementing recruitment strategies or databases, and piloting before actual data acquisition (Hurwitz et al., 2017; Ribisl et al., 1996). The accelerated longitudinal design is an alternative to longitudinal studies, which usually present high attrition rates (Galbraith et al., 2017). This method involves the recruitment of multiple cohorts at different ages, each covering a part of the broader targeted age range instead of a single cohort spanning all ages. In addition to decreasing attrition rates, its main advantage is that all ages are studied longitudinally for a given age range but within a shorter period than a classical longitudinal design. As attrition rates are very variable within the literature, similar studies should be compared to estimate the expected amount of data loss. In any case, while several EEG artifact management procedures are available nowadays, it remains crucial to remember that the researcher should prepare the experimental task and lab setting in the most appropriate way to minimize noisy activity. In other words, the most critical aspect of developmental EEG research remains that prevention is better than cure.

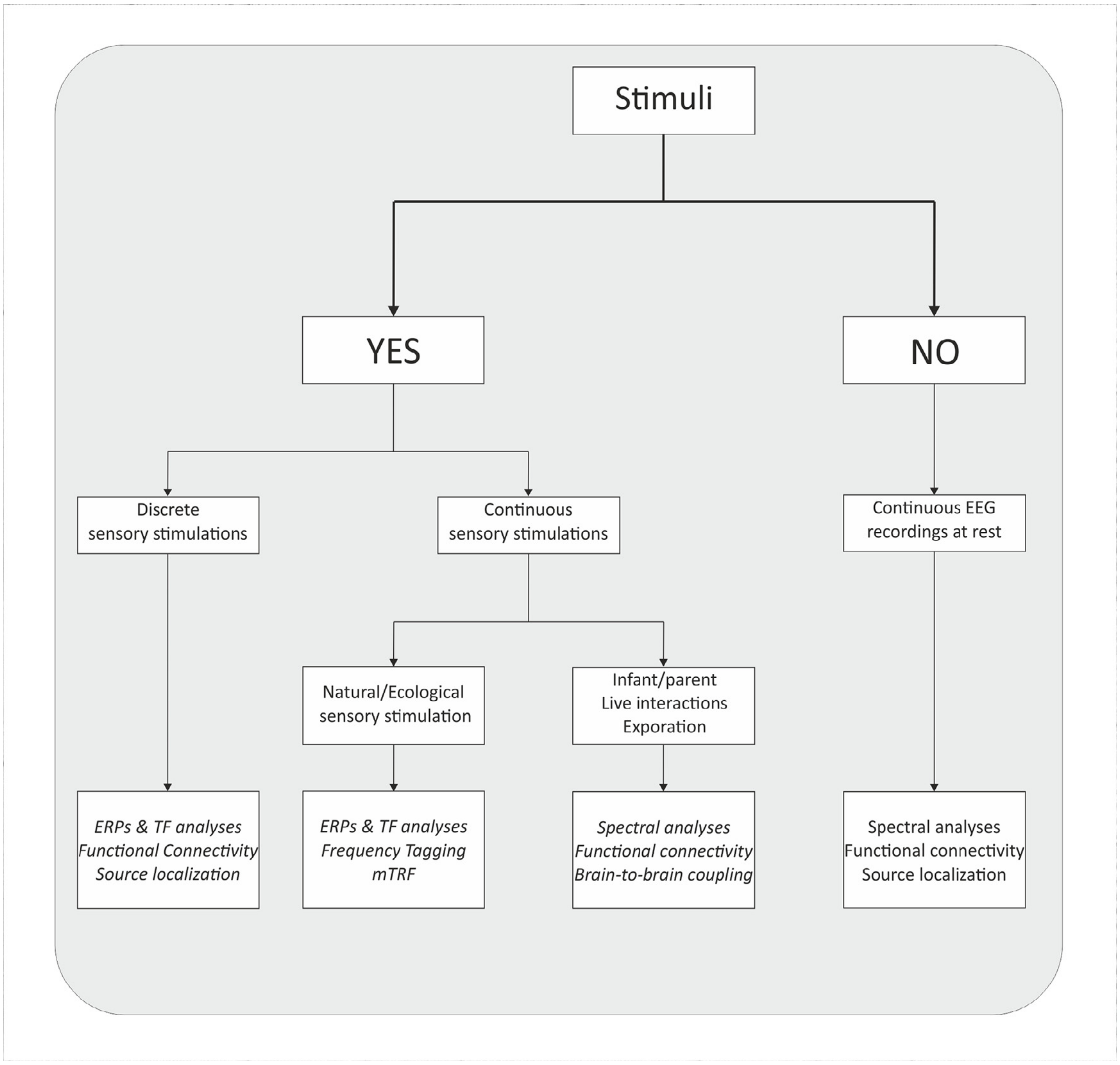

Fig. 4. Decision tree illustrating the different analyses available for current developmental EEG research. Continuous resting-state EEG data can be analyzed when no stimulation is used using advanced methods such as spectral, functional connectivity, or source localization, depending on the electrode layout. Different experimental paradigms with continuous or discrete stimulations can be analyzed using various methods depending on the electrode layout.

2.2. Classical paradigms and time-domain analyses

When designing an experiment for developmental populations, the first challenge is to provide an attractive experiment that captivates the child's attention and avoids boredom. If stimuli are presented, they must be carefully chosen, and attention-grabbers (pictures, videos, sounds) can be displayed between trials depending on the task. Because infants have limited attentional, cognitive, and behavioral abilities, the second challenge is to use specific tasks adapted to the age of the participants. Indeed, unlike adults, infants can hardly follow instructions (de Haan, 2013), which must be considered when designing the experiment. Consequently, collecting EEG during rest or passive paradigms can overcome this limitation while allowing the analysis of brain activity (see Fig. 4 for an illustration of the different options for the analysis of EEG data during development and Table 1 for an integrative summary of the main ERP results). Similarly, splitting passive tasks into short blocks may help obtain good quality data for restless babies. When the experimental setting is divided into small blocks, the changes in the behavioural state may not negatively impact the entire experiment but only a single recording block which may be particularly relevant for experimental designs interested in observing changes over the recording session.

2.2.1. Auditory paradigms

The auditory oddball paradigm is one of the most common paradigms in infants' EEG studies. When presented with auditory stimuli such as tone bips or speech sounds, a succession of waves forming the cortical auditory evoked potentials (CAEPs) can be observed over frontocentral electrodes (see Wunderlich and Cone-Wesson, 2006 for a review). Wunderlich et al. (2006) showed that the CAEPs elicited by pure tones or complex speech sounds such as a consonant-vowel-consonant word develop from early infancy showing a gradual increase in peak amplitude. Specifically, they collected CAEPs in newborns ($N = 10$), toddlers ($N = 19$), children ($N = 20$), and adults ($N = 9$) and showed that the P1 and N2 peak amplitudes decreased, whereas the N1 and P2 peak amplitudes increased with age. The oddball paradigm is also referred to as the "MMN" paradigm for "Mismatch Negativity", the brain response peaking between 170 and 250 ms after stimulus onset elicited by the preattentive detection of deviants (Näätänen et al., 2005, 2007; Kushnerenko et al., 2002). It relies on the brain sensitivity to rarely occurring deviant stimuli that are pseudo-randomly presented within a series of repeated standard stimuli. Deviant stimuli have a lower probability compared to standard ones, which generally occur with a probability comprised between 0.75 and 0.90 (Sambeth et al., 2006; Cheour et al., 2002b; Kushnerenko et al., 2002; Leppänen, Eklund and Heikki, 1997;

Table 1

Summary table showing the main ERP components obtained in classic EEG paradigms used in developmental research. Note that the adult components are also mentioned but should not be considered similar to the infant's components. Instead, ERPs obtained during early development should be seen as precursors of adult ERPs because they originate from an immature brain. For example, although the infant and adult MMNs may reflect a similar change detection process, the neural generators may differ. NI = No information. ISI: Inter-Stimulus-Interval.

Component	Age	Polarity	Latency (ms)	Spatial distribution	Cognitive correlate	Studies
CAEPs						
P1	Newborns	+	74-86	NI	Automatic brain responses to tones or complex sounds	Wunderlich & Cone-Wesson, 2006; Kushnerenko et al., 2002; Barnet, 1971
	Toddlers	+	67-90	Fronto-temporal		
	Children	+	77-93	Fronto-central		
	Adults	+	46-58	Fronto-central		
N1	Newborns	-	154-186	Fronto-central		
	Toddlers	-	136-150	Distributed across frontal, central, temporal and parietal regions		
	Children	-	157-177			
	Adults	-	107-114	Fronto-central		
P2	Newborns	+	214-241	Fronto-central & temporal		
	Toddlers	+	255-297	Distributed across frontal, central, temporal and parietal regions		
	Children	+	254-287			
	Adults	+	175-215	Fronto-central		
N2	Newborns	-	373-422	Distributed across the scalp		
	Toddlers	-	373-450	Distributed across the scalp		
	Children	-	376-400	Fronto-central		
	Adults	-	290-312	Fronto-central		
MMN	Newborns	- / +	350-550	Fronto-parietal	Automatic change detection (auditory stimuli)	Partanen et al., 2013; Tanaka et al., 2001; Nätäänen, 2000; Cheour et al. 2000
	Toddlers	- / +	200-250	Fronto-parietal		
	Children	- / +	200-400	Fronto-central		
	Adults	-	100-200	Fronto-central		
N170	Newborns	NI	NI	NI	Visual face and face inversion processing	Halit et al., 2003; de Haan et al., 2002; Gliga & Dehaene-Lambertz, 2007; Kadosh & Johnson, 2007; Taylor et al., 2001
	Toddlers	- or +	220-350 or 400	Occipito-temporal		
	Children	-	170-250	Occipito-temporal		
	Adults	-	144-200	Occipito-temporal		
Pb	Newborns	NI	NI	NI	Stimulus expectancy and contextual processing	Karrer et al., 1998; Webb et al., 2005 ; Jonkman, 2006 ; Squires et al., 1976
	Toddlers	+	200-400	Occipito-temporal		
	Children	+	300	Occipital		
	Adults	+	300	Central		
PSW	Newborns	NI	NI	NI	Visual working memory updating	de Haan & Nelson, 1997 ; Duarte et al., ; 2013 ; Pelegrina et al., 2020
	Toddlers	+	1000	Fronto-central		
	Children	+	500-700	Parieto-occipital		
	Adults	+	300-700	Centro-Parietal		
Nc	Newborns	-	1000-1200	Fronto-central	Stimulus familiarity and frequency Attention allocation	DeBoer, Scott & Nelson, 2004; Nelson, 1996 ; De Lorenzo et al., 2020 ; Grune et al., 1996 ; Gomarus et al., 2006
	Toddlers	-	400-600	Fronto-central		
	Children	+	300-400	Fronto-central		
	Adults	+	300	Centro-parietal		
CNV	Newborns	NI	NI	NI	Stimulus expectancy	Mento & Valenza, 2016; Mento & Vallesi, 2016; Mento, 2013
	Toddlers	-	ISI-related	Fronto-parietal		
	Children	-	ISI-related	Fronto-parietal		
	Adults	-	ISI-related	Fronto-parietal		

Winkler et al., 2003). The oddball paradigm has been consistently used with deviants in sound duration (Ceponiene et al., 2002; Clarkson et al., 1989), frequency (Alho et al., 1990a,b; Kushnerenko et al., 2002; Leppänen et al., 2010; Bisiacchi et al., 2009; Mento et al., 2010), intensity (Kushnerenko et al., 2002; Partanen et al., 2013), phonetic features of speech sounds (Dehaene-Lambertz, 2000; Cheour et al., 1998a,b; Pang et al., 1998; François et al., 2021), complex musical or speech sequences (Háden et al., 2015a, b; François et al., 2017; Mueller et al., 2012). Importantly, the term "Mismatch Response" or MMR is often preferred in developmental studies because of its high intersubject variability. Indeed, this component tends to be positive in younger infants and sometimes up to school age, depending on the developmental status of children (Bisiacchi et al., 2009; Mento and Bisiacchi, 2012; François et al., 2017; Moser et al., 2020; Kailaheimo-Lönnqvist et al., 2020; Hoehl and Wahl, 2012; Partanen et al., 2013; Maurer et al., 2003; Putkinen et al., 2014; see also Virtala et al., 2002 for a recent discussion on positive vs. negative MMR in a large longitudinal study). Similarly, positive and negative MMRs have been reported in infants between 2 and 6 months of age, suggesting that experiments with small sample sizes might be more likely to result in erroneous results than adult studies (Trainor et al., 2003). Various versions of this paradigm have been developed depending on the aim of the study and the infant's age (see Virtala et al., 2022 for a longitudinal study). For instance, the familiarization-test oddball paradigm is adapted for more complex stimuli such as words, nonwords, or longer sequences of sounds (Bosseler et al., 2016; François et al., 2017; Kabdebon et al., 2015; Teixidó et al., 2018). Importantly, the oddball paradigm can include multiple deviant types in one experimental session (Näätänen et al., 2005; Partanen et al., 2013). Using multiple deviants inserted in the sequence (also known as *Multi-feature Oddball* or *Optimum 1;* Näätänen et al., 2004) is a methodologically sound choice for developmental EEG research. First, it allows to partial out the effect of probability from the nature of the deviance *per se.* Using three different deviants (e.g., duration, pitch, and intensity; 10% each) allows to directly compare the processing of different deviant stimuli neat of their absolute frequency while keeping the SNR constant. Second, it allows testing of up to four or five different deviants in a single session, thus providing a wide-range profile of brain responses according to stimulus deviance properties. This experimental paradigm has proven particularly useful for investigating infants' language development (Lovio et al., 2009; Partanen et al., 2013). Another modified version of the oddball paradigm, particularly useful to study speech processing in early infancy, involves multiple trains of five stimuli with four standards and a final deviant that can differ according to either local or global perceptual features (Dehaene-Lambertz and Dehaene, 1994; Dehaene-Lambertz, 2000; Bekinschtein et al., 2009). Importantly, this modified paradigm disentangles the effect of response habituation to repetition (the progressive peak amplitude reduction across the standards) from deviant-related processes. Finally, a multimodal version of the oddball paradigm that involves the simultaneous presentation of auditory and visual stimuli can also be used to evaluate audiovisual integration in 5-month-old infants (Kushnerenko et al., 2008).

Although extensively used in developmental EEG studies, the oddball paradigm is not the only auditory paradigm available. Priming paradigms are particularly adapted to study lexico-phonological processing in developmental populations (Becker, Schild, and Friedrich, 2014; Friedrich and Friederici, 2005). Such paradigms allow analyzing the effect of a "prime" stimulus on a subsequently presented target which can provide relevant information on the interaction between phonology and semantic processes early in development. Becker et al. (2014) investigated the emergence of phonological representations and predictive processing in young infants. Specifically, they presented 6-to-24-month-old infants with word onset primes that were phonologically congruent ("ma" before "Mama") or incongruent with a target word ("so" before "Mama"). As expected from adult data, the authors observed an immature N100 in the congruent condition reflecting abstract phonological processing (Friedrich et al., 2009). However, they only reported a P350-like effect in the group of 24 months old infants suggesting that phonological processing may not interact with lexical access before age two. Multimodal priming paradigms with visual stimuli are also used to study word recognition and semantic priming during development (Friedrich and Friederici, 2004; Mani and Plunkett, 2008). For example, Friedrich and Friederici reported that 19-month-old infants show an N400 to incongruent condition, suggesting that semantic processing interacts with word recognition mechanisms early in life. Other paradigms used in developmental EEG studies have evaluated speech segmentation ability based on statistical learning using ERP analyses (Bosseler et al., 2016; François et al., 2017; Kabdebon et al., 2015; Kooijman et al., 2005). These experiments rely on the human ability to detect statistical regularities to segment words contained in continuous speech (Saffran et al., 1996). For example, Bosseler et al. (2016) showed that newborns' brains are sensitive to prosodic information and syllable position for speech segmentation, indicating that statistical learning processes can already be observed from the first days of life (see also François et al., 2017). Overall, various auditory paradigms have been successfully adapted to babies, infants, and children that have provided crucial information about the early neurophysiological changes that occur during the maturation of the auditory pathway.

2.2.2. *Visual paradigms*

In the visual modality, the priming or repetition suppression paradigm has mainly been used to study infants' processing of faces, movements, or categories (Gliga and Dehaene-Lambertz, 2007; Webb and Nelson, 2001; Geangu et al., 2021; Jeschonek et al., 2010). In adults, the N170 is consistently observed in response to faces (Kappenman and Luck, 2011) and is larger for inverted than upright faces (de Haan et al., 2002). During development, the N290 may constitute a reliable precursor of the N170 as its latency decreases from 350 ms to 220 ms between 3 and 12 months (Halit et al., 2003; de Haan, 2013). The infants' N290 may assume the same functional role as in adults only after six months before this age; it is not sensitive to face inversion (de Haan et al., 2002). The P400 is another face-sensitive ERP response observed over posterior lateral electrodes between 3 and 12 months. This response has also been proposed as a precursor of the adult N170 since it shows similar face-dependent amplitude modulation (Gliga and Dehaene-Lambertz, 2007). However, these two ERP components have different morphology, polarity, and scalp distribution, suggesting that the underlying neural generators may undergo dramatic changes during the first year of life. While the exact functional meaning of the N290 and P400 has not been entirely understood yet, both ERPs have been successfully used to predict both typical and atypical development (Leppänen et al., 2007; Gredebäck et al., 2015; McCleery et al., 2009). The Pb ("positive before") develops beween 200 to 400 ms after stimulus onset and is associated with stimulus expectancy or contextual processing during visual oddball paradigms (Karrer et al., 1998). Its latency decreases, whereas its amplitude and sensitivity to experimental changes increase with age (Webb et al., 2005). The Nc is another ERP component originally associated with stimulus familiarity and frequency in visual paradigms (Courchesne et al., 1981; Karrer and Ackles, 1987; de Haan and Nelson, 1997, 1999 Nelson and Collins, 1992; Kopp and Lindenberger, 2011). However, most recent studies linked this component to attention allocation (di Lorenzo et al., 2020; Webb et al., 2005; see Conte et al., 2020 for a recent review). In newborns, the Nc shows a maximum amplitude between 1000 and 1200 ms after stimulus onset and around 500 ms in 12-month-olds (DeBoer et al., 2004; Nelson, 1997). Nonetheless, recent studies reported an Nc peaking between 400 and 600 ms even in infants younger than 12 months (di Lorenzo et al., 2020, Conte et al., 2020, Xie et al., 2019). Finally, the Positive Slow Wave (PSW, 1000 ms after stimulus onset) can occur when familiar faces are similar to unfamiliar ones and may thus represent visual working memory updating (de Haan and Nelson, 1997).

3. Working with young participants: advanced methods

EEG recordings are particularly relevant to understanding the maturational processes that support the emergence and development of early brain oscillations (Schaworonkow and Voytek, 2021). A crucial aspect of developmental EEG studies is that the structural and functional changes support the acquisition of increasingly complex behaviors (Johnson, 2001). Interestingly, learning may be supported by the synchronized activity of long-distance brain regions (Fries, 2005), and the intrinsic hierarchical organization of brain oscillations may facilitate stimulus processing (Lakatos et al., 2005). Besides, phase synchrony between different brain regions has been proposed as a mechanism for long-range communication of information (Varela et al., 2001; Lachaux et al., 1999) that is required during specific cognitive tasks (Buzsáki and Dragun, 2004). Therefore, TF analyses applied to infants' data may be particularly relevant and more informative than ERPs in studying the emergence of high-level cognitive functions.

3.1. Spectro-temporal analyses

Classical TF analyses of EEG data allow estimating the dynamic amplitude and phase modulations in different frequencies by computing the absolute power, the relative power, the coherence, or the hemispheric asymmetry in specific frequency bands. Indeed, TF transforms can be applied to resting-state or task-related data allowing the analysis of evoked and induced oscillatory brain activity (de Haan, 2013; Tallon-Baudry and Bertrand, 1999). The Fourier transform allows the decomposition of the signal in different frequency bands such as delta waves (<3.5 Hz), theta waves (4–7 Hz), alpha waves (8–13 Hz), beta waves (13–30 Hz), and gamma waves (>30 Hz). These different frequency bands described in infants' EEG research are slightly lower than those reported in adults but may support similar cognitive processes such as attention, memory, and emotion (Saby and Marshall, 2012).

Theta, alpha, beta, and gamma activity have been reported during different experimental paradigms and across different ages, with results showing modulations in power and phase synchrony throughout development (Begus and Bonawitz, 2020; Bazhenova et al., 2007; Bell and Wolfe, 2007; Bosseler et al., 2013; Musacchia et al., 2013; Orekhova et al., 2006, 2014; Ortiz-Mantilla et al., 2013; Stroganova et al., 1998; Csibra et al., 2000; Kaufmann, Csibra and Johnson, 2003). The alpha wave, with a frequency of 6-9 Hz in infants, is related to visual attention, emotional expression, working memory, and inhibitory control (Fox et al., 2001; Morasch and Bell, 2011; Orekhova et al., 2001). For example, Bell and Wolfe (2007) performed TF analyses of EEG data collected during a working-memory task in fifty infants and at two time points (8-m-o and four y-o). Results revealed that relative to baseline, working memory process was associated with an increased alpha power (6–9 Hz) over all the electrodes at eight months but over medial frontal electrodes only at four years. This more focal activity was interpreted as an increased functional specialization through development. The mu rhythm (8–13 Hz in adults) is observed in the sensorimotor cortex and associated with understanding others' actions using mirroring properties (Cuevas et al., 2014; Debnath et al., 2019).

TF analyses are particularly relevant to studying infants' cognitive repertoire during ecologically valid situations as they may help capture brain activity not observable using classic ERP analyses (Debnath et al., 2019; Morales and Bowers, 2022). In adults, increased alpha activity is observed at rest, whereas decreased alpha is triggered during cognitively demanding tasks. Besides, increased theta rhythm has been associated with high attentional and emotional loads (Klimesch, 1999). Interestingly, Orekhova et al. (2006) analyzed TF transforms obtained in 8- to 12-month-old infants during attentionally demanding situations such as interacting with an adult or exploring a new toy. Compared to baseline, results showed a clear reduction of alpha and an increase in theta during the more demanding situations. Because such live paradigms do not allow to easily spot brain activity time-locked to specific events required for ERPs, TF analyses may constitute a more appropriate tool to decipher the cognitive processes involved during ecologically valid situations. In addition, compared to passive studies, more interactive tasks such as conversations or games might allow longer recordings by enhancing children's interest. For example, toddlers' action observation during conversational turn-taking with caregivers may be associated with a suppression of mu rhythm (Liao et al., 2015; Meyer et al., 2022). Thus, TF analyses during ecologically valid paradigms may offer new perspectives into more socially-driven cognitive processes that ERP studies could hardly explore. In addition, different analyses can be combined to provide complementary information about the brain responses underlying specific cognitive processes (Isler et al., 2012). For instance, combined TF and ERP analyses have been successfully used to study brain responses from sleeping newborns during an auditory MMN paradigm (Isler et al., 2012). While TF analysis revealed a theta power increase to deviant stimuli at multiple scalp locations and latencies, ERPs failed to detect a difference between standard and deviant stimuli. Similarly, combined TF and functional connectivity analyses have been used to show that mu desynchronization during movement mirroring may occur in both motor and occipital areas, thus supporting a functional coupling between these two brain networks (Debnath et al., 2019). If classical TF analyses of EEG data can be very useful to study early brain functioning during realistic situations, new advanced analyses have been recently developed and may provide further insight into early brain organization.

3.2. Advanced spectro-temporal analyses

Derived from TF analyses, functional connectivity measures of resting-state or task-related data have also gained interest in the developmental research community (Boersma et al., 2011; He et al., 2019; Tóth et al., 2017; Tokariev et al., 2016; 2019; Tran et al., 2021; Cuevas et al., 2012). For example, Tokariev et al. (2016) studied 38 sleeping newborns during active and quiet sleep while recording EEG from 19 electrodes at two time points after birth. The results showed that vigilance states and postnatal age largely modulated functional connectivity measures. Similarly, Mariscal et al. (2021) recently examined the spectral changes of EEG data collected during resting-state in 98 children from three months to three years. The analysis of phase-amplitude-coupling between alpha, beta, and gamma frequencies showed opposite patterns of preferential coupling over anterior and posterior electrodes that increased with age, revealing the building of early regional phase preferential coupling. In another recent study (Xie et al., 2019), fifty-nine infants were evaluated cross-sectionally at 6 ($N = 15$), 8 ($N = 14$), 10 ($N = 17$), and 12 months of age ($N = 13$) during a sustained attention paradigm while EEG was recorded. The authors applied graph theory analyses to (i) weighted phase lag index measures (wPLI; Vinck et al., 2011) computed between scalp electrodes and (ii) seed-based connectivity measures computed between reconstructed sources. At the source level, seed-based connectivity analyses showed that sustained attention induced a decrease in the alpha band localized within the dorsal attention and default mode networks. Importantly, the strength of functional connectivity in this alpha band increased with age within specific brain networks only (visual, somatosensory, dorsal attention, and ventral attention networks). These results suggest that the development of early sustained attention is accompanied by distinct brain functional connectivity patterns representing different functional brain-network topologies that may go through rapid configurational changes during early development. In the case of sensor-space analyses, the wPLI can be particularly relevant to reducing the effects of volume conduction since zero-lag synchronization is left out from the analysis, thus implying that the result is not based on shared neural sources (Bastos and Schoffelen, 2016). Nonetheless, care must be taken when interpreting functional connectivity results in young participants because the number of electrodes constrains the accuracy of the measures and the duration of the recordings impacts these measures

(Tokariev et al., 2016; Haartsen et al., 2020). Moreover, synchrony analyses at the scalp level may give ambiguous information about the underlying brain networks due to the physical changes occurring during development. Therefore, translating scalp-level coherence patterns to functional connectivity in the source space requires a certain degree of cautiousness (Hu et al., 2010; Schiff, 2005; see Michel and Murray, 2012 for a review).

Continuous natural speech, music, or movies can also be used while recording EEG in infants (Begus et al., 2015; Carver and Vaccaro, 2007; Leong et al., 2017; Striano et al., 2006; Hoehl et al., 2014a, 2014b). Further, dual-EEG recordings during live interactions can allow collecting simultaneous EEG in infants and caregivers (Piazza et al., 2020; Haresign et al., 2022; see Noreika et al., 2020 for a review on dual-EEG during development). Most of these studies consist of interactive sessions between infants and caregivers, allowing the analysis of brain activity to objects or complex adult behaviors. These paradigms allow researchers to create more ecologically valid conditions but are often harder to control; consequently, data are harder to analyze.

Nonetheless, time-resolved analyses exploring the online neural tracking of speech, music, movies, or live interactions can help study brain development in an ecological context. Such analyses capitalize on the brain property to adapt its oscillatory activity to the rhythm of a visual or auditory stimulus presented periodically (Regan, 1982; Picton et al., 2003). For example, in adults, scalp or intracranial EEG collected during continuous stimuli such as speech or musical pieces has been successfully used to demonstrate that neural tuning occurs at the specific frequencies contained in the input (Nozaradan et al., 2014; Giraud and Poeppel, 2012; Teng and Poeppel, 2020; Lerousseau et al., 2021; Henin et al., 2021; Elmer et al., 2021; Ramos-Escobar et al., 2021, 2022). Typically, adults' brain activity shows a clear peak at stimulation frequency for auditory, visual, and somatosensory continuous inputs (Galambos et al., 1981; Namerow et al., 1974; Norcia et al., 2015). This type of analysis has been applied to various paradigms using auditory and visual continuous stimulations (see Kabdebon et al., 2022, in this special issue). For instance, previous studies in adults show that auditory cortical EEG activity can robustly track the speech envelope through neural synchronization to specific rates such as the syllabic and phrasal rates (Giraud and and Poeppel, 2012; Ding and Simon, 2012, 2014). Such neural tracking can be quantified with different approaches that rely on (i) the computation of the coherence between the auditory input and the EEG signal, (ii) the analysis of power and phase variability across trials, and (iii) the frequency tagging approach that quantifies the rhythmicity of the neural response in the frequency domain. Coherence relies on the linear correlation between the "entrained" EEG signal and specific features of long stimuli such as musical pieces or natural sentences (Doelling and Poeppel, 2015; Mesgarani et al., 2014; Peelle et al., 2013). This approach ignores the phase information and thus provides an overall estimation of neural tracking during the stimulation. In infants, frequency tagging has been recently used to study the development of high-level cognitive processes such as speech segmentation, grammatical rule-learning, musical beat processing or even face processing (Fló et al., 2022a; Choi et al., 2020; Kabdebon et al., 2015; Cirelli et al., 2016; Buiatti et al., 2019; de Heering and Rossion, 2015; Leleu et al., 2020; Köster, Langeloh, and Hoel, 2019).

A recent method to study the early development of brain functioning in response to continuous and ecologically valid stimuli relies on the so-called multivariate Temporal Response Function (mTRF, Crosse et al., 2016). This method uses linear regression to quantify the relationship between a continuous EEG signal and an ongoing stimulus. The mTRFs have been successfully applied to infants' EEG data to unravel the mechanisms supporting sensory processing of natural stimuli such as movies or spoken sentences (Attaheri et al., 2022; Jessen et al., 2019, 2021; Kalashnikova et al., 2018; Menn et al., 2022; see also Ashton et al., 2022). Briefly, it allows the mapping between specific features of continuous stimuli and the corresponding neural response in a forward and backward manner. The forward or encoding modeling approach predicts the neural response based on specific input features. It has been used to decipher the gradual weighting of speech auditory features during early development (Kalashnikova et al., 2018). By contrast, backward or decoding models allow the opposite estimation in a multivariate manner, predicting the sensory input based only on the neural EEG data. In the context of developmental EEG studies, decoding models can be particularly relevant to compare the amount of neural tracking depending on the attentional level or the linguistic environment.

Another advanced method in EEG research aims to estimate the cortical generators underlying the activity obtained in the sensor space. Accurate source localization of several ERP components across different ages based on distributed or dipole source models has now been made possible through the use of high-density EEG systems adapted to infants (Guy et al., 2016; Hämäläinen et al., 2011; Mento and Valenza, 2016; Ortiz-Mantilla et al., 2012, 2013, 2019; Xie and Richards, 2017; Lunghi et al., 2019). For example, Xie et al. (2019) collected cross-sectional EEG data from 5- ($N = 49$), 7- ($N = 50$), and 12-month-old ($N = 51$) infants during the presentation of faces. Results showed successful source reconstruction of the N290 and P400/Nc in the fusiform gyrus and posterior cingulate cortex. Similarly, Mento and Valenza (2016) reported the source reconstruction of the sustained face anticipatory contingent negative variation (CNV) in a group of fifteen 9-month-old infants. They showed that a distributed fronto-parietal cortical network was engaged about one second before the onset of faces when these were temporally predicted through a peek-a-boo play simulation. Remarkably, the presence of reliable stimulus anticipatory ERP activity in young infants highlights the importance of targeting prestimulus bran activity as a proxy to study predictive cognition from a developmental perspective.

Overall, the combined scalp- and source-level investigation suggests that EEG may also be an appropriate neuroimaging tool for the developmental community, as proposed for adults (Michel and Murray, 2012). Noteworthy, a direct comparison of brain source reconstruction across different ages is difficult due to brain structural differences, brain volume conduction, scalp thickness, and dipole orientation (Reynolds and Richards, 2009). Nevertheless, the use of a high-density electrode array (i.e., ≥128), together with other age-appropriate adjustments, has allowed applying this analysis to developmental research successfully (Bathelt et al., 2014). However, considerable caution is still required, especially for young children. A critical issue is that cortical generators' reconstruction should be performed using individual MRI to locate specific anatomical landmarks as precisely as possible (Kabdebon et al., 2015). Indeed, a wrong anatomical representation, as in the case of inappropriate MRI templates, could turn into aberrant source-map solutions. Further, age-related anatomical peculiarities, as in the case of newborns' fontanels, may considerably bias the inverse modeling (Lew et al., 2013; Gargiulo et al., 2015). The ideal solution to limit these concerns is to obtain single-subject MRI scans to inform the forward modeling most realistically, considering the individual differences in the cortical morphology. This issue is crucial, especially when comparing different age groups. One of the most challenging methodological goals of developmental EEG research is to build accurate models of age-related diffusion parameters that consider the changes in the physical properties of infants' developing brains. Indeed, because infants' ERPs tend to be larger than adults due to a better diffusion, fewer trials are needed to obtain clear ERPs but with lower SNR. Therefore, such models would greatly help in considering SNR variability at different ages. Acquiring anatomical MRI is not always possible; thus, one may use age-appropriate MRI age templates that are publicly available instead (Almli et al., 2007; Richards et al., 2016). Recently, several groups collected MRI scans of children of different ages cross-sectionally. In particular, Sanchez et al. (2012) provided age-specific MRI brain templates for thirteen age groups from birth through 4.3 years of age based on more than 150 scans. More recently, another research group released pediatric brain surface templates for infants between two weeks and two years of age (O'reilly et al., 2021). Importantly, O'Reilly and colleagues evaluated the validity of the MRI templates by performing source localization of visual ERP components obtained in 100 high-density EEG datasets from this age range. Results revealed accurate source reconstruction with differences in estimated sources increasing with template age differences. Similarly, Kabdebon et al. (2014) examined the relationship between the 10–20 sensor placement and the underlying cerebral structures in 16 infants (3–17 weeks post-term). The authors quantified the variability in the brain-electrodes distance and the sensor locations between infants based on the anatomical variability of six main cortical sulci of an infant template parcelled in 94 regions. Results revealed increased scalp-brain distances from occipital to frontal and inferior to superior regions thus highlighting the importance of acquiring individual MRI cortical generators' for optimal source reconstruction.

4. Standardized processing pipelines

The infants' EEG research community is much smaller than the adult one; thus, it does not rely on a myriad of toolboxes with various standardized methods. In adults, EEG data processing can be done using EEGLAB (Delorme and Makeig, 2004), Fieldtrip (Oostenveld et al., 2011), MNE (Gramfort et al., 2013), Brainstorm (Tadel et al., 2011), or any compatible EEG data processing software. However, while these toolboxes have been successfully used to analyze developmental EEG data, to our knowledge, only three processing pipelines have been purposely developed for this kind of population so far. Of particular importance for infants' EEG research is detecting and correcting either bad channels or large artifacts most of the time obtained in short continuous time segments, thus hampering classic algorithms that operate well on adult data. Here, we briefly describe the main characteristics and advantages of each standardized pipeline found in the literature.

First, the "Maryland analysis of developmental EEG pipeline" (MADE; Debnath et al., 2020; https://github.com/ChildDevLab/MADE-EEG-preprocessing-pipeline) is a Matlab-based toolbox that combines EEGLAB functions with customizable processing parameters that are well adapted for infants EEG data such as trial-level channel interpolation (Buzzell et al., 2019). The MADE toolbox includes different preprocessing steps such as filtering, automated identification/rejection of bad channels, identification, and removal of artifacts based on ICA, epoching, artifact rejection on epoched data using simple thresholding, bad channel interpolation, and re-referencing of epoched data. In particular, the bad channel identification is based on a multivariate approach that takes into account three different parameters (Hurst exponent, correlation with other channels, and channel variance; for more details, see Debnath et al., 2020). These three parameters are combined and normalized to obtain a Z score. Values higher than 3 allow marking bad electrodes. This system may allow a more accurate screening of electrodes with artifactual activity resulting in a more conservative outcome (fewer electrodes to interpolate). Another advantage of this pipeline is that it implements a modified version of the adjust tool (Mognon et al., 2011) already implemented in EEGLAB and created explicitly for automatic labeling of artifactual ICs (eye movements, blinks, muscular activity, others). In particular, the authors added the possibility of quantifying the alpha activity of each IC using this parameter as a constraint to keep the components. This specific option further increases the reproducibility and the reliability of ICs classification by making the preprocessing procedure more operator-independent. The MADE pipeline has been validated on resting-state and task-based EEG data from three groups (infants, children, and late adolescents) and compared to two more traditional processing pipelines that included the interpolation of bad channels or not. The results showed that the MADE toolbox significantly retained more trials than the other two pipelines for the three age ranges. Therefore, the MADE provides an appropriate pipeline for infants, children, and adolescents' EEG data based on automated processing steps, thus ensuring a higher degree of objectivity and replicability than manual operator-dependent processing pipelines. However, the MADE toolbox may not be recommended for EEG data collected with low-density montages (i.e., less than 32 electrodes) as it may require modifying the optimal default parameters used in most of the processing steps implemented in the MADE toolbox.

Second, the Harvard Automated Processing Pipeline for EEG (HAPPE; Gabard-Durnam et al., 2018; https://github.com/lcnhappe/happe) has been proposed to optimize the processing of short-duration resting-state and task-related recordings obtained with different electrode layouts and systems. Importantly, the HAPPE toolbox implements a specific preprocessing step involving a w-ICA that improves the decomposition of the EEG data (Castellanos and Makarov, 2006). It also implements the Multiple Artifact Rejection Algorithm (MARA) to automatically identify artifactual ICs, thus allowing a more objective classification than a manual one. Interestingly, the toolbox provides individual post-processing reports containing data quality metrics that allow the objective classification of each dataset for further analyses. The performance of the HAPPE toolbox has been assessed on ten infants' EEG datasets and compared with seven alternative methods that rely on the same pre-processing steps except for the w-ICA and MARA. Results revealed that the HAPPE toolbox outperformed the alternative methods by removing more artifacts while preserving a similar amount of data compared to the seven alternative methods. Furthermore, the authors provided the distribution of post-processing data quality metrics obtained in 867 infant datasets from 3 to 36 months of age, thus offering a normative database useful to classify future EEG files objectively. However, most of the alternatives relied on the same pre-processing steps that started with a 1 Hz low-pass filter preventing the analysis of ERPs. Besides, even though the implementation of combined w-ICA/MARA identified 42% of ICs as artifactual, this number increased to 85% when using MARA only, thus suggesting that further improvements are needed to optimize automatic classification algorithms for infants' EEG data (Haresign et al., 2021). Interestingly, an adapted version of the HAPPE toolbox has been recently proposed for low-density EEG montages (Lopez et al., 2021). However, no clear comparison with alternative pipelines is provided in the current version of the article.

Third, Fló et al. (2022b) have recently developed the "Automated Pipeline for Infants Continuous EEG" (APICE toolbox; https://github.com/neurokidslab/eeg_preprocessing), in which automatized artifact detection is performed on the continuous data before further preprocessing. APICE is Matlab-based and builds on the EEGLAB toolbox (for importing the data, filtering, and epoching) and custom functions. Of particular interest is the implementation of different algorithms for artifact detection and correction optimized for infants' EEG data. Specifically, the APICE toolbox performs ICA combined with the iMARA algorithm, an adapted version of the original MARA algorithm optimized for infants' EEG data, for automatic component selection (Haresign et al., 2021) and Denoise Source Separation (DSS, De Cheveigné and Parra, 2014; de Cheveigné and Simon, 2008). The APICE pipeline has been validated on high-density task-based ERP data obtained in neonates and infants. Specifically, the authors compared the number of trials retained and the standardized measurement error (SME; Luck et al., 2021) obtained with the APICE toolbox, a standard, and a MADE-based processing pipeline. Results revealed that the APICE toolbox significantly retained more trials and reached lower SME values than the other two pipelines for infant ERP datasets. The standard pipeline retained significantly more trials than the APICE toolbox for the neonatal dataset, but this was accompanied by higher SME values suggesting lower data quality. Overall, the APICE toolbox seems promising as it may ensure high flexibility, good data recovery, and thus high reproducibility across populations.

These three toolboxes offer many customizable outputs for further analyses using appropriate software. Importantly, even though they do not offer direct visualization of the significant results, they offer crucial individual data quality metrics that allow the objective classification of individual datasets and automatic artifacts identification. While univariate statistics are still highly used in infant EEG research, future studies should prefer cluster-based permutation tests as done in adults

(Meyer et al., 2021). Indeed, ERP components recorded during early development may be ambiguous and traditional peak picking methods may not be optimal. Cluster-based permutation analyses can overcome this difficulty by not placing any a priori assumptions on component latencies. Multivariate analyses such as TRFs may be well adapted for analyzing EEG data gathered during continuous sensory stimulations (Jessen et al., 2019; 2021; see also Ashton et al., 2022). Spatial filters that reduce data dimensionality or multiway generalized canonical correlation analyses may also be very useful for analyzing multiple high-density infants' EEG data (De Cheveigné and Parra, 2014; de Cheveigné and Simon, 2008; Gloaguen et al., 2020). Moreover, the EEG-BIDS format (for Brain Imaging Data Structure; BIDS) has gained interest in the adult community because it provides harmonized metadata and offers a common baseline for comparisons of results from similar studies (Gorgolewski et al., 2016; Pernet et al., 2019; Niso et al., 2018), Nonetheless, the EEG-BIDS format, with a few exceptions (Meyer et al., 2021; Van Noordt et al., 2020) is still under-represented in the developmental community and not considered in the three previously mentioned toolboxes.

5. Conclusion

The recent methodological advances observed in developmental EEG and signal processing are of utmost importance to better understand brain-mind interaction from a developmental point of view, progressively reducing the gap between adult and developmental neuroimaging studies. In other words, the old Berger's promise that the EEG would provide a "window into the brain" (Berger, 1929; Michel and Murray, 2012) is also becoming more and more attainable for developmental research. Nonetheless, working with developmental populations clearly constrains most of the choices related to the experimental design, procedure, and analyses. The classic ERP approach is still essential to ensure the comparability and reliability of the results and determine the developmental continuum of specific cognitive processes from early infancy to adulthood. However, ERPs may not fully capture some oscillatory brain patterns that explain specific developmental cognitive changes (Morales and Bowers, 2022). In this sense, TF analyses applied to resting-state or task-related data are particularly relevant for studying ecologically valid paradigms involving long recordings. Until the recent development of standardized processing pipelines adapted to infants' EEG data, these choices primarily relied on the specific expertise that developmental researchers had acquired, rendering them almost exclusively operator-dependent. Moreover, even though specific designs and procedures can be more suitable than others to tackle specific cognitive questions, such choices may inherently vary with the age of the participants. For instance, the physical characteristics of different ages are still a major issue that must be considered. Indeed, one of the most challenging methodological goals of developmental EEG research is to build accurate models of age-related diffusion parameters that consider the changes in the physical properties of infants' developing brains. Because of their physical characteristics, infants' ERPs tend to be larger than adults due to a better diffusion, and fewer trials are needed to obtain clear ERPs but with lower SNR. Such models will significantly help in considering SNR variability at different ages. Furthermore, longitudinal and cross-sectional developmental studies should prefer within- instead of between-group comparisons to determine how a given effect occurs at different ages, net of obvious anatomical maturational differences. Additionally, the brain changes reported in developmental studies should be associated with later behavioral standardized outcomes to control and minimize the effects of the rapid physiological changes that occur in these populations.

Therefore, by offering fine-grained signal processing tools best adapted to each age range and data, standardized pipelines will help promote replicability and comparability across experiments and ages. While the MADE pipeline might be well adapted for standardized processing of resting-state and task-based EEG data acquired with high-density EEG systems, it may not be compatible with data acquired with low-density EEG setups. The HAPPE pipeline appears more flexible because it allows processing of short-duration resting-state and task-related recordings obtained with different electrode layouts and systems. Nonetheless, the mandatory 1 Hz High-pass filter prevents using this toolbox for developmental studies targeting low-frequency ERP components. Finally, APICE may be the more flexible pipeline for data compatibility as it offers an extensive range of denoising tools adapted to developmental data. Although challenging, the acquisition of EEG during early development offers a unique opportunity to understand better the emergence of complex cognitive functions in humans. The development of standardized pipelines, new experimental paradigms, and analysis tools pave the way to a bright future for cognitive developmental EEG studies, inevitably bringing new challenges and exciting perspectives.

Data and code availability statement

No data presented in this manuscript was newly acquired. No code was specifically written for this manuscript.

Declaration of Competing Interest

The authors declare they have no conflict of interest.

Credit authorship contribution statement

Estelle Hervé: Conceptualization, Writing – original draft. **Giovanni Mento:** Conceptualization, Writing – review & editing. **Béatrice Desnous:** Conceptualization, Writing – review & editing. **Clément François:** Conceptualization, Supervision, Writing – review & editing.

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