Multi-method exploration of the relationship between sleep and infant neurocognitive development

MULTI-METHOD EXPLORATION OF THE RELATIONSHIP BETWEEN SLEEP AND INFANT NEUROCOGNITIVE DEVELOPMENT

Louisa Katharina Gossé

A thesis submitted for the degree of

Doctor of Philosophy (PhD)

University of London

2021

Birkbeck College, Malet Street, London, WC1E 7HX

ORIGINALITY STATEMENT

'I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at the University of London or any other educational institution, except where due acknowledgment is made in the thesis. Any contribution made to the research by others, with whom I have worked at University of London or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation, and linguistic expression is acknowledged.'

Louisa Gossé

Signed: _____

ABSTRACT

The first year of life is a time of numerous developmental milestones. At the same time an infant's sleep undergoes many fundamental changes. Research has shown that sleep can impact aspects of development; however, findings are mixed, often fail to include objective measures of both development and sleep, and longitudinal studies are missing. This project uses a multi-method approach to exploring the relationship between sleep and neurocognitive development in the first year of life. For this purpose, longitudinal and cross-sectional experimental designs were combined with a multitude of objective and subjective methods (such as electroencephalography (EEG), actigraphy, eye-tracking, near-infrared spectroscopy (NIRS), parent-report questionnaires), and analysis approaches (cluster analysis, mixed modelling, and functional connectivity analysis).

Key insights from the longitudinal study showed that cross-method agreement between different sleep measures varied depending on sleep parameters, infant age, and maternal stress. Moreover, sleep measurement choice can influence how the relationship between sleep and development is described. Associations with behavioural and parent-report measures of infant development were fragmented. However, a clearer cross-method consistent picture emerged with regard to brain measures that highlighted the importance of studying sleep fragmentation. The study also underscored the need to study the relationship between sleep and development continuously as there was evidence for age-related changes in the association between sleep and development.

The second, cross-sectional study contributed a new methodology to studying the relationship between sleep (quality) and neurocognitive development. A customised NIRS-EEG system was used as a novel way to study infant brain activity during sleep.

This project enables further research into sleep in a developmental context including the potential use of a wireless NIRS-EEG system to study sleep in naturalistic settings and of sleep fragmentation as a target for sleep-based interventions for children with neurodevelopmental disorders.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my supervisors, Professor Emily Jones (Birkbeck, University of London), Dr Frank Wiesemann (R&D Procter & Gamble), and Professor Clare Elwell (University College London), whose unconditional support and dedication – both intellectually and on a personal level – have made this project possible. I feel incredibly lucky to have had such a fantastic team of supervisors to teach me how to become a scientist. Thank you, Emily, for your never-ending creativity and enthusiasm for science, for pushing me to continuously improve, and for letting me explore ideas even if they never led anywhere. It is truly inspiring to work with you. Frank, thank you for always showing up, for introducing me to research in industry, and for providing me with opportunities I otherwise would not have had. You have made sure that I was able to learn as much as possible from my time at P&G. Clare, thank you for your support, especially with regard to everything NIRS and your kind words, when I needed things to be put into perspective - it meant so much to me.

I am grateful to the EU and the Horizon 2020 programme (Marie Sklodowska-Curie Grant Agreement No. 721895) for providing this fantastic fellowship that meant I could travel and experience both research in industry and in academia.

Special thanks to Susanna B. and Angela C. who were so integral to getting the longitudinal study started at P&G and to Aleks and Monika who helped me with testing for my second study.

Isabel, Anabel, and Berta, thank you for making everything run so smoothly and of course Leslie for your open ear and practical support.

Thank you to Luke Mason for trouble-shooting the experiment remotely more times than I can count and for the help with the eye-tracking data.

I am also very grateful to Professor Patricia Franco for welcoming me into her lab in Lyon so I could learn about infant sleep stage coding.

Thank you to my colleagues at the CBCD who so generously shared their knowledge and time with me to teach me NIRS, EEG, and infant testing - Anna, Rianne, JJ, and especially Maheen. Maheen, your support and friendliness has been so appreciated.

Chiara - I could not have asked for a better mentor. Thank you for having an open ear always and for helping me out in so many ways during my time at the CBCD.

Paola, you have taught me so much about NIRS and your constant (moral and practical) support in the last year of my PhD were invaluable. Thank you also for putting time aside to comment on the NIRS work in this thesis. I hope we make many more serendipitous headgear discoveries together.

Emma, Aude, JJ, Chiara, Paola, Frauke, Casey, and especially Victoria - thank you for commenting on parts of this thesis for me, I like to think your valuable feedback improved it a lot.

A huge thanks to my friends (you know who you are!) for keeping me sane while trying to write a thesis during a pandemic, for celebrating every success with me, and supporting me throughout the failures even from far away.

Thank you to my family, my biggest cheerleaders, whose unconditional support means the world to me and has kept me going. Zoé und Tore, thank you for making me smile and for always having my back and above all, Mama und Papa. Mama, thank you for your open ears and compassion, and for reminding me that there are other (more important things) than science. Maybe now I can finally become an actress :). Papa, thank you for truly understanding, your advice, and for the inspirational (and infuriating) discussions about artificial brains and data analysis, that remind me why I love research.

Casey; thank you for your endless patience when teaching me to code and for being my rock throughout this experience, even from the other side of the world. This would have been infinitely harder without you by my side.

Last but not least - the biggest thank you is to all the patient families and babies without whose participation in my studies this thesis would literally not exist. You have made this job so enjoyable!

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AOI	Area of interest
ARAS	Ascending reticular arousal system
AS	Active sleep
ASQ	Ages and Stages Questionnaire
ASD	Autism Spectrum Disorder
BA plot	Bland-Altman plot
BISQ	Brief Infant Sleep Questionnaire
CAP	Cyclic alternating pattern
CBF	Cerebral blood flow
EEG	Electroencephalography
EMR	Eye movement response
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy
HbO_2	Oxygenated blood
HbR	Deoxygenated blood
IBQ-R	Infant Behaviour Questionnaire-Revised
LMM	Linear mixed effects models
LSP	Longest sleep period
LTP	Long-term potentiation
MBLL	Modified Beer-Lambert Law
MD	Mean difference
NREM	Non-rapid eye movement sleep
NW	Night wakening
PSG	Polysomnography

QS	Quiet sleep
REM	Rapid eye movement sleep
rsFC	Resting state functional connectivity
SCN	Suprachiasmatic Nucleus
SES	Socio-economic Status
SHY	Synaptic homeostasis hypothesis
SI	Sleep Index
SOL	Sleep onset latency
SSQ	Sleep and Settle Questionnaire
SWA / SWS	Slow wave activity/ Slow wave sleep
WASO	Wakefulness after sleep onset

CHAPTER 1 - Studying sleep and development in the first year of life

"Sleep is of the brain, for the brain and by the brain."
Hobson, 2005

Hobson's eloquent title of his 2005 paper sums up what has taken (sleep) researchers centuries to uncover: the bidirectional relationship between sleep and the brain (Hobson, 2005). The brain evokes and regulates sleep but sleep can also impact the brains function. This is particularly the case for the developing brain, a time period of sensitive changes and key milestones in a child's development that sets the foundation for the future development of brain and behaviour. Still, it is not clear how this relationship unfolds in the first year of life. A healthy brain is of utmost importance for development. Brain plasticity means an increased opportunity for the positive impact but conversely also for the negative impact of sleep on development, and researchers must learn more about the role that sleep can play for a child's developmental trajectory.

This is crucial as it represents a chance for sleep as an intervention in the long run. It is important to fill the present gaps in knowledge, so we can understand the relationship between sleep and development in children with neurodevelopmental disorders and whether sleep may function as a neuroprotective mechanism. Sleep is comparably easy to target via intervention; sleep interventions have been proven to work efficiently and might help especially children at risk for neurodevelopmental disorders or children in vulnerable situations. For example, El-Sheik (World Sleep Congress, 2019) recently suggested that children at risk for poverty and children from minority households might receive the greatest benefit from "good sleep". Thus, to understand the relationship between sleep and development is not only important for science and understanding the mechanism of sleep's function in development but also as potential intervention for societies' most vulnerable populations.

The present thesis aims to uncover the ways in which sleep may impact development of the brain and cognition in the critical period of the first year of life. In the following, it is first discussed what sleep is, its function and components, and how it changes in the course of development. Thereafter, the relation of sleep to cognition is reviewed, and studies into the relationship of sleep and neurocognition in the course of

the first year of life are presented. Lastly, the research design and questions to be answered in the thesis are discussed.

1.1 Definition of sleep

Sleep can be defined as a naturally repeating, multidimensional, active, and dynamic state of the human body that is triggered by activating specific neurotransmitters and brain structures. It is universal to many (perhaps all) species, regulated tightly by the brain and as far as researchers can tell, necessary for survival (Guilleminault, 2005).

Historically, Aristotle had his theory about sleep, what it should be defined as and its function (Guilleminault, 2005). However, it is not until Hans Berger developed electroencephalography (EEG; Berger, 1929) and described the onset of the sleeping brain electrical activity by the disappearance of “alpha” rhythms that sleep research was born, and with it a formal definition of what sleep is (Kanda et al., 2016). Thus, it is not until almost 2000 years after Aristotle that humanity started studying sleep in earnest (e.g., Loomis et al., 1935).

While describing the structural components and neural underpinnings of sleep in detail is beyond the scope of this thesis, a general understanding of the brain anatomy underlying sleep-wake maintenance and characteristics of sleep structure are essential to understand the literature presented in the course of the thesis. These are briefly discussed below.

1.2 Structure of sleep

Sleep can be divided into multiple subcomponents, so-called sleep stages. Sleep stages are identified using electroencephalography (EEG). EEG measures electrical activity of the brain by placing electrodes on the human scalp. The electrodes pick up electrical activity of groups of cortical neurons as amplified changes in microvolt. The output generated from an EEG can be interpreted by the inspection of waveforms or decomposition of the signal into different frequency bands. The inspection of the waveforms shows different characteristics depending on sleep stages. The two distinct phases of sleep are called rapid eye movement (REM) sleep and non-rapid eye movement (NREM) sleep. They were first described by Aserinsky and Kleitman in 1953, who noted the movement of eyes during certain periods in sleep, giving REM sleep its name (Aserinsky & Kleitman, 1953). Dement & Kleitman characterized the distinct electrical

brain activity patterns associated with different sleep stages for the first time in 1957 (Dement & Kleitman, 1957).

Each sleep stage has characteristic brain and physiological patterns and functions. The following sleep stages can be identified in adults (see below for more details on sleep stages in the course of development), defined by EEG assessments of brain activity: three different stages of NREM sleep (stage 1, stage 2, stage 3) and REM sleep, which alternate throughout the night in 90 to 110 minutes epochs (see *Figure 1.1.A* for illustration of sleep stages). Older publications cite four different stages of NREM sleep, however new guidelines abandoned this classification, consolidating stages 3 and 4 into one stage 3.

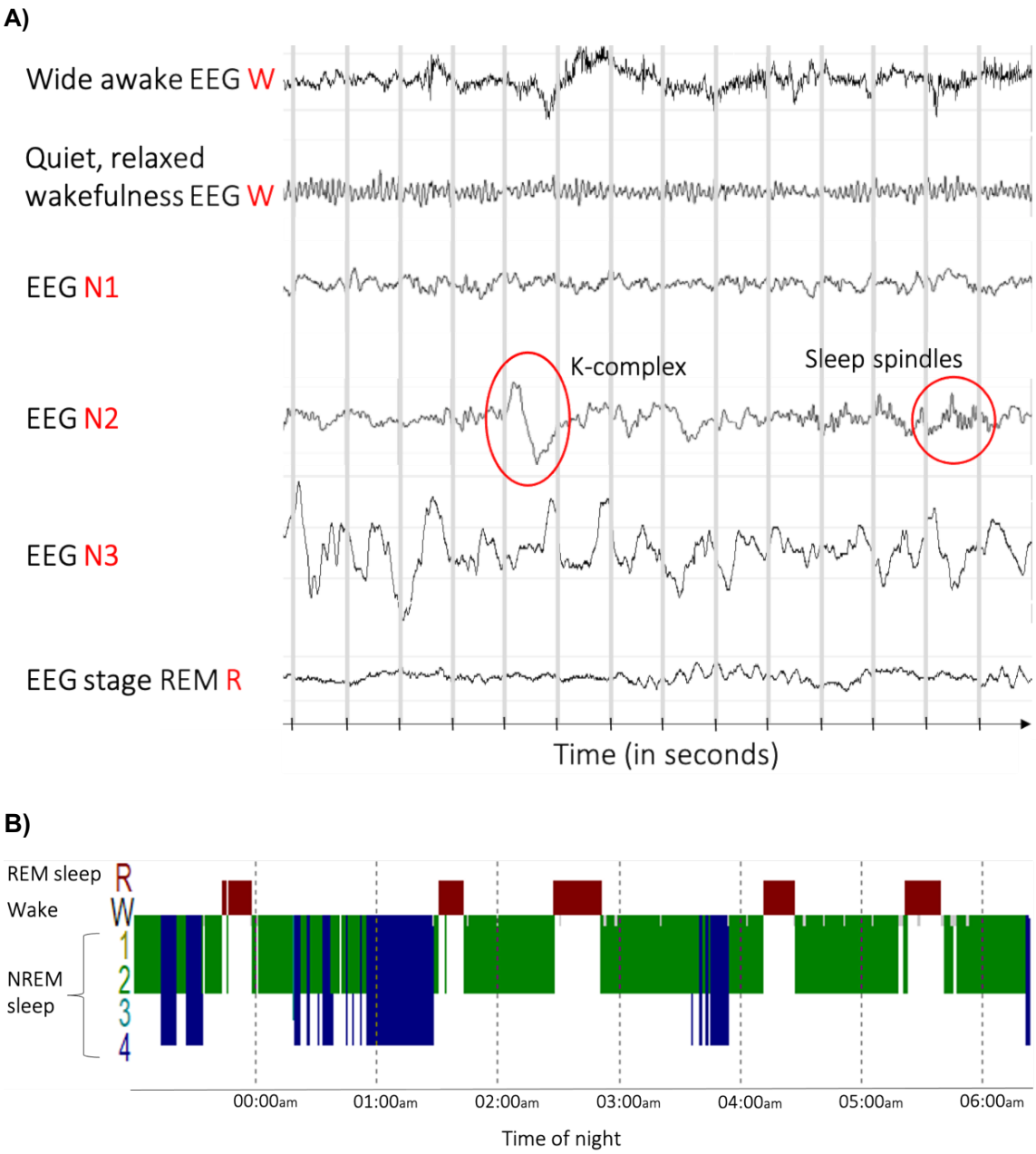


Figure 1.1. A) Illustration of EEG signal for different sleep stages. B) Sleep stage scored hypnogram. Adapted with permission from Sleep Consultancy Ltd.

1.2.1 NREM sleep

NREM sleep is often also called slow-wave sleep, as the predominant EEG-measured electrical brain activity of NREM are slow waves (electrical brain activity in the delta frequency range = 0.5 – 4 Hz) and represent the hallmark of NREM sleep.

NREM stage 1 describes the transition of waking to sleep that is characterized by the presence of alpha-waves (EEG frequency range: 8 – 13 Hz) that are associated with

relaxed and closed-eye wakefulness interspersed with theta waves (EEG frequency range: 5 – 8 Hz) that mark sleep onset. Other features seen in the EEG patterns are so called *vertex sharp waves*, sharp contoured waves with a duration of < 0.5 seconds accompanied by slow, rolling eye movements. The latter may also be seen in NREM stage 2 sleep.

NREM stage 2 makes up around 50% of the night sleep stages. Stage 2 sleep is characterized by larger theta amplitude sleep that carries characteristic hallmarks such as sleep spindles (i.e., >0.5 seconds of train of sinusoidal waves in the frequency of 11 – 16 Hz) and K-Complexes (i.e., bursts of >0.5 seconds duration of negative voltage (>100mV in amplitude) followed by a large positive deflection) accompanied by low muscle tone.

NREM stage 3 is characterized by high amplitude (>75 mV), low frequency delta waves (EEG frequency range 0.5 – 2 Hz). Spindles may be apparent in this sleep stage, too. This slow-wave activity represents mass cortical synchrony (Amzica & Steriade, 1995) and it may be harder for people to wake up during this phase. Human adults commonly progress through NREM sleep stages first before entering REM sleep, the sleep that has historically been linked to dreaming. Rotation through these sleep cycles in adults takes approximately 90 to 110 minutes, with the proportion of REM sleep at the beginning being lower and increasing across the course of the night. The transition between the phases across the night can be seen as an example in *Figure 1.1B.* and is called a hypnogram (Guilleminault, 2005).

1.2.2 REM sleep

REM sleep is characterized by low-voltage desynchronized, low voltage and high frequency waves in the theta band range (4 – 7 Hz), low muscle tone and rapid bursts of periodic movement of the eyes. Absence of sleep spindles and K-complexes is essential for determining presence of REM sleep. The amount of REM sleep increases as the night progresses, where the first REM cycle might only last 10 minutes the last one can last up to an hour, in total REM sleep can make up to 20% of a night's sleep in adults (Guilleminault, 2005).

Sleep architecture varies fundamentally across different stages of life; below briefly outlined are the differences across the lifespan in terms of sleep and sleep architecture, with a focus on infancy, the time period of life that is the focus of the present thesis.

1.3 Neurobiology of sleep-wake maintenance

Regulation and maintenance of sleep and wake involves both sleep and arousal mechanisms that are governed by complex neurobiological processes, whose neuroanatomical structures interact in a delicate balance and are tightly coupled to the circadian rhythm/light-dark cycle. It is beyond the scope of the present thesis to go into great details of underlying molecular and genetic underpinnings of sleep-wake regulation (for reviews on the topic check: Brown et al., 2012; Hobson & Pace-Schott, 2002; Saper, 2013). The aim is instead to provide the reader with a basic understanding of the complexity and functioning of the different brain structures and systems involved. In order to regulate and maintain regular sleeping and waking patterns, the arousal system interacts with a sleep promoting system, influenced by circadian and homeostatic factors.

1.3.1 Wake promoting system

One of the key systems involved in the promotion of wakefulness is the arousal system whose existence was first postulated by Moruzzi & Magoun in 1949 as the ascending reticular arousal system (ARAS; Moruzzi & Magoun, 1949). While the idea has been abandoned that it is the only relevant wake-promoting system, the key neuroanatomical structures comprising the ARAS are key to control of wakefulness and arousal. These structures and neurotransmitters include two pathways (dorsal and ventral stream) innervating widespread regions in the brain and connecting serotonergic neurons in the raphe nuclei, noradrenergic neurons of the locus coerules, glutaminergic and cholinergic neurons of pontine, basal forebrain, tuberomammillary nucleus, medullary reticular formation and tegmental nuclei. These regions connect with the thalamus (relay nuclei /reticular nuclei) and inhibitory GABAergic and orexin neurons of the hypothalamus and/or ultimately the cortex (Brown et al., 2012; Saper, 2013).

These wake-promoting systems interact closely with the sleep promoting systems. Research has shown that the switch between sleep and wake is facilitated by the existence of a neural flip-flop switch between the arousal and sleep system. Due to bidirectional, inhibitory connections between arousal and sleep systems, conditions for a so-called neural flip-flop switch are provided: when one side gains control, the other one is switched off. An important input to this switch is the circadian system, with the “switch” preferring either the arousal or sleep system depending on time of day and the other input being the accumulation of homeostatic sleep pressure across the day. For description of

circadian vs. homeostatic processes see below (Bathory & Tomopoulos, 2017; Brown et al., 2012; Saper & Fuller, 2017).

1.3.2 Sleep promoting system

Activation of the above-described arousal systems is inhibited during sleep by GABAergic neurons that act upon most of the wake-promoting neurons in the arousal system, much of which is controlled by the (sleep-active) ventrolateral preoptic nucleus (VLPO) and the median preoptic nucleus, parts of the hypothalamus (Saper, 2013). As mentioned above, the switch between sleep and arousal systems is influenced by the time of the day (circadian system) and the amount of sleep pressure accumulating in the course of the day (homeostatic system). These two systems are crucial in sleep regulation and interact in a fine-tuned manner to initiate sleep or wake. Their interaction was first described by Borbély (1982) in his *2-process model*, the most basic theory of sleep regulation (Borbély, 1982). The model posits that homeostatic processes, termed process S, representing sleep debt interact with a circadian pacemaker, termed Process C, to determine sleep-wake cycles. Process S accumulates during wakefulness and declines during sleep within limited parameters of day and night periodicity determined by Process C. When Process S approaches upper boundaries of night periodicity, sleep is triggered; when it approaches lower boundaries, wake is triggered. The model has since been adapted to incorporate more complex findings of recent research, e.g., the discovery that sleep is not a global but also a regional phenomenon (Borbély, 1982; Borbély et al., 2016; Krueger et al., 2016; Krueger & Tononi, 2011). Nonetheless its basic framework is still conceptually useful to understand the sleep promoting system and myriad of factors playing together. *Figure 1.2.* illustrates Borbély's 2-process model.

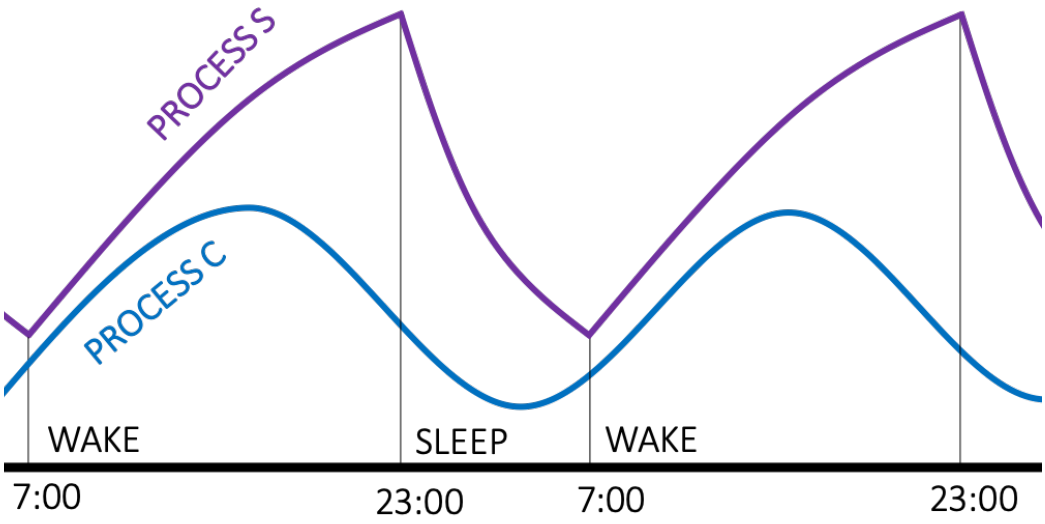


Figure 1.2. Illustration of Process S and Process C. Adapted from Borbéley (1982).

Circadian rhythm. One of the important systems in sleep promotion is the circadian system termed Process C by Borbély. The circadian rhythm is driven by the 24h daily rhythm; to some extent by external cures (such as light) but also by internal (brain-based/brain driven) cues. It is independent of prior wake and sleep activities (Dijk & Czeisler, 1995).

The master centre of the circadian system is considered to be the suprachiasmatic nucleus (SCN; Bernard et al., 2007), often also called the pacemaker of the circadian rhythm in humans. The SNC is located bilaterally in the ventral hypothalamus and receives its input via retinohypothalamic tracts leading from the eyes integrating it with input from other molecular/cellular sources, passing the input on via intricate molecular processes (Brown et al., 2012; Hobson & Pace-Schott, 2002). Environmental cues (called Zeitgebers) help regulate and provide important input to the SCN, for example the light, eating meals, or fluctuation of body temperature which helps synchronize the SCN's 20000 neurons to a daily rhythm of 24 hours (Hobson & Pace-Schott, 2002; Roenneberg et al., 2007). The SCN interacts with the ventrolateral preoptic nucleus to influence the wake-promoting systems (see above).

Homeostatic system. Homeostatic control of sleep is described by the increased propensity for sleep the longer the person is awake as well as the increase in sleep length and depth (sleep debt) after sleep deprivation. Several sleep homeostatic factors influence/inhibit the wake promoting arousal system and associated cortical neurons that promote wakefulness and thus enable NREM sleep initialisation. The homeostatic system,

also called Process S by Borbeley, is the system that guides the level of sleepiness in the body, and leads to the accumulation of so-called somnogens in the central nervous system. A somnogen is a substance that increases sleepiness, such as the neuromodulator adenosine, that accumulates with activity and increases with sleep propensity (causing the feeling of increased sleepiness as day wears on (Brown et al., 2012). It disappears with rest, inhibits arousal and promotes sleep by binding to presynaptic sites in the hypothalamic ventrolateral preoptic nucleus, that inhibit arousal promoting ventral and dorsal streams of the arousal system (see above). Process S has been shown to be tightly linked to slow wave activity, the latter of which is thought to be the direct reflection of Process S and thus depends on prior wake and sleep activity (Borb & Achermann, 1999).

Ultradian system. The ultradian system is a rhythm that occurs multiple times within a 24-hour cycle, such as the REM/NREM sleep stage cycle. Thus, the ultradian system is in charge of regulating the switch from NREM stage 1 to NREM stage 2 to NREM stage 3 and then REM sleep. Two distinct neurobiological circuits control the REM /NREM switch. These include noradrenergic and serotonergic brainstem REM-off neurons that are linked to cholinergic REM-on sleep neurons in the brainstem, which are linked by another flip-flop switch and GABAergic inhibitory neurons in the forebrain that feedback onto the lateral hypothalamus. Check Lu et al. (2006) for details on the neurobiological dynamics of the interaction of REM vs NREM sleep (Lu et al., 2006).

Of note, sleep stage transitions have been proposed to be triggered by changes in cerebral blood flow (CBF; Näsi et al., 2011). Moreover, fundamental differences between arousal states in terms of CBF have been reported, e.g., local and global changes in CBF during NREM sleep when compared with wakefulness that were furthermore related to neuroanatomical areas not only in the sleep-wake circuits but also in areas crucial for cognition, i.e., prefrontal cortex (Tüshaus et al., 2017). This indicates that it may be necessary to investigate other aspects of underlying neurobiology such as cerebral blood flow and cerebral hemodynamics in order to understand more how these different biological systems interact with each other.

A major milestone in development constitutes the emergence of these systems. As the brain is still immature and developing, naturally so are the sleep-wake maintenance systems. Thus, it comes as no surprise that sleep and wake patterns are fundamentally different in the first years of life. Below they are briefly described.

1.4 Sleep across the first years of life

Sleep is fundamentally different in infants compared to adults. Rapid changes occur in sleep patterns in the first years of life, but especially in the first months of life (Goodlin-Jones et al., 2001). These can be grouped into changes in sleep microstructure (e.g., changes in sleep stage composition) and sleep macrostructure (e.g., more global changes such as changes in sleep duration). Many of these changes are linked to the rapid physiological changes that an infant's body and brain undertakes during that time period (Bathory & Tomopoulos, 2017; Mindell et al., 1999; Shimko, 2019). These include bodily growth and myelination/synapse pruning in the brain but also maturation of physiological systems like the circadian timing system, body temperature, and neurotransmitter systems underlying sleep-wake regulation that is described above (Bathory & Tomopoulos, 2017; Rivkees, 2003).

Subsequently, the main transformations in infant sleep architecture in the first year of life are described to provide a background against which to evaluate the findings of the current study.

1.4.1 Changes in sleep macrostructure

Macrostructure changes in sleep include changes in sleep quantity, Night Wakening Number and Duration, sleep onset timing (circadian rhythm), sleep consolidation, and sleep regulation. Largely, day sleep undertakes more macrostructural changes than night sleep (Peters, 2017).

Sleep regulation refers to infants learning to transition between sleep and wake on their own without needing external support. Sleep regulation represents a crucial step in development (Camerota et al., 2019; Goodlin-Jones et al., 2001)

Sleep consolidation is the process of the emergence of regular (adult-like) sleep and wake patterns (Camerota et al., 2019).

Sleep quantity. Total sleep duration decreases gradually in the course of infancy, childhood, and adolescence. Newborns sleep between 17 and 21 hours a day, half a year later infants sleep around 14 hours a day, and by the end of the first year of life most infants sleep about 12 to 13 hours, much of which is due to a reduction in day time sleep (Dias et al., 2018; Iglowstein et al., 2003; Mindell et al., 1999). Notably, there are large ranges of day, night, and total sleep duration reported in infant sleep studies which illustrate the considerable inter-individual variability in sleep duration. Another aspect of sleep quantity refers to the so-called "longest sleep period" (LSP), which is the longest

time period an infant spends asleep continuously at night. LSP tends to increase from 3 to 5 hours at three months of age to approximately 9 hours a night at age one year (Henderson et al., 2011).

Night wakening. Not only sleep duration decreases over time but also the number of times an infant wakes up decreases with age (Galland et al., 2012; Scher, 2005). Newborns wake up every 2 to 3 hours due to the need for feeding. However, by their first birthday, 80% to 95% of infants do not wake up during the night, concurrent to the increase in LSP (Henderson et al., 2011).

Sleep rhythmicity. Another notable change in sleep macrostructure concerns the timing of sleep., specifically the distribution of total sleep into day and night sleep and the timing of sleep onset. Newborns typically have not yet developed a circadian rhythm and hence sleep as much during the day as during the night. With further maturation of the SCN and concurrent increase of levels of melatonin by the half year mark, the majority of the baby's sleep has shifted to the night, with one or two 2-hour naps during the day (El-Sheikh & Sadeh, 2015; Sadeh et al., 2009). Learning a circadian rhythm is a key feature of sleep development (Mirmiran et al., 2003) and is strongly influenced by environmental (parental) cues.

Underlying mechanisms of developmental changes in sleep macrostructure. Many of the macrostructural changes in sleep that are described above are rooted in the rapid physiological changes that happen in an infant's brain and body in the first year of life. Initially, infants grow so quickly that their need to feed every couple of hours leads to more fragmented sleep (more night wakenings) and consequently increased sleep during the day. In the course of the first year of life, night wakenings in particular are influenced by the infants' ability to self-soothe, but also by parental attitudes towards infant night wakening and potential difficulty with coping with infant crying at night (Sadeh et al., 2016; Tikotzky & Volkovich, 2019). Concurrent with the deceleration of growth in relation to size (Bathory & Tomopoulos, 2017), the reduced need for calorie intake every 3 hours, parental interventions, and the maturation of physiological systems like the SCN and melatonin release, general sleep patterns slowly start to resemble adult sleep patterns. Although, overall sleep duration still remains longer than for adults well into adolescence.

1.4.2 Changes in sleep microstructure

Changes in sleep microstructure include primarily changes in sleep EEG patterns such as sleep stage composition, emergence of sleep spindles and K-complexes and other sleep EEG features.

Sleep stage composition. While adults have four sleep stages, term-born newborns usually present with immature sleep stages that may be divided into active sleep/REM sleep and quiet sleep/NREM sleep and indeterminate sleep (i.e., sleep that cannot be clearly classified as either REM or NREM; Galland et al., 2012; Gorgoni et al., 2019; Grigg-Damberger, 2017). The old distinction of active sleep and quiet sleep is not commonly used anymore where mostly NREM and REM sleep and indeterminate sleep are distinguished. In newborns and in early infancy the proportion of REM sleep is much higher. It initially takes up more than 50% of the sleep cycle compared to 15-20% in adults. By 12 months of age, NREM sleep dominates night sleep (Anders & Keener, 1985; Grigg-Damberger et al., 2007), REM sleep proportion reduces, and indeterminate sleep disappears. Distinct NREM sleep (seen by presence of delta frequencies) is present by month 5, though overall amplitudes are much larger in infants than in adults and older children. Distinct stages of NREM sleep (1, 2, and 3) develop over the first year (Grigg-Damberger et al., 2007). Sleep cycle durations are shorter than the adult length of 90 minutes - approximately 50 to 60 minutes in infants (Davis et al., 2004).

Sleep spindle and K-complex development. Sleep spindles emerge by week 8 and K-complexes by month 6 (Galland et al., 2012). See above for a definition of sleep spindles and K-complexes. Some patterns of sleep spindles differ compared to adults, e.g., spindle runs occur longer, occur more often asymmetrically/asynchronously, and some of the adult-typical amplitude modulation is occasionally missing (Grigg-Damberger et al., 2007; Anders & Keener, 1985). K-complexes in development are best seen over the frontal regions. Illustrations of K-complexes and spindles in adults are highlighted in *Figure 1.1.A.*

Additional differences with adult sleep include transient markers of arousal found in infant sleep EEG - cyclic alternating pattern (CAP) and tracé alternant (TA). The latter describes a periodic discontinuity of NREM sleep (Bruni et al., 2010) that disappears by postnatal age 4 weeks and concurrent with appearance of sleep spindles. CAP refers to a similar phenomenon of transient electro-cortico activation periods within periodic EEG activity. CAP can only be distinguished after sleep spindles and K-complexes occur. CAP rate seems to be lower in typically developing infants than in adults (Bruni et al., 2010).

In summary, substantial changes in sleep microstructure and macrostructure exist in the first years of life compared to adult sleep. Given those differences, studying sleep in development should consider those changes, if not study those changes with regard to development in particular.

1.5 The function of sleep

The real puzzle of sleep pertains to the question of its function. Why is it that humans fall unconscious every day for eight hours if it does not serve a crucial function? Moreover, evidence is emerging that sleep is universal not only to mammals but also to other species such as reptiles or fish (Cirelli & Tononi, 2008). Given its supposed vital function, it is perhaps surprising that a clear consensus about its function has not yet been reached, even after multiple theories have been proposed. The fact remains that humans cannot survive without sleep. Perhaps best and terrifyingly illustrated by the consequences of the genetic disorder Fatal Familial Insomnia, that causes inability to sleep and ultimately leads to death (Montagna et al., 2003).

Sleep has been proven to be essential for the body in terms of strengthening the immune system (e.g., Bryant et al., 2004), combating obesity (e.g., Beccuti & Pannain, 2011), and repairing the body's cells and tissues (e.g., Adam & Oswald, 1977). Nonetheless, sleep is not only for the body but, as Hobson says, for the brain (Hobson, 2005).

As mentioned above, no conclusive answer has been reached as to the function of sleep. Researchers have proposed numerous theories, many of which are complementary or contradictory. In fact, the field of sleep research is stepping away from trying to identify one single function of sleep, towards a more holistic approach. This approach focuses on the idea that sleep serves a multitude of purposes. Theories identified so far nonetheless are informative and likely provide information to complete the puzzle. These theories range from evolutionary theories (Meddis, 1975; Webb, 1974), which view sleeps' main function as preserving energy or protecting the body, to theories about the discharge of emotional memories during sleep (*overnight therapy theory*; Walker & van der Helm, 2009) , where sleep functions as a way to enable healthy emotion regulation, to specific theories about brain plasticity and learning (Roffwarg et al., 1966).

Evidence by animal as well as human studies has been provided for and against many of the theories. In the following, the focus will be on the function of sleep as discussed by few major theories in the field that are deemed important for the role of

sleep in development and learning or brain plasticity, as discussing all theories would be beyond the scope of this thesis.

1.5.1 Ontogenetic hypothesis

A major theory recognizing the importance of REM sleep is the *ontogenetic hypothesis*. The ontogenetic hypothesis (Roffwarg, Muzio & Dement, 1966) postulates that REM sleep promotes normal brain development by regulating experience-dependent plasticity. During REM sleep, the brainstem is particularly active and shows high amounts of spontaneous endogenous neural activity, thus initiating maturation of fundamental sensory-motor brain networks (Frank, 2011). Evidence for the ontogenetic hypothesis arises from animal studies showing associations of REM sleep neuronal activation patterns specifically with development of sensory and motor systems (Blumberg, 2010; Mohns & Blumberg, 2010). As such, the developing brain triggers during REM sleep observable muscle twitches (= mycolonic twitches), specifically as a type of proprioceptive feedback loop to learn about neuronal connections between spinal cord, hippocampus, thalamus, and somatosensory cortex (Blumberg 2010; Mohns & Blumberg, 2010). This theory has implications in particular for motor development, in such that differences or reductions in REM sleep proportion could lead to disruptions in the development of sensory and motor systems. For example, this could mean, that infants sleeping less, consequently have less REM sleep, and therefore less chance to exercise the proposed proprioceptive feedback loop.

1.5.2 Synaptic homeostasis hypothesis

Another key theory important in development that makes predictions about learning and neuroplasticity is the *synaptic homeostasis hypothesis* (SHY; Tononi & Cirelli, 2003). Contrary to the ontogenetic hypothesis that puts REM sleep in the centre of plasticity-induced learning via endogenous neural activity, NREM sleep is the focus of the SHY, where plasticity is thought to arise from exogenous spontaneous neural activity (Peters, 2017). The theory postulates that sleeps' key function lies in its ability to restore synaptic homeostasis. During wake, learning of new information strengthens synapses through long-term potentiation (LTP) to enable encoding of new information. These synapses need to be down-scaled during sleep to restore an energetic equilibrium, and this process is assumed to be facilitated by slow oscillations during slow-wave sleep. Down-scaling is needed in order to return the continually increasing synaptic strength that occurs during the day to baseline level and thus prepare neurons for another day of

learning new information. The SHY describes sleep as a necessity to offset the increase in synaptic connections that occur during wake as a consequence of the LTP-driven encoding of new information. Evidence for the SHY today comes mainly from animal studies (Tononi & Cirelli, 2014). The SHY could come into play especially as synaptogenesis becomes critical. The occurrence of slow-wave sleep has been linked to memory and consolidation processes (e.g., Diekelmann, Wilhelm & Born, 2009), supporting the idea that it is crucial for learning. Disruptions in NREM sleep and the ensuing synaptic down-scaling could lead to an impairment of the ability to learn new information during the day, a skill particularly crucial for development. This importance of NREM sleep for plasticity could be why human infants sleep more than adults, as the need for plasticity is much higher in infancy than the rest of life.

1.5.3 Two-Stage Model of Memory Theory

A particularly important avenue in sleep research has emerged in recent decades – the role of sleep in memory consolidation. One of the more popular theories is the *Two-Stage Model of Memory Theory* (Buzsáki, 1989). During sleep, neuronal activation patterns that encoded relevant wake information are reactivated and thus enables the information flow from hippocampus to neocortex by a hippocampal-neocortical and thalamo-cortical neuronal dialogue. This happens in the following manner: during sleep, relevant information stored in the hippocampus is transmitted to the neocortex by way of hippocampal ripples (i.e., hippocampus-generated high frequency field oscillations; Girardeau & Zugaro, 2011), thalamocortical spindles and slow oscillations in the range of 0.5 – 1 Hz (Born & Wilhelm, 2012; Moelle & Born, 2011; Rasch & Born, 2013). While this theory puts the emphasis on NREM sleep as carrying an essential function of sleep, it is not believed to be entirely independent of REM sleep (Grosmark et al., 2012). Of note, recently scientists have also highlighted the importance of sleep in maintaining functional integrity of the fronto-parietal networks essential for sustained attention (Pisch, 2015). In line with the above integration of the roles of REM and NREM sleep in development, this theory is also underscoring the need for more sleep in infancy. The transfer of information from hippocampus to neocortex could be especially important during development, when infants are learning a vast amount of information every day. Differences in sleep patterns and disruption of the processes that underlie memory consolidation during sleep (e.g., by insufficient sleep) could have cascading effects of the acquisition of new skills, learning and development in general.

As alluded to above, it is likely that more than one of the above theories are correct in part. Functions of REM and NREM sleep cannot be regarded separately, especially as evidence is emerging that the two sleep states may not be as independent as previously thought.

The theories above are specific to functioning of sleep and different sleep stages with regard to learning and plasticity, but not necessarily to developmental sleep. However, many of these theories explain certain characteristics of sleep in infancy, for instance the high prevalence of REM sleep in the course of development. To properly study the function of sleep, it is not sufficient to merely study the mechanisms. It is also important to study environmental factors that may influence sleep. Developmental changes in sleep and the individual differences in these changes in sleep will be influenced by infant characteristics as well as parental characteristics. Therefore, it is imperative to consider the latter when investigating differences in sleep patterns and their neurodevelopmental correlates.

1.5.4 Transactional Model

One such approach to look at sleep during development has been proposed by Sadeh, which is called the *Transactional Model* (El-Sheikh & Sadeh, 2015; Sadeh et al., 2010). This model proposes that a myriad of internal characteristics of the infants (e.g., temperament), parental behaviours (e.g., stress level) and other effects, such as cultural or social (e.g., socio-economic status), interact to impact infant sleep. While not proposing a specific function of sleep, it highlights the importance of studying sleep within a whole systems approach rather than looking at specific isolated mechanisms. This matches other evidence portraying sleep as a developmental cascade (Camerota et al., 2019), in which early sleep is influenced by parent-child interaction but also influences parent-child interaction and where sleep may influence development along multiple pathways (Camerota et al., 2019).

In summary, the reviewed studies show the importance of examining the environmental factors of infant sleep in addition to investigating (mechanistic) brain activation patterns during sleep. There is need for unifying theoretical models that tie together the microlevel information of how sleep impacts cognition, learning or brain plasticity and how that link might be affected by sleep habits and sleep environment.

1.6 Sleep and Cognition

As Hobson insinuates, and many studies have demonstrated, the brain is impacted by sleep, positively as well as negatively. This is reflected in decades of research showing the impact of sleep deprivation on human cognition. For example, in adults sleep deprivation, i.e., less than the recommended 7 to 8 hours of sleep, is associated with lower performance on (sustained) attention, working memory, or decision-making tasks (Lim & Dinges, 2010). Other cognitive domains such as processing speed and even general IQ remained unaffected by sleep deprivation in most adults (Lim & Dinges, 2010). However, one does not necessarily need to be deprived of sleep to experience impaired cognition. As such, poor sleep quality was associated with worse sustained attention and better memory for negative stimuli, the latter indicates potentially a failure of the memory consolidation system, that usually successfully rids the brain of too many negative stimuli resulting in heightened emotional sensitivity (Gobin et al., 2015). However, not only disrupted sleep but also abnormally long or short habitual sleep (i.e., sleep over time) are related to poorer cognitive functioning (Kronholm et al., 2009). Even across individuals with seemingly similar sleep duration, factors such as sleep stage composition and sleep microstructure might affect IQ and memory (Schabus et al., 2006). Consequently, good sleep, or even adequate sleep in general has been shown to be beneficial for problem solving or emotional regulation (Sio et al., 2013; Walker & van der Helm, 2009).

The above research indicates that particularly memory and attention are dependent on sleep. In fact, research assumes that sleep is crucial for successful memory consolidation (i.e., the forming and rehearsing of new memories), which forms the foundation of learning (see above for theories of memory consolidation on sleep). Sleep's role in memory consolidation is crucial not only in adulthood but also when considering development - a time where learning of new information is critical to adjusting to the new experiences/challenges posed in the world. This is particularly true early on in development. Evidence points towards the fact that sleeps' impact on cognition is fundamentally different in children than in adults (Astill et al., 2012; Gorgoni et al., 2019). Evidence from studies with older children suggests a link between sleep and cognition that looks different to the adult literature with different domains affected by poor sleep than in adults (Astill et al., 2012). For instance, while primarily sustained attention and memory were related to sleep duration in adults, in children the meta-analysis showed no associations of sleep with either of these. Interestingly, there was a strong link between school performance and sleep duration. The observed differences

between adult and children may stem partially from differences in underlying neurobiology, i.e., the brain is not yet as developed as during adulthood, affording a potentially bigger opportunity for positive but also detrimental effects of sleep on cognition. However, disparities could also stem from substantial differences in methodology between adult and developmental studies as sleep deprivation studies are not easily performed in developmental populations, meaning researchers rely on observational studies where a causal link is difficult to establish.

Astill & colleagues (2012) analysed 86 studies of sleep research in children and its relation to cognition. The authors studied night sleep and found that shorter duration was associated with worse cognitive functioning, in particular executive functioning, integration of multiple cognitive domains, and worse academic performance. However, the authors could not establish a relationship between Night Sleep Duration or efficiency with sustained attention, memory, or general IQ. Another more recent review found contrary evidence highlighting that only IQ was associated with sleep duration in school children (Short et al., 2018). One difference between these two reviews may be the fact that the review by Short and Colleagues (2018) only looked at objectively measured sleep (i.e., actigraphy). This aspect in sleep research is thus far neglected and represents an important consideration. It is possible that differences in methodologies of the sleep research method used could lead to disparity in results.

1.6.1 Methodologies to study sleep and development

As alluded to above, the choice of method to assess sleep might drive differences in results found in the association between sleep and development. There are objective as well as subjective measures available to measure sleep of infants. Objective measures include polysomnography (PSG), videosomnography or actigraphy and subjective measures include parent-report sleep questionnaires and sleep diaries. In infancy, many studies still rely on parent-report measures, though actigraphy measures are emerging. PSG is not commonly used to assess habitual sleep, but rather to study brain activity for a limited amount of time (< 24 hours). This is due to the intrusive nature of the method and low tolerability in developmental populations (further explained in *Chapter 2*).

Similarly, there are objective and subjective measures available to assess neurocognitive development. Subjective parent-report measures (i.e., questionnaires) to assess developmental status of the child, temperament or other aspects of development are commonly used, due to their relative ease of use (Addyman & Mason, 2016). Due to the potential inherent biases that parent-report yields in assessing (their) children's

development (e.g., Seifer et al., 2004), developmental scientists have developed behavioural methods such as eye-tracking where (visual) attention patterns can be tracked in young infants. These looking patterns develop in specific patterns across the first year of life and have been linked to other markers of development such as brain maturation and have been shown to be predictive of later developmental status and cognitive abilities.

However, another avenue for assessing developmental status, that has been shown to often provide information above and beyond behavioural and parent report measures, is the investigation of brain activation patterns. The brain undertakes many significant (anatomical) changes in the first year of life, forming new connections and discarding others. These patterns can be measured using neuroimaging methods such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI) or functional near-infrared spectroscopy (fNIRS). Using these neuroimaging methods, changes in functional connectivity (i.e., the statistical dependencies between different brain regions, see *Chapter 7*) using fMRI or fNIRS can be measured and used as proxy for developmental status. Moreover, changes in electrical brain activity patterns, for example in a certain EEG frequency band, follow specific developmental patterns across the first year of life and beyond and therefore constitute a more objective marker of brain development than e.g., parent-reported infant developmental status. Much of the research that is described below focuses on the use of parent report measures or behavioural measures to assess development and sleep. The use of neuroimaging methods to study both sleep and development is still a rarity.

1.7 Neurocognitive development, cognition and sleep in infancy

If children's sleep patterns seem to impact cognition and the brain differently compared to adults, the question arises how the two domains are related in infancy. As described above, sleep differs fundamentally across development, in particular the first year of life yields many changes in sleep. Infants sleep much longer than adults and have fundamentally different sleep architecture than even older children (see above). Simultaneously, the first year is a time of many developmental key milestones; and the foundation for future socio-neurocognitive development is built. These include major motor developmental milestones such as rolling over, crawling and walking, major communication milestones such as smiling or babbling, or major developments in cognitive functioning such as attention or action planning.

To date, it is not yet clear how an infants' sleep relates to his/her brain and cognitive development or if the same domains are affected as in adults or older children. Given the many anatomical and structural changes that the infant brain undertakes in the first year of life, many of which mirror the appearance of specific EEG signatures (i.e., sleep spindles (Buchmann et al., 2011), it would not be a surprise should the relationship between sleep and development and cognition prove to be different in infants than in children.

Only in the past two decades researchers have attempted to study the relationship of sleep and cognition in the first year of life. This is partially due to the complexity of the study of infant development but also because it is harder to study infant sleep. Sleep deprivation studies are not an option with infants, though some studies have attempted to manipulate sleep disruption. For example, one study used the naturally occurring wakening of cloth diapers vs commercial diapers as a proxy measure of manipulated sleep disruption (Lukowski et al., 2015). Still, it is not possible to wake infants up regularly at night in order to study the impact that sleep disruptions have on their development.

Therefore, much past research was done into atypical populations such as infants with epilepsy or obstructive sleep apnoea syndrome; populations which already have to receive an invasive procedure such as polysomnography (PSG, see *Chapter 2*) to study their sleep. Yet, it has become more evident that in order to understand sleep and its relation to development and why and how it is impaired in neurodevelopmental disorders we need to understand its role in typical development first.

1.7.1 General infant development and sleep

Many of the studies conducted relate sleep to an index of general developmental status, for example the Bayley Scales of Infant and Toddler Development III (Bayley, 2009) or the Ages & Stages Questionnaire (ASQ; Squires et al., 1997). Several characteristics of sleep have been found to be associated with indices of general development or other indices of cognitive functioning, such as academic performance. These characteristics include sleep efficiency, duration, fragmentation, or aspects of sleep microstructure. Below the different associations of the sleep parameters with general development are reviewed.

Sleep Efficiency. Sleep efficiency (i.e., the time in bed that is actually spent asleep) is often taken as a marker for good sleep quality. Two cross-sectional studies showed that higher objectively measured (by actigraphy) infant sleep efficiency in 10-month-old infants was positively associated with mental development (Scher, 2005) as measured by

the Bayley Scales and positively associated with the cognitive and motor subscales of the (parent-reported) ASQ in 11- to 13-month-old infants (Gibson et al., 2012). These two studies suggest that better sleep efficiency was associated with better cognitive developmental scores towards the end of the first year of life.

Sleep duration. Another important feature of sleep is the duration of night sleep. Night Sleep Duration is often studied in addition to measures of sleep efficiency (see above) and sleep fragmentation (see below). A higher proportion of Night Sleep Duration is thought to signify more mature sleep patterns, especially if there is more night than day sleep.

Objectively measured sleep at night was positively related to scores on the problem-solving and fine motor scales of the (parent-report) ASQ at 12-months of age (Gibson et al., 2012). However, Spruyt et al. (2008) did not find an association between objectively measured sleep duration and Bayley Scale scores in 12-month-olds and neither did Camerota et al. (2020) in 6-month-olds (Camerota et al., 2020; Spruyt et al., 2008a). However, other studies used subjective sleep measures. These showed a (longitudinal) relationship between longer Night Sleep Duration and better higher-order executive functioning later on (Bernier et al., 2010). These findings were corroborated by Bernier and colleagues in later studies into older children (Bernier et al., 2013). These two studies are solely based on parents' reports, which are especially prone to under- or over--estimating their infant's night sleep (Sadeh, 1994). Studies into the relationship between sleep duration and development were mixed in their use of objective and subjective sleep measures and findings, but overall seem to indicate that longer sleep duration was better general development.

Sleep Fragmentation. Night sleep characteristics were also shown to be important in another way and that is in relation to the duration of night awakenings, that is the time an infant spends awake at night in between sleep bouts or to the number of times an infant wakes up at night. Sun et al. (2018) found that the longer the duration of objectively assessed night awakenings, the slower the later cognitive development was, especially during late infancy and early toddlerhood (Sun et al., 2018). The other study that looked at the direct association between (subjective) sleep fragmentation parameters and general development (Bayley Scales) did not find an association in 6-month-olds (Pennestri et al., 2018). Studies looking at the role of sleep fragmentation in association with general development are still scarce and show mixed findings that at this point do not allow to draw preliminary conclusions.

Day sleep. Not only do night sleep parameters appear to be crucial to development but also day sleeps or naps seem to play a role with regard to development and sleep. For example, frequent day time naps as reported by parents at 7-months-old, predict vocabulary growth in early childhood (Horváth & Plunkett, 2016). Other studies investigating the role of habitual day sleep in relation to development are still lacking.

Microstructure of sleep association with general development. Researchers have proposed that sleep microstructure in habitual sleep may be the key feature relevant to later general development. Preliminary evidence suggests this may be the case. For example, fewer microarousals per minute as well as lower amount of rapid eye movements per minute were associated with a higher mental development score at 1 year of age in both preterm and term-born infants (Scher et al., 1996). Similarly, specific characteristics of REM sleep were associated with general mental development scores (Becker & Thoman, 1981). These studies provide a promising avenue for future research and suggest that underlying sleep characteristics might provide useful information on the relationship between general development and sleep.

Other sleep parameters. Several other studies have investigated aspects of sleep that cannot be grouped under one of the above parameters but are nonetheless informative. For example, in newborns, the longest (objectively-measured) sleep period (LSP) in the first days of life correlated with developmental scores (Bayley Scale) at 6 months (Freudigman & Thoman, 1993). The LSP is occasionally seen in the literature as an indicator of more mature, adult-like sleep patterns, as evidenced by the ability to maintain sleep continuously for a longer amount of time. This research is in line with research by Judge and colleagues (2015), showing that early sleep characteristics were reflective of later infant development in the first year (Judge et al., 2015). The Bailey Scales were also associated with another aspect that indicated poor sleep – snoring. Snoring was negatively related to developmental scores at 6- (Piteo, Kennedy, et al., 2011), 8- (Montgomery-Downs & Gozal, 2006), and 12-month-olds (Piteo, Lushington, et al., 2011). Interestingly, poor sleep, as reported by parents as sleep problems on the Brief Infant Sleep Questionnaire (BISQ; see *Chapter 2*), was not associated with developmental outcomes as measured by the (parent-report) ASQ in a sample of infants ages 3 to 13 months, though an effect on infant mood was found (Mindell & Lee, 2015).

In summary, the above findings illustrate mixed findings with regard to general developmental outcomes. Some studies found effects whereas other studies did not. Considering publication bias, it is likely that there is still no cohesive answer as to the

question of which aspect of sleep might be particularly crucial for general development. Methodology, i.e., the use of subjective vs. objective methods to assess sleep or developmental status, varied from study to study. This makes cross-study comparison difficult. Moreover, many of the above studies did not track sleep or general development across time and studies looking at the changes happening between 6-month-old and 12-month-old are also scarce. Given that development as well as sleep undergo many changes in the first year of life and particularly between month 6 and 12, a conclusion cannot be drawn at this point.

1.7.2 Memory and sleep in development

As mentioned above in the section on adult sleep, sleep's role in memory consolidation is pivotal. This may be particularly true for infants, as learning of new information happens more intensely in the first year of life than in any other time of life. This means that sleep's role for synaptic plasticity is also crucial (Frank et al., 2001; Tononi & Cirelli, 2014). Memory is the most studied function in infants in its relation to sleep. Within this field, the most common studies into learning and memory and sleep in infancy are (cross-sectional) studies on learning in relation to naps/short-term sleep, likely due to the convenience of the experimental design. This may be further divided into learning during sleep, learning before sleep, and learning in response to habitual sleep.

Day sleep. Studies with infants on learning during sleep are mostly conducted with newborns using eye-blink habituation paradigms or auditory stimuli. For example, in one of the early studies by Cheour and colleagues (2002), infants learned to discriminate between vowels while they were sleeping (Cheour et al., 2002). This study and others (Gilley et al., 2017) show that newborns are indeed capable of learning about and from their environment while they are asleep. In addition, sleep state seems to be important in how readily new information is learned during sleep. Infants were more likely to produce a conditioned eye movement response (EMR) during quiet sleep than during active sleep (Tarullo et al., 2016). In summary, very young infants are capable of associative learning (i.e., EMR studies) and even the basics of language learning during sleep. In the course of toddlerhood, this ability to learn during sleep fades (Tarullo et al., 2011). Apparently, as sleep is approaching more adults-like patterns, infants lose the ability to learn during sleep. Much like adults, perhaps even more so, infants also benefit from naps. (Cross-sectional) studies on learning in relationship to naps/short-term sleep are the most common in the infant literature. As such, research has shown so far that infants who napped after an experimental task learned rules for an artificial language more readily

(Friedrich et al., 2017; Gómez et al., 2006; Hupbach et al., 2009), generalised learned findings more readily (Friedrich et al., 2015, 2019), learned words faster (Horváth et al., 2015), and performed better on a motor (memory) task (Berger & Scher, 2017; Rovee-Collier et al., 1980). Additionally, a nap after learning is essential for babies to commit information into short- (Horváth et al., 2017) and long-term memory (Konrad et al., 2016; Seehagen et al., 2015). These studies show that napping benefits memory and language development in particular. Most of these studies refer to infants in the first year of life between 6- and 12-months of age. This might represent a bias in the literature, where other types of learning have not yet been explored. A review from 2018 suggests the critical role of daytime naps for memory consolidation, and thus learning (Horváth & Plunkett, 2018).

Habitual sleep. Interestingly, the importance of naps is also exemplified, when enquiring about habitual sleep patterns from parents, i.e., using the sleep habit questionnaire, Brief Infant Sleep Questionnaire (BISQ; Sadeh, 2004). Infants, whose parents indicated (using the BISQ) that they napped frequently, were better at generalising previously-memorised information (Lukowski & Milojevich, 2013). Pisch (2018) found that infants that habitually showed less actigraphy-measured wake after sleep onset (WASO) at 4-months of age showed better working memory abilities over development (Pisch et al., 2018). Another study found habitual sleep duration to be important for another type of learning. Six-month-olds with habitually shorter sleep durations than their peers show a reduced preference for social stimuli (i.e., human face) compared to non-social stimuli (Sun et al., 2016), indicating that socio-emotional learning may also be affected by sleep. Not only duration and frequency of naps but also sleep fragmentation (the number of night awakenings) is potentially related to cognitive development.

These studies show the importance of sleep for memory consolidation which further underscores how important sleep is for brain plasticity. While there was a bias towards language learning in relation to sleep and nap studies, it seems clear that sleep in infants, like in adults, facilitates memory consolidation.

1.7.3 Other neurocognitive domains in development and sleep

Attention. Much less research has been conducted into the relationship of attention and sleep, partially perhaps because studying attention in infancy is harder and more volatile than in older children or adults. A longitudinal study found that higher sleep percent (an actigraphic measure similar to sleep efficiency) and fewer night wakings at

12-months predicted better executive attention when children were 3-4 years of age (Sadeh et al., 2015). Conversely, some research indicates that there was no association between various measures of attention in association with objectively or subjectively measured sleep (Pisch, 2015), though participants were slightly younger (4- to 10-months old). Another PhD thesis postulates that attention may not be directly impacted by sleep for all infants. Camerota (2018) showed that maternal education interacted with sleep regulation to predict infant attention at 3-months of age (positive correlation). These, albeit few findings show that the relationship between attention and sleep may be less clear than e.g., the relationship between sleep and memory. Studying certain aspects of attention in relation to sleep may provide further insight into this question.

Motor development. Recalling the research presented above, showing that REM sleep motor twitches are related to sensory-motor development, it is not surprising that some research has found associations between sleep and motor learning/development. However, Ednick et al. (2009) concluded based on their review that the relationship between motor development and sleep was not as clear as the relationship between cognitive development and sleep (Ednick et al., 2009). For example, 3 of the 5 reviewed studies did not find associations between motor development and sleep (Montgomery-Downs & Thoman, 1998; Scher, 2005; Scher et al., 2008). However, Pisch (2015) found an association of actigraphy-measured sleep with the gross motor subscale of the ASQ across the first year of life but not with other, more cognitive subscales such as problem-solving. Another study showed improvement in the efficiency of solving a novel motor problem only in a nap study but not in the no nap group (Berger & Scher, 2017).

1.7.4 Summary

This review of the literature illustrates that many aspects of sleep appear to relate to many different domains in development. However, a cohesive picture is still lacking. While there seems to be ample evidence of an impact of sleep on (language) learning/memory consolidation, for attention and measures of general development the evidence is less clear. It could mean that sleep impacts development mainly in the short term/immediate functioning via learning rather than having a significant impact on overall development. Although, this may also represent a bias in the literature. The key difference in memory studies is that they are often experiments under tightly controlled conditions using objective measures to assess memory. The same is not true for many of the studies on, for example, general development that use parent-report measures like the ASQ.

It could also be that sleep only impacts more short-term functions, like attention or memory rather than development, as proposed by Mindell and Lee (2015). Though many of the above studies have taken an approach to studying sleep and development that makes it hard to provide a definite answer to this hypothesis. Below these approaches are discussed and alternative approaches are presented.

1.8 Caveats of current studies

Understanding how sleep impacts cognition and memory while these functions are emerging is likely to provide us with a better understanding of the relationship between the two. It is currently unclear which aspects of sleep matter most for beneficial cognitive development. The review of the literature shows that sleep is related to many aspects of development and early neurocognition and likely in a distinct way to adults. However, while the above-mentioned studies are a great first step towards disentangling the relationship between sleep and neurocognitive development some drawbacks are apparent that make it hard to extrapolate the findings and integrate them to form a complete picture.

Many of the above studies show mixed results. This poses the question of how to interpret these results. In particular when considering publication bias, there is a need to treat current results with caution. Many of the studies of developmental outcomes in relation to sleep's non-significant results, likely means that sleep is only part of what contributes to neurocognitive development. Sleep may interact with other factors such as parental characteristics (Camerota et al., 2020) to impact development. This means that sleep cannot be disentangled from environmental characteristics, such as parental characteristics, sociocultural background, or infant genetic background. However, many of the above studies fail to control or assess these.

Recent evidence (Sun et al., 2018; Pisch, 2015) suggests that the relationship between cognitive development and learning, respectively, with sleep is likely not linear but more non-linear with different ages benefitting from different aspects of sleep, e.g., increased sleep duration may be beneficial at age 4-months but not at age 8-months and then beneficial again at age 12-months. Moreover, there is high inter -and intra-individual variability in infant populations with regard to both sleep patterns and cognitive development (Bernier et al., 2013; Tham et al., 2017). Development progresses at different rates for different individuals in different domains. As such, one child might progress faster in motor skills than in language skills and vice versa for another child,

influenced by their individual external and internal environment. Thus, studying sleep and development at a single time point in different individuals is not sufficient. To understand this relationship, properly tracking both development and sleep over time is crucial. However, many of the above-reviewed studies did not do so. In order to account for rapid changes happening in development and sleep in the first year of life, longitudinal studies are needed.

Another aspect that stands out when reviewing the above studies is methodology-based. Camerota et al. (2019) state that around 40% of reviewed infant sleep studies use only subjective, parent-report measures, such as a sleep diary or sleep questionnaires as indicators for infant sleep (Camerota et al., 2019). However, research has shown that parents are not very good at estimating their infants' sleep, often under- or overestimating their infants' sleep compared to more objective measures (Camerota et al., 2018; Sadeh, 1994). Moreover, while some of the above studies use similar subjective sleep assessment measures, such as the BISQ, sleep diaries often differ across studies. The same applies for questionnaires assessing general infant development or temperament. These are reliant on parental estimation only.

The second issue lies in the use of objective measures. Many studies are not using any objective measures at all, due to the involved nature of conducting these studies. In the studies that do use objective measures such as actigraphy, many different types of actigraphs and algorithms are used in the studies, some of which yield slightly different results (Henderson et al., 2011). Moreover, some cross-sectional studies find that there are relationships between actigraph assessments but not parental reports of infant sleep and cognition respectively (Scher, 2005). These findings indicate that choice of methodology might systematically influence results when investigating the relationship between sleep and development. This might be circumvented by studying both objective and subjective measures to assess sleep together. However, currently there is a lack of studies that investigate both cognition/development and sleep with subjective and objective methodology, especially continuously across the first year of life. Differences in the timing and methodology of assessment may contribute to the mixed findings reported above (Ednick et al., 2009). Thus, there is a need to integrate objective measures preferably for both cognition and sleep with longitudinal measures.

Additionally, many of these studies are slow to make use of rapid advances that novel technology might provide for assessing sleep and development. While some studies have made use of eye-tracking and EEG, many have not tracked neural activation patterns across the first year of life. Novel techniques, such as near-infrared spectroscopy (NIRS,

see *Chapter 2*) may add additionally information on how the brain and cognition are linked to sleep in development.

Apart from methodology, the way the information collected with sleep measures is used could be critiqued. Often, in sleep research sleep parameters such as sleep duration or fragmentation (night wakening parameters) are associated with cognitive measures. Then, if one parameter is found to be significantly associated with cognition, that parameter is taken as an indicator for poor sleep quality, e.g., lower sleep duration equates with poor sleep quality. However, looking at isolated parameters might not be the ideal solution. Rarely can one factor be dissociated completely from the other. It might be better to look at several sleep parameters together and group them in patterns of sleep as indicators for sleep quality rather than take one parameter singularly. This could provide researchers with groups of sleepers whose cognitive trajectory might be tracked across times more easily.

Lastly, more studies in infants under 12-months of age in the period of middle of the first year of life are needed. Currently many studies are published with infants older than 12 months or newborns. The time period before 12-months is especially interesting, as it is when sleep patterns change the most (Hirshkowitz et al., 2015).

Thus, in order to properly study the relationship between sleep and development in infancy, objective as well as subjective measures for assessing sleep and neurocognitive development need to be integrated into a longitudinal study that specifically looks at the critical time period of the first year of life.

1.9 Research questions: the present project

In this thesis, the goal is to investigate the relationship between sleep and neurocognitive development in the first year of life using a multi-method approach.

The central research aim is to clarify if infants who suffer from habitually poor sleep experience a fundamentally different neurocognitive profile than infants who experience habitually good sleep. Prior research (see above) has shown the need for more longitudinal studies that incorporate both objective and subjective measures of developmental status and sleep, while recording environmental factors that may influence development. Moreover, in order to understand how all of these factors interrelate, there is a need to link this to underlying mechanistic explanations of sleep and development. Thus, here I have set out to do just that by combining longitudinal and cross-sectional experimental designs with a multitude of objective and subjective methods

(such as EEG, actigraphy, eye-tracking, parent-report questionnaires, near-infrared spectroscopy) and (novel) analysis approaches (cluster analysis, mixed modelling and functional connectivity analysis) to study the brain and development. In addition to studying infant development in general, the aim is to study specific functions of cognition such as sustained attention, which has not been given enough attention in past research. The goal is to see the impact that a child's habitual sleep has on general development but also on specific functioning.

The central research questions are as follows.

1. Can distinct groups of sleepers be identified by objective and subjective measures of sleep in a sample of longitudinal infants? What is the concordance between objective and subjective measures of sleep? What might influence that concordance?
2. How do these groups of sleepers relate to parent-report measures of general development and infant temperament? Do these groups of sleepers show differences in socio-cultural environment (e.g., parental SES or maternal stress and anxiety)?
3. How do these groups of sleepers relate to sustained and social attention patterns as measured by three eye-tracking tasks and how do they relate across development?
4. How do these groups of sleepers relate to a neural measure of general information processing/attention as measured by EEG and how do they relate across development?
5. How can the development of a customised NIRS-EEG system help measure the sleeping infant's brain? Can studying the sleeping infants brain activity help learn more about the relationship between sleep and development?

To investigate these questions for this thesis, two studies were conducted: a longitudinal Study 1 and a cross-sectional Study 2. Study 1 aimed at an exploration of the research question identifying profiles of sleepers in the first year of life and relating it to early markers of development such as attention in eye-tracking and EEG tasks as well as general developmental markers measured by a developmental questionnaire (research questions 1 – 4). *Chapter 2* will give a detailed background on methodologies used in the current study and serves as a reference chapter throughout for the other chapters. *Chapter 3* describes the habitual sleep patterns of the present sample in depth and compares

agreement across subjective and objective sleep measures. Sources of bias are examined. *Chapter 4* relates profiles of sleepers to measures of infant general development and temperament and to parental characteristics such as SES, and maternal stress and anxiety. *Chapter 5* relates profiles of sleepers to visual attentional measures as measured by eye-tracking to link sleep to neurocognitive development. *Chapter 6* relates profiles of sleepers to a marker of neural information processing as measured by EEG to link sleep to neurocognitive development. *Chapter 7* describes Study 2 and the work to image the sleeping infants brain using a custom built, combined NIRS-EEG headgear to link the biological mechanisms during sleep to habitual sleep patterns and cognition in a cross-sectional nap study (research question 5). *Chapter 8* discusses results and proposes future research directions and relevance of the findings. *Figure 1.3.* describes the objective and subjective measures of development and sleep respectively used in the present thesis.

<table>
<tr><th></th><th>SLEEP</th><th>DEVELOPMENT</th></tr>
<tr><td>Subjective (parent-report) measure</td><td>Diary (Chapter 3 - 6)
Questionnaires (SSQ, BISQ; Chapter 3 - 6)</td><td>Temperament (IBQ-R; Chapter 4)
General developmental status (ASQ; Chapter 4)</td></tr>
<tr><td>Objective measure</td><td>Actigraphy (Chapter 3 - 6)</td><td>Attention/Looking behavior (Eye-tracking; Chapter 5)
Theta power/ theta change (EEG; Chapter 6)</td></tr>
<tr><td></td><td colspan="2">fNIRS-EEG during a nap to measure sleep microstructure and fronto-temporal functional connectivity (Chapter 7)</td></tr>
</table>

Figure 1.3. Illustration of objective and subjective measures of sleep and neurocognitive development used in each chapter *(SSQ = Sleep and Settle Questionnaire, BISQ = Brief Infant Sleep Questionnaire, IBQ-R = Infant Behaviour Questionnaire-Revised, ASQ = Ages and Stages Questionnaire, EEG = electroencephalography, fNIRS = functional near-infrared spectroscopy)*.

CHAPTER 2 - Methodology

This thesis examines the relationship between sleep and neurocognitive development in several chapters. *Chapters 3, 4, 5* and *6* will address findings from longitudinal Study 1 and *Chapter 7* will address results from cross-sectional *Study 2*. *Chapter 8* will be a general discussion. This chapter (2) describes the methodology of both Study 1 and Study 2 of the PhD project.

2.1 General set-up of this PhD project

This PhD project was funded by the Marie-Sklodowska Curie Actions (HORIZON 2020) under the European Industrial Doctorate (EID) scheme. Per EID requirements the doctoral students spent half of her time in industry and half of her time in an academic institution. Therefore, this PhD project was divided into two eighteen months periods, where the first were spent at Procter & Gamble (P&G), German Innovation Center (GIC, Schwalbach am Taunus, Germany), the industrial partner, and the latter at the Centre for Brain and Cognitive Development (CBCD, Birkbeck College, University of London (London, UK), the academic partner. The two studies conducted in the frame of this PhD project are designed to leverage the advantages of expertise and technologies of both sites. At P&G this means that there is expertise in large-scale projects on infant sleep research, using actigraphy as well as a large pool of potential participants. Moreover, P&G has previous experience with an EU-funded PhD project on sleep in collaboration with the CBCD. P&G's main interest in the present project lies in incorporating new insights of sleep research into (diaper) product design and consumer information guidelines. At the CBCD this means an expertise in novel neuroimaging techniques (e.g., near-infra-red spectroscopy (NIRS), electroencephalography (EEG), …) and sophisticated experimental protocols for assessing infant development.

Study 1 took place from March 2018 to February 2019 at P&G GIC near Frankfurt in Germany. As discussed in *Chapter 1*, there is a need for longitudinal studies to explore the relationship between sleep and early neurocognitive development. Thus, the first study constituted a longitudinal study exploring the relationship between habitual sleep and neurocognitive development in 4- to 14-months-old infants to understand if certain patterns of sleep might be especially beneficial or detrimental to development. The majority of this thesis focuses on results of Study 1 with Study 2 extending Study 1 by adding crucial method development aspects.

Study 2 took place from July 2019 to February 2020 at the Centre of Brain and Cognitive Development, Birkbeck College, University of London, and was focused on developing methods to measure brain activity during sleep. The information collected during the cross-sectional nap study using a custom-built, combined NIRS-EEG system/headgear would then be linked to cognition and to habitual sleep.

Below, first the procedures of Study 1 and 2 are described. Thereafter the technologies used in the thesis to assess sleep and neurocognitive development are described.

2.2 Study 1

Study 1 of the PhD aimed at exploring the relationship between sleep and neurocognitive development using a multi-method longitudinal design, incorporating objective (eye-tracking, EEG, actigraphy) and subjective measures (parent-report questionnaires and sleep diary) of both sleep and development.

2.2.1 Experimental Design

Experimental design of Study 1 was an accelerated longitudinal design to achieve larger sample size with participants enrolled at 4, 6, 8, 10, 12, and 14 months of age. Below an illustration of the design and methodology used at each visit. Participants were tested up to four times every two months or until they were 14 months old.

Figure 2.1. Illustration of experimental design in Study 1.

2.2.2 Recruitment

Participants were recruited in a number of ways:

1. Clinical panel data base for the diaper testing at the consumer research center at the P&G German Innovation Center Site.
2. Flyers in Hospitals and clinics in the surrounding areas of the P&G baby discovery center.
3. P&G internally via messages displayed on company screens and on the P&G webpage shop

It is unclear which was the most effective way to recruit as participants upon signing up did not indicate where they had learned about the study. An initial email was sent explaining the aim of the study and a short description of the experiment. If parents expressed interest they were given more information in the form of a short information sheet and the inclusion/exclusion criteria were assessed. Inclusion/exclusion criteria were as follows: the participants should have no previous family history of neurodevelopmental/metabolic/sleep/psychiatric disorders, seizures or premature birth date (birthdate 37+ weeks gestation). Participants should not have foreseeable plans to move away from the Schwalbach area. Participants were recruited for the ages 4, 6, 8, 10, 12, and 14 months of age to cover the entire age range of the first year of life, participants were included if they were +/- 14 days of that age group, except for the 4 months age group where participants were all 4 months or older. This procedure was followed by prior research (Pisch, 2015). Some infants fell out of the 14-day rule at certain visits, these participants were still included to reduce further data loss.

2.2.3 Procedure

Potential participants could contact the researcher via email or phone and they would be sent a short version of the information sheet. If interest persisted after the first information sheet was sent out a first appointment was made. Consent and a long information sheet were sent out prior to the first appointment, so participants would have sufficient time to read through, think about the content and ask any questions.

Information about the study duration, inclusion criteria and procedure was explained to the parents and the opportunity to ask any questions was given. Upon agreeing to participate, parents came to the Baby Discovery Center, German Innovation Center at P&G, Schwalbach am Taunus (Germany). On the day of the visit, after administration of consent, the workings of the actigraph for sleep monitoring was explained and physical characteristics (head circumference, height and weight) of the

infant were written down. Each visit was structured the same way, with the EEG session being performed first if possible. If the infant started crying during head measurements the eye-tracking session was performed first. The infants watched a short, animated movie to keep them distracted, while the researcher placed the cap with the electrodes on the infants' head and placed two mastoid gel electrodes behind the right ear of the infant. Every child was seated on their parent's/caregiver's lap in front of the stimulus screen. The full EEG testing battery took approximately 25 minutes. After EEG tasks were presented, the infants participated (following an optional break) in the eye-tracking session, where they were seated a car seat that was on the parent's lap. Every visit took approximately 90 minutes, including time for breaks. Afterwards parents took home the questionnaires (see below), a sleep diary and the actigraph. Using the latter two they assessed their child's sleep at home for a period of seven days and also recorded the times that the actigraph was removed from the infant's ankle. Sleep diary and actigraphy data were collected for seven consecutive days. After 7 days parents returned the actigraphs and the questionnaire package. Parents were reimbursed 20 Euro/visit and given Pampers diapers for the week that the baby wore the actigraph. Lastly, parents were scheduled for their next study visit two months later (if applicable). However, they were given the opportunity to opt out of the study at any time.

Figure 2.2. Set-up of testing room at P&G, GIC, Schwalbach where both EEG and Eye-tracking took place.

2.2.4 Chapter outlook Study 1

Chapter 3 is a longitudinal examination of the sleep data of the first study. The aim is to distinguish different groups of sleepers via application of cluster analysis. *Chapter 4* relates sleep data to family environment, parental characteristics and general child development and temperament. Specifically, the focus is on relating visual attention measures to different groups of sleepers identified in *Chapter 3*. *Chapter 5* relates sleep data to the eye-tracking data. *Chapter 6* describes relates sleep data to brain activity measured with EEG. Specifically, the focus is on relating the neural brain activity patterns to different groups of sleepers identified in *Chapter 3*.

2.2.5 Overarching statistical analysis plan Study 1

The main analysis method for *Chapters 4, 5,* and *6* was the same and therefore in the following is briefly explained. Linear mixed effects models (LMMs) were used to analyse the data. LMMs were chosen as they have the ability to handle much missing data. The accelerated longitudinal design allowed for rapid data collection in the limited amount of time that was available, due to its enrolment at every age. Drawbacks of this included more missing data as no participants had data at all six time points. Apart from their flexibility to deal with missing data LMMs also allow accounting for within participants dependence and for inter-individual variability better than comparable analyses like repeated measures ANOVA (Fields, 2005). In the analyses (using IBM SPSS Statistics v25) a random intercept was added for subject ID and a repeated measures effect for age groups as an indicator for time to account for the fact that some participants were tested more than once. Age group was chosen as a categorical predictor of developmental change to potentially identify critical periods and fine-grained age-related changes in the relationship between sleep and development. Estimating age by including it as a continuous predictor would complicate interpretation and discovery of these potential critical periods. Covariance structures were specified as autoregressive type 1 (AR1) for the repeated group effect, as AR1 covariance structure assumes that two measures taken close together in time from a participant are more likely to be correlated than two measures taken further apart in time (Field, 2005). Random intercept was given a covariance structure of variance components that assumes all random effects to be independent. Pairwise comparisons corrected for multiple comparisons using the Bonferroni were performed for age groups and for sleep clusters where applicable. The following models were tested. A baseline model is the developmental change model assessing how the neurocognitive parameters change over time. Model 1 describes a

model where main effects of age group as well as sleep variables on neurocognitive parameters are assessed. Model 2 describes a model where main effects of age group as well as sleep variable and an interaction effect of age group by sleep variable on neurocognitive parameters are assessed. Model 3 describes a model where main effects of age group as well as sleep variable and potentially an interaction effect of age group by sleep variable and gender on neurocognitive parameters are assessed. Model fit statistics were compared between models to choose the best model. Here, the Akaike Information Index (AIC) was used for model comparison (smaller the better the model fit). This was done as the AIC takes into account the number of predictors when calculating model fit (Field, 2005).

In the course of this thesis a large number of LMM analyses were conducted for each of the research questions asked in *Chapters 4, 5,* and *6* to be able to compare results of the different sleep measures. When performing many different models caution has to be warranted not to over-interpret the findings due to the multiple comparison problem (Field, 2005). I will provide explanations for findings of the LMM analyses in relevant parts of this thesis. However, it is likely that only when sleep measures converge into the same pattern in association with development that we can infer stronger conclusions from it. Furthermore, I performed multiple comparison correction, using the Bonferroni correction for all follow-up tests as well as for correlational analyses. Correction was performed per model conducted, as different modes target different research questions. Though Bonferroni correction is the most conservative of the corrections (Field, 2005), due to the large number of models run the aim was to be more conservative rather than not conservative enough.

2.3 Study 2

Study 1 linked habitual sleep to measures of wake brain activity, however I also wanted to study how brain activity during sleep relates to neurocognitive development. However, for this purpose different recording methods were needed. Study 2 focused on the development of a combined NIRS-EEG system to investigate sleep microstructure. The end goal was to relate it to developmental markers such as functional connectivity, questionnaire-assessed general development, and neural as well as behavioural markers (using EEG and eye-tracking). Of note, this study was terminated prematurely due to the imposed government restrictions of the Covid-19 pandemic.

2.3.1 Experimental design

Contrary to Study 1 Study 2 features a cross-sectional design. This was due to the experimental nature of the paradigm as well as the high dropout rate of infant nap studies. Below an illustration of the study protocol and the methodology used.

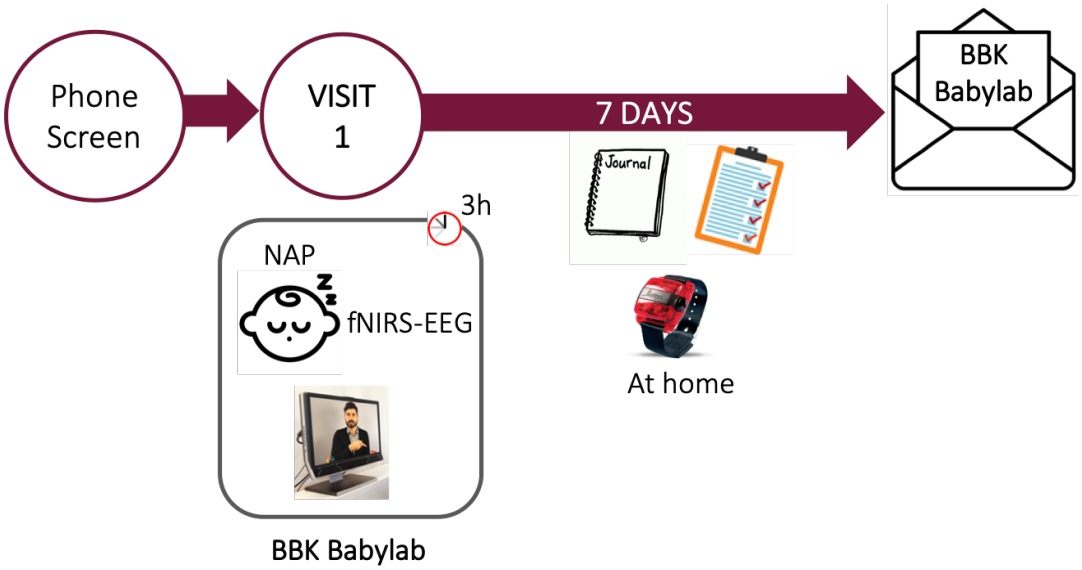


Figure 2.3. Illustration of experimental design in Study 2.

2.3.2 Recruitment

Participants were recruited via the volunteer database of the Birkbeck Babylab and via flyers on social media (Facebook and Twitter). An initial email was sent explaining the aim of the study and a short description of the study visit. If parents expressed interest, they were given more information and the inclusion/exclusion criteria were assessed. Inclusion/exclusion criteria were as follows: the participants should have no previous/ family history of neurodevelopmental/metabolic/sleep/psychiatric disorders or seizures or premature birth date (birthdate 37+ weeks gestation). Infants must not have any known hearing or vision difficulties and be of age 5 to 8 months, though some recruitment was started at 4.5 months.

2.3.3 Procedure

If caregivers were interested in participating in the study, an initial phone screening interview was conducted where the infants habitual sleeping patterns and in particular their nap routines were assessed. The study visit was planned around the infants' regular nap routine, about 60 minutes before the approximate regular start of the nap. Additionally, routines regarding naps are recorded in order to replicate the infants regular

sleep routine as closely as possible during a visit. Parents/caregivers received a detailed information sheet outlining the purpose, consent, the procedures involved and contact details for those involved in the study via email prior to the study visit. During the study visit parents were given the opportunity to ask any questions and address doubts before signing an informed consent form. Duration of the study visit was approximately one to three hours, depending on whether and how long the infant slept. Procedures that are the same across Study 1 and Study 2 (e.g., eye-tracking) are followed as closely as possible in Study 2 in order to allow for cross-study comparison. After welcoming the baby and the caregiver, they were accompanied to the room, where the stroller and the customised NIRS-EEG headgear is located. Regular pre-nap routines were replicated in the lab environment as closely as possible e.g., caregivers brought their infants blanket/sleeping bag, familiar toys or plush animals as well as familiar music/lullabies/white noise. After putting the sleep headgear on the infant, he/she was put into the stroller. If the infant usually slept in the caregiver's arms, infants were held for the duration of their nap by their parent. Thereafter, the researcher waited until the infants woke up again, recording the duration of the sleep. Following wake the same eye-tracking battery as in Study 1 was administered. The infants sat on the parent's lap, while the stimuli were presented. Following the eye-tracking, the sleep diary was explained and distributed to the parent/caregiver. The workings of the actigraph for sleep and activity monitoring was explained to the guardians, as in Study 1. After the visit there was a week of in-home sleep measurements (i.e., actigraphy and sleep diary). Parents returned the actigraph and questionnaire package via post after the week of sleep recording was over.

2.4 Measures to assess sleep

2.4.1 Technologies used to assess sleep

In the following the different technologies (i.e., actigraphy and brain imaging during sleep) used in the present PhD project for assessing sleep are discussed. Study 1 used actigraphy as an objective technology to measure sleep. Study 2 used actigraphy and EEG as well as NIRS measurements to image the sleeping infants' brain.

2.4.1.1 Actigraphy

Actigraphy refers to a continuous measurement of human activity and rest periods using a watch-like tri-axial accelerometer. These accelerometers may be used for the purpose of sleep recording on the wrist, ankle, waist or upper arm, making use of the fact

that humans move more when they are awake than when they are asleep. Tri-axial accelerometer data are translated into digital counts, through several pre-processing steps and then summarised across a specified epoch interval (60 seconds for this project; Sadeh et al., 1994). Actigraphs generally use signal frequency band pass filtering (at 1 - 2 Hz) to attenuate unwanted human movements.

One of the first researchers to report investigation of activity patterns in humans for the purpose of sleep-wake classification was Szymanski in 1918 in infants (Szymanski, 1918). In the course of the 20th century actigraphy evolved to become a popular, easy-to-use tool to monitor sleep-wake patterns in humans (Cole et al., 1992; Sadeh, 1994; Sadeh et al., 1989; Sadeh et al., 1995; Sadeh et al., 1991).The 1995 publication by the American Sleep Disorders Association (ASDA) on the use of actigraphy for sleep medicine represents a changing point after which actigraphy was formally recognised as a suitable tool for sleep research and sleep medicine (Sadeh et al., 1995). Though not without problems (see below) its light weight and the potential to study habitual sleep using objective methodology made it an attractive method especially for paediatric research.

Sleep-wake scoring algorithms. As mentioned above actigraphy devices output raw accelerometer data that may then be translated into activity counts for the purpose of sleep-wake classification. With the collection of large datasets of habitual sleep data, the need for automatic sleep-wake scoring algorithms became pressing. Webster and colleagues (1982) devised one of the first automatic sleep scoring algorithm (Webster et al., 1982). However, the algorithm commonly used for pediatric populations was created by Sadeh and colleagues in 1994 (Sadeh et al., 1994), which was validated for paediatric populations in 1995. This is the algorithm used in the present PhD project to analyse the infant sleep data, based on literature suggesting it is the most appropriate algorithm for infant sleep research (Meltzer et al., 2012). The Sadeh algorithm is a discriminant function, using only the y-axis information and requiring data in 60-seconds epochs. The data is segmented into an 11-minute (rolling) window considering the epoch in question as well as the preceding 5 and following 5 epochs. Five relevant actigraphy variables were identified: mean activity counts in the 11-minute window, centred at epoch in question (μ), the standard deviation of activity in the preceding 6 minutes including the epoch in question (σ), the natural (base e) logarithm of the activity of the epoch in question (*LogActivity*) and the number of epochs in the 11-minute window that has an activity count above 50 and below 100 activity counts (*nat*) (Sadeh, 1994; Sadeh et al., 1995). Thereafter a, so called sleep index (SI) is calculated:

$$SleepIndex(SI) = 7.601 - 0.065\mu - 0.056\sigma - 0.0703LogActivity - 1.08nat$$

If SI is above 0 then the current epoch is classified as sleep otherwise it is classified as wake. Sadeh's algorithm has been shown to correctly classify sleep-wake (compared to PSG and compared to observational methods (Sadeh, 1994; Sadeh et al., 1995, 1994)).

Advantages and disadvantages. Actigraphy's main advantage is without doubt its high ecological validity. It may be worn at home for several consecutive days, weeks and even decades (Borbély et al., 2017), assessing real-life sleep-wake patterns and circadian rhythms that are not distorted by laboratory settings, unlike polysomnography (PSG; for details see below) that often shows a first night effect (sleep in a different place/situation is fundamentally different from how people normally sleep) (Ancoli-Israel et al., 2003). It is therefore a more reliable measure for habitual sleep than PSG which is often recorded only for 24 – 48 hours (Ancoli-Israel et al., 2003). Moreover, the watch-like device is much less invasive than a full PSG set-up (see below), making it a good tool for sleep studies into infant populations and clinical populations like children with autism spectrum disorder (Yavuz-Kodat et al., 2019). A third advantage is its cost-effectiveness compared to PSG. Especially with rapidly developing wearables technology in the private sector (e.g., Fitbit), precise, wearable sleep assessments may soon be at our finger tips for the fraction of the cost of a PSG system. Not to mention that the development of automatic actigraphy scoring algorithms enables sleep-wake scoring without having to pay a trained sleep technician as in PSG studies. Lastly, it may increase compliance to experimental protocol as it, in theory does not rely on parent-report measures, which are often biased (Sadeh, 2011). However, in actuality parental reports are needed most of the time. As accelerometers actigraphs do not discriminate well between external movements (such as a jostling pram) and real movements of the subject (Tsai et al., 2009). Moreover, actigraphs are typically unable to distinguish between motionless wakefulness and sleep (Sadeh, 2015). Therefore, researchers often supplement actigraphy analysis with sleep diaries and parental logs of when the actigraph was worn.

Quiet wake is a problem for actigraphs as the low-frequency movements of the quiet wake state are misclassified as sleep. Not surprisingly then that actigraphy often overestimates sleep and underestimates wake-time; this low specificity in detecting wake/sleep is one of actigraphy's main disadvantages. Though, it should be noted that in very young infants, periods of quiet wake without any movement are rare. In general, Sadeh concluded that with infants, actigraphy should be paired with parental sleep logs

for screening infant sleep problems, although actigraphy appeared to be a more consistent measure than parents' sleep logs of the child's sleep/wake (Ancoli-Israel et al., 2003; Sadeh, 1994). Therefore, actigraphy needs to be accompanied by sleep diaries or log-removal data to exclude periods of time when the actigraph was not used or worn at different time point. Third, actigraphy has the ability to measure a wide variety of sleep parameters such as sleep duration, number of night awakenings (sleep fragmentation) or sleep onset latency. However, to date it is not possible to measure sleep stages with actigraphy. Another disadvantage is that many different types of actigraphs are used in research, some use proprietary algorithms to score sleep-wake and some are more validated than others, which means findings of one study may not be easily generalizable to others.

Validity of actigraphy. Actigraphy's validity is often compared to the gold standard of PSG. Here the focus is on its validity with regard to pediatric populations, as this is relevant for the present project. Overall, actigraphy has been shown to correctly predict sleep-wake patterns in infants when compared to the gold standard of sleep research PSG (So et al., 2005) citing validities as high as 97 % in accurately predicting sleep in 6-month-olds (So et al., 2007). It also has good validity compared to diaries (Sadeh, 1994; Werner et al., 2008). However, the validity of actigraphy compared to PSG is highly variable across devices. A review by Meltzer et al. (2012), where amongst others PSG and AG are compared also looks at the sensitivity and specificity of actigraphy in pediatric sleep research. They report: "*… ranges of sensitivities = 83.4 – 99.3 and specificities = 17.0 – 97.8* ", this means that sensitivity, i.e., determining the time point when infants fell asleep, is relatively accurate using actigraphy (Meltzer et al., 2012). In general, actigraphy is more likely to detect sleep (sensitivity) but less reliable at detecting wake (specificity) (Ancoli-Israel et al., 2003). However, detecting (short) wakening within a sleep period is more dependent on the device used (Meltzer et al., 2012). The researchers argue the discrepancy in specificity is likely also due to large variability in algorithms used, devices used and differential placement of the actigraph (ankle vs. wrist).

In summary, even though actigraphy has some disadvantages, as long as clear guidelines are followed with regard to analysis steps, parental logs and validated sleep-wake algorithms are used (such as the Sadeh algorithm) it has great potential as a cost-effective, non-invasive, easy-to-use tool for infant sleep research.

ActiGraph wGT3X-BT. The actigraph used in both Study 1 and 2 was the *ActiGraph wGT3X-BT* from ActiGraph Corp. (dimensions: 4.6 x 3.3 x 1.5 cm/ weight: 19 g: Low frequency band pass filter: 0.25 - 2.50 Hz). Based on literature (Meltzer et al., 2012,

Pisch, 2015) sampling frequency for the present device was 60 Hz and at least five 24-hour segments of data were required for the data set to qualify for inclusion in the final actigraphy dataset. The actigraph was set to zero-crossing mode. Zero-crossing mode refers to a way of actigraphy analysis by which an activity threshold is set at zero or very low level of activity (without an artefact) which indicates absence of activity. Data is then counted per epoch by the amount of times that zero was crossed.

The wGT3X-BT, the device that was used in the current study, has been used successfully in infant studies in the industry setting (not publicly available data due to confidentiality concerns) but also in research studies into adult populations (Barreira et al., 2018; Nyström et al., 2017; Reddy et al., 2018). Caregivers were encouraged to let the infant wear the actigraph for 24 hours for 7 days and asked to record duration and dates for when the actigraph was removed. These were later used during analysis to exclude periods. Strategies to improve compliance included instruction sheets for use of the actigraph and personal communication with parents during the study week.

Figure 2.4. Illustration of the ActiGraph wGT3X-BT (ActiGraph Corp.).

Actigraph comparison study. As the ActiGraph wGT3X-BT is not as validated in the literature in infant research as other actigraphs, a brief validation study was conducted in which infants wore the ActiGraph wGT3X-BT as well as an Actiwatch (CamNtech, UK) for a week, delivering 111 days of night sleep actigraphy from 11 infants. 13 days were excluded because data was missing for one actigraphy or the other one. Basic agreement analyses were conducted, i.e., correlational tests and test of equivalence on Night Sleep Duration, WASO and Sleep Efficiency. Results indicate that, while both actigraphs are not providing equivalent results, general trends and patterns are captured by both actigraph types. This matched prior literature showing that different devices show acceptable but not perfect agreement (Cellini et al., 2013; Weiss et al., 2010). *Appendix - Chapter 2* shows the detailed results from the actigraph comparison study.

2.4.1.2 Brain imaging for sleep assessment 1 – EEG and other measures

During Study 2 brain activity during sleep is measured using electroencephalography (EEG; see below) and near-infrared spectroscopy (NIRS; see below) and a custom-built headgear was used for this purpose. The gold standard in sleep research is so called *polysomnography (PSG)*, termed by Holland, Dement and Raynal in 1974 (Guilleminault, 2005) about 20 years after Aserinsky and Kleitman first recorded an all-night EEG recording showing alternation of REM and NREM sleep, for more information on REM/ NREM sleep see *Chapter 1* (Aserinsky & Kleitman, 1953). In the past decades PSG has evolved to become the benchmark tool for diagnosing sleep disorders like sleep apnea, narcolepsy or insomnia and is to date the only sleep assessment method that can reliably classify sleep stages.

PSG incorporates multiple electrophysiological measures like EEG, electromyography - the measurement of electrical activity generated by contraction of muscles; electrooculography - the measurement of the changes in electrical properties of eyes that results out of eye movements; electrocardiography - the recording of the electrical activity of the heart as well as respiration/breathing information (nasal/oral airflow, pulse oximetry, respiratory effort) and body movements that are recorded simultaneously during sleep.

These are placed by a trained sleep technician according to a specific set of rules (for example based on rules by the American Association for Sleep Medicine, AASM). Duration of PSG recordings can be any number of minutes or hours, lasting from naps to overnight PSG to 24-hour monitoring of infant's brain activity during wake and during sleep. After PSG has been recorded a trained sleep technician scores the data in 30-seconds epochs according to predefined set of rules. In the case of adults, rules set by Rechtschaffen et al. and in the case of infants Anders et al.'s rules are used (Anders et al., 1971; Rechtschaffen, 1968). For specific markers of infant sleep refer to *Chapter 1*. Both are continuously revised by the AASM or the European Sleep Research Society (ESRS). Occasionally a reduced set-up of PSG is used in the field.

Advantages and disadvantages. As mentioned above most sleep disorders may only be formally diagnosed with an overnight PSG. The biggest advantage of PSG therefore lies herein: if information on sleep stages and sleep microstructure (like sleep spindle occurrence) is required, for clinical or research purposes, a full PSG has to be conducted. However, a PSG study is labour- and cost-intensive as it generally requires a trained (pediatric) sleep technician to administer and score the recording. Another disadvantage is that the scoring rules change frequently, causing slight variations in how

sleep is scored between sleep medicine/research centres. Pediatric PSG data sets are hard to come by in particular those of normative sample of typically developing infants, due to the involved nature of the study which often means less experienced sleep scorers do not have ample opportunity to practice scoring. Additionally, due to the set-up PSG is unlikely to provide much information about habitual sleep to date, infants are likely to sleep differently with the full PSG set-up and to date it is still not possible to record many nights of PSG data in a row. Thus, PSG provides important information about brain activity during sleep and about sleep micro- and macrostructure, but perhaps is less useful in obtaining information about habitual sleep, information that may be better provided by a measure such as actigraphy (see above). As such it is often a good idea, if possible, to record both actigraphy and PSG to get a more complete picture about an infant's sleep.

Despite these disadvantages PSG remains the gold standard against which to compare all other sleep assessment methods. Though, one should carefully consider whether a PSG study is indeed necessary. Due to the invasive nature of the set-up PSG recording are most commonly conducted in sleep-disorder specialized clinical or research labs, though companies (such as Phillips) are increasingly designing reduced PSG systems for the laypersons use. Some people have taken to record PSG in reduced set-ups to minimize the invasiveness of the procedure for the participants. For example, Bennet and colleagues (2016) used only 2-EEG channels to classify active and quiet sleep in newborns successfully (Bennet et al., 2016). Another group used only respiratory information to distinguish the two sleep states in 6-months-old infants and succeeded (Terrill et al., 2010). Further approaches to improve cost-effectiveness and involvement of PSG studies include attempts to automatize sleep stage scoring, a process that usually requires experts and is highly time consuming. First studies show initial promising results, though more research is certainly needed (Mikkelsen et al., 2017, 2019). Future research will show if one might replace the full PSG set-up with reduced version to lessen burden for participants.

Brain imaging set-up of Study 2. For Study 2 a wireless 20-channel EEG system (Enobio, see below section on EEG for information on Enobio) was used to record sleep data. 13 electrodes of EEG, as well as EOG and EMG were recorded (set-up see *Chapter 7*). Therefore, a reduced set-up of the PSG set-up was used. In this thesis a reduced version of classical PSG, usually yielding good temporal information and ability to classify sleep stages is combined with a novel neuroimaging called near-infra-red spectroscopy (NIRS, see below), that has great potential to provide additional information on spatial

brain activation patterns during sleep. For a detailed description of the development of the customised NIRS-EEG headgear refer to *Chapter 7*.

2.4.1.3 Brain imaging for sleep assessment 2 - Near-infrared spectroscopy

Near-infrared spectroscopy (NIRS) is a novel, non-invasive neuroimaging technique that uses near-infra-red light (700 – 1000nm) properties to image changes in oxygenated and deoxygenated cerebral haemoglobin, allowing researchers to make inferences about brain activation patterns (Ferrari et al., 2004; Gervain et al., 2011; Scholkmann et al., 2014).

F. Jöbsis first discovered in 1977 that near-infra-red light can be used to measure brain oxygenation (Ferrari & Quaresima, 2012; Jobsis, 1977). Less than two decades later single channel functional NIRS (fNIRS) was first used (e.g., Villringer et al., 1993). Since then, fNIRS technology has rapidly evolved from single channel to multichannel and now multi-channel wireless applications. Concurrent to the technological advances there was a rapid increase in NIRS studies all over the world, not only in a lab setting, but in a variety of contexts, such as sport medicine (Quaresima et al., 2003), during naturalistic social interaction (e.g., Cui et al., 2012), and in rural developing countries such as The Gambia (e.g., Begus et al., 2016; Katus et al., 2019).

NIRS technology makes use of the fact that each frequency band on the electromagnetic spectrum of light reacts differently to different biological tissues in terms of absorption and scattering. Light in the NIR spectrum is shined onto the head, passing (scattering) through the scalp, skull and other biological tissue, without being absorbed. This is thought to follow a "banana-shape" (see *Figure 2.5*). Interestingly, there is an exception to this: the light is absorbed by so-called chromophores (i.e., pigmented compounds), like hemoglobin in the blood. The penetration depth of the light is proportional to the source-detector distance. How much NIR light is absorbed by hemoglobin is dependent on the amount of oxygen carried. Thus, the absorption spectra for oxygenated (HbO_2) and deoxygenated (HbR) hemoglobin are different. In actuality much less light is absorbed (~20%) than lost due to tissue scattering (e.g., Elwell et al., 1994; Everdell et al., 2005; Ferrari et al., 2004; Kocsis et al., 2006). Changes in light attenuation are the basis of NIRS methodology and can be described by the *modified Beer-Lambert-Law* (MBLL, Baker et al., 2014; Cope & Delpy, 1988; Elwell et al., 1994; Kocsis et al., 2006). The MBLL is based on two assumptions: 1) the loss of light due to scattering is constant and 2) the absorption of the tissue changes homogenously (Kocsis et al., 2006; Villringer et al., 1993). It states that the change in light attenuation is proportional to the

changes in the tissue chromophores, in the case of NIRS HbO_2 and HbR. Thus, if attenuation changes are measured at two or more wavelengths, for HbO_2 and HbR typically 750mn and 830 nm, changes in HbO_2 and HbR concentrations can be recorded. This in turn can be used by researchers to derive information about brain activation changes e.g., following stimuli exposure. Traditionally, continuous-wave NIRS (the system used for the present project) uses source-detector pairs that can pick up the light attenuation change. Continuous wave systems flash light continuously, thus rather than absolute reflections of the oxygenated blood content changes in oxygenated blood are measured. The underlying assumption here is of course that only blood oxygenation level changes throughout an experiment, while all other factors stay constant. The area of the cerebral cortex that is captured by the source-detector pair is called a "channel" (Everdell et al., 2005). For detailed explanation/formulae see e.g., Kosics et al. (2006).

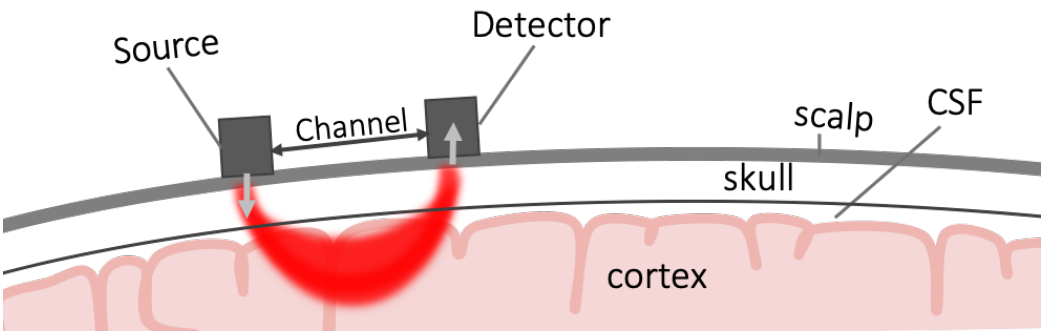


Figure 2.5. Path followed by the NIR light when it is shown onto the scalp. The penetration depth of the light is proportional to the source-detector distance. A source-detector pair is called a channel.

Advantages and disadvantages of fNIRS research. The surge that is seen in publications using fNIRS technology is not without foundation. fNIRS has many advantages over traditional neuroimaging like fMRI or EEG, its primary one lying in its portability and robustness to movement artifacts. This makes measuring brain activation patterns possible where fMRI and EEG are faced with challenges and limits like testing infant populations (Gervain et al., 2011; Lloyd-Fox et al., 2010). Infants can be held by their caregiver with new wireless technology and toddlers are able to move around freely (Pinti et al., 2015). As mentioned above, fNIRS may be used during exercise, in live interaction (Pinti, Aichelburg, et al., 2018) of multiple subjects (Cui et al., 2012) or in naturalistic environments (Pinti, Aichelburg, et al., 2018) like home environments but also in field research in developing countries (Begus et al., 2016; Katus et al., 2019). This

provides the opportunity for good ecological validity, which is essential for generalization of research findings. Moreover, NIRS technology is fairly inexpensive compared to fMRI (Cui et al., 2011; Lloyd-Fox et al., 2010). Lastly, fNIRS affords good cortical spatial resolution, much better than EEG (Lloyd-Fox et al., 2010), though admittedly worse than fMRI, and can give information on deoxygenated as well as oxygenated haemoglobin, thus delivering a clearer picture of brain activation. It also has a better temporal resolution than fMRI, though admittedly worse than EEG, allowing for more fine-tuned examination of cerebral blood flow compared to fMRI (Cui et al., 2011). For a comparison of the different neuroimaging methods refer to the figure taken from Lloyd-Fox et al. (2010) (*Figure 2.6*). The biggest disadvantage of fNIRS research to date is undoubtedly its inability to imagine deep brain structures. As mentioned above NIR light can only pass through to about 3-4 cm of cortical depth. Another disadvantage is that the relative novelty of the method means that different labs still have differing practices of where and how to place the array as well as differing strategies in pre-processing the fNIRS data. With regard to the latter, streamlined analyses are starting to emerge which will facilitate cross-study comparison (Pinti, Scholkmann, et al., 2018).

In order to be sure about the underlying brain anatomy fMRI co-registration is needed. In the present study the fNIRS probe placement and design (see *Chapter* 7) is based on a study in the same age range co-registering fNIRS probe placement with fMRI anatomical images (Lloyd-Fox et al., 2014). Still, this is not an option for every study, as fMRI data is hard to acquire.

On a concluding note, fNIRS measures blood oxygenation changes. These changes occur due to increased/decreased neuronal oxygen consumption, that ensue as a neuron increases its activity. This process is called *neurovascular coupling*. Due to the close relation between blood flow that transports oxygen to the neurons and neuronal activation, researchers can make an inference about underlying brain activity. Therefore, fNIRS is based on an indirect measure of neuronal activity. Comparably, EEG directly measures electrical activity of the neurons firing in the brain (see details below).

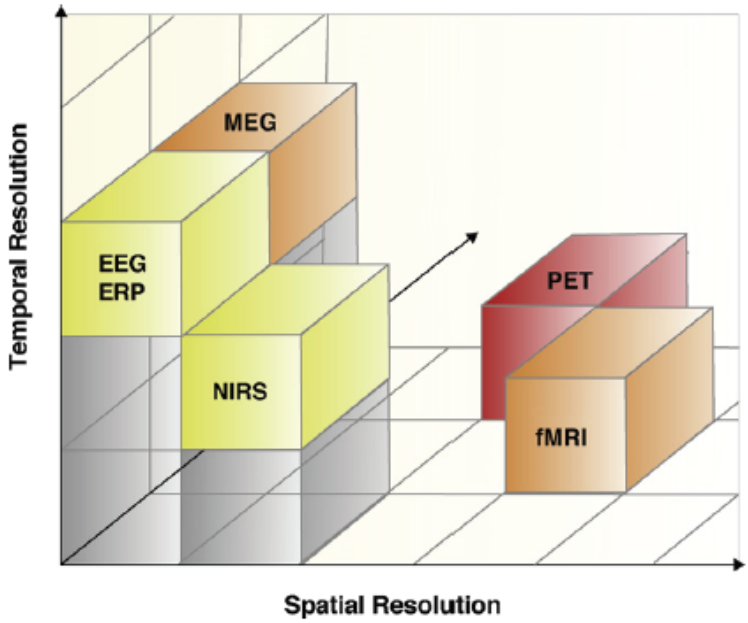


Figure 2.6. Illustration of the main neuroimaging methods used with infants showing temporal (y-axis) vs. spatial resolution (x-axis) vs. infant tolerability (yellow - infants tolerate the method well, orange – infants tolerate moderately well, red – infants do not tolerate the method well) of the different neuroimaging methods - reproduced from (Lloyd-Fox et al., 2010).

NIRS system used in current work. NTS UCL 44-channel, continuous wave NIRS system (Everdell et al., 2005) using wavelengths 780 and 850 nm, was used in this project. The sampling rate of the acquisition was 10Hz. The system has 32 laser diode sources (16 x 780nm; 16 x 850nm) and 16 detectors (see *Figure 2.7C*). Sources and detectors heads are connected to the system via glass optical fibres that send the infra-red light along to the system (see *Figure 2.7A-B*). These were embedded in a customised, combined NIRS-EEG headgear, where the Enobio EEG cap (see below) was used as a basis. *Chapter 7* contains description of the design and development of the customised headgear.

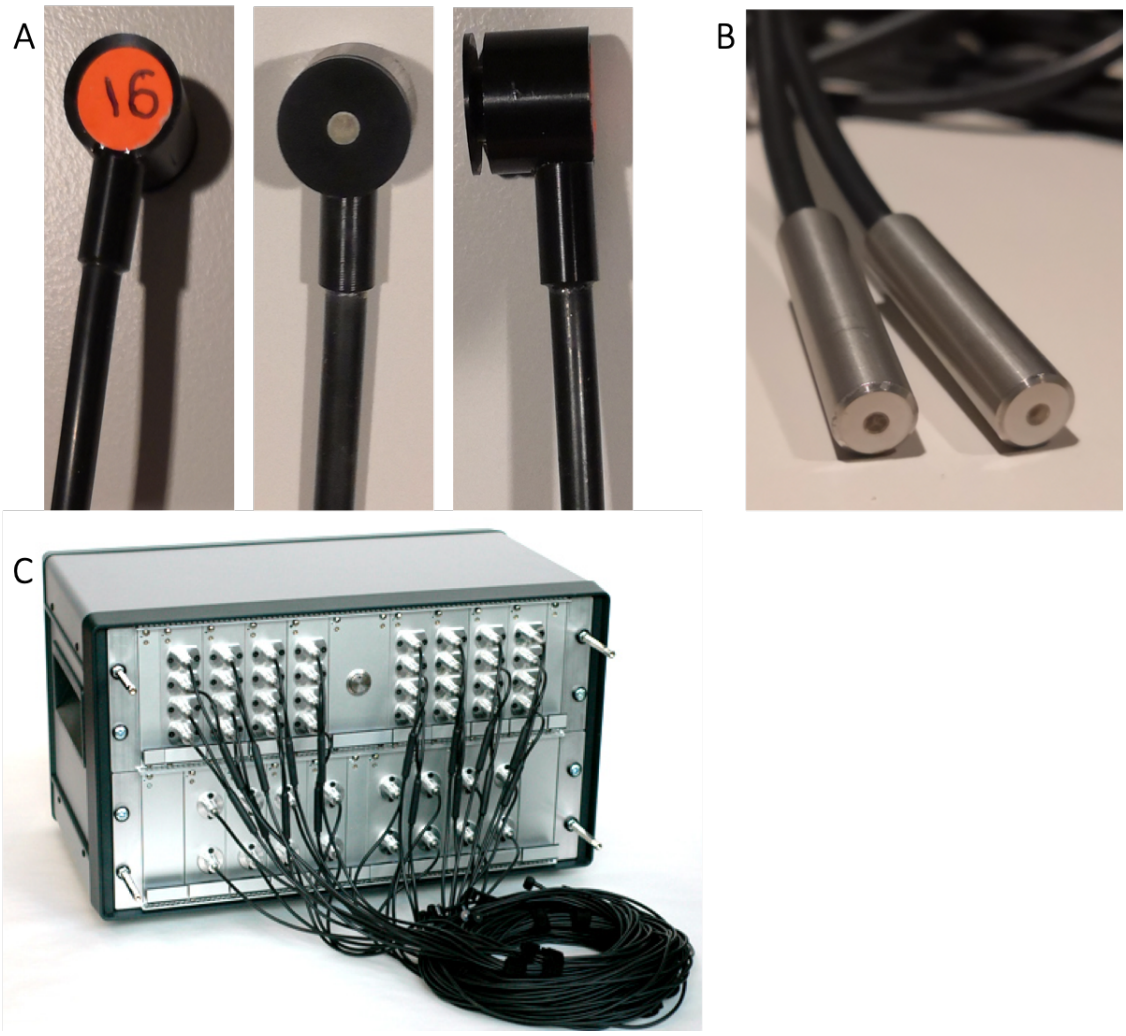


Figure 2.7. Illustration of optodes (A) and ends of fibre optic cables (B) and the NTS2 NIRS system (C) Image of NTS reproduced from https://www.gowerlabs.co.uk/, Gowerlabs, UCL.

2.4.2 Parent report measures used to assess sleep

In addition to objective measures, subjective parent-report measures were also used to assess infant sleep. These subjective measures were the same across both studies.

2.4.2.1 Brief Infant Sleep Questionnaire (BISQ; Sadeh, 2004)

The BISQ is a short, standardized screening questionnaire that assesses habitual infant sleep patterns of the week prior to completion date. BISQ completion time is 5 to 10 minutes. Questions enquire about classical sleep parameters such as sleep duration or number of night wakening but also about parental perception of sleep and sleep routines. Good validity was established by Sadeh (2004) originally compared to actigraphy and

sleep diaries. Test-retest reliability ranged from 0.82 to 0.95 (Sadeh, 2004). BISQ measures correlated well with actigraphy and daily sleep logs. Lewandowski et al. (2011) found moderate correlation of BISQ and caregiver reports but stated that the BISQ was sensitive enough to track developmental sleep trends (Lewandowski et al., 2011). Based on Pisch's (2015) thesis one additional question on sleep rituals and six additionally questions on parental sleep and parental perception of infant sleep were included. These were included to understand parental interaction with infants at nighttime better. For questions of the modified BISQ see *Appendix – Chapter 2*.

2.4.2.2 Sleep and Settle Questionnaire (SSQ; Matthey, 2001)

The SSQ is a 34-item questionnaire that assesses infant sleep and settling behaviour, as well as level of parental concern over these behaviours of the week prior to completion date. It is thus a screening tool for identifying infants with difficulties of falling asleep and staying asleep as well as their daytime behaviour (Lewandowski et al., 2011; Matthey, 2001). Test–rest reliability ranged from 0.14 – 0.76 on the individual items.

2.4.2.3 Sleep Diary

The sleep diary was distributed to the parent/caregiver and filled out every day for a week at a time. The sleep diary enquires about an infant's sleep duration, sleep onset time, bedtime routines (like lullabies, story reading or feeding at bedtime), night wakenings, naps and nap routines. The diary used in the course of this thesis is adapted from Pisch's sleep diary used in her PhD project at P&G/CBCD (Pisch, 2015). It was modified on the basis of a pilot run with parents at the P&G Geneva site (see below, pilot results). The sleep diary is the same for both Study 1 and Study 2, except that for Study 1 it was in German language and results were translated to English.

Sleep diary pilot - Sample. Nineteen parents (1 excl. due to wrong scanning of the questionnaire) filled out a preliminary version of the diary for 5 days in a row in November and December 2017. In addition to the questionnaire responses, 15 minute - skype interviews were conducted with four caregivers to gain additional feedback. Age of the infants whose parents were participating ranged from 0 (2 weeks old) to 30 months old (mean age = 17.25 months; SD = 9.26).

Adaptation of sleep diary. Based on the questionnaire and the interviews I adapted the sleep journal in the below way and used the new version for Study 1 (N = 21 tested with adapted diary vs. N = 19 for the pilot of the old diary).

1. Multiple choice format instead of open answers.

2. An exploratory question about parents noting nightmares in their infants. A mother mentioned during the interview that the baby frequently cries in her sleep without waking up. Other participants indicated they witnessed a similar behaviour. This could be a sign that infants were dreaming something distressing. Which in turn is potentially important for quality of sleep. Some adult studies have shown that nightmares change sleep architecture (Simor et al., 2012) and perception of sleep quality (Paul et al., 2015). There are no studies in infants on this yet. This is relevant to study in an exploratory research. I would get an overview of the frequency of this behaviour and if some infants are more prone to exhibit these behaviours or if there is an association with sleep quality.
3. Inclusion of a 5-point Likert scale of caregiver's everyday stress level.
4. Inclusion of an option to indicate how the baby was put to sleep during night awakenings (e.g., he/she was taken to parent's bed, they were fed, …)

An excerpt of the final sleep diary (translated into English, German version available upon request) can be found in *Appendix - Chapter 2*.

2.5 Measures to assess development

2.5.1 Technologies used to assess development

There are a variety of techniques that may be used to assess development (Addyman & Mason, 2016). Electroencephalography (EEG) was used to assess changes in neural activation patterns and eye-tracking was used to study attention differences across the first year of life.

2.5.1.1 Electroencephalography (EEG)

Electroencephalography (EEG) is one of the oldest brain imaging methods, first used in the 19th century by Caton in animals and in 1924 by Hans Berger in humans (Britton et al., 2016; Guilleminault, 2005). Electrodes are attached to the scalp and using either gel or saline a connection to the scalp is formed and neural activity can be recorded. Electrical activity generated by groups of cortical neurons in the brain can be picked up by the electrodes as voltage changes (in micro Volt) and is then amplified. For illustration see *Figure 2.8.* Using methods like pairs of electrodes (neighbouring electrodes or further away reference electrodes) differences in electrical potentials can be measured and resulting, so called EEG waveforms, can be analysed. Commonly, waveforms can be

decomposed into oscillations occurring at different frequencies into distinct groups such as delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz), beta (> 13 Hz) and gamma (> 35 Hz) (Britton et al., 2016). These distinct groups have been associated with e.g., with different states of arousal. For instance, delta activity is associated with slow-wave sleep and gamma frequency oscillations have been shown to be associated with attentional mechanism in humans (Guilleminault, 2005; Jensen et al., 2007).

There are different ways to analyse EEG data but the most common ones are by studying evoked related potential (ERP) and frequency analyses. In this thesis, frequency analyses are used to study a marker of infant developmental status and general information processing (theta power).

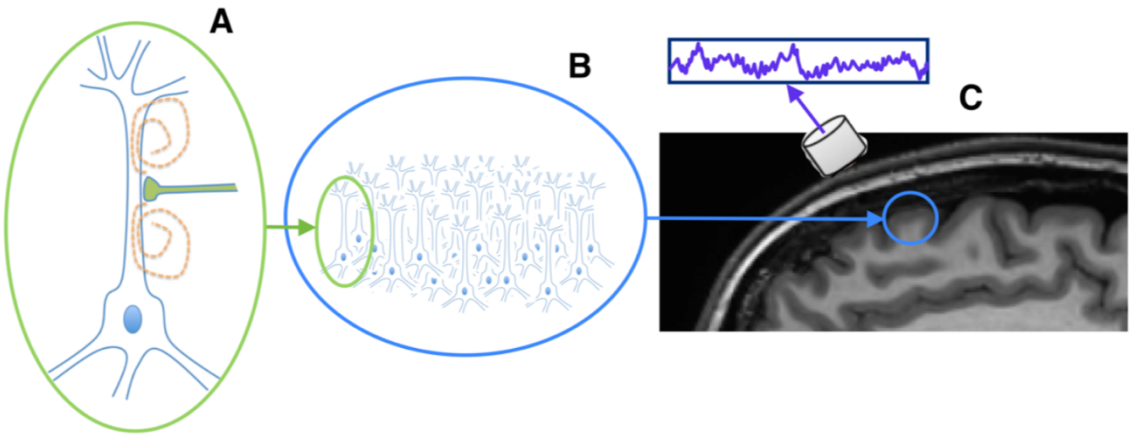


Figure 2.8. A neuron generated electrical activity (A) and the sum of the many cortical neurons (B) can be measured by the electrode that is placed on the human scalp (C). Image reproduced with permission from R. Haartsen (Haartsen, 2018).

Frequency analyses. Frequency analyses provide information on properties of the EEG signal at a certain frequency (see above). The EEG signal is transformed using Fourier analyses from time into frequency domain (Cohen, 2014). Frequency analyses reveal information on the amplitude, phase and power of the EEG signal across a specified amount of time. Compared to ERP analyses, they provide information on neural dynamics and oscillations have been shown to reflect underlying neural mechanisms. Different frequency bands are implicated in a range of cognitive processes (Cohen, 2014) and using time-frequency analyses one can obtain a more complete picture of the dynamically interacting processes that happen in the brain. Studying the brain in this way during development might provide a more holistic understanding of how cognitive processes

interact with each other as they develop. In this thesis, the focus is on investigating the power in a specific frequency band (theta band). Power is calculated by the square amplitude of the EEG oscillation.

Advantage & disadvantages. EEG has excellent temporal resolution, enabling researchers to study neural activity that happens within milliseconds of a stimulus occurring. In certain research paradigms it is essential to study time-locked neural responses that would not be measured by using fNIRS or fMRI, which need to account for the slower hemodynamic response function. Moreover, EEG measures electrical activity of the brain and not like NIRS or fMRI hemodynamic patterns that are downstream consequences of neuronal activity. Measurements of NIRS/fMRI are dependent on the coupling remaining constant across stimuli on its being similar across stimuli. Compared to other techniques, EEG has been shown to be well tolerated by different populations including clinical populations. Moreover, a vast amount of research has been conducted into different EEG set-ups, paradigms and analyses techniques. Therefore, it is easy to set-up streamlined experiments that can be compared across different contexts and centres. A disadvantage is certainly that EEG recordings are very sensitive to noise of many types: electrical (e.g., phones, power lines), physiological (e.g., muscles, eye-blink), participant movements and recording noise (electrode pop, bridging of electrodes) (Britton et al., 2016). Further, spatial information derived from EEG is not as good as it is with fMRI or fNIRS due to the so-called inverse problem. The electrical signal is conducted from the neural source through several tissues (e.g., bone, scalp). Though in order to deduce where the neural source is located precisely, researchers to know the properties of the fields of those tissues and how the electrical signal flows through. Additionally, electrical signals measured at the scalp can arise from either one strong neural source or several smaller neural sources. These might lead to the same response measured by EEG. Thus, inversing the signal and localising where it originates is an issue. Using data recorded using high-density EEG systems computational methods can be used to solve the inverse problem to a certain extend to obtain spatial information. However, often these methods require strict assumptions, which are often not satisfied in infant research.

EEG system. The EEG system used in this study is a 20-channel wireless Enobio System (Neuroelectrics, BCN, ES, *Figure 2.9C*). It uses gel-based electrodes embedded in a soft neoprene cap and a Bluetooth transmitter with a sampling frequency of 500Hz. Two types of electrodes were used, one for Study 1 (*Figure 2.9A*) and one for Study 2 (*Figure 2.9B*). Caps come in different size to allow for head size differences in infants. Cap sizes in cm that were used in the current study were 39cm, 42cm and 45 cm which

allowed accurate measurement of data of infants in the age range of 4 to 14 months. The task used in the EEG part of the experiment are described in *Chapter 6*.

Figure 2.9. Illustration of the EEG electrodes used in Study 1 (electrode A) and Study 2 (electrode B). And an illustration of the wireless EEG system used in Study 1, that was later adapted for Study 2 and integrated with NIRS optodes (C).

2.5.1.2 Eye-tracking

Eye-tracking is a particularly useful technique for pre-verbal infants and young children to assess learning and attention capacity and social interaction (Holmqvist et al., 2011). It uses the fact that where an infant or a child looks preferably can tell a lot about the ways in which they are processing stimuli. Although looking patterns do not directly

reveal information about brain functioning, they allow to draw conclusions about what and how an infant is processing information. Visual attention has been shown to be a marker for both present and future neurocognitive status (Colombo, 2001). Visual attention guides what and how infants learn in the world. Mechanical, attaching apparatus to the eye and then recording eye movements, as well as observational versions of eye-tracking were first used in the late 19th century, with the 20th century Dodge and Cline being the first ones to make use of photographing the eye lens to image eye movement (Holmqvist et al., 2011; Wade & Tatler, 2005). Today, much like the other techniques described earlier, technology has evolved to the point where it is no longer necessary to attach a mechanical set-up to the eye itself. Eye-trackers now use an infra-red camera, light emitting diodes as well as image processing software to determine where a person (i.e., a baby) is looking at a visual stimulus. The most commonly used technique to determine looking patterns is the pupil-and-corneal-reflection method (Holmqvist et al., 2011). In this method infra-red light from the diodes in the camera are directed onto the pupil. Those lights are invisible to the participants and therefore do not distract their attention. This light direction onto the pupil causes the first Purkinje image, which is a strong reflection in the cornea, that remains fixed while the eye moves. The Purkinje image and other pupillary information can be picked up by the camera and the image processing software in the eye-tracker itself and translated into eye-movements which can then be further analysed by the researcher (Holmqvist et al., 2011). In order to calculate the eye-movements accurately, eye-trackers need to have information on the angle at which the infra-red camera and diodes are positioned as well as distance to the participant and dimensions of the looking area (i.e., screen dimensions). The researchers have to input this information into the image processing software when setting up the eye-tracker. Most eye-trackers, in particular the Tobii eye-trackers used in Study 1 and Study 2 allow for some degree of head motion.

In addition, eye-trackers allow for pupillometry, a method that is gaining more popularity in infant research. Pupillometry measures the very small changes in pupil size that occur in response to stimuli. Pupil diameter changes in infancy have been related to, e.g., motivation or emotional arousal to social stimuli (for review see Hepach & Westermann, 2016).

Parameters that can be measured. Researchers can extract a multitude of information from eye-tracking data all cantered around look location and duration. Commonly, researchers look at *fixations*. A fixation describes the situation where the eye is not moving for a period of time, which is taken to represent attention to a stimulus.

Another aspect researchers look at are *saccades*, the shift of the eye from one fixation to the next and the latency (i.e., the time it takes an infant to make the saccade of interest) of those saccades. Furthermore, in infancy research time to disengge from a present stimulus is sometimes used (called *disengagement*). The tasks used in the present thesis include the gap-overlap task, a novelty habituation task, and the face pop-out task. These are further explained in *Chapter 5*.

Advantages and Disadvantages. Eye-tracking is a great method to explore infants learning ability, information processing and social interaction noninvasively. As eye-trackers are easily installed, recording data in the field or at home in addition to in the lab is possible (Katus et al., 2019; Meißner et al., 2019). Secondly, eye-tracking is a particular useful technique for investigating populations and situations where verbal instructions cannot be used like in pre-verbal infants/toddlers. It represents a way to investigate eye movements without bias introduced by the researchers. A disadvantage is that with much movement the eye-tracker fails to capture the eyes (Gredebäck et al., 2009). This is particularly true if infants move during the calibration period. This often means that accurate data cannot be collected. Accurate capturing of the pupil is furthermore influenced by eye colour and eye properties. In some infants, especially after crying, it can be hard to capture the eyes for tracking.

Eye-trackers used in this project. Eye-trackers used in Study 1 was the TOBI X120 (sampling frequency of 60 Hz) and in study two the TOBI X300 (sampling frequency of 120 Hz). Below is an illustration of the set-up for Study 1 and Study 2. Tasks used in the eye-tracking part of the experiment are described in *Chapter 5*.

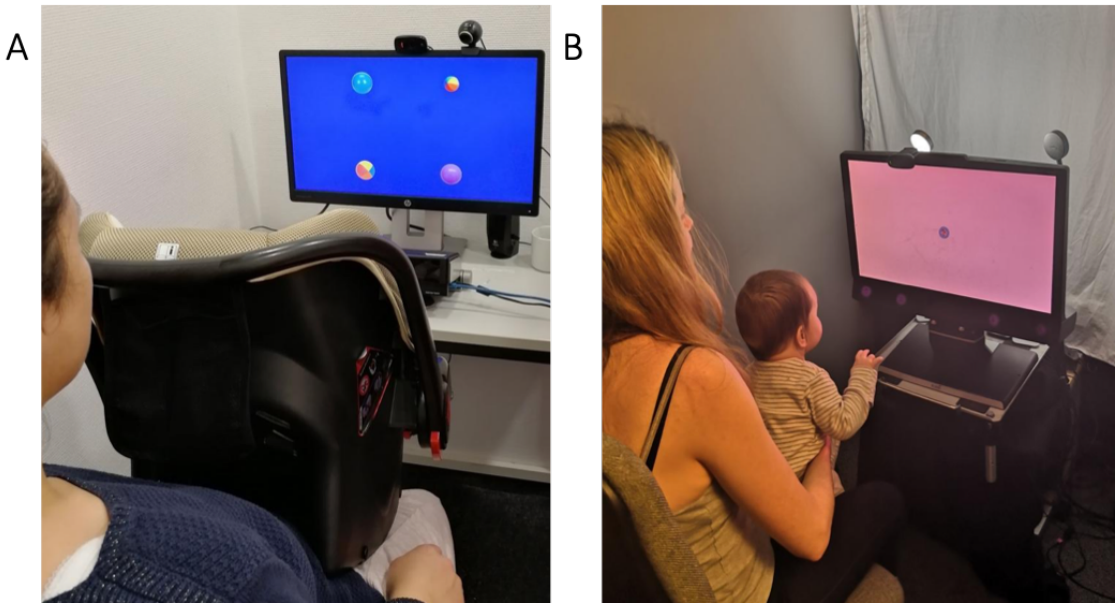


Figure 2.10. Eye-tracking set-up Study 1 (A) and Study 2 (B).

2.5.2 Parent-report measures assessing infant characteristics and family socio-cultural environment

Parent-report measures are the easiest way to collect data about infant's behaviour or sleep patterns and about the socio-cultural background of the family. Additionally, the data is usually easy to analyse and process, especially if internet-based questionnaires are used.

Parents filled out questionnaires about their own socio-economic background and their family medical history. In addition to that they also filled out standardized questionnaires assessing infant development (ASQ) and temperament (IBQ-R) and maternal stress (STAI, PSS) and depression (EPDS). Below the questionnaires are described including their reliability and validity. Results from these questionnaires are described in detail in *Chapter 4*. All questionnaires were used both in Study 1 as well as Study 2. For Study 1 a German translation of the questionnaires was used.

2.5.2.1 Ages & Stages Questionnaire (ASQ)

The ASQ is a parent-report measure similar to the milestone interview that assesses and infants' activities over time providing a picture of general developmental status on five subscales: communication, social personal, problem-solving, fine motor and gross motor. Parents answer the questions with "yes", "no" and "sometimes". The questionnaire has high test-retest reliability (94%) and has been validated against another popular assessment of development the Bayley Scales of Infant development (Schonhaut et al., 2013; Squires et al., 1997).

2.5.2.2 Infant Behaviour Questionnaire - Revised short form (IBQ-R)

The IBQ-R short form is a 91-item questionnaire that assesses infant temperament (until age one) and asks the parents/caregivers to report on activity and sensitivity levels of their infants of the past two weeks using a 7-point Likert scale with response options that range from never (1) to always (7). It is composed of 14 subscales: approach, vocal reactivity, high pleasure, smile and laughter, activity level, perceptual sensitivity, sadness, distress to limitations, fear, falling reactivity, low pleasure, cuddliness, duration of orienting, and soothability with the overarching 3 subscales of Surgency/Extraversion, Negative Affectivity and Orienting/Regulatory Capacity. Subscale reliability ranged from

0.70 to 0.90. (Gartstein & Rothbart, 2003; Putnam et al., 2014). Completion time is estimated to be around 30 minutes (Putnam et al., 2014).

2.5.2.3 Demographics/Socio-economic status (SES)

Parents furthermore received a general questionnaire that enquiring about SES status and other demographics, such as highest level of education, years of education, household income, number of bedrooms, parental age and languages spoken at home. Additionally, medical history including infant birth weight/height, family history of developmental and psychiatric disorders and other circumstances surrounding birth and pregnancy. This questionnaire is an in-home questionnaire of the Birkbeck Babylab.

2.5.2.4 Perceived stress Scale (PSS)

The PSS is a 10-item questionnaire filled out by the mother to assess life stress appraisal. Completion time is around 5 minutes. A high total score on the PSS is indicative of a larger temporary vulnerability to life-event-evoked depression symptomatology. Predictive validity of PSS is short due to it being influenced by daily events (Cohen et al., 1994).

2.5.2.5 State trait anxiety inventory (STAI)

The STAI is composed of two 4-point Likert subscales. One assesses state anxiety (how anxious the person is filling in a given moment (20 items) and one trait anxiety measure of how anxious the person is feeling generally (20 items). Its main merit is that it is easy to understand across different levels of education. Completion time is around 10 minutes (Spielberger, 2010).

2.5.2.6 Edinburgh Postnatal Depression Scale (EPDS)

The EPDS is a 10-item questionnaire that assesses postpartum depression. It can also be used to assess depression in other populations but young mothers. Completion time is around 5 minutes. The EPDS was found to have satisfactory sensitivity (79%) and specificity (85%). Questions relate to feelings of anxiety and sadness as well as suicidality (Cox et al., 1987, 1996). Results of the EPDS were carefully monitored in participating parents. Any mental health concerns identified in the participating parents were discussed with Prof Jones and Dr Wiesemann. Thereafter these concerns were carefully addressed in a scheduled meeting with the parent. Note I have clinical psychology training to be able to handle sensitive situation such as these.

In summary, this chapter describes the background of the objective and subjective methodologies and procedures for both Study 1 and 2. *Chapter 3* will examine sleep measures of the longitudinal Study 1 in more detail.

CHAPTER 3 - (Longitudinal) Examination of Sleep Patterns in the first year of life using objective and subjective sleep assessment methods

This chapter discusses sleep parameters and their measurement and their changes across the first year of life rather than aspects surrounding infant sleep. *Chapter 4* will touch upon sleep rituals and parental subjective experience of infant sleep and family socio-cultural environment in relation to sleep.

One of the most important issues for new parents is their infants' sleep. Camerota et al. (2019) state that the majority of parents enquire about sleep during their initial visits to healthcare professionals. This illustrates the importance of researching sleep in infancy not only for the scientific community but also to inform and educate parents.

As described in *Chapter 1* infant sleep differs fundamentally to adult sleep in a number of ways. For instance, infants sleep more both during the night and also during the day and they frequently wake up at night. Moreover, sleep microstructure composition is also different with infants showing e.g., more REM sleep than adults. Due to sleep's apparent importance for development it is crucial that researchers understand how they can measure it correctly. Sleep can be assessed using objective and subjective measures. In order to capture inter- as well as intraindividual differences in sleep, habitual measurement of several days of sleep is necessary. Below I discuss in detail different sleep assessment methods and their concordance.

3.1 Measuring infant sleep

3.1.1 Subjective vs. objective methods to assess infant sleep and their challenges

Measuring infant sleep is more complex than measuring sleep in adults for a number of reasons. Infants cannot report on their own sleep – consequently, subjective reports are entirely based on parent-report measures. Parent-report measures for infant sleep assessment are easy to use, scalable, non-invasive to the infant and can be used for a long duration. However, some drawbacks are associated with using parent-report. (un)Surprisingly, parents are not very good at estimating their infants sleep parameters, e.g., either over- or underestimating sleep duration (Camerota et al., 2018). Accuracy of estimating their infants sleep might be influenced by e.g., parents' personal characteristics, habits and schedule, sleep location (co-sleeping vs own room), stress level

or fatigue causing difficulty in recording and remembering infants sleep-wake times (Camerota et al. 2019).

Subjective measures include parent-reported sleep diaries/logs or sleep questionnaires such as the Brief Infant Sleep Questionnaire (BISQ; Sadeh, 2004) or the Sleep and Settle Questionnaires (SSQ; Matthey, 2001) described in detail in *Chapter 2*. To briefly review, the BISQ is a short, standardized screening questionnaire with questions about average sleep duration, average Night Wakening Number or average bedtime. Other questions in the BISQ center around sleep and bedtime routines. The SSQ assesses infant settling behaviour in addition to questions about sleep. Both BISQ and SSQ ask parents to estimate habitual infant sleep patterns of the week prior to completion date. Contrary to this, there are sleep diaries where parents record accurate wake and sleep onset times and daily routines every day for a week, from which researchers then calculate the average sleep duration per day. Although more time-consuming than filling out one-time questionnaires, diaries' biggest advantage constitutes in their ability to provide information about variability in duration and they have shown better overlap with objective measures (Sadeh, 2015).

An alternative approach is to use objective recording devices in the home or in the lab. Acquiring objective data is harder than in adults due to parents' hesitancy to their infant wearing devices for an extended period of time. The gold standard, against which all sleep data is compared (see *Chapter 2*) is polysomnography (PSG). However, it is not feasible to acquire polysomnographic data at home for a long time period especially with infants. Thus, for studying habitual sleep, researchers often have to revert back to subjective parent-report. In recent decades, the use of actigraphy (see *Chapter 2*) has become more prevalent in infant research as an option to collect ecologically valid and non-biased data. Though there are still few validated guidelines and options available for infant actigraphy scoring-algorithms. Most commonly used and validated for infants is the Sadeh algorithm (Melzer et al., 2012). The Sadeh algorithm aggregates 11 of the 60-seconds actigraphy data epochs into scoring each 60 seconds epoch in a given period as awake or asleep according to a pre-defined treshhold. Sadeh's algorithm has been shown to correctly classify sleep-wake (compared to PSG and compared to observational methods; Sadeh, 1994; Sadeh et al., 1994, 1995).

These measures are all providing a glimpse at (infant) sleep from different angles. Therefore, there is a need to compare these methods to each other and evaluate their commonalities and differences. However, quality of the data collected varied greatly amongst different studies as found by the review of Henderson et al. (2011). Moreover,

guidelines used to assess day and night sleep varied, taking different ranges for night and day sleep in different studies, mixed data types further increase heterogeneity in the data sets and impedes easy cross-study comparison. Henderson (2011) highlights the lack of objective measures in many infant studies. The datasets that do exist are often of infants or young children with sleep disorders or neurodevelopmental disorders with high comorbidity with sleep disorders, for whom there has been more interest in acquiring sleep data. This impairs generalizability to the general population.

A few recent studies have compared different methods of sleep assessment in infants. Most notably a study by Camerota et al. (2018) compared one subjective method and two objective methods, videosomnography and actigraphy (Camerota et al., 2018) in 90 African-American 3-months-old infants. Both sleep quality and quantity were measured. Correlations for sleep methods were good for sleep schedule and moderate for night wakening. Actigraphy and sleep diaries coincided better than either of those measures coincided with videosomnography. Another study by Tikotzky and Volkovich (2019) only assessed Night Wakening Number and Duration using two subjective (BISQ, sleep diaries) and one objective (actigraphy). The researchers report greater actigraphy-assessed WASO at 6, 12, and 18 months of age, but no differences at 3 months of age, but overall higher number of night wakenings reported by subjective measures. Agreement between methods was higher for the younger age group than the older age groups, and while correlations were high between the measures, agreement between methods (as measured by Krippendorfs alpha) was poor, especially for BISQ and actigraphy. Though, Bland-Altman (BA) plots showed that agreement for WASO was good between diary and actigraphy for 12- and 18-months-olds. These findings contrast with earlier findings showing that actigraphy overestimated night wakenings compared to diary and Night Sleep Duration was different across a sample of 5.5 to 8 months old infants (Hall et al., 2015). However, they are in line with findings by Müller et al. (2011) that found good agreement between sleep diary and actigraphy in infants 1 to 9 months of age. A key difference between the studies is that Müller and colleagues (2011) pooled the large age range and did not differentiate between age groups.

These results suggest that in some studies agreement between objective and subjective measures is good while other studies report unsatisfactory agreement across methods, and that it varies with infant age. To date it is not clear what exactly drives these cross-method differences. In addition, there is a lack of studies comparing the different methods across the first year of life. When designing the sleep assessment part of this study, these results highlighted that choosing one method over the other is

currently not possible, as it is unclear which habitual sleep assessment method provides the best estimate of true, underlying sleep. Therefore, I determined using various objective and subjective sleep assessment methods would be the best approach to get a more complete understanding of the agreement between the sleep measures and what might influence cross-method agreement.

3.1.2 Sleep quality assessment in infants

Perhaps intuitively every parent determines if their child is a good or a poor sleeper. But what makes an infant a good or a poor sleeper? For parents, good sleep often means that their infants sleep many hours without waking up, so that they may themselves sleep undisturbed. However, in adults it has been shown that too much sleep may not be ideal for brain and cognitive functioning either (e.g., Ohayon & Vecchierini, 2005). Thus, it is entirely possible that good sleep for infants' development might not agree with what a parent might interpret as good sleep. Thus, what a parent thinks is good sleep does not necessarily mean it is equally as good for the infant. On the other hand, an infant's long and continuous sleep means the parent sleeps well and provides parents with opportunities for self-care/housework/relaxation while the infant is sleeping. This means they will be more available to provide a positive environment and interaction for the baby when they are awake.

Furthermore, whether an infant may be viewed as a good or a poor sleeper could lie in sleep's ability to positively affect development. For example, Pisch (2015) and Sun et al. (2016) conjecture that the relationship between sleep and neurocognition might be a U-shaped one across development, implying that the relationship between sleep and development can change across the first year of life.

In summary, sleep for development might be different from the parental perception of infants' sleep for development.

In order to quantify sleep, sleep researchers use a number of variables that can be inferred from the abovementioned objective and subjective methods. Variables used in sleep research are as follows. One of the most commonly used parameters to measure infant sleep is sleep quantity (duration of day, night and total sleep). Other parameters include the number and duration of awakenings that the child has at night (also called sleep fragmentation), the number of naps an infant has during the day (number of daytime naps), the ratio of day and nighttime sleep and lastly, the duration of the longest self-regulated sleep period (LSP). These different variables, rarely used all in the same study, provide researcher with an estimate of the child's sleep quality.

Researchers have struggled so far to establish a clear consensus on which of the above-mentioned parameter(s) to use for infant sleep quality assessment, even though sleep quality is recognised to be of utmost importance for different aspects of cognition and general health (NSF sleep report, 2017). There is a lack of agreement as to how to define sleep quality, in particular with regard to infants, who are still unable to express subjective feelings about their sleep. In adults, often the subjective questionnaires are used, e.g., PSQI. Overall, the 2017 report, based on extensive literature review conducted by an expert panel highlights the following factors as relevant in determining good sleep in infants: sleep latency < 30 min and sleep efficiency ≥85%. Experts seem to think that the ratio of duration and fragmentation is more relevant than the absolute values of the single measures. This is at odds with current literature in infant sleep research where the latter two are primarily used. This lack of consensus with regard to sleep quality variables may also be due to the large intra- interindividual variability in sleep, due to the lack of comparable longitudinal infant data and due to methodological differences, that occur when different measures are used to assess sleep.

Sleep quality in infants is based on parent-report or on quantifying an objective measure, unlike in adults who are asked how well they slept in one form or the other. Thus, some studies merely ask the parents if their infant slept well, and many studies take sleep duration as marker for quality, reasoning that greater amount of night time sleep can mean that the child is adapted earlier to the “adult rhythm” which might indicate a better bio-behavioural/neural organization (Bernier et al., 2010). Sleep fragmentation is another common measure of sleep quality in the literature where fragmented sleep is reasoned to reflect a lower ability to regulate sleep (Meltzer et al., 2012; Scher, 2005; Teti et al., 2010). Other studies take the measures mentioned by the NSF report and use sleep latency or efficiency measures (NSF sleep report, 2017).

3.2 Research aim and current study

In face of the lack of methodological consensus on measuring infant sleep quality, measurability of the sleep parameters needs to be addressed and examined before questions can be asked about the relationship of sleep quality and the brain. Therefore, a key goal of this thesis is to identify which sleep parameter might serve best in determining sleep quality in studies of neurocognitive development and in finding a way to categorise infant sleep data into meaningful groups of poor and good sleepers. This chapter primarily

focuses on the exploration of different sleep parameters and how they may be used to measure sleep quality in infants.

Still, studies comparing different methods are hard to come by, even more so when it comes to comprehensive sleep data in longitudinal studies. Tracking different methods side-by-side longitudinally, in typically developing infants, is crucial to identify whether objective or subjective methods might provide different consistency across time points.

The aim of this chapter is twofold: to investigate the sleep trajectories as well as sleep quality in a large multi-method longitudinal sample of infants and to identify which sleep assessment method might serve best as sleep quality measure for use in studies of neurocognitive development.

The research questions therefore are as follows.

Research question 1: What is the concordance between different sleep assessment methods and do they change with development?

In order to determine which method is most appropriate as sleep quality measure for use in studies of neurocognitive development, first we have to look at how well different sleep measures (subjective vs. objective methods) agree with each other and if one measure might be more useful in assessing sleep than others or if they are all equivalent and may thus be used interchangeably.

Research question 2: Are there developmental patterns with regard to the sleep parameters (e.g., sleep duration, night wakening, …) and how is the intra-individual consistency with regard to development?

Secondly, I investigate the potential developmental patterns in the data, e.g., the decrease in overall sleep duration and whether agreement between methods changes depending on which age group is assessed.

Research question 3: Are there distinct groups of sleepers, that can be identified by sleep measurements and how do these groups behave across development?

Lastly, I was interested in whether distinct groups of sleepers can be identified from the data collected and if participant groupings may change across development. The goal is to see if these groups may be relevant for sleep quality assessment.

3.3 Methods

Sleep data was collected in the context of a larger longitudinal study assessing the relationship of sleep and development using eye-tracking, EEG, actigraphy, sleep diary and parent-report questionnaires (see *Chapter 2* for study design of full study). In this

chapter I discuss the sleep data and in subsequent *Chapters 4, 5*, and *6* how they relate to cognitive and brain development as measured by eye-tracking and EEG and to infant general development and temperament, socio-cultural environment and maternal characteristics.

3.3.1 Sample

The sample of the present data included 76 typically developing, term-born (GA > 37 weeks) infants without a (familial) medical history of sleep, neurodevelopmental or neuropsychiatric disorders (42 female), where I excluded 1 participant due to premature birth. The age range at recruitment ranged from 4 to 14 months (mean age: 282 days, SD = 92 days, range in days: 116 to 456 days). Participants were primarily of German or German-Turkish (N=11/76) ethnicity. Participants were tested every 2 months for 6 months or until they were 14 months old, resulting in an accelerated longitudinal design. For information on how many infants were at every visit see *Table 3.1*.

Table 3.1. Sample sizes at each visit of Study 1

	Age (in months) tested →					
Age (in months) enrolled ↓	**4**	**6**	**8**	**10**	**12**	**14**
4	17 (9f)	5	6	5	-	-
6	-	19 (10f)	15	12	9	-
8	-	-	22 (11f)	11	6	5
10	-	-	-	5 (2f)	4	3
12	-	-	-	-	9 (7f)	9
14	-	-	-	-	-	4(3f)
Total N/ age group	17	24	43	33	28	21

Notes. Final sample size for each cohort, as well number of girls for each age group. f = girls. Total N = 76 participants (42f).

Exclusion criteria were a family history of neurodevelopmental and/or sleep disorders, premature birth (< 37 GA), and families with plans to move away from the Frankfurt area in the months following the start of the study.

This study was approved by the Department of Psychological Sciences, Birkbeck, University of London, Ethics committee in accordance with the Declaration of Helsinki.

3.3.2 Study design

This study features an accelerated longitudinal design as due to time and person constraints, as well as high drop-out rates. 38 participants dropped out (after either the second or the third visit) in the course of the longitudinal part of the study after having planned to participate in the whole study, i.e., all four visits in cohorts 4, 6 and 8 months of age. Additional cross-sectional data was therefore collected at each time point (4, 6, 8,

10, 12, and 14 months of age) to increase the sample size. Moreover, participants in age groups 10 and 12 months of age were also given the option to participate in more than on visit.

Figure 3.1. Design of longitudinal sleep data collection. BISQ = Brief Infant Sleep Questionnaire (Sadeh, 1996), SSQ = Sleep and Settle Questionnaire (Matthey, 2001)

3.3.3 Sleep assessment measures

3.3.3.1 Subjective measures

Two sleep questionnaires were used: the Brief Infant Sleep Scale (BISQ) that enquires about habitual sleep patterns (sleep fragmentation and duration) at every visit and the Sleep & Settle Questionnaire (SSQ) that compares sleep as well as settling behaviour. Sleep duration and the duration of night wakenings, as assessed by SSQ and BISQ refers to the parents estimate of the average sleep duration/night wakening duration (WASO) in the one week prior to the lab visits. Similarly, Night Wakening Number refers to the parents estimate of the average number of night wakenings in the one week prior to the lab visits. In the two See *Chapter 2* for details on questionnaires and on validity.

Sleep diary. To enable cross-study comparison this sleep diary is adapted from Pisch's sleep diary used in her PhD project at P&G/CBCD (Pisch, 2015). This mirrors prior research by e.g., Hall et al. (2015), where parents were explicitly asked about duration and timings of wakings. Concurrent to the week where the infant wears the actigraph, the parents were asked to fill out a sleep diary every day. Questions with regard to sleep duration and sleep-related routines (bedtime routines etc.) are asked. It was modified on

the basis of a pilot run with parents at the P&G Geneva site (see *Chapter 2*, development of sleep diary). Parents reported the sleep and wake times every day for a week in the diary. Sleep duration / wakening duration / Night Wakening Number is calculated by the researchers as the 7-day average of the respective measure.

3.3.3.2 Objective measure

For objective assessment of sleep an actigraph, wGT3X-BT (Actigraph Corp., Fl, US) was used. Sampling rate was set to 60 Hz, based on literature (Meltzer et al., 2012; Sadeh, Sharkey, & Carskadon, 1994) and epoch length was 60 seconds (for details on actigraphy see *Chapter 2*). The actigraph was attached to the infants' ankle for a 7-day period. The raw accelerometer data objectively provides information about sleep-wake periods of the infants and gives a conclusive picture of the participants' habitual sleep patterns. *Table 3.2.* describes the sleep parameter information that was collected in the scope of the current study. The parameters highlighted in blue are investigated more closely in this chapter and form the basis for the sleep quality clusters that are identified below. The parameters highlighted in dark blue are investigated more closely as continuous parameters in this thesis in relation to parameters of neurocognitive development. This subset was selected based on parameters investigated in prior research and to make sure that all parameters were. Future research will include investigating the other parameters as well.

Table 3.2. Sleep variables assessed by subjective and objective sleep measures

BISQ	SSQ	Sleep diary	Actigraphy
Subjective measures			Objective measure
Sleep Duration* - Day - Night - Total	Sleep Duration* - Day - Night - Total	Sleep Duration ° - Day - Night - Total	Sleep Duration ° - Day - Night - Total
		Sleep duration variability in the course of a week	Sleep duration variability in the course of a week
Night wakening* - Number - Duration (WASO)	Night wakening* - Number	Night wakening - Number - Duration (WASO) - Variability in the course of a week	Night wakening - Number - Duration (WASO) - Variability in the course of a week
		Longest sleep period day/night	Longest sleep period day/ night
Ratio Day-Night sleep	Ratio Day-Night sleep	Ratio Day-Night sleep	Ratio Day-Night sleep
percentage of total time in bed actually spent in sleep		percentage of total time in bed actually spent in sleep	percentage of total time in bed actually spent in sleep
Sleep onset - timing - latency		Sleep onset - timing - latency	Sleep onset - timing
		Infant dreamed? (y/n)	
Co-sleeping (y/n)		Co-sleeping/partial co-sleeping over 7-day period	

Note. *Based on parents' perception of average, ° 7-day-average

3.3.4 Data collection procedure

Sleep data was collected from the parents as described in *Chapter 2*. Parents received a detailed instruction sheet for attaching the actigraph to their child's ankle and were asked to always attach it on the same side (i.e., left or right). Parents practiced

under supervision of the researcher to safely attach the actigraph. Parents were explained the diary and the questionnaires and were given the opportunity to ask any questions.

3.3.5 Data quality description

The quality of the data collected varied depending on the tool used to collect the data. For sleep questionnaires all questions that were answered were included in the analysis. For actigraphy data, the data set was excluded if there was less than three complete days of data available. To minimize data loss, for some of the infants, only night sleep assessments were also counted as valid (based on Meltzer et al., 2012).

Table 3.3. Data quality for each sleep measure (for pooled N)

	Actigraphy	**Diary**	**BISQ**	**SSQ**
Data complete	86.1 %	84 %	98.2 %	85.7 %
Missing Data	13.9 %	16 %	1.8 %	14.3 %

Note. BISQ = Brief Infant Sleep Questionnaire, SSQ = Sleep and Settle Questionnaire.

3.3.6 Analysis plan

Statistical software R version 3.5.3 (Team, 2016) and SPSS v25 (IBM, Chicago, IL) were used for analysing sleep data. ActiGraph proprietary software ActiLife version 6.3. was used to pre-process actigraphy data (Actigrah Corp.). First, descriptive statistics for objective and subjective sleep measures were performed. Thereafter, cross-sectional as well as longitudinal examination of the sleep data was done to check for differences of sleep measures between age groups. Concordance between different measures (across subjective measures as well as across subjective and objective measures) using correlational analysis (Pearson correlation, intra-class correlation) as well as Bland-Altman plots and equivalence testing using R packages ‘blandr’ (Datta, 2017) and ‘TOSTER’ (Lakens et al., 2018) were used. Lastly, k-Means cluster analysis was performed on the pooled sleep data to answer the research question if there are groups of sleepers using R-packages ‘kmeans’ and ‘cluster’. Plots were created using Rpackages ‘ggplot2’ and ‘corrplot’ (Wei & Simko, 2017).

3.3.6.1 Descriptions of analysis procedure/algorithms used

Actigraphy pre-processing. Pre-processing of Actigraph data was done using the ActiLife software (ActiGraph Corp.). Raw accelerometer data was collected at 60 Hz and aggregated to 60 seconds epochs. Sadeh algorithm was used to classify sleep and wake (see methodology chapter for description of algorithm). Exclusion of non-wear periods was based on Actilife algorithm and based on parent-report of actigraph removal. Parents noted down the times when they took off the actigraph and put it back on. Actigraphy data was included into further analysis if there was at least three 24h segments of data, based on recommendations by Meltzer et al. (2012). For participants, where only nighttime actigraphy was conducted, at least three nights of full data was deemed sufficient to be included into the analysis for night wakening and night sleep duration.

Multilevel linear modelling. IBM SPSS statistics v25 was used to conduct simple linear mixed models (also called growth curve modelling; Curran et al., 2010) to test for longitudinal differences in sleep data (BISQ, SSQ, sleep diary, actigraphy) across age groups. The variance-covariance matrix was assumed to be first order autoregressive type. This variance structure was chosen as it allows for potential systematic changes in the relationship between variances. In other words, correlations between time points are allowed to be more similar than correlations further apart in time (Field, 2005). As the present sleep data set covers the entire range of the first year of life it is likely that timepoints closer together correlate higher than time points further apart. Heterogeneous structure of variances was chosen, as differences in variances of sleep parameters across age ranges are to be expected due to the high variability in sleep patterns in the first year of life (see *Chapter 1*).

Correlational analyses. Pearson's correlational analyses between the different sleep measures were conducted as indices for associations between sleep variables using Statistical software R v3.5.3 using package 'corrplot' (Wei & Simko, 2017).

Intra-class correlation (ICC). The ICC is a measure of reliability that can help determine agreement between different raters (in this case the subjective questionnaires as well as diary) assessing the same question (in this case sleep parameters). An ICC closer to 0 indicates lower agreement than an ICC closer to 1 (see below *Figure 3.2*). In this case a 2-way mixed effects ICC using absolute agreement was used (Field, 2005; McGraw & Wong, 1996).

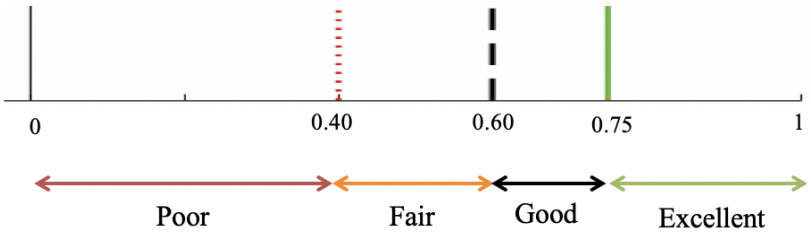


Figure 3.2. Intra-class correlation agreement rate cut-off indications. (Adapted from Haartsen et al., 2019)

Bland-Altman plots (BA plots). Agreement between objective measure (i.e., actigraphy) and subjective measures (i.e., SSQ, BISQ, diary) was assessed using BA plots. BA plots are commonly used in sleep research to investigate agreement between the gold standard measure of polysomnography and other measures like actigraphy (Tikotzky & Volkovich, 2019; Yavuz-Kodat et al., 2019). Here it is used to compare the subjective measure (questionnaires and diary) to the objective measure (actigraphy). Limits of agreement are plotted using the mean and standard deviation of the differences between the two measures with 95% of the data ideally falling within +/- 1.96*SD of the mean difference. A line of proportional differences can be drawn and proportional bias towards one measure or the other can be identified by investigating the plots mean difference line (Bland & Altman, 1986, 1999). As both diary and actigraphy represent a more accurate picture of habitual sleep for equivalence analyses, BA plots and cluster analyses diary and actigraphy are used as subjective and objective measures respectively.

Equivalence test (TOST). Similarly, to Yavuz-Kodat (2019) equivalence testing rather than conventional t-tests are used to test for differences between the two respective measures (e.g., actigraphy and BISQ parameters). Mangardich and Cribbie (2015) argue that the goal of equivalence testing is opposite to that of traditional t-tests in that contrary to traditional t-tests the goal is to confirm and not reject the null hypothesis (Mangardich & Cribbie, 2015; van Wieringen & Cribbie, 2014). First, a range was established under which both methods are considered to be equivalent in terms of the sleep parameter ($-\delta$, δ). This range was established to be 30 minutes for Night Sleep Duration based on Yavuz-Kodat et al.'s (2019) study, who conducted a similar study comparison. However, the range may also be determined by enforcing effect size bounds. The default effect size d = 0.50 was chosen for the other equivalence tests. Thereafter two one tailed t-tests are conducted on the two null hypotheses H_{01} and H_{02}.

$$H_{01} = \mu_{Method\ 1} - \mu_{Method\ 2} >= \delta;\ H_{02} = \mu_{Method\ 1} - \mu_{Method\ 2} =< -\delta$$

$$H_{11} = \mu_{Method\ 1} - \mu_{Method\ 2} < \delta\ ;\ H_{12} = \mu_{Method\ 1} - \mu_{Method\ 2} > -\delta$$

A significant result for the equivalence test would mean that the two methods are not showing significantly different means across methods. The main advantage of equivalence testing is that it considers that differences between measures are rarely zero and rather assesses whether differences fall within an acceptable, pre-specified range of differences. Often equivalence test results are reported together with traditional null hypothesis testing results in order to provide further evidence for/against the equivalence of the two measures.

Investigation of bias. In order to make sure that there is no systematic bias in the BA plots, correlational analyses (Pearson's correlation coefficient) between the mean differences of actigraphy and diary (i.e., the bias) and other factors influencing sleep were investigated. These factors included infant age (in days), maternal stress and depression measures and parental demographic information to investigate a potential systematic bias.

K-means cluster analysis. To identify potential groups of sleep types in the sleep data, k-means cluster analysis was performed. K-means was chosen as the objective was to group types of sleepers instead of groups of sleep variables (as e.g., a factor analysis would have given us). All data was standardized prior to running the algorithm to enable comparison across the different sleep variables.

K-means cluster analysis falls under the category of unsupervised machine learning algorithms, particularly useful in identifying patterns in data. K-means is an iterative algorithm that determines clusters of data points so that the variation within each cluster is minimized and the distances to other clusters maximized. It works by determining a k number of cluster centres (so called centroids) randomly from the data and then assigning each data point to the cluster centres based on their distance to the centroid. K-means requires the number of clusters to be pre-specified. In order to obtain a clearer idea of how many clusters were the ideal fit for the present data set, several iterations of the algorithm using various different k number of clusters values were conducted. A scree plot was obtained, displaying the total within sum of square of the cluster variation (WSS) by number of clusters (k). This allowed me to determine the ideal number of clusters. In order to increase validity in number of cluster selection, the data set was randomly split

into a training set and a test set. 80% of the data were assigned to the training set. K-means was run 50 times on the training set using different numbers of k (1-10) and each time a total WSS value was obtained. In the end the minimum value of total WSS was selected as the interest was in selecting the optimal model. This was then plotted in the screeplots for each k number of clusters. Actigraphy data, BISQ data and sleep diary data was used to run three separate cluster analyses on each data set.

In order to determine the optimal cluster/centroid values and number of participants in each cluster k-means was run 100 times and the cluster model with the best total within sum of squares was selected.

3.4 Results

3.4.1 Descriptive statistics of sleep questionnaires

Table 3.4. shows pooled descriptive statistics across all age groups for sleep questionnaires (SSQ and BISQ) for four main sleep parameters (night and Day Sleep Duration and Night Wakening Number and WASO). Other descriptive statistics for SSQ and BISQ can be found in *Appendix – Chapter 3*.

Table 3.4. Questionnaire-measured sleep parameters - Mean and SD for whole sample (all data pooled)

	BISQ Mean*(SD)* N	**SSQ** Mean*(SD)* N
Day Sleep Duration (minutes)	166.6 *(80)* 162	177 *(98.4)* 143
Night Sleep Duration (minutes)	610.5 *(79.8)* 163	586.5 *(150.5)* 142
Night Wakening Number	2.3 *(1.7)* 163	2.4 *(1.8)* 143
WASO (minutes)	27.1 *(29.0)* 161	N/A*

Notes. SD = standard deviation, WASO = wake after sleep onset, *SSQ does not provide information on WASO. Durations are in minutes and night wakening in number of times awake.

3.4.2 Descriptive statistics sleep diary and actigraphy

Table 3.5 shows pooled descriptive statistics across all age groups for sleep questionnaires (actigraphy and sleep diary) for four main sleep parameters (Night and Day Sleep Duration and Night Wakening Number and WASO). Other descriptive statistics for actigraphy and sleep diary can be found in *Appendix – Chapter 3* including for other sleep parameters assessed.

Table 3.5. Actigraphy- and diary-measured sleep parameters - Mean and SD for whole sample (all data pooled)

	Sleep diary Mean*(SD)* N	**Actigraphy** Mean*(SD)* N
Day Sleep Duration (minutes)	133.4 *(43.3)* 143	115 *(37.9)* 142
Night Sleep Duration (minutes)	624.3 *(57.3)* 144	450.9 *(69.8)* 147
Night Wakening Number	2.2 *(2.1)* 144	3.9 *(1.2)* 148
WASO (minutes)	31.1 *(25.0)* 140	55.3 *(15.4)* 152

Notes. SD = standard deviation. Durations are in minutes and night wakening in number of times awake.

Note the differences in Night Sleep Duration between actigraphy and diary as seen in *Table 3.5*. though these differences do not match differences between actigraphy and diary in WASO. This could be explained in two ways: a) sleep onset latency (= the time it takes someone to fall asleep) and b) wake-up time in the morning. It is possible that parents put their infant down to sleep assuming they would fall asleep immediately but the infant stays awake for longer, which would be captured by actigraphy but not by parent-report. Similarly in the morning, the infant might be awake before they start signalling to their parents that they are awake, which again would be captured by actigraphy as wake but not by parent-report.

3.4.3 Developmental changes in subjective and objective sleep data

Data is collapsed across visits and thus includes some participants on more than one age group. Visual inspection of the data shows potential developmental changes in subjective Day Sleep Duration mean *(see Figure 3.3A-B* and *Figure 3.4A*) but not in objective day sleep (*Figure 3.4B)*. Visual inspections for questionnaires-measured Night Sleep Duration across age groups did not indicate group differences but could potentially be seen for diary and actigraphy. For graphs of developmental changes in main sleep parameters see *Appendix – Chapter 3*. A potential decrease in Night Wakening Number in BISQ and actigraphy might be inferred from visual inspection, though likely not for diary and SSQ. For WASO only diary seemed to show developmental changes.

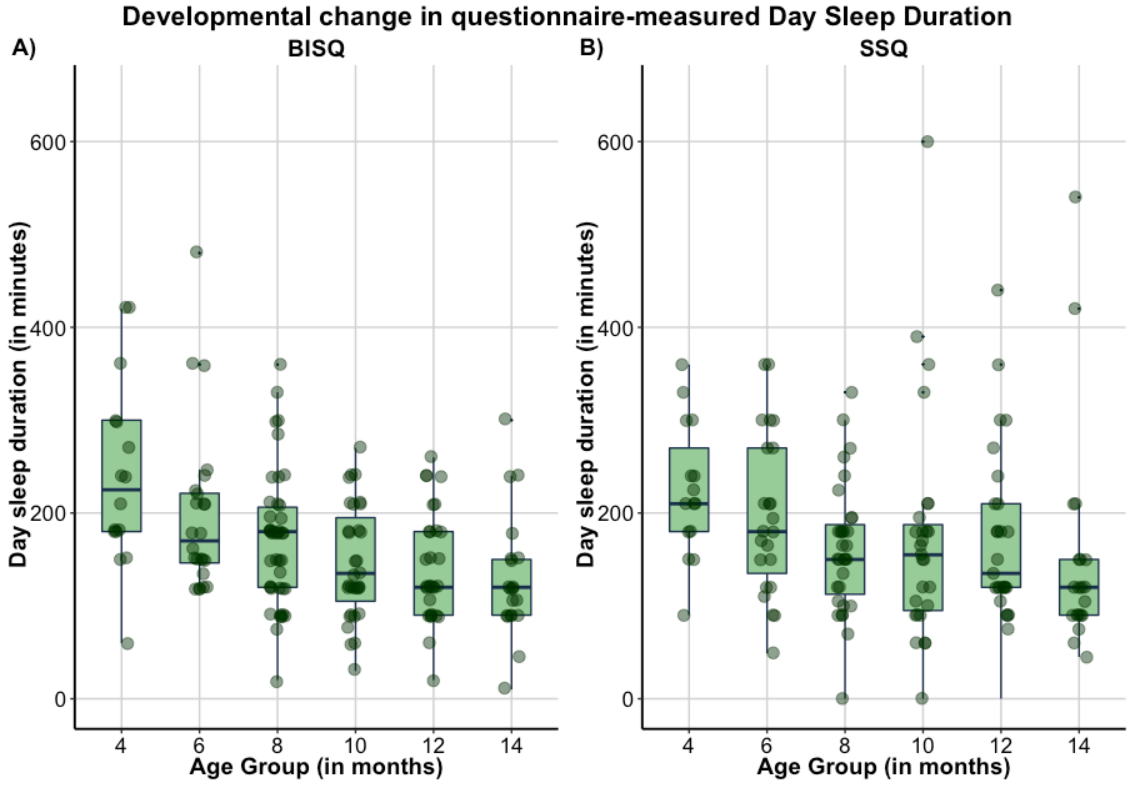


Figure 3.3. Day Sleep Duration (in minutes) for Brief Infant sleep questionnaire (BISQ; A) and for Sleep and Settle Questionnaire (SSQ; B).

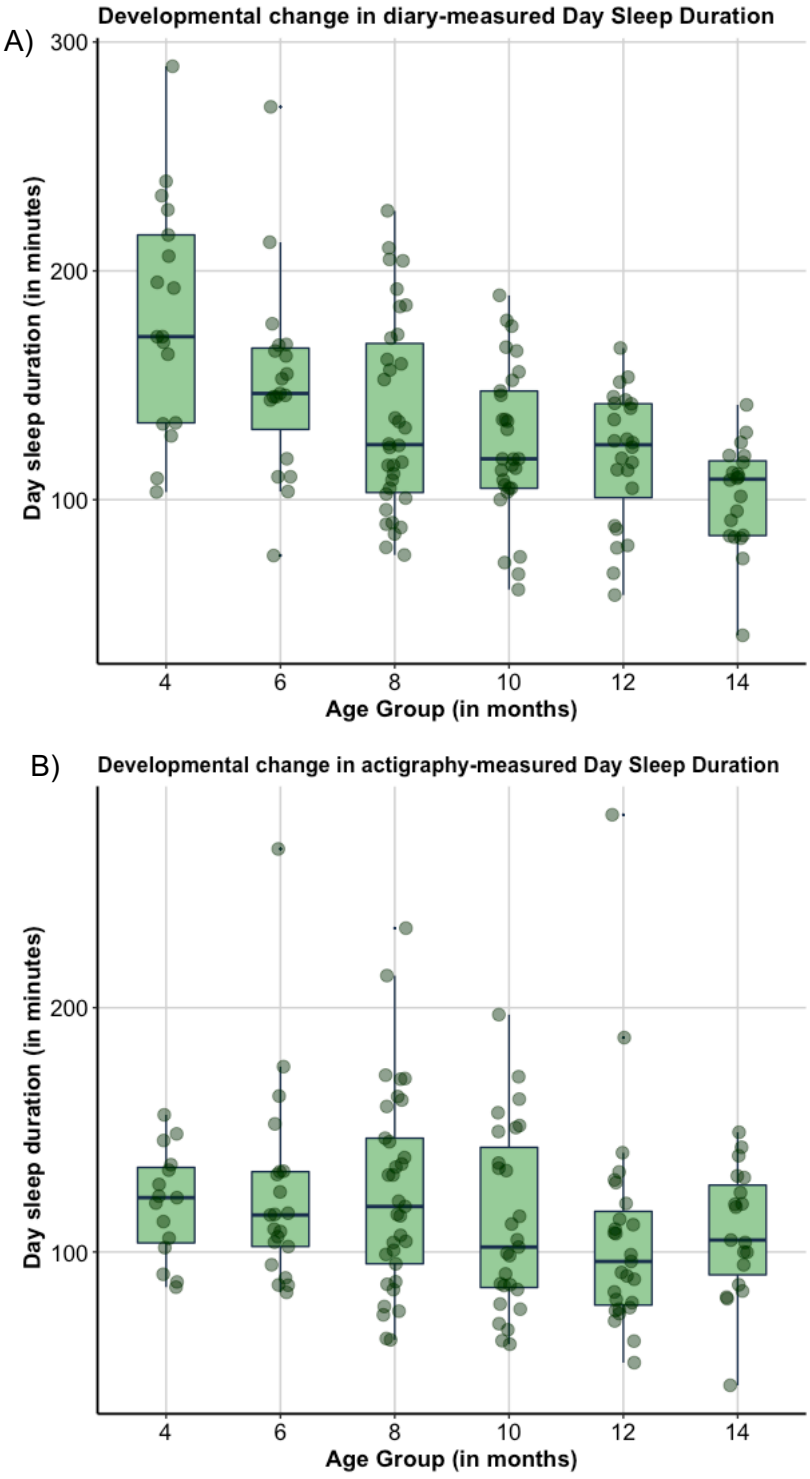


Figure 3.4. Day Sleep Duration (in minutes) for diary (A) and for actigraphy (B).

To investigate if the visually observed developmental changes were significant, growth curve analysis was performed. Objectively measured but not subjectively measured night wakening decreased significantly with age with a linear effect. Objectively measured and BISQ-measured WASO increase with age with a linear and quadratic effect respectively, diary-measured WASO showed a decrease with age and linear effect.

Objectively measured and diary-measured Night Sleep Duration increased significantly with age with a linear trend. SSQ-measured Night Sleep Duration showed a significant cubic effect but BISQ did not show an effect. Subjectively measured but not objectively measured Day Sleep Duration decreased significantly with age with a linear effect. For detailed statistical results refer to *Table 3.6*. Taken together, while the specific changes differed slightly between objective and subjective measures, some significant qualitative changes in the sleep parameters across development are apparent that necessitate further scrutiny.

Table 3.6. Results of Growth Curve Models for different sleep measures and parameters

	Parameter	**Effect**	**F**	**df**	**p**	**b**	**SE**
Actigraphy	Night Wakening Number	Linear	8.33	140	.005**	-0.10	0.03
	WASO	Linear	5.83	120	.017*	1.01	0.42
	Night sleep duration	Linear	8.56	141	.004**	5.63	1.93
	Day Sleep Duration	-	2.26	118	.136	-1.67	1.11
Diary	Night Wakening Number	-	2.65	144	.106	-0.09	0.06
	WASO	Linear	8.17	126	.005**	-1.97	0.69
	Night sleep duration	Linear	10.55	140	.001***	4.69	1.44
	Day Sleep Duration	Linear	43.70	125	<.001***	-7.17	1.08
BISQ	Night Wakening Number	-	1.31	157	.253	-0.05	0.05
	WASO	Quadratic	4.97	160	.027*	0.53	0.24
	Night sleep duration	-	2.83	140	.095	3.68	2.19
	Day Sleep Duration	Linear	23.11	134	<.001***	-9.92	2.06
SSQ	Night Wakening Number	-	1.08	136	.300	-0.05	0.05
	Night sleep duration	Cubic	4.00	128	.048*	0.92	0.46
	Day Sleep Duration	Linear	4.05	122	.046*	-5.44	2.70

Notes. WASO = Wake after sleep onset; SE = Standard Error, * p < .05, ** p <.01, ***p < .001.

3.3.5. Correlations between sleep measures

Pearson correlational analysis showed either no association or low to moderate strength of association between different sleep measures (see *Figure 3.5*.). Weak associations were found for example between day sleep in BISQ and actigraphy (r =.177, p =.035). Moderately strong associations were found for example in day sleep in BISQ

and SSQ (r =.358, p <.001) and SSQ and actigraphy (r = .343, p <.001) and in night sleep for diary and actigraphy (r =.403, p <.001). Associations were strongest for number of night wakening (e.g., $r_{diary\text{-}SSQ}$ = .789, p <.001; $r_{diary\text{-}BISQ}$ = .778, p <.001, $r_{diary\text{-}actigraphy}$ = .307, p <.001, $r_{actigraphy\text{-}BISQ}$ = .264, p <.001). For complete correlation table between main sleep measures refer to *Appendix – Chapter 3*.

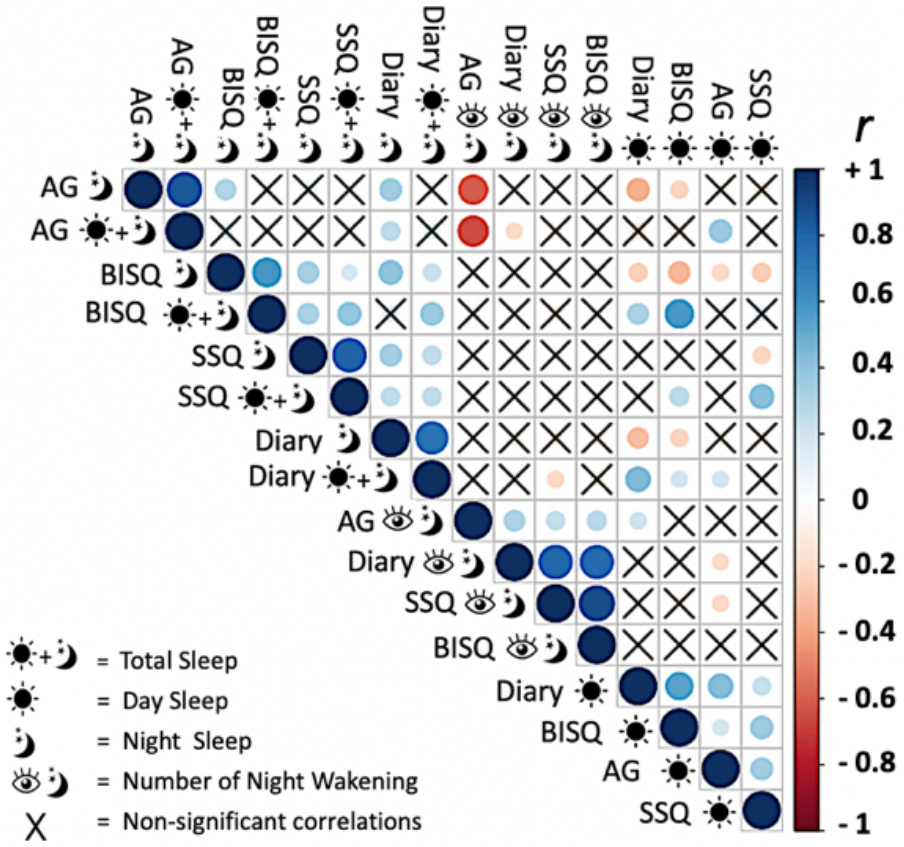


Figure 3.5. Illustration of correlations between the four different sleep parameters of objective and subjective sleep measures, AG = Actigraphy, BISQ = Brief Infant Sleep Questionnaire, SSQ = Sleep & Settle Questionnaire, diary = sleep diary.

3.4.4 Concordance between subjective measures

Results of the ICC analyses are reported in *Table 3.7*. ICCs were in the excellent range only for night wakening. This means agreement between subjective sleep parameters was generally poor for duration measures.

Table 3.7. Intra-class correlation results for subjective sleep parameters

	Day Sleep Duration	Night Sleep Duration	Night Wakening Number
Single	.328	.269	.807
Average	.594	.525	.926

Notes. 2-way mixed effects ICC, absolute agreement for BISQ, SSQ, diary

3.4.5 Bland Altman plots of agreement between subjective (diary) and objective measures (actigraphy)

In the following, to reduce the complexity of the data presented, only four main sleep parameters are further investigated in the methods of agreement. See *Figure 3.6.* for BA plots for diary and actigraphy and *Appendix – Chapter 3* for further BA plots of actigraphy vs. the other subjective measures (BISQ, SSQ). Visual inspection of the graphs shows that agreement between actigraphy and diary is worse for night sleep measures than for day sleep measures. Even for day sleep agreement is not optimal. The dotted lines represent the +/- 1.96*SD margins of the mean difference between the measures. The blue line indicates bias between the two method. If method show good agreement the bias line should coincide with x = 0 line. If bias line is parallel to x = 0 it means that the bias is the same across participants. Some variables show larger bias than others, e.g., Night Sleep Duration or WASO shows larger bias (i.e., steeper slope) than day sleep variables. Additionally, WASO shows a bias that differs across participants. Some participants exhibit a larger bias than others. To investigate this bias/cross-method difference a series of additional correlational analyses were conducted on the bias (mean difference score between actigraphy and diary) and parameters that might influence parental reporting of sleep and/or actigraphy measurements.

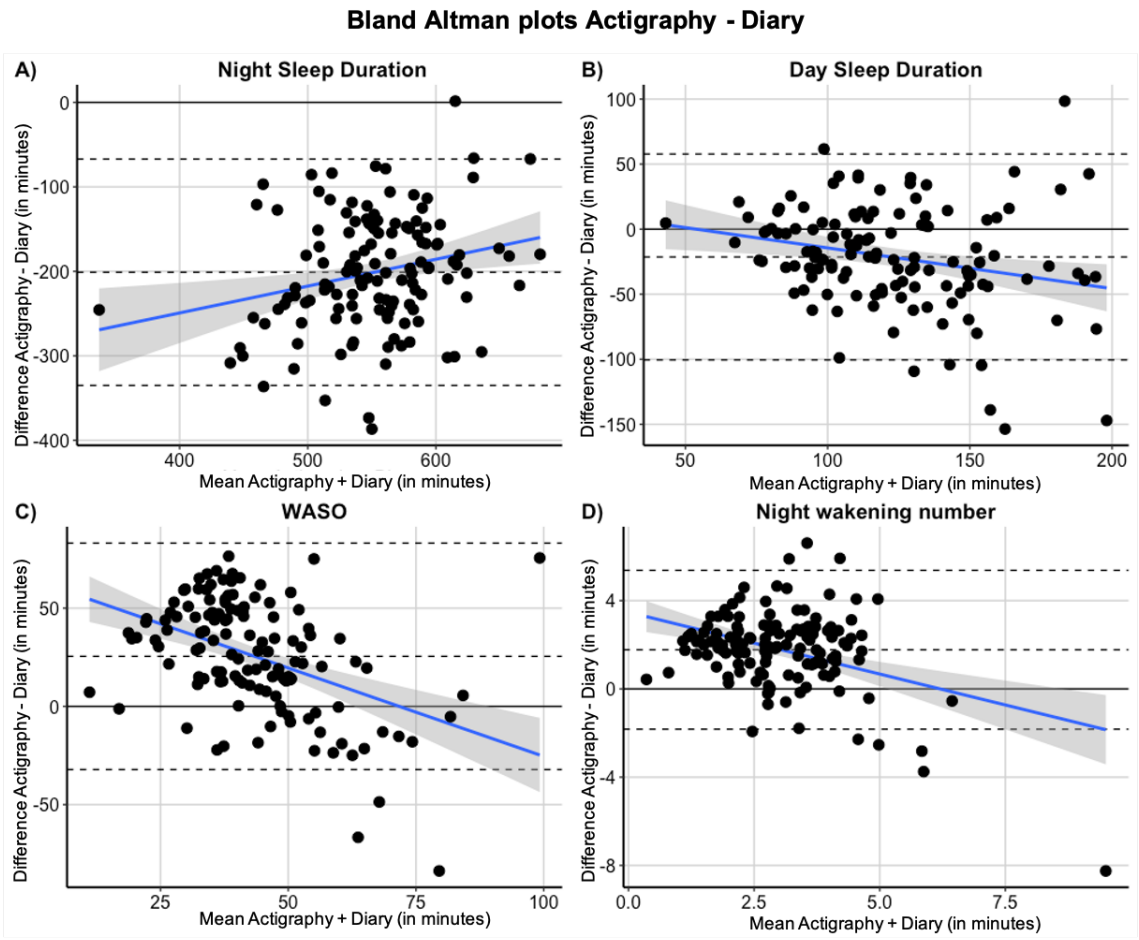


Figure 3.6. Bland Altman plots for main sleep parameters (A) Night Sleep Duration, B) Day Sleep Duration, C) WASO, D) Night Wakening Number for Actigraphy – Diary plotting mean of the two measures (x) against Difference of the two measures (y). Blue line = proportional bias line i.e., mean difference between the two measures. Dotted lines = +/- 1.96*SD margins of the mean difference between the measures.

3.4.6 Results of Equivalence tests

Equivalence tests were performed to investigate whether actigraphy and diary were truly not equivalent as suggested by inspection of the BA plots. For all sleep variables, actigraphy measures were significantly different/ not equivalent from diary measures. Illustration of results for main sleep parameters for actigraphy vs. diary (all p's <.001 for NHST and all p's >.10 for TOST) can be seen below (*Figure 3.7.*) and detailed statistical test results for actigraphy vs. BISQ and actigraphy vs. diary can be found in *Appendix – Chapter 3*. Of note, for Day Sleep Duration BISQ and actigraphy showed a significant equivalence test indicating that the two methods were equivalent [$t(140)=1.95$, $p=.03$,

CI(-24.84;10.27)]. However, the NHST was also still significant, indicating that the results of the equivalence test should be interpreted with caution.

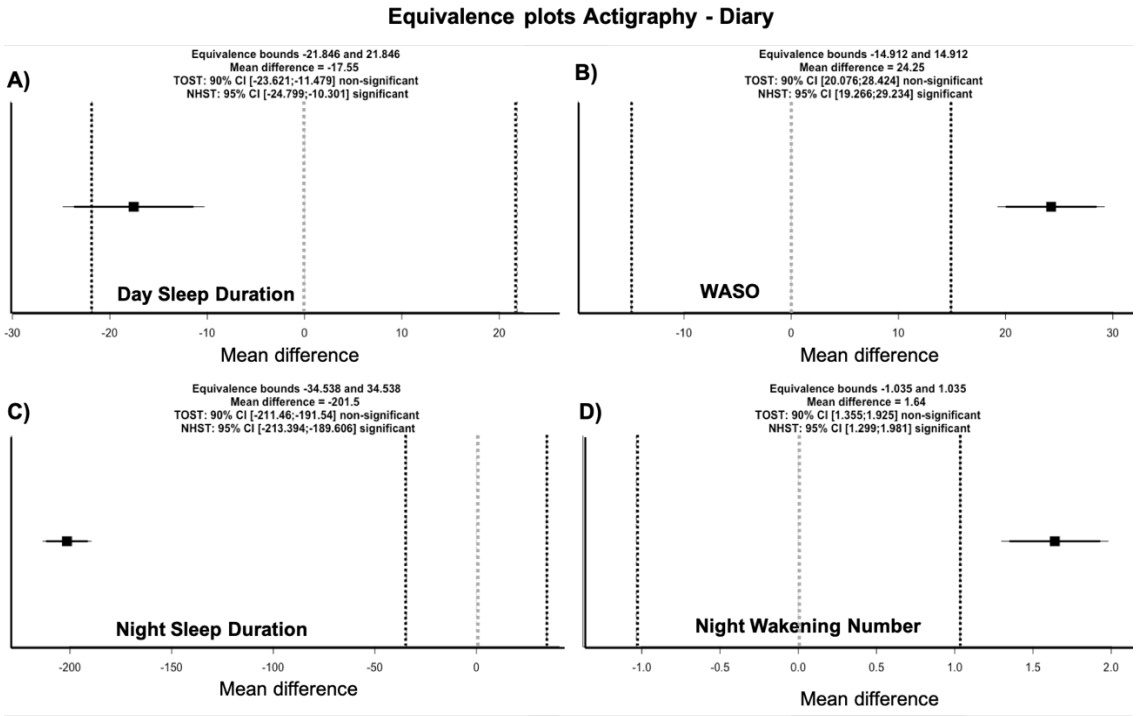


Figure 3.7. Equivalence plots for main sleep parameters (A) Day Sleep Duration, B) WASO, C) Night Sleep Duration, D) Night Wakening Number. *Note.* NHST = Null Hypothesis Testing, TOST = equivalence test, CI = confidence interval (plots produced with R package 'TOSTER')

3.4.7 Investigation of mean differences between actigraphy and diary

Below the results of correlational analyses for investigation of the proportional bias that was found by visual inspection of the BA plots. Correlational analyses were conducted between infant age and main sleep variables to investigate if age of the infant had an impact on how well parent-reported sleep coincided with actigraphy-measured sleep. I will refer to how well parent reports coincides with actigraphy measures as "accuracy", though of course actigraphy is also not an unbiased measure of true underlying sleep. Significant associations were found for infant age and difference (actigraphy vs. diary) in Day Sleep Duration (r = 0.38, p = <.001) and WASO (r = 0.29, p = <.001) see *Figure 3.8*. for illustration. For data reduction purposes a stress composite score was created from the data of the three stress questionnaires (PSS, STAI-S, STAI-T). The data was z-

scored and then averaged (for details see *Chapter 4*). The difference between actigraphy and diary measures decreased for mothers who reported higher stress for Night Sleep Duration (r = 0.27, p <.05) and for WASO (r = -0.21, p <.05).

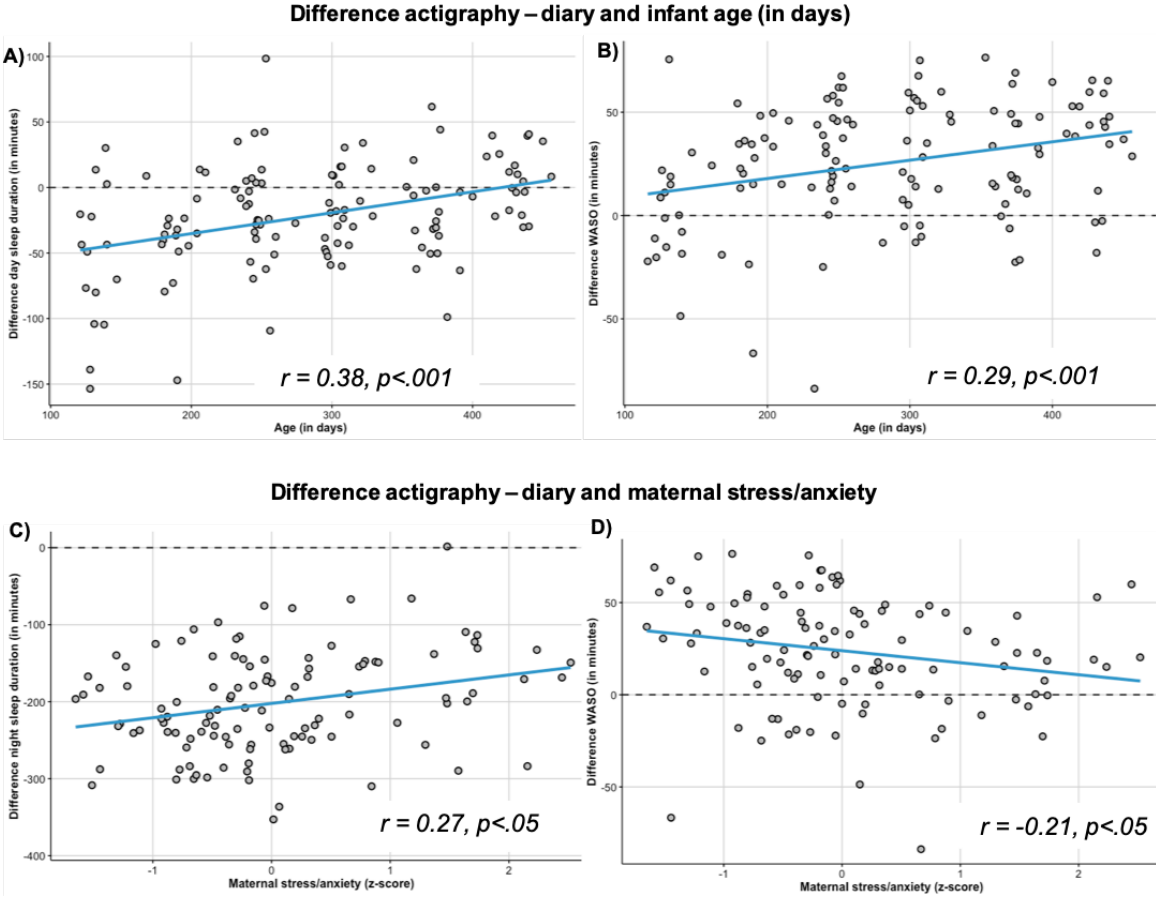
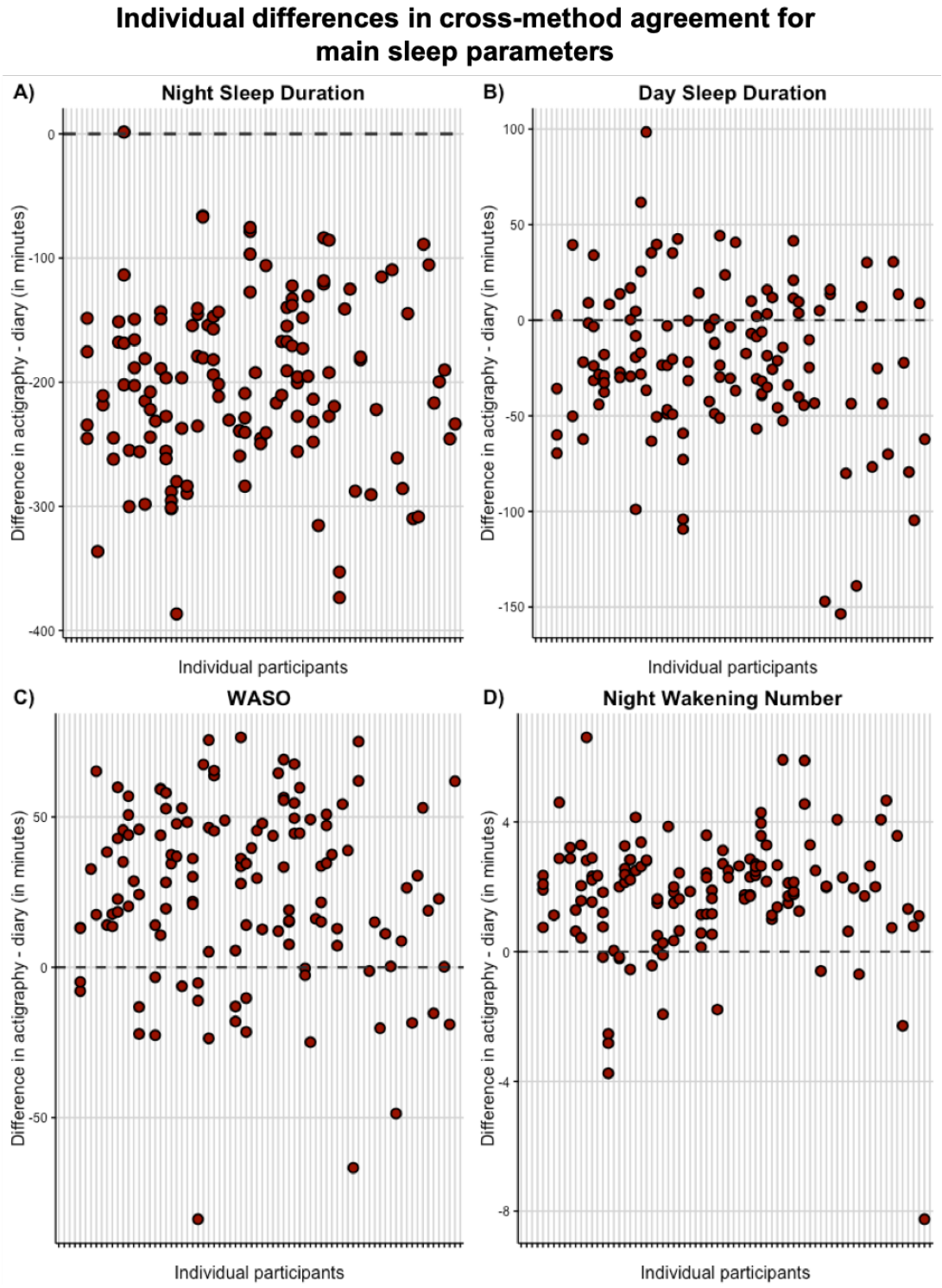


Figure 3.8. Illustration of cross-method difference of actigraph vs. diary in several sleep variables by infant age and maternal stress/anxiety level. *Notes*. r = Pearson correlation, maternal stress/anxiety score = z-scored composite score of PSS and STAI-T/-S.

Additional analyses showed that older age of mother and father was weakly associated with better actigraphy-diary cross-method agreement of nighttime sleep parameters such as Night Sleep Duration (e.g., $r_{fathers\ age}$ = .269, p = .004), and WASO ($r_{fathers\ age}$ = -.262, p = .006; $r_{mothers\ age}$ = -.192, p = .044).

Furthermore, it was important to check whether there were simply some participants whose description of infant sleep patterns coincided better with actigraphy. This was done for the actigraphy vs. diary data. Plots indicate that parents were overall worse at accurately estimating night sleep parameters, especially in terms of duration compared to actigraphy. Example plots are displayed in *Figure 3.9*.



Figures 3.9. Illustration showing the mean differences (actigraphy - diary, y-axis) per participant (x-axis) in Night Sleep Duration (A), Day Sleep Duration (B), WASO (C) and Night Wakening Number (D). Dotted line indicates perfect agreement of actigraphy and diary. The further the individual scatter dot is from the vertical line the worse the parent-reported sleep variable estimation compared to actigraphy.

In summary, day sleep estimation seems to agree better between actigraphy and diary with increasing age. WASO estimation seems to agree less between actigraphy and diary with increasing age. The difference between actigraphy and diary measures decreased in mothers who reported higher stress for Night Sleep Duration and for WASO. Actigraphy and diary coincided worse for night sleep parameters, especially in terms of duration. These results indicate that it might be important to use both actigraphy and diary as they provide different results and therefore potentially different information.

3.4.8 Cluster Analysis

In order to identify whether there were groups of infants who slept similarly a k-means cluster analysis was performed using R statistical software packages 'cluster', 'Kmeans'. Age was dropped from the model, all sleep parameters were included. Number of optimal clusters to use for actigraphy, BISQ, and diary data sets was determined by dividing the respective data into a test set (80% of the data) and a training set (20%). Given the low agreement between types of measures (/the existing bias), I avoided combining measures, and ran separate cluster analysis for the different measures. K-means was run using multiple iterations (N =100) and for different numbers of clusters (k=1:10). For every k cluster the average for the 100 iterations of k-means algorithm was taken and the minimum WSS for each k was used to plot total WSS per k. This provided us with a scree plot that can be used to determine the optimal number of clusters k. I then performed validation of the number k by running the same analysis on the test set and comparing the value obtained on the test set and the train set. Missing data was excluded listwise.

3.4.8.1 Results of cluster analysis: objective sleep data

Actigraphy data has N = 142 data points after missing data exclusion. As the classification of sleep quality should not be impacted by intraindividual differences all data was pooled, such that some longitudinal participants were in the sample more than once for different time points. Train and test set validation indicated a cluster number of k=3. For scree plots see *Figure 3.10A-B.*

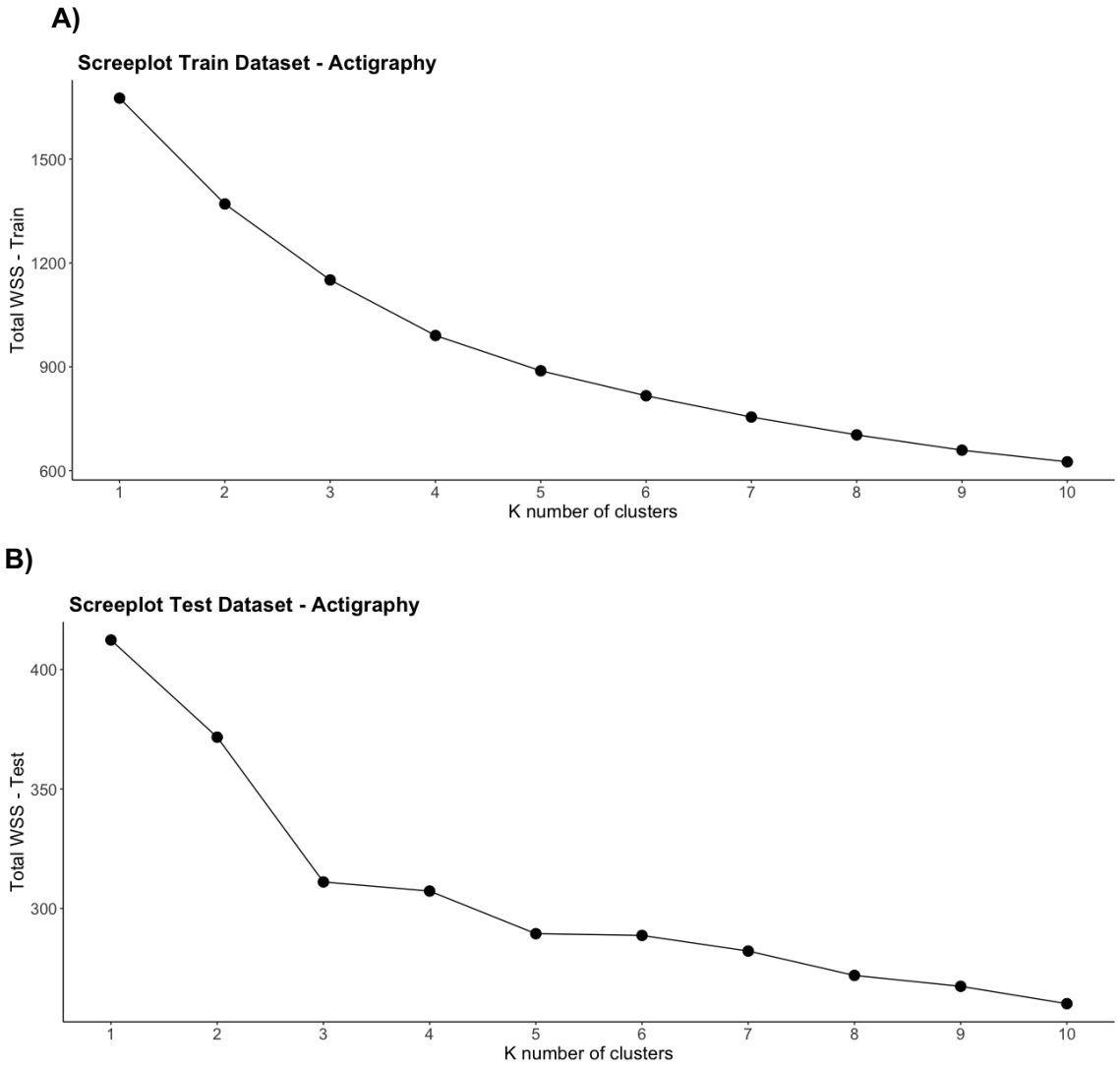


Figure 3.10. Screeplots for actigraphy training set (A) and test set (B) - total WSS by numbers of k clusters. *Note.* *Total WSS are influenced by N which is why the overall shape rather than the WSS values should be interpreted.

Running k-means provided the following centroids: see *Table 3.8* for unstandardized centroid values and *Figure 3.11*. for an illustration of standardized clusters. The cluster analysis revealed three clusters for actigraphy data. Cluster 1 contained 9 participants, cluster 2 contained 60 participants and cluster 3 contained 71 participants.

Cluster 1 seems to be mostly characterized by day sleep. It shows a higher than average Day Sleep Duration and variability in Day Sleep Duration as well longer day sleep periods and higher variability in longest day sleep period. It is also characterized by higher

variability in Night Sleep Duration and slightly lower night sleep than average. I thus denote children who belong to this cluster as day sleepers.

Results seem to indicate that clusters 2 and 3 differ primarily by parameters describing night sleep and not by parameters differing in day sleep, which is lower in both 2 and 3 compared to the day sleepers. Cluster 2 shows higher than average night sleep duration, higher than average longest night sleep period, higher variability in longest night sleep period and lower than average Night Wakening Number. Night Sleep Duration variability, WASO, and variability in WASO seem to be slightly higher than average in cluster 2 compared to cluster 3. Due to the focus on night sleep and lower number of night wakenings I denote children who belong to this cluster as adult-like sleepers.

Cluster 3 shows lower than average Night Sleep Duration, lower than average longest night sleep period, lower variability in longest night sleep period and higher than average Night Wakening Number. There do not seem to be many differences on variables like sleep efficiency. Night Sleep Duration variability, wakening after sleep onset and variability in night wake after sleep onset seem to be slightly lower than average in cluster 3 compared to cluster 2. Based on the larger number of night wakenings and lower overall sleep duration I denote children who belong to this cluster as poor sleepers.

Table 3.8. Actigraphy cluster centroids

	Day Sleepers	**Adult-like Sleepers**	**Poor sleepers**
Day sleep duration	199.7	110.4	111.3
Day Sleep Duration variability	161.4	48.4	49.6
Nap number	2.2	1.9	2.0
Nap number variability	1.0	0.8	0.8
Day longest sleep period	168.3	73.2	71.7
Day longest sleep period variability	141.3	31.1	31.4
Night Sleep Duration	431.5	503.6	413.2
Night Sleep Duration variability	122.3	69.5	65.6
WASO	50.1	58.2	54.7
WASO variability	23.2	23.3	18.9
Night Wakening Number	3.3	3.0	4.8
Night longest sleep period	274.3	280.9	162.1
Night longest sleep period variability	111.2	116.2	59.4
Night sleep ratio	0.7	0.8	0.8
Total sleep duration	628.1	617.0	524.4

Note. Durations in minutes; WASO = wake after sleep onset.

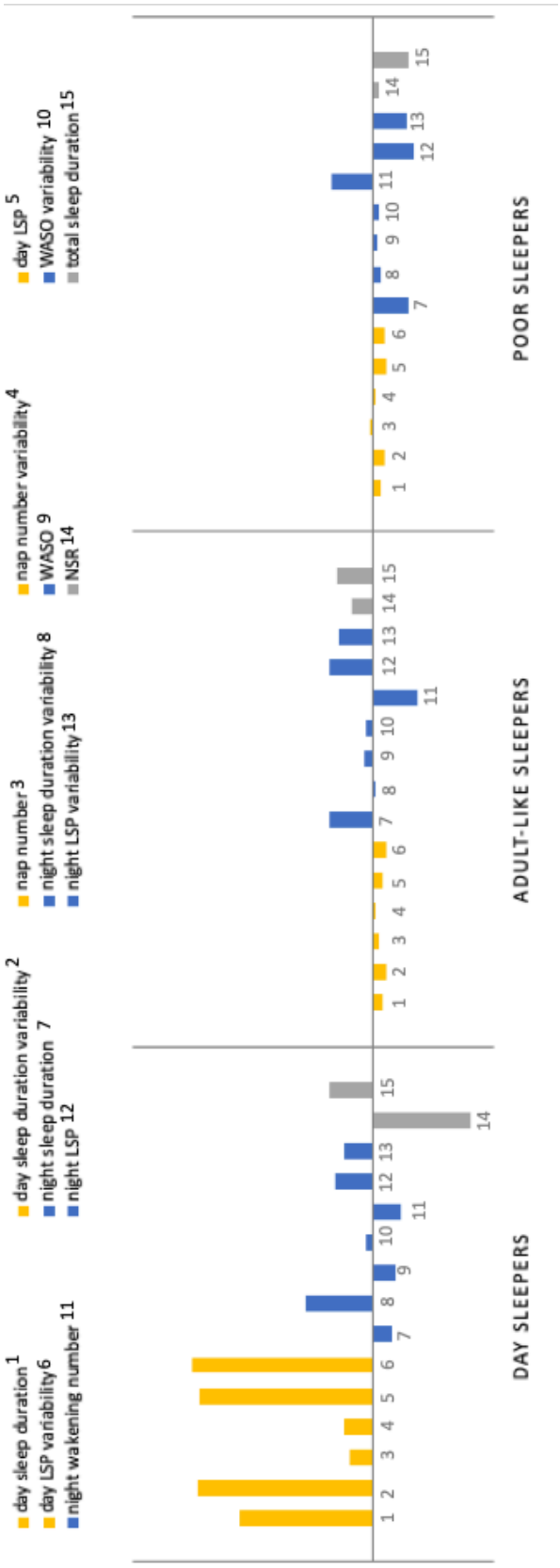


Figure 3.11. Actigraphy clusters and their standardized centroids for each variable. *Note.* LSP = longest sleep period, WASO = night wake after sleep onset, NSR = Night sleep ratio.

3.4.8.2 Results of cluster analysis: subjective data - diary

Sleep diary data has N = 123 data points after missing data exclusion. As the classification of sleep quality should not be impacted by intraindividual differences all data was pooled, such that some longitudinal participants were in the sample more than once for different time points. Train and test set validation indicated a cluster number of k=4. For scree plots see *Figure 3.12A-B.*

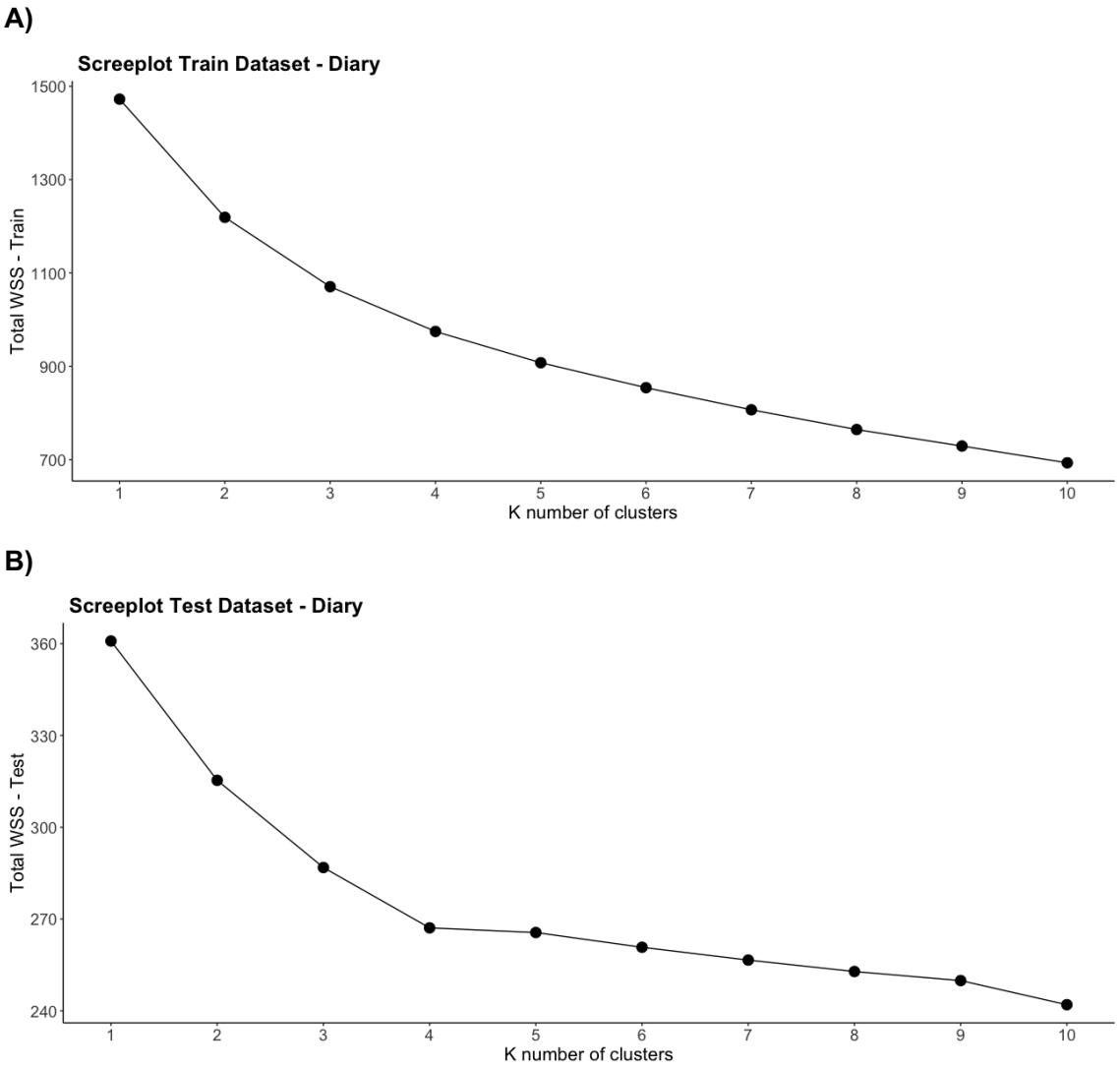


Figure 3.12. Screeplots for sleep diary training set (A) and test set (B) - total WSS by numbers of k clusters. *Note.* *Total WSS are influenced by N which is why the overall shape rather than the WSS values should be interpreted.

Running k-means provided the following centroids: see *Table 3.8.* for unstandardized values and *Figure 3.13.* for an illustration of standardized clusters. Cluster

analysis revealed four clusters for diary data. Cluster 1 contained 39 participants, cluster 2 contained 37 participants, cluster 3 contained 36 participants and cluster 4 contained 11 participants.

Cluster 1 seems to be mostly characterized by slightly lower day sleep duration, higher than average Night Wakening Number and WASO, and lower longest night sleep period. Night Sleep Duration is higher than for cluster 3 and cluster 4 but lower than for cluster 2. Based on the larger Night Wakening Number and WASO; I denote children who belong to this cluster as poor sleepers.

Cluster 2 is characterized by slightly lower than average day sleep parameters but higher than average night sleep duration, higher than average longest night sleep period, lower than average Night Wakening Number and WASO. Overall sleep duration is higher as is the night sleep ratio. Due to the focus on night sleep and lower number of night wakenings I denote children who belong to this cluster as adult-like sleepers.

Cluster 3 seems to be a mix of many of the characteristics defining the other clusters. That is lower Night Wakening Number and duration but also lower total sleep and a high variability in night sleep and about an average day sleep duration.

Cluster 4 seems to be mostly characterized by a large amount of day sleep. It shows a higher than average Day Sleep Duration and variability in Day Sleep Duration and more naps as well longer day sleep periods and higher variability in longest day sleep period. It is also characterized by higher variability in Night Sleep Duration and slightly lower night sleep than average. I thus denote children who belong to this cluster as day sleepers.

Table 3.9. Diary cluster centroids

Diary	Poor Sleepers	Adult-like sleepers	Mixed	Day sleepers
Day sleep duration	118.6	113.1	155.5	212.8
Day Sleep Duration variability	38.1	36.8	42.0	74.1
Nap number	2.1	1.4	2.2	2.9
Nap number variability	0.6	0.3	0.5	0.6
Day longest sleep period	76.0	93.2	98.0	117.4
Day longest sleep period variability	25.7	29.8	33.0	56.7
night sleep duration	677.1	694.4	606.2	649.4
Night Sleep Duration variability	41.6	37.3	57.2	59.1
WASO	46.0	13.0	24.1	55.8
WASO variability	21.8	14.7	15.5	39.4
Night Wakening Number	3.4	0.7	1.6	2.5
Night longest sleep period	286.5	556.9	376.1	280.5
Night longest sleep period variability	65.0	110.1	93.2	66.7
Night sleep ratio	0.9	0.9	0.8	0.8
Total sleep duration	795.7	807.5	761.7	862.2

Note. Durations in minutes; WASO = wake after sleep onset.

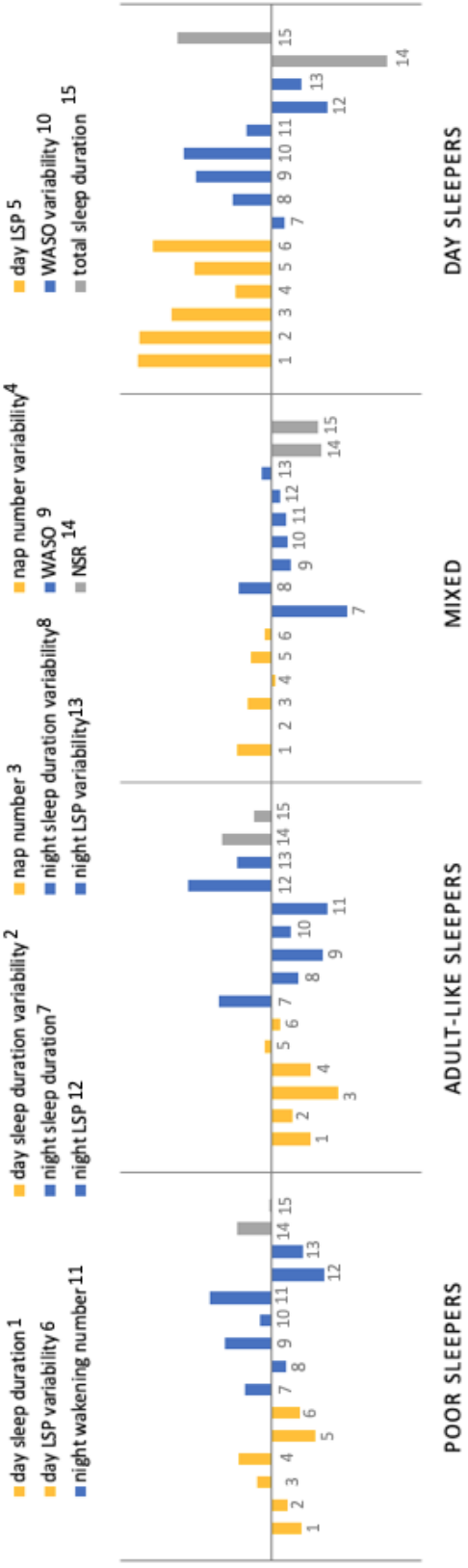


Figure 3.13. Diary clusters and their standardized centroids for each variable, LSP = longest sleep period, NSR = Night sleep ratio, WASO = night wake after sleep onset.

3.4.8.3 Results of cluster analysis: subjective data – BISQ

BISQ data has N = 160 data points after missing data exclusion. As the classification of sleep quality should not be impacted by intraindividual differences all data was pooled, such that some longitudinal participants were in the sample more than once for different time points. Train and test set validation indicated a cluster number of k=3. For scree plots see *Figure 3.14A-B.*

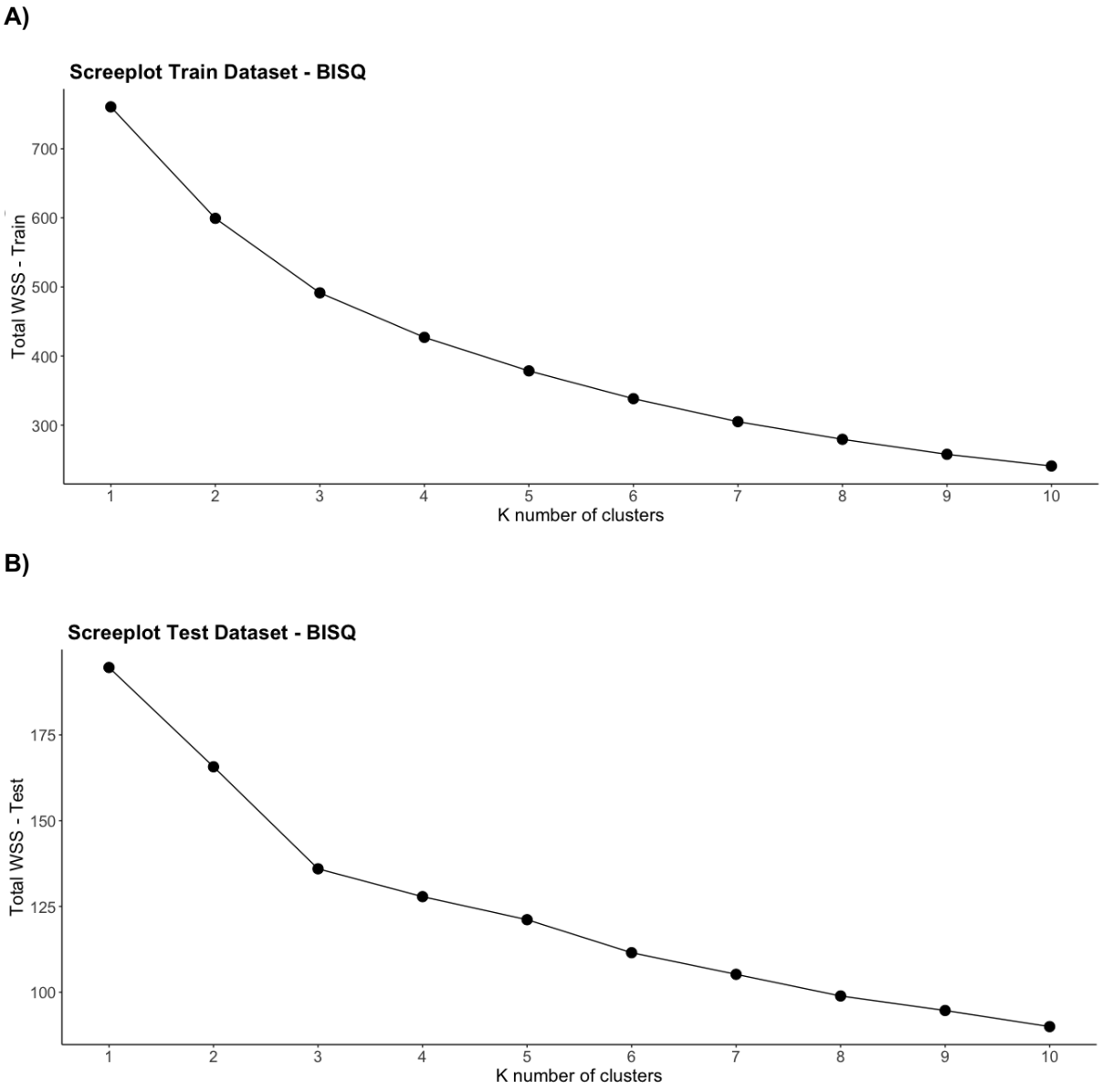


Figure 3.14. Screeplots for BISQ training set (A) and test set (B) - total WSS by numbers of k clusters. *Note*. *total WSS are influenced by N which is why the overall shape rather than the WSS values should be interpreted.

Running k-means provided the following centroids: see *Table 3.10.* for unstandardized values and *Figure 3.15.* for an illustration of standardized clusters. Cluster analysis revealed three clusters for diary data. Cluster 1 contained 54 participants, cluster 2 contained 26 participants and cluster 3 contained 80 participants

Cluster 1 seems to be mostly characterized by day sleep. It shows a higher than average Day Sleep Duration and higher variability in longest day sleep period. It is also characterized by higher Night Sleep Duration than average and less night wakenings and night wakening duration than average. Given the cluster is driven by a large amount of day sleep, I denote children who belong to this cluster as day sleepers.

Results seem to indicate that cluster 2 differs cluster 1 and cluster 3 by night sleep parameters and not by parameters differing in day sleep. Cluster 2 shows lower than average night sleep duration, higher than average Night Wakening Number, higher than average WASO, higher sleep onset latency and lower overall sleep than average. Based on the larger number of night wakenings and lower overall sleep duration I denote children who belong to this cluster as poor sleepers.

Cluster 3 shows slightly higher than average Night Sleep Duration and Night Wakening Number but overall lower wake after sleep onset time and overall lower sleep onset latency than average. Overall sleep duration is shorter than in the day sleepers but longer than compared to poor sleepers. Due to the focus on night sleep and lower number of wake after sleep onset, I denote children who belong to this cluster as adult-like sleepers.

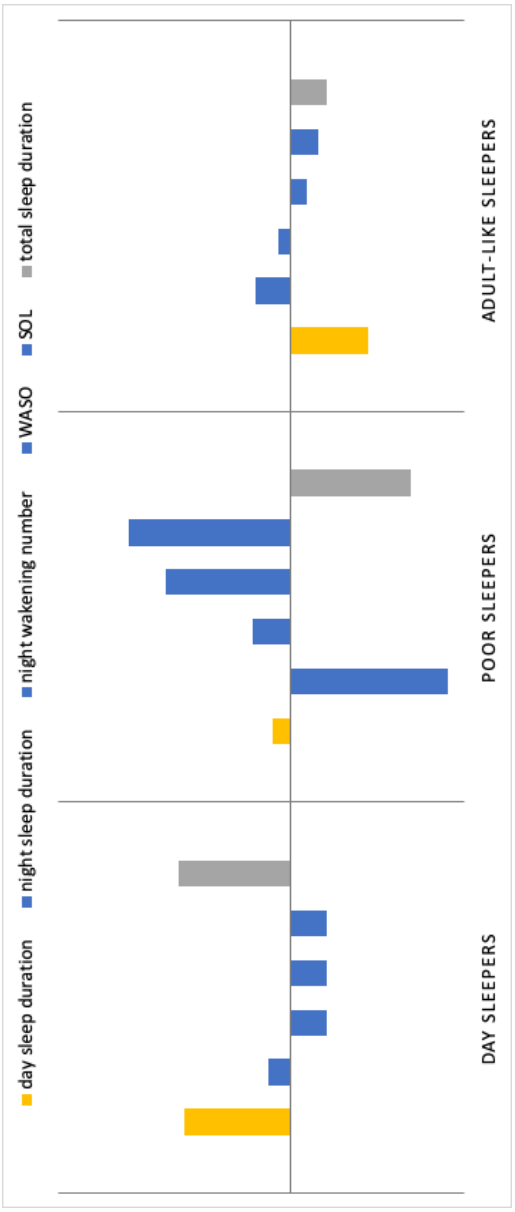


Figure 3.15. BISQ clusters and their standardized centroids for each variable, WASO = wake after sleep onset, SOL= sleep onset latency.

Table 3.10. BISQ cluster centroids

	Day sleepers	**Poor sleepers**	**Adult-like sleepers**
Day sleep Duration	240.7	179.6	113.5
Night Sleep Duration	627.5	504.2	636.2
Night Wakening Number	1.8	2.9	2.5
WASO	17.7	58.8	23.1
Sleep Onset Latency	21.0	60.8	22.6
Total Sleep Duration	868.1	683.8	750.4

Notes. Duration in minutes; WASO = wake after sleep onset.

3.4.8.4 Consistency of cross-method cluster membership

The above results show that different methods yield clusters that can be characterized by similar broad characteristics/clusters. However, the question arose whether the same topical/thematic cluster is identified cross methods for each participant or if the same participant might get sorted into different clusters by different methods. I classified each participant and visit as belonging in the same cluster type (e.g., day sleeper, poor sleeper, adult-like sleepers) across all three methods, across none, or across two methods. For the latter, I further show at which frequency each set of two methods yields the same classification.

As illustrated by *Figure 3.16.*, for the majority of participants and visits, methods do not yield the same result.

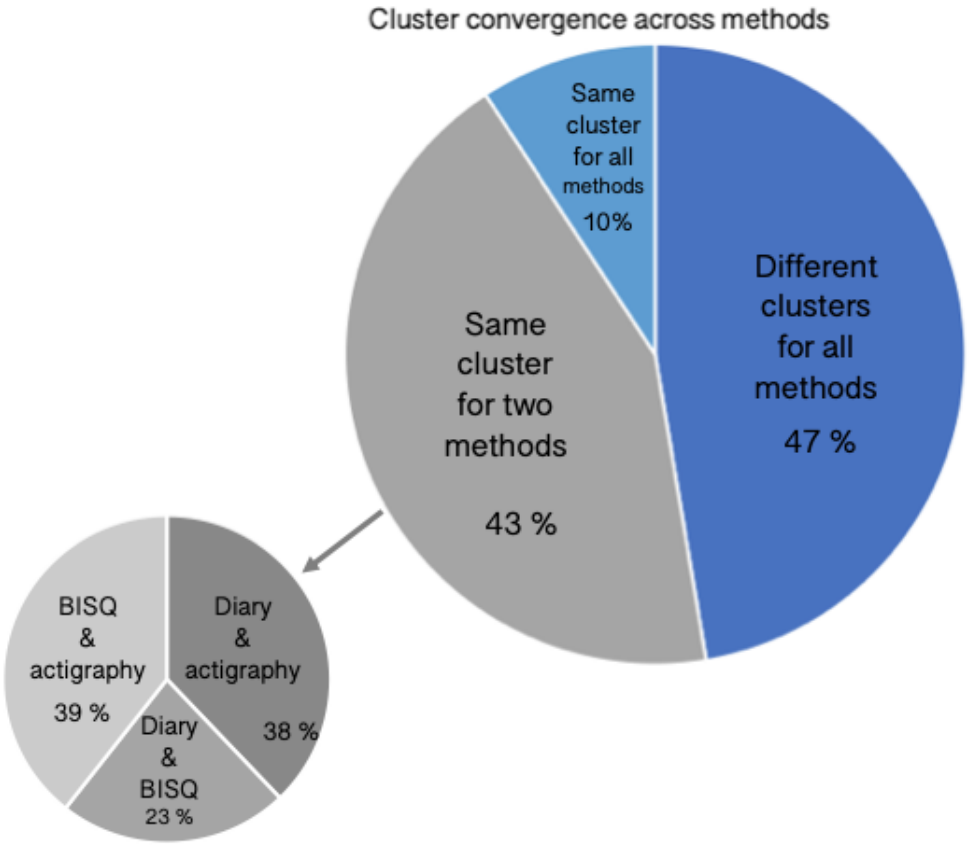


Figure 3.16. Figure illustrating cross-method cluster convergence.

The tables (*Tables 3.11. – 3.13.*) show the investigation of the characteristics, such as age, gender and age group, of infants grouped together in a cluster, for actigraphy-, diary- and BISQ-based clustering. While there were no apparent differences in these categories in the actigraphy clusters these seem to differ across diary clusters and BISQ cluster to a certain extent especially in terms of age and age groups.

Table 3.11. Investigation of actigraphy cluster characteristics based on infant characteristics

	Adult-like cluster	**Day sleepers**	**Poor sleepers**
Age in days - mean(SD)	284 (97)	286 (73)	283 (93)
Gender (% female)	68.0	44.4	49.3
% age group 4	10.0	0	12.7
% age group 6	16.7	22.2	12.7
% age group 8	23.3	22.2	25.4
% age group 10	20.0	22.2	18.3
% age group 12	13.3	33.3	18.3
% age group 14	16.7	0	12.7

Table 3.12. Investigation of diary cluster characteristics based on infant characteristics

	Adult-like cluster	**Day Sleepers**	**Poor sleepers**	**Mixed sleepers**
Age in days - mean(SD)	348 (73)	170 (51)	287 (88)	241 (83)
Gender (% female)	56.8	66.7	53.8	41.7
% age group 4	0	58.3	7.7	16.7
% age group 6	2.7	16.7	15.4	25.0
% age group 8	18.9	25.0	23.1	27.8
% age group 10	24.3	0	23.1	13.9
% age group 12	24.3	0	17.9	13.9
% age group 14	29.7	0	12.8	2.8

Table 3.13. Investigation of BISQ cluster characteristics based on infant characteristics

	Adult-like cluster	**Day sleepers**	**Poor sleepers**
Age in days - mean(SD)	314 (87)	257(84)	238 (89)
Gender (% female)	56.3	53.7	46.2
% age group 4	5.0	14.8	15.4
% age group 6	7.5	18.5	30.8
% age group 8	21.3	27.8	34.6
% age group 10	23.8	22.2	0
% age group 12	23.8	11.1	11.5
% age group 14	18.8	5.6	7.7

3.5 Discussion

The aim of this chapter was to investigate the sleep trajectories and sleep quality in the first year of life in a longitudinal, multi-method dataset. Furthermore, the goal was to pick a sleep assessment method that might serve as a sleep quality measure for use in studies of neurocognitive development. Here, the results are described and viewed in the context of current literature, in particular to see whether sleep patterns in the present sample differed compared to the prior literature.

3.5.1 Concordance between sleep research methods

The first question this chapter tried to answer concerned the concordance between different sleep assessment methods and whether concordance between measures changed with development.

3.5.1.1 Subjective sleep measures

Prior research suggests that subjective measures such as questionnaires and sleep diaries correlate highly with each other (Cassanello et al., 2018; Matthey, 2001; Sadeh,

2004). For example, Titzkoky and Volkovich (2019) report moderate to high correlations between all BISQ- and diary-measured sleep variables except WASO, where no differences in concordance were found. In the present study, contrary to these findings, associations between questionnaires and diary were moderate at best, if they reached significance. Furthermore, the two sleep questionnaires (SSQ and BISQ) did not yield high agreement, despite having been filled out by the same parent for the same week and infant. The sleep variable showing highest correlations amongst subjective measures was Night Wakening Number. This matches results of the intra-class correlations that showed similar patterns indicating better agreement on night wakening than estimations of sleep quantity. Researchers have proposed that accuracy of true underlying Night Wakening Number estimation is associated with an infant's inherent ability to self-soothe (Camerota et al., 2018; Hall et al., 2015). Young infants often cry when waking up at night, to which parents respond and in turn can more accurately report the number of night wakenings (Goodlin-Jones et al., 2001). The sample of the current study is relatively young and it may be that some of the infants have not started to self-soothe yet. Furthermore, there was a substantial number of co-sleepers in the sample, which has been shown to be related to higher (and thus more accurate?) reporting of infant night wakenings (Volkovich, Ben-Zion, Karny, Meiri, & Tikotzky, 2015). In the present sample the role of co-sleeping was not more closely examined, due to the large amount of data that was handled. Future research will investigate this hypothesis more closely.

3.5.1.2 Objective measures vs. subjective measures

Validation of actigraphy often occurs by comparing actigraphy data to sleep diary information. Limited studies examined BISQ measures compared to actigraphy, perhaps due to them measuring slightly different aspects of infant sleep: estimated average across a one-week period (BISQ) vs. habitual sleep patterns across one week (actigraphy). Though, Sadeh and colleagues reported good agreement between average measures of actigraphy and BISQ parent-report (Acebo et al., 2005, Sadeh, 2004). No study was comparing SSQ to actigraphy. The present study found only moderate or no correlations between actigraphy and the questionnaire variables. Agreement patterns, measured by BA plots with actigraphy for BISQ and SSQ, looked similar for both measures and showed that agreement overall was slightly better for reported day sleep than for night sleep and better yet for Night Wakening Number.

Comparing actigraphy and diary directly is a better choice as both are able to record multiple nights of sleep patterns rather than providing one average. Prior research

showed overall good agreement between actigraphy and diary sleep variables as indicated by moderate to high correlations (Müller et al., 2011; Sadeh, 1994, Tikotzky & Volkovich, 2019). However, differences between sleep variables in terms of their cross-method agreement were found. For example, in previous research diary-recorded night wakenings coincided less well with actigraphy than sleep timing information, with actigraphy seemingly overestimating the amount of night wakening (Hall et al., 2015; Meltzer et al., 2012; Sadeh et al., 1994). Werner (2008) concludes that actigraphy and diary may be used interchangeably for assessing sleep rhythmicity but not for investigation of night sleep parameters like nocturnal wake time or Night Wakening Number (Werner et al., 2008). This matches other research findings, including findings from longitudinal studies (Camerota et al., 2018; Hall et al., 2015; Tikotzky & Volkovich, 2019). Contrary to these findings, in this study systematic differences between actigraphy and diary were found not only in night wakenings but also in sleep duration variables. Some studies in prior literature have also reported a slight overestimation of Night Sleep Duration compared to actigraphy data, though differences are not as severe as in the present study (Asaka & Takada, 2011; So et al., 2007). Overall correlations between subjective and objective measures were larger for diary and actigraphy than for actigraphy and questionnaires and higher for night wakening than for duration measures, a finding conflicting with prior research (Camerota et al., 2018; Hall et al., 2015). Likewise, Yavuz-Kodat (2019), extending results from correlational analyses (i.e., using equivalence testing and BA plots) found good agreement between objective and subjective measures. Using similar methods to Yavuz-Kodat, BA plots, equivalence tests and paired samples t-tests, it was confirmed that both methods did not show good agreement in this study. A plausible explanation may be publication bias in the literature, where only studies are reported that show good agreement. Additionally, differences could arise from the very different age range in the present sample. Yavuz-Kodat (2019) examined children around age 5. Moreover, the sample in their study was relatively small sample (N=26). It could be that the larger sample of the present sample and the wider age range provided a more fine-grained picture of the cross-method agreement between subjective and objective measures. Future studies should try and replicate both the present study's findings as well as Yavuz-Kodat's (2019) findings in children with a larger sample.

Closer investigation of the BA plots hinted towards a systematic bias in the agreement between methods. Further correlational analyses showed that with higher maternal stress level (on all stress questionnaires) diary and actigraphy coincided better. Moreover, higher parental age was associated with better cross-method agreement in

sleep variables related to night sleep. It could be that mothers with higher stress levels were more likely to be awake at night, as stress levels have been associated with insomnia (Taylor et al., 2005) and thus may be able to report their infants sleep that is also captured by the actigraph. Another possibility is that mothers with a higher stress level primarily have infants who vocalize often during the night and are not able to self-soothe or mothers with infants who vocalize more often and are therefore more often awoken by the baby are more stressed. The association of parental age with more consistent diary/actigraphy data could be explained in several ways. One, older parental age could mean that the infant may not be the first child of those parents and parents could be more aware of their second child's sleep patterns, comparing them to their other children. Secondly, older age has been shown to be associated with an increase in sleep problems (Morin et al., 2011), further advancement in their working career and consequently higher stress levels, which in turn influence their recording of their infant's sleep. This matches findings in the present data set of older parental age and higher scores on the stress scales.

Additionally, I find that cross-method agreement differed by infant age on a number of sleep variables. The correlation between age and the cross-method agreement seemed to be slightly weaker for those parameters that had better agreement between methods as evidenced by BA plots and equivalence testing. This might serve as further evidence for the robustness of this finding. Diary and actigraphy coincided slightly better for day sleep measures, the older the child was, and slightly better for night sleep measures, the younger the infant was. This again might be explained by potential increase of self-soothing of the older participants, making it harder for parents to accurately estimate their infants sleep, whereas the younger infants vocalize when waking up at night (Goodlin-Jones et al., 2001). Moreover, young infants are still developing a fixed circadian rhythm (Shimko, 2019), thus show a larger number of naps and more variability in naps, which may make it harder to accurately record their sleep patterns. Moreover, inspection of mean difference by participants showed that some parents were systematically more accurate at recording their infants sleep, across visits than others. This supports the above-mentioned results of inherent parent characteristics that influence agreement between diary and actigraphy above and beyond infant age.

Two questions remain at this point. 1) why is there a lack of agreement between measures in the sample in general and 2) what does this lack of agreement mean for the selecting one sleep measure to assess sleep in the context of neurocognitive development. Above all, it has to be recognised that it is not possible to determine whether actigraphy,

diary or questionnaires reflect the true underlying sleep, as unless PSG data or videosomnography is collected, it is impossible to know the ground truth of an infant's sleep state. The discrepancy that can be seen between objective and subjective measures, more specifically between actigraphy and diary could originate from multiple sources.

First, it may be that actigraphy indeed overestimates or underestimates wakefulness after sleep onset due to inaccurately detecting movement during sleep as wakefulness or quiet wakefulness as sleep as suggested by prior research (e.g., Meltzer et al., 2012). Concordantly, it may be that parental estimation of infant's sleep is inaccurate if infants self-soothe to sleep and parents are unware of their infants wake at night, some parents in the present sample co-slept and this could have influenced accuracy of parental recording (e.g., Camerota et al., 2018). Another reason for this discrepancy could lie in the infants interindividual variability of sleep. Parents were asked to fill out the questionnaires in the course of the week that infants wore the actigraph, it is possible questionnaire answers were influenced by the prior night's sleep that may have differed from night to night substantially. Also, parents were asked to record accurately the timings of when they removed the actigraph. If they did not follow those instructions diligently there may be differences in accuracy of actigraphy recordings. Differences observed between the actigraphy and subjective measures may arise due to the actigraph used in this study. As mentioned in the introduction above use of a different actigraph may result in inherent differences in recording even across the same participants (Henderson, France, & Blampied, 2011). The actigraph used in this study is not commonly used in infant populations in the scientific community, only in industry settings. However, due to intellectual property concerns, their validation data is not publicly available. The actigraphy here was validated against another more commonly used actigraph (Actiwatch) in a small comparison study that I conducted. While this study showed general trends to be the same, there were fine-grained differences. It is possible that the exacerbated cross-method differences observed in this study are partially driven by the device. Moreover, in this study a large age range was covered than in prior studies.

The question remains, however, to determine which method should be used to assess infant sleep in particular in the context of assessment of neurocognitive development. Some researchers suggest that diaries should be used over questionnaires (Price et al., 2014) for assessing sleep rhythm/schedule while others argue that to truly understand sleep, especially night wakening patterns, actigraphy is necessary (Asaka & Takada, 2011). To date no consensus has been formed and each research centre makes their own decisions.

The current results indicate strongly that the choice of method to assess sleep may influence results that are produced by the study. I found that agreement rates amongst methods differ by infant age and other external factors and sleep patterns seem to differ depending on the method used to collect the data. This is a crucial point to consider especially when the aim is to explore the impact of sleep on neurocognitive development. It is concerning insofar also as it questions the research community's ability for cross-study comparison, indicating that parent-reported infant sleep using the same method diary or questionnaires) might not be as replicable and comparable as previously thought. Moreover, it challenges the validity of using parental report as a repeat measure in longitudinal studies. If parents are unable to consistently estimate their child's sleep across subjective sleep measures, this variability will extend to any study visit of a longitudinal study.

Considerations for future studies. In conclusion, it is unlikely that objective and subjective measures of infant sleep can be used interchangeably and that one method is superior in assessing infant sleep to the other. Moreover, we may wonder to what extent it is desirable to put actigraphy and parent-report measures against each other in terms of accuracy. Fundamentally, they measure slightly different aspects of infant sleep. While actigraphy measures infant sleep via the recording of movement and is a great measure to record habitual sleep patterns that cannot be captured easily with other methods, diary to some extend reflects a parentally biased perception of their infant's sleep. Even though parents are asked to report sleep onset and other sleep timing parents' inherent characteristics (such as consciousness, stress level etc.) will likely influence the way they record their infants sleep even on a diary. Moreover, actigraphy assesses sleep continuously in small increments (e.g., every 60 seconds) whereas parents monitor their infants sleep discontinuously and in much larger increments (e.g., morning, night, and when baby signals wake). Thus, there are some underlying differences in parent-report measures when compared to actigraphy in terms of what measures they represent. Therefore, when choosing a sleep assessment method for a new study, research questions and hypotheses must be carefully considered. Based on the above results using multiple measures can be valuable or even required if multiple sleep parameters need to be measured.

For this reason, rather than forming one composite sleep score or choosing one method over the other, in subsequent chapters all analyses will be performed separately on actigraphy and on parent-report measures. I expect this to provide a more multi-

dimensional picture of the relationship between sleep measures and measures of neurocognitive development.

3.5.2 Developmental patterns in sleep data

The second question concerned the developmental patterns in the sleep data in general and whether differences in age groups can be found as would be expected when investigating sleep across the first year of life. As I just argued, different methods might provide different information regarding the developmental patterns, hence results will be discussed alongside strengths and limitations of the methods.

Prior research suggests that major changes in sleep macrostructure happen in the first year of life, in particular concerning day sleep (Peters, 2017). In the present sample, results from descriptive statistics and from GCMs generally support this in the subjective measures, where a linear reduction in day sleep was found. This result however was not supported by the objective (actigraphy) data, which may perhaps be explained by the fact that actigraphy data showed a number of outliers, that might have masked underlying developmental effects. The variability in the 4-month-olds was lower than for the subjective measures. Visual inspection of the graph seems to suggest similar patterns to subjective measures (*Figure 3.4B.*). The lower variability in the 4-months-olds could be related to some parents rejecting to have their small infant wearing the device but agreeing to fill out the diary. This could potentially indicate that the cross-method differences might also arise from underlying algorithms and procedures used to analyse and collect actigraphy data. Actigraphy data could provide fine-grained information that is missed by subjective methods. When comparing both actigraphy and diary directly these fine-grained differences could then mask overall effects. Future should identify ways in which both diary and actigraphy can be jointly analysed to create a combined picture of infant sleep, perhaps by analysing visual trends.

Findings with regard to night sleep parameters were more varied as to be expected by prior research (Peters, 2017). Generally, an increase in Night Sleep Duration with age in the questionnaire data as well as in actigraphy and diary data could be found, corroborating the developmental shift from day sleep to primarily night sleep that occurs in the course of the first year of life (El-Sheikh & Sadeh, 2015). Though less clear the typical decline of Night Wakening Number (e.g., Galland et al., 2012) is also evident in this dataset but only for actigraphy (linear) and for SSQ (quadratic). The quadratic effect in SSQ data and the non-significant results for BISQ and diary for night wakening may be suggestive of some variability in Night Wakening Number across the first year of life.

Overall, the analyses of the sleep patterns in the present study broadly match prior research in terms of general developmental changes, e.g., the general decline in Day Sleep Duration and increase in Night Sleep Duration. However, there were also distinct patterns of sleep for different sleep measures which is contrary to prior research by Tikotzky and Volkovich (2019) who found general patterns across methods to be mostly overlapping (Tikotzky & Volkovich, 2019).

These findings support the claim above that choice of sleep measure (objective vs. subjective, questionnaires vs. diary) and sleep variables (sleep duration or fragmentation) may influence study results above and beyond underlying true sleep. This is mirrored by the fact that method agreement changed depending on age of infant, indicating that certain sleep variables provide better agreement depending on age, i.e., night sleep for younger infants and day sleep for older infants.

Overall, there seems to be large variability within the longitudinal data with regard to most sleep parameters. This variability is interindividual but also intraindividual. The goal for subsequent chapter is to determine if these individual differences in sleep are related to neurocognitive functioning in the first year of life.

3.5.3 Distinct groups of sleepers in infant sleep data

The last research question enquired whether it was possible to generate groups of sleepers, that may or may not be classified into poor and good sleepers and how those groups change across development. Sleep researchers do not generally group sleepers based on data-driven approaches, rather focusing on theoretically driven approaches, making the approach used here unique. Sleep fragmentation and short sleep duration have often been named as hallmarks of poor infant sleep (Meltzer & Mindell, 2006; Sadeh et al., 2010). For example, Sadeh (1991) found that approximately 20-30 % of infants did not sleep through the night in the first year of life and classified them as suffering from sleep problems. To my knowledge only one study has used cluster analysis to group infant sleep data, but only on questionnaire data and external factors such as sleep location and parental perception of infant sleep were included (Hughes et al., 2015). This study showed that it was possible to use data-driven approaches to cluster infant sleep data. The current study corroborates this by showing that sleep data can be clustered into theoretically meaningful groups of sleepers using a data-driven approach. For both actigraphy and BISQ three clusters were identified, for diary four clusters were identified.

The three clusters identified in the objective sleep data were as follows. One cluster could be denoted as what research would characterize as poor sleepers, as it shows lower

than average Night Sleep Duration and higher Night Wakening Number while not showing a difference in Day Sleep Duration compared to the day sleep cluster. Another cluster would perhaps be classified as having a more mature sleep patterns, as it shows higher than average Night Sleep Duration and lower than average night wakening. I thus denoted that cluster as the adult-like/mature sleepers. The last cluster on the other hand seems to be a cluster that is distinguishable by their increased day sleep features. However, there were only 9 infants in this cluster.

With regard to the subjective sleep data, four clusters were identified in the diary data that broadly mirror patterns identified in the objective data with the addition of a fourth cluster. This fourth cluster seemed comprised of a mixture of sleep patterns, which I therefore denoted as mixed sleepers. Three clusters were identified in the BISQ data, that were of similar general patterns as for diary and actigraphy with clusters identified as poor, day or adult-like/mature sleepers.

These clusters map onto prior literature, validating the data-driven approach that was chosen here. However, I consider these clusters to be most meaningful in relation to neurocognitive development or for instance to parameters of socio-cultural environment (see *Chapter 1* for the importance of investigating an infant's environment). Poor sleep quality as a standalone phenomenon is redundant, whereas investigating the impact of sleep quality on other variables, such as parental stress level or cognition, is meaningful.

Concordance between clusters. Interestingly, when investigating whether the same infant is sorted into the same cluster type (e.g., poor sleepers) by both objective and subjective methods, I found that this was not the case. I found that one child may be classified by actigraphy as poor sleeper and by diary as an adult-like sleeper. This variation in cluster memberships between actigraphy, BISQ and diary links back towards the lack of agreement in the sleep assessment methods (see above). More fundamentally, it could indicate that there are differences between how parents perceive their infants sleep and how infants actually sleep. It could be that a parent-report might identify a child as a poor sleeper whereas an actigraphy assessment might not. This highlights the fact that both subjective and objective methods cannot be used interchangeably. Of note, behavioural infant sleep problems are often identified using questionnaire measures. The question poses itself if the same percentage of infants would be classified with infant sleep problems using objective measures. Future research should investigate the prevalence of parent-reported infant sleep problems in the general populations and aim to understand the percentage of how many of those infants also report sleep problems based on actigraphy. Infants identified via questionnaires as poor sleepers might be better labelled

as exhibiting problematic sleep behaviour according to parents, to refer to the interaction between child sleep and parental characteristics. In addition, the closer examination of the different clusters indicated that in subjective measures there were age differences between clusters, this was not true for actigraphy. This finding should be examined further in the future. It is possible that parental perception of infant sleep is influenced by infant age, but an objective estimation of infant sleep is not. Elucidating this question could be done by including a PSG measurement of true underlying sleep.

Due to the cross-method discrepancies that are apparent in the sleep data and the association of that discrepancy with infant age and maternal/stress characteristics, the sleep measures cannot be used interchangeably. Moreover, objective and subjective measures might represent slightly different aspects of infant sleep, which might yield interesting information in itself. Therefore, in subsequent chapters, subjective (diary, BISQ) and objective (actigraphy) are studied separately in relation to neurocognitive measures. The aim is to see which of the clusters identified (adult-like/mature, poor, or day sleep in subjective vs objective measures) may relate to a beneficial neurocognitive trajectory. It would allow us to make a statement about how optimal infant sleep quality for neurocognitive measures could be drawn.

3.5.4 Limitations

There are some limitations that have to be acknowledged. The first concerned the actigraph that was used in the present study. The wGT3X-BT is a relatively novel device that has not been validated in many studies and has not yet been compared to PSG in infants. As prior research suggests that choice of actigraph may influence study results. However, I validated the actigraph of the present study against another actigraph commonly used in sleep research and found satisfactory agreement (see *Chapter 2 / Appendix - Chapter 2*). While the two actigraphs did not give the exact same results, they showed the same overall patterns suggesting that both actigraphs collect valid data in infants. Future work should focus on validating this actigraph against PSG in an infant sample.

Another aspect is the choice of actigraphy sleep-wake classification algorithm, which in this case was the Sadeh algorithm that uses a so-called zero-crossing algorithm. The zero-crossing algorithm ignores the amplitude/acceleration of movements, potentially using less information than other algorithms that may calculate the area under the curve of acceleration movements. Yet, the Sadeh algorithms' advantage of being well-

validated in infant populations outweighs the disadvantage of not taking information about movement amplitude into account.

Third, there was a high amount of missing data in the present sample. By using mixed model techniques and techniques like k-means cluster analysis, both of which are known to be robust to missing data, potential problems arising from missing data are minimized (Boyd & Vandenberghe, 2018; Field, 2005). Lastly, a problem of exploratory data analyses such as k-means, is that it is always possible to identify clusters in data, even in noisy data where clustering might not actually yield a meaningful result. Though theoretical inspection of the resulting clusters seemed to indicate a meaningful clustering of the data occurred. Future work should replicate the clusters found in the present analysis in another sample.

Lastly, as mentioned previously there is no way of knowing the underlying true sleep as both actigraphy and diary have limitations (see above). Videosomnography or portable PSG should be added to night sleep at home to gain some insight into true sleep and investigate the bias between actigraphy and diary in relation to a ground truth measure.

3.5.5 Conclusion

In summary, overall agreement between subjective measures amongst each other and between subjective and objective measures is worse than expected based on prior research. Specifically, agreement between sleep questionnaires and actigraphy is not good. Diary and actigraphy coincide better on some sleep measures (e.g., day sleep) than on others (e.g., night sleep). This study also showed that agreement rates amongst methods differ by infant age and other external factors (parental age and maternal stress levels) and sleep patterns seem to differ depending on method used to collect the data. Based on the present data it is unlikely that the methods can be used interchangeably. Lastly, it is possible to use data-driven approaches to cluster infant sleep data.

The current findings suggest that the choice of method to assess sleep may dictate what results are produced by the study. Different sleep assessment methods provide distinctive information about an infant's sleep. As such, subjective measures reflect the parental perception of infant sleep but likely include information about parental awareness whilst actigraphy reflects the infant's sleep but is likely to display motion patterns in general, that are not inherent to the child. This is a key explanation regarding the lack of the cross-method agreement. This means that future research studying habitual infant sleep needs to consider multidimensional measurement of sleep.

Therefore, in subsequent chapter all sleep measures, i.e., actigraphy, diary, and BISQ are related to the developmental measures. The hypothesis is that strong effects in the relation between sleep and development should be captured by all sleep assessment methods, while cross-method differences in the association with development could provide better understanding of the relationship in the first place. Lastly, the importance of considering context in an infant's sleep (see maternal stress results above) is highlighted by this first study. The next chapter (*Chapter 4*) examines how an infant's external and internal factors relate to sleep quality (as identified by the data-driven sleep clusters) and to continuous sleep parameters.

CHAPTER 4 - Characterising the relationship between sleep and maternal characteristics, and temperament and general development

Chapter 3 showed that there were inter- and intraindividual changes in sleep, and that the agreement between methods could be dependent on infant characteristics and maternal characteristics. The results indicated that a multi-method measurement of sleep is critical to capture different dimensions of infant sleep and investigate its association with aspects of neurocognitive development. Therefore, the main goal of this chapter is to explore how individual differences in sleeping patterns might relate to aspects of an infant's environment and to infant characteristics. More specifically, I will examine how objective and subjective sleep measures relate to infant temperament/general development and to environmental factors such as their socio-cultural background, where maternal education is used as a proxy, bedtime rituals and maternal mental health.

4.1 Infant environmental factors/socio-economic status and infant sleep

The environment, place and people a person grows up with influences how they develop and the person they become. Moreover, evidence is emerging that these factors such as culture and socio-economic background also influence how humans, and especially infants sleep. Sadeh's *Transactional Model* (see *Chapter 1*) highlights the importance of considering an infant's environment when studying the relationship between sleep and development.

One of the most important factors in a child's environment are the child's caregivers/parents. Caregivers dictate *how, when* and *where* their infant is put to sleep, all of which have been shown to influence infants' sleep duration and quality. For example, caregivers determine the infant's bedtime or whether they sleep in the same bed as the caregivers (called co-sleeping), both of which have been shown to influence sleep duration and sleep fragmentation (e.g., Volkovich et al., 2015). Other factors such as feeding or physical closeness at bedtime have also been shown to impact sleep (Mindell et al., 2009; Philbrook & Teti, 2016). Relatedly, a common treatment for sleep problems includes having a fixed bedtime routine/ritual (Mindell et al., 2009); however, there is not much research yet on which types of routines parents follow or whether having many different nightly rituals, such as music playing, story reading, or nursing might impact

infant sleep. The presence of a bedtime routine/rituals is an important aspect in an infant's sleep environment and can also serve as a marker for parental interaction with the child at nighttime.

Parental interaction with their children often differs by socio-economic status (SES; Andersen et al., 2020; Bluestone & Tamis-LeMonda, 1999; Rie et al., 2020). Simultaneously, research has shown socio-economic differences in infants' sleep. SES is measured in different ways in the literature. One way is to look at neighbourhood SES of where parents and infants live. For instance, studies show an effect of neighbourhood SES on sleep in children, though studies are scarce to date.

A recent meta-analysis by Tomfohr-Madsen and colleagues (2020) revealed that the higher the neighbourhood SES of the child, the longer the objectively as well as subjectively reported sleep duration (Tomfohr-Madsen et al., 2020). Another review article highlights the potential role of sleep quality as a protective factor where children in lower SES backgrounds might have both a greater detriment but also a greater benefit of sleep (Bernier et al., 2014). This shows that when disentangling the effect of sleep on development, is it crucial to consider other factors too, like SES.

One study finds no association of objectively measured (actigraphy) infant sleep quality with sociodemographic risk score (a combination of poverty risk parameters and parental education) in 3-months-old African American infants but does show an association with neighbourhood deprivation (Grimes et al., 2018). This indicated that, rather than parental socio-demographics variables (e.g., education), the environment in which an infant sleeps is crucial. It could be that some infants are exposed to more noise levels and other factors, which impacts their sleep (Grimes et al., 2018). Similarly, a recent study showed that 12-month-old infants who experienced lower neighbourhood SES, lower perceived safety and higher crimes exhibited less consolidated sleep at night based on parent-report (MacKinnon et al., 2020). The authors note that higher maternal stress levels (about the unsafe situation) could subsequently influence infant sleep.

Maternal education level is often used as an indicator for SES rather than neighbourhood SES, primarily because maternal education is easily assessed with questionnaires and does not require calculation of factors such as neighbourhood crime. Maternal education has been linked to factors such as parent-child interaction (Tamis-LeMonda et al., 2009) and infant cognitive development (Patra et al., 2016), likely through a myriad of factors that include hereditary as well as other environmental factors. Maternal education has also been associated with infant sleep duration. For example, Matenchuk et al. (2019) found that 3-months old infants slept 40 minutes longer on

average if the mother had a university degree (Matenchuk et al., 2019). Similarly, in older infants and toddlers, lower maternal education was associated with lower sleep duration (McDonald et al., 2014). The authors suggest this is mainly due to later bedtimes. Interestingly, this effect develops across the first year of life. Yu et al. (2020) found that there were no differences in (objectively measured) sleep duration in infants at 1 months of age. At 6 months, infants of mothers with lower education levels showed less Night Sleep Duration and higher Day Sleep Duration than infants of mothers with higher education levels, but showed no differences in sleep fragmentation parameters (Yu et al., 2020).

Infant sleep duration can also interact with maternal education to influence aspects of infant development. Camerota et al. (2020) found that infant sleep regulation moderated the relationship between maternal education and infant attentional abilities. The authors interpret this as evidence for the so-called *vantage sensitivity model*, that proposes that sleep and an enriched environment (i.e., higher maternal education) leads to the best developmental outcomes (Camerota et al., 2020).

Researchers suggest that the impact of maternal education or SES factors on infant sleep is likely due to a complex interaction of SES differences in bedtime routines, environmental factors such as noise, nutritional aspects and maternal characteristics. The latter are discussed in further detail below.

4.2 Maternal mental health and infant sleep

Above-and-beyond broad environmental influences in how, where and when infants are put to sleep, parental characteristics such as mental health or stress level are also associated with infant sleep patterns. Most notably, these include maternal depression and maternal stress/anxiety levels. Especially well-researched is the impact of maternal depression on infant sleep and vice versa. This research shows that postnatal depression and/or maternal depressive disorders are associated with shorter BISQ-measured infant sleep duration (e.g., Matenchuk et al., 2019), with presence of parent-reported sleep problems (e.g., Martini et al., 2017) and with increased parent-reported night wakening (e.g., Karraker & Young, 2007).

However, recent evidence suggests that the relationship between sleep and maternal depression might not be as clear cut as previously assumed. For example, Pennestri et al. (2018) found no associations between maternal mood and parent-reported infant night wakening/sleeping through the night at 6 or at 12 months of age.

Another explanation is that maternal depressive symptomatology may be linked to maternal sleep problems or vice versa (Dørheim et al., 2009; Field et al., 2007), which in turn may be linked to infant sleep problems (Nakahara et al., 2020).

Research also suggests that maternal stress and anxiety levels are relevant to infant sleep. As discussed in *Chapter 3*, stress levels may affect how mothers reported their infant's sleep and the consistency of subjective and objective sleep measures. It is therefore crucial to investigate how levels of maternal stress develop in relation to sleep in the first year of life. For example, maternal stress levels have been associated with lower infant Night Sleep Duration, shorter Day Sleep Duration at 4 - 5 months old, more variability in night sleep, more night wakenings and higher parent-reported infant sleep problems (Goldberg et al., 2013; Sadeh et al., 2010; Sinai & Tikotzky, 2012). Interestingly, Sinai and Tikotzky (2012) find that maternal stress levels were only related to infant sleep patterns amongst mothers who were on maternity leave. There are some conflicting findings on this topic. For instance, it seems as though the relationship between maternal stress and infant sleep might change depending on infant age, with a positive association in younger infants and a negative association in older infants (Sorondo & Reeb-Sutherland, 2015). Additionally, in the latter study, longer instead of shorter Day Sleep Duration was associated with higher maternal stress levels.

In conclusion, worse maternal mental health might have a negative impact on an infant's sleep, though the role of objective vs. subjective sleep measures in assessing this relationship is not yet clear. Given the findings in *Chapter 3* that cross-method discrepancies differed depending on maternal stress/anxiety levels, future studies investigating infant sleep need to consider the role of maternal stress, too.

4.3 Infant temperament, general development and infant sleep

In addition to environmental influences on infant sleep infants' internal characteristics may be related to their sleep, though the directionality of these relationships remains unclear. Most importantly, these internal characteristics include general development and temperament.

4.3.1 Infant temperament

Infant temperament refers to an infant's behavioural style, i.e., how they regulate their emotions and interact with the world around them. It can be measured across three overarching dimensions: orienting/regulation (= self-regulation), negative

affectivity/negativity and surgency/positive affectivity (= reactivity) using parent-report (Rothbart, 1981; Weissbluth, 1981). Temperament is related to various aspects of infant sleep. For instance, reactive infant temperament has been associated with shorter sleep duration and more night wakenings (Netsi et al., 2017) and an easy temperament (e.g., increased approachability or low distractibility) was associated with longer overall objectively and parent-reported sleep duration (Kaley et al., 2012; Spruyt et al., 2008). Higher infant surgency (or an easy temperament) also moderated the impact of maternal emotional availability on sleep duration, suggesting a potential role of infant temperament on maternal mood and on sleep (Jian & Teti, 2016). Specifically, for infants with high surgency, higher maternal emotional availability was associated with higher sleep duration. No such effects were found for low surgency or the other subdimensions.

Interestingly, Spruyt et al. (2008) showed that lower Day Sleep Duration was actually associated with *better* emotion regulation at 12 months, contrary to what Netsi et al. (2017)'s results suggest. It could be that night and day sleep have different effects on temperament. Sordono and Reeb-Sutherland (2015) found associations of BISQ-reported sleep problems with negative reactivity score of the IBQ-R at 9 months but not at 5 or 12 months of age. Moreover, overall higher negative reactivity was related to greater BISQ-reported wake after sleep onset (WASO).

In contrast, in a longitudinal study, Morales-Muñoz (2020) found that Negativity/Negative affectivity at 6 months predicted parent-reported sleep problems later at 12 months of age. While these longitudinal results are contradictory to concurrent associations between sleep and temperament, they imply potential developmental differences in the relationship (Morales-Muñoz et al., 2020). In addition, various domains of temperament in early infancy have been associated with sleep problems (e.g., greater WASO) in later infancy (Scher & Asher, 2004) and in toddlerhood (Bastien et al., 2020; Weinraub et al., 2012; Weissbluth, 1981). Interestingly, association differed depending on the temperament domain that was studied. Conversely, sleep in early infancy was also related to later temperament, such that disrupted sleep patterns early on (Halpern et al., 1994; Novosad et al., 1999) were associated with difficult temperament later in infancy. Differences between boys and girls in terms of the relationship between sleep and temperament were also found in some studies (Netsi et al., 2017; Sordono & Reeb-Sutherland, 2015). While many studies have found a link between temperament and sleep, some studies fail to replicate those findings. For instance, Martini et al. (2017) did not find an association between infant temperament and mothers' reports of infant sleep

problems at 16 months of age (Martini et al., 2017). This mirrors earlier findings (DeLeon & Karraker, 2007).

Mixed findings about the relationship between sleep and temperament might be related to developmental changes that the relationship seems to undergo (see above). Many of the studies reviewed above did not assess sleep or temperament continuously, and thus might have missed periods of that relationship that were relevant. For example, De Marcas and colleagues (2015) propose an inverted-U relationship between sleep and temperament, where both hyper-reactivity and hypo-reactivity were associated with less improvement in sleep quality with age (De Marcas et al., 2015).

Underlying patterns such as these necessitate a longitudinal examination of the relationship between sleep and development. Moreover, it is possible that the use of different types of sleep assessment methods might have masked some underlying patterns that could only be apparent in either objective or subjective patterns.

4.3.2 General development

As mentioned in *Chapter 1*, there are some associations between general development and sleep patterns in the first year of life, though findings appear to be mixed. For detailed review refer to *Chapter 1*. Previous studies showed better infant sleep (as indicated by better sleep efficiency and longer sleep duration) was positively associated with later mental development at 10 months (Scher, 2005) and subscales of the ASQ at 11-13 months (Gibson et al., 2012). In newborns, longest sleep period (LSP) correlated with developmental scales (Bailey Scale scores) at 6 months (Freudigman & Thoman, 1993). Another (longitudinal) study showed that early sleep characteristics were reflective of infant development in the first year (Judge et al., 2015). It has also been shown that longer night awakenings are related to slower later cognitive development, especially during late infancy and early toddlerhood (Sun et al., 2016). Importantly, day sleep seems to be scarcely studied, though some evidence suggests more daytime naps in 7-month-old infants predicts increased vocabulary growth in early childhood (Horváth & Plunkett, 2016).

However, neither Spruyt et al. (2008) nor Mindell and Lee (2015) found the association between infant sleep and cognition reported by Scher and colleagues (2005). Additionally, Camerota et al. (2020) did not find a direct association between cognition, as measured by the Bayley-III, an infant attention task and any measures of sleep, as assessed by actigraphy and videosomnography in 6-months old infants (Camerota et al., 2020). These opposing findings might relate to the mixed methods used. Studies used

different age group as well as sleep measures. Moreover, general development comprises many aspects of development, such as language, attention and motor development to name a few examples. It is possible that infant sleep is related to certain subcategories of development. Measures of general development would potentially miss these effects.

Findings on general measures of developmental status in relation to sleep are mixed. These might be due to a lack of studies comparing different sleep measures in relation to general development but could also mean that the investigation of subcategories of general development (e.g., language, motor development) in relation to sleep is essential. Therefore, in this study, a general measure of development that provides information on subscales is included in the questionnaire measures. The aim is to investigate whether previous claims that measures of general development rather than nuanced features (i.e., infant attention) are related to infant sleep.

In summary, the studies reviewed above paint a complex picture where many aspects of infant sleep such as SES, maternal characteristics, maternal interaction with infants at nighttime (bedtime rituals) and inherent infant characteristics (i.e., temperament/general developmental status) appear to be associated with infant sleep patterns.

However, many of the studies described above are cross-sectional or only contain 2 visits, instead of spanning the entire first year of life. Most past research also does not compare different measures of sleep and sleep quality comprehensively with each other. Results from the findings are mixed. By investigating the different questionnaire measures (i.e., temperament, general development and maternal characteristics) in relation to both objective and subjective sleep in one sample, I aim to shed some light on which relationships may be robust, as well as which may be linked to methodological differences. This study aims to contribute to a better understanding of how these questionnaire measures relate to sleep in infancy.

In addition, as Sordono and Reeb-Sutherland (2015) suggest, it is possible that the relationship between infant sleep and maternal characteristics changes depending on infant age. Similarly, findings suggest that the relationship between temperament and infant sleep may change across the course of development. This may also be true for the other questionnaire measures. These findings necessitate a study spanning the duration of the first year of life instead of measuring only one or two time points. A longitudinal investigation of developmental changes in general development, temperament and maternal characteristics in relation to sleep may clarify previously mixed findings.

4.4 Research aim and current study

The overarching goal of this chapter focused on exploring the relationship between infant sleep (using objective and subjective measures of infant sleep quality and other sleep parameters) and infant temperament and general development, as well as measures of maternal mental health. Further, the impact of bedtime rituals/routine as indicator of parental interaction with infant child at nighttime and of maternal education was examined.

The research aims were as follows:

- Explore how maternal education impacts infant sleep parameters (Night Wakening Number, wake after sleep onset (WASO), Day and Night Sleep Duration) as measured objectively and subjectively.
- Explore how infant sleep quality as measured by infant sleep cluster membership (see *Chapter 3*) is related to a) sleep ritual/routine number as indicator of parental interaction with the infant at nighttime b) maternal stress measures, as measured by various stress scales and c) infant temperament as measured by the Infant Behaviour Questionnaire-Revised Short Form (IBQ-R, SF) and to d) infant general development as measured by the Ages and Stages Questionnaire(ASQ).
- Explore how continuous sleep parameters (Night Wakening Number, wake after sleep onset (WASO), Day and Night Sleep Duration) are related to a) sleep ritual/routine number as indicator of parental interaction with the infant at night time b) maternal stress measures, as measured by various stress scales and c) infant temperament as measured by the Infant Behaviour Questionnaire-Revised Short Form (IBQ-R, SF) and to d) infant general development as measured by the Ages and Stages Questionnaire (ASQ).

4.5 Methods

This chapter describes the questionnaire portion of Study 1 (see *Chapter 2* for study set-up).

4.5.1 Experimental Set-up

The experimental set-up of Study 1 is described in detail in *Chapter 2.* In summary, an accelerated longitudinal study was conducted, measuring sleep and indices of neurocognitive development in the first year of life using objective and subjective methods. The study was comprised of up to 4 visits per infant at which eye-tracking and

EEG was performed and following which parents used actigraphy, a sleep diary and questionnaires to record their infants sleep for a week. Additional questionnaire measures were collected at each visit. These questionnaire measures are the focus of the present chapter.

4.5.2 Participants

Participants were infants aged 4 to 14 months tested at up to 4 visits (see *Chapter 2*). *Appendix – Chapter 4* shows how much data was collected from questionnaires across visits. EPDS and SES/Demographics were only assessed at the baseline visit.

4.5.3 Questionnaire measures

Below the questionnaires administered are briefly reviewed; for details refer to *Chapter 2*.

STAI. The STAI (Spielberger, 2010) measures both state anxiety (how anxious the person is filling in a given moment and trait anxiety (how anxious the person is feeling generally). Here it is filled out by the mothers.

PSS. The PSS (Cohen et al., 1994) measures life stress appraisal. As with STAI, it is filled out by the mothers.

EDPS. The EPDS (Cox et al., 1987,1996) is a questionnaire that assesses postpartum depression but may be used as a depression measure. Here, it was only measured at baseline (i.e., Visit 1).

IBQ-R. The IBQ-R assesses infant temperament (until age one) by providing scores on three subscales: Surgency/Extraversion, Negative Affectivity/Negativity and Orienting/Regulatory Capacity. It was also used here to test the 14-months-old infants so as not to introduce a different questionnaire at that age (Gartstein & Rothbart, 2003; Putnam et al., 2014).

ASQ. The ASQ (Schonhaut et al., 2013; Squires et al., 1997) assesses an infant's activities over time to provide a picture of general developmental status on 5 subscales: communication skills, social skills, problem-solving skills, and fine motor and gross motor skills.

SES/Demographics. This questionnaire assesses factors such parental education level, income, parental age, languages spoken at home and number of bedrooms. Furthermore, details about the medical history and details on the infant's birth are assessed.

4.5.4 Sleep measures

The clusters identified in *Chapter 3* were used for sleep quality assessment. These were as follows: poor, adult-like and day sleepers for actigraphy and Brief Infant Sleep Questionnaire (BISQ) and poor, adult-like, day and mixed sleepers for sleep diary. Further sleep parameters investigated were Night and Day Sleep Duration, Night Wakening Number (sleep fragmentation) and wake after sleep onset (WASO). These were investigated separately for each sleep measure.

Sleep rituals and habits. In addition to information of sleep patterns, BISQ and diary also provided information on sleep habits and routines. These included asking parents to report on bedtime activities. Here, the focus is on results of BISQ as indicator of habitual sleep routines and habits. The main focus will be on number of sleep rituals, as a measure of parental interaction with the infant at nighttime and whether parents indicated that their infant had sleep problems or not.

4.5.5 Analysis Plan

Pre-processing of sleep data. For details on actigraphy data pre-processing, refer to *Chapter 2* and *Chapter 3*. The sleep quality clusters identified in *Chapter 3* through k-means cluster analysis were used. These were as follows: poor, adult-like and day sleepers for actigraphy and BISQ and poor, adult-like, day and mixed sleepers for sleep diary. Sleep clusters (i.e., adult-like, poor and day sleepers/ mixed sleepers) identified in *Chapter 3* were used to identify a relationship between sleep quality and development. Additional analyses were performed on sleep parameters commonly used in the literature, i.e., Night and Day Sleep Duration, Night Wakening Number and WASO, this was done because the broad sleep clusters might miss more fine-grained aspects of sleep/more specific relationships. For the actigraphy clusters of poor and day sleepers were merged as there were only nine participants in clusters for day sleep. For diary clusters, clusters of mixed and day sleepers were merged again due to the limited number of participants in the day sleep cluster. No clusters were merged for the BISQ as cluster sizes were roughly equal.

Analysis of tasks. Linear mixed effects modelling (LMMs) was used to analyse the data. For details with regard to different models tested and rationale for analysis choice see *Chapter 2*. Below the full linear mixed models (LMMs) tested are specified. Each analysis was performed three times for each sleep method once. For questionnaire parameters tested refer to *Table 4.1*. The LMMs tested are as follows:

1. The **baseline model** is the developmental change model assessing how the questionnaire parameters change over time.

   Baseline: questionnaire parameter = random intercept for participant + age group

2. **Model 1** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameters) on the questionnaire parameters are assessed

   Model 1 (M1): questionnaire parameter **=** random intercept for participant + age groups + sleep variable

3. **Model 2** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameters) and an interaction effect of age group by sleep variable on the questionnaire parameters are assessed.

   Model 2 (M2): questionnaire parameter = random intercept for participant + age groups + sleep variable + age group by sleep variable interaction

4. **Model 3** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameters) and gender and potentially an interaction effect of age group by sleep variable on the questionnaire parameters are assessed.

   Model 3 (M3): questionnaire parameter = random intercept for participant + age groups + sleep variable + (age group by sleep variable interaction) + gender

Table 4.1. Questionnaires administered and associated measures

Questionnaire	Dependent variables tested	Measures
SES/Demographics	○ Maternal education	Indicator of socioeconomic status
EPDS	○ EPDS total score at baseline	Maternal depression at baseline
PSS & STAI	○ Stress score (z-score)	Average measure of maternal anxiety
ASQ	○ Communication total score ○ Gross motor total score ○ Fine motor total score ○ Problem-solving total score ○ Social total score	Measures of general development
IBQ-R	○ Surgency mean score ○ Negativity mean score ○ Regulation mean score	Infant temperament
BISQ	○ Number of bedtime routines ○ Co-sleeping ○ Sleep problems (yes, no, somewhat)	Sleep habits

Note. EPDS = Edinburgh Postnatal Depression Scale, PSS = Perceived Stress Scale, STAI = State-Trait Anxiety Inventory, ASQ = Ages and Stages Questionnaire, IBQ-R = Infant Behaviour Questionnaire-Revised (Short Form), BISQ= Brief Infant Sleep Questionnaire

4.6 Results

4.6.1 Descriptive statistics

For description of socio-economic and cultural background of the sample please refer to *Chapter 2*.

4.6.1.1 Sleep routines as assessed by BISQ

Bedtime routines. *Figure 4.1A-B* illustrates the patterns of habitual bedtime rituals/sleep routines parents reported in the BISQ. Infants contributing longitudinal data were entered into the analysis more than once at each time point once. The majority of the sample reported 1 or 2 sleep rituals, with some reporting no sleep rituals or as many as 4 or more. The most common rituals were feeding (which included either breast feeding, bottle feeding or solid food) and music.

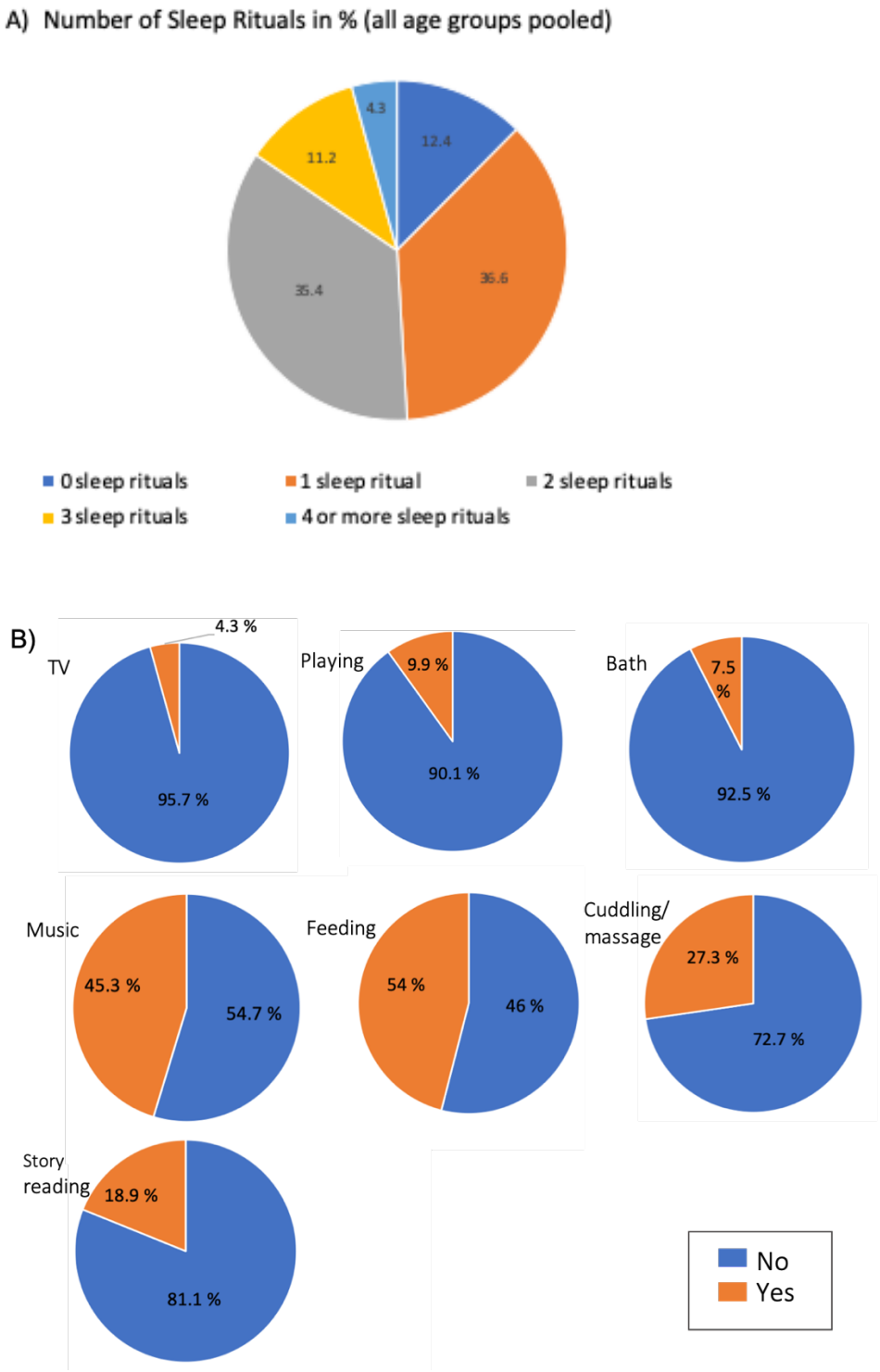


Figure 4.1. A) Number of (habitual) sleep rituals. B) Sleep rituals in percent across all age groups pooled.

Co-sleeping. 36.3% reported no co-sleeping after night wakening, 11.5% sometimes brought their baby to bed and 52.2% reported always bringing their baby with them to bed after they woke up at night.

Parent reported sleep problems. In the present sample (all age groups pooled) 65.4% of the infants had not reported sleep problems, 23.5% reported that the sleep was somewhat of a problem and 11.1% reported their infants sleep to be very much of a problem.

4.6.1.2 Maternal mental health (PSS, STAI, EPDS)

Correlational analyses revealed high correlations between the three stress measures (see *Table 4.2.*). As expected, stress measures correlated highly with baseline measures of EPDS (Rawson et al., 1994). In order to reduce the amount of data, a composite measure of maternal stress level was created by applying z-score transformation to raw score of PSS and STAI-S/-T and average the raw z-scores. This stress score is used in subsequent analyses.

Table 4.2. Pearson correlation coefficients (*r*) for Stress and depression measures

	PSS	**STAI-S**	**STAI-T**	**EPDS**
PSS	1	.677**	.739**	.500
STAI-S		1	.807	.607**
STAI-T			1	.658**
EPDS				1

Note. PSS = Perceived Stress Scale, STAI-S= State Trait Anxiety Inventory - State, STAI-T = State Trait Anxiety Inventory - Trait, EPDS = Edinburgh Postnatal Depression Scale, significant at p = .001, adjusted for multiple comparison.

EPDS. As the EPDS was only assessed at baseline, the focus will be on the relationship between baseline EPDS score and sleep parameters. Correlational analyses revealed no correlations between diary-measured or BISQ-measured sleep parameters and EPDS. There was a positive correlation between actigraphy-measured night sleep and EPDS-scale (r = .275, p = .001) such that more actigraphy-measured night sleep was associated with greater depression symptoms. As correlational analyses indicated no consistent association and there was only baseline data, EPDS was not further examined at this point.

4.6.1.3 Infant temperament (IBQ-R)

Mean and standard deviations for IBQ-R subscales can be found in Table 4.3. For Pearson correlations between the different subscales see *Appendix – Chapter 4*.

4.6.1.4 General infant development (Ages and Stages Questionnaires)

Mean and standard deviations for ASQ subscales are reported in Table 4.3. For Pearson correlations between the different subscales see *Appendix – Chapter 4*.

Table 4.3. Descriptive Statistics ASQ & IBQ-R

	ASQ: COM	ASQ: GM	ASQ: FM	ASQ: PS	ASQ: SOC	IBQ-R SF: Surgency	IBQ-R SF: Negativity	IBQ-R SF: Regulation
Mean	47.16	47.50	50.28	48.85	46.53	4.89	3.52	4.99
SD	10.99	13.65	10.19	11.09	11.63	0.68	0.88	0.61

Notes. ASQ = Ages and Stages Questionnaire; IBQ-R SF = Infant Behaviour Questionnaire - Revised Short Form; COM = communication subscale; GM = gross motor subscale, FM = fine motor subscale; PS = problem-solving subscale; SOC= social subscale.

4.6.2 Developmental changes

The baseline model of the LMMs assessed potential age group differences in the questionnaire measures. The ASQ age group differences are not further discussed, as the ASQ is age-normed posing different questions for each age group. For detailed statistics see *Appendix – Chapter 4*.

4.6.2.1 Developmental changes in sleep routines (number)

Results revealed no significant developmental changes in sleep ritual number in the present sample as measured by the baseline model of the LMMs ($p > .10$; see *Appendix – Chapter 4*).

4.6.2.2 Developmental changes in maternal mental health

There were no developmental differences in baseline EPDS scores. Moreover, there were no developmental changes in maternal stress score in the present sample as measured by the Baseline model of the LMMs (all p's >.10).

4.6.2.3 Developmental changes of infant temperament (IBQ-R)

There were no significant developmental changes in the Regulation or Negativity subscale as measured by the baseline model of the LMMs (all p's >.05 see *Appendix – Chapter 4*). There were developmental changes for the surgency subscale as measured by the baseline model of the LMMs, surgency subscale scores increased with age. Surgency scores were significantly different between ages 4 months and 8 months (*MD* = -0.62, *p* = .006), 4 and 10 months (*MD* = -0.82, *p* <.001, 4 and 12 months (*MD* = -0.78, *p* = .001) and 4 and 14 months (*MD* = -0.73, *p* = .005) of age. Other age group differences were not significant. *MD = Mean Difference*

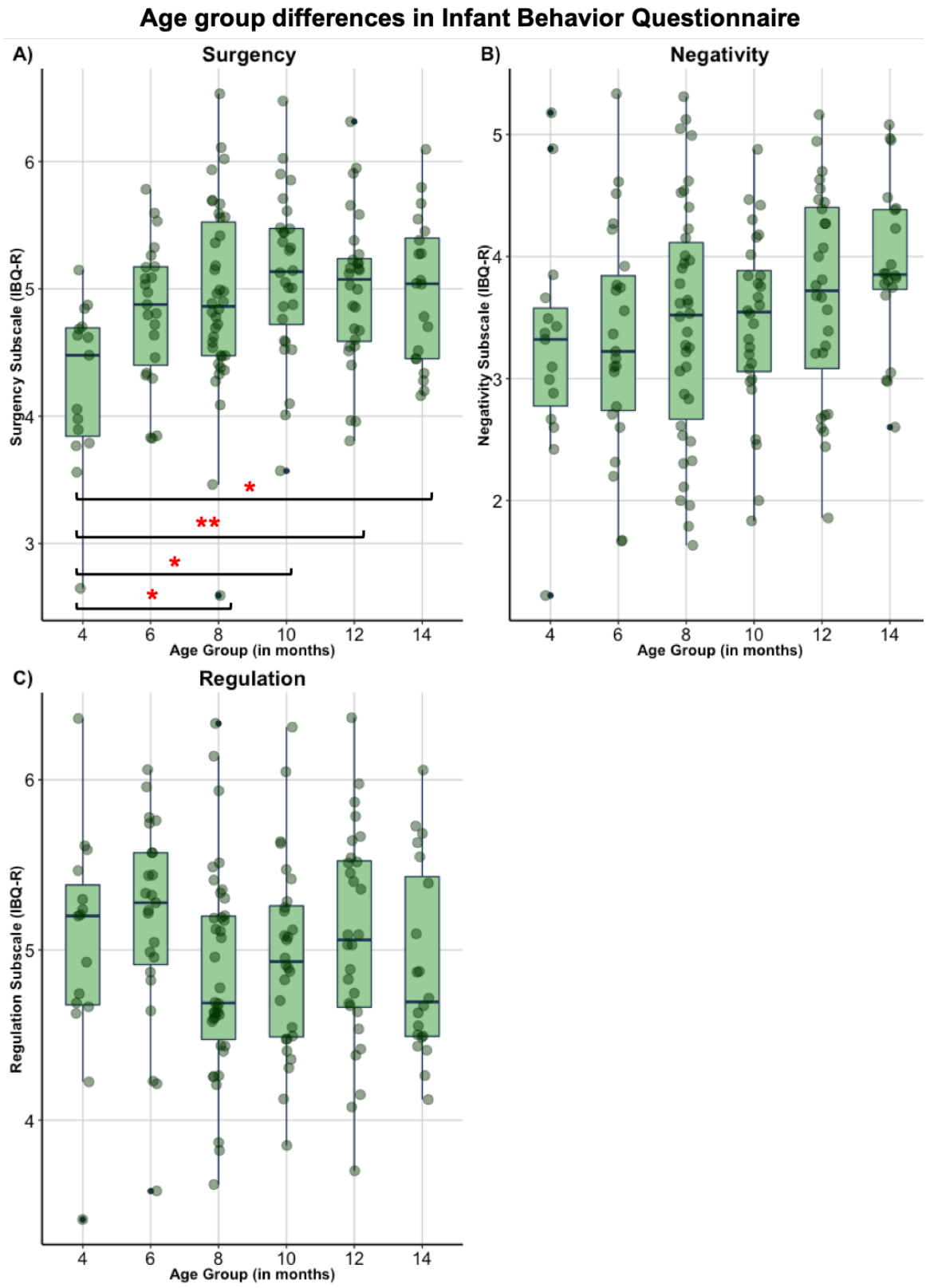


Figure 4.2. Developmental changes in IBQ-R subscales. *$p < .01$, **$p < .001$. Corrected for multiple comparisons using the Bonferroni method.

4.6.3 Infant sleep quality and maternal education, maternal mental health, infant temperament and general development and number of sleep routines

Below, the relation between maternal mental health (i.e., stress score), infant temperament, general development and number of sleep rituals in relation to infant sleep quality is examined. Sleep quality is denoted here by sleep cluster membership that was identified in *Chapter 3*. LMMs were performed for actigraphy-, diary- and BISQ-measured sleep clusters and each parameter separately. All significant results are summarised in *Table 4.4*.

4.6.3.1 LMMs Stress

There were no significant associations of objectively (actigraphy) or subjectively measured (BISQ or diary) sleep quality (as measured by cluster membership) on stress scores in the LMMs (all p's >.05; see *Appendix – Chapter 4)*.

4.6.3.2 LMMs general infant development

There were no significant effects of objectively (actigraphy) or subjectively measured (BISQ or diary) sleep quality (as measured by cluster membership) on any ASQ-subscales (Communication, Gross motor, Fine motor, Problem-solving, Social) as assessed by LMMs (all p's >.05; see *Appendix – Chapter 4)*.

4.6.3.3 LMMs infant temperament.

***Key Findings**:* There were some associations between subjective sleep quality and the temperament subscales, though results did not show cross-method consistency.

For the **s**leep diary, sleep quality was significantly associated with the negativity subscale [$F(2,80) = 4.07$, $p = .021$]. However, the post-hoc testing showed no difference between clusters, as they did not survive correction for multiple comparisons using the Bonferroni method. Though the mixed sleepers seem to be slightly higher in negativity score (best model: model 2). There were no significant associations between the negativity subscale and BISQ sleep quality. For the BISQ, sleep quality was significantly associated with the negativity subscale [$F(2,112) = 4.34$, $p = .015$] where the day sleepers showed a significantly higher surgency score (5.07 ± 0.10) than adult like (4.74 ± 0.08; $MD_{adult\text{-}like\ –\ day\ sleepers} = -0.33 \pm 0.12$, $p = .02$) but not than poor sleepers (4.73 ± 0.15, $p > .05$) (best model: model 2). BISQ sleep quality was also significantly associated with the regulatory subscale [$F(2, 114) = 4.19$, $p = .02$] with day sleepers (5.14 ± 0.09) having a higher mean regulatory score than poor sleepers (4.77 ± 0.11; $MD_{poor\ sleepers\ –\ day}$

$_{sleepers}$ = -0.36, SE = 0.13, p = .01) but not than adult-like sleepers (4.99 ± 0.08, p >.05) .There were no significant effects of objectively (actigraphy) measured sleep quality (as measured by cluster membership) on any of the subscales of IBQ-R (all p's >.05; see *Appendix – Chapter 4)*.

4.6.3.4 LMMs sleep ritual number

Key Findings: Overall sleep ritual number was not consistently associated with either subjectively or objectively measured sleep quality.

There was a significant diary sleep quality effect for sleep ritual number [F(2,109) = 3.48, p = .034]. However, differences between clusters did not survive correction for multiple comparisons and are therefore not further discussed. There were no significant effects of actigraphy- or BISQ-measured sleep quality on stress scores in the LMMs (all p's >.05; see *Appendix – Chapter 4)*.

4.6.4 Continuous sleep parameters and maternal mental health, infant temperament and general development and number of sleep routines

In addition to sleep quality, LMMs were conducted with the four main sleep parameters (Night and Day Sleep Duration, WASO and Night Wakening Number) and questionnaire parameters as dependent variables.

4.6.4.1 Stress

Key Findings: Overall results did not show clear cross-method consistency. Objectively measured Day Sleep Duration showed developmental changes in the association with maternal stress. Higher BISQ-measured WASO was associated with higher maternal stress. There were no associations between diary-measured sleep parameters and maternal stress.

There were no significant correlations between any of the sleep variables (Night Wakening Number, WASO, Night/Day Sleep Duration) of any of the different sleep measures except for BISQ-measured WASO with stress score (r = .247, p = .003).

WASO. For BISQ-measured WASO, there was no association at 4 months of age between stress and WASO, whereas that association was stronger in the older children [F(5,138) = 3.96, p = .05]. Higher stress was associated with higher BISQ-measured WASO. There were no associations between actigraphy-measured or diary-measured WASO and the composite stress score (all p's >.05; see *Appendix – Chapter 4)*.

Night Wakening Number. There were no associations between objectively or subjectively measured Night Wakening Number on the stress score (all p's >.05; see *Appendix – Chapter 4)*.

Night Sleep Duration. There were no associations between objectively or subjectively measured Night Sleep Duration and the stress score (all p's >.05; see *Appendix – Chapter 4)*.

Day Sleep Duration. There was an interaction effect of objectively-measured day sleep by age groups on stress score with higher maternal stress for more day sleep in older children and lower stress for higher day sleep in younger children [$F(5,70) = 3.27$, $p = .010$]. Though the 12-months old age group showed lower maternal stress scores for more infant day sleep. There were no associations between subjectively-measured Day Sleep Duration and the composite stress score (all p's >.05; see *Appendix – Chapter 4)*.

4.6.4.2 General infant development

Key Findings: The main finding was that Day Sleep Duration showed cross-method-consistent developmental changes in the association with some of the ASQ subscales (problem-solving, fine motor skills). Day sleep in general seemed to be associated with parent-reported general development. Findings with regard to other parameters were more fragmented though many parameters showed age-related changes in the association of sleep and general development.

WASO. For objectively measured WASO only an association with gross motor subscale was found. This was an interaction effect of age group by WASO on gross motor skills [$F(5,107) = 2.76$, $p = .022$]. Age groups 4 months, 6 months, 8 months and 14 months showed a positive relationship between WASO and gross motor scores, age groups 10 months and 12 months showed a negative relationship between WASO and gross motor scores. All other subscales showed no association (all p's >.05; see *Appendix – Chapter 4)*. For illustration see *Figure 4.3*. There were no associations between diary-measured WASO and ASQ-subscales (all p's >.05; see *Appendix – Chapter 4)* expect for the social subscale where there was a significant interaction for age group by diary-measured WASO [$F(5,101) = 2.48$, $p = .040$] with a negative relationship between WASO and ASQ social score in age groups 8 months, 10 months, and 14 months of age and no relationship between the two parameters in all other age groups. There were no associations between BISQ-measured WASO and any of the subscales of ASQ (all p's >.05; see *Appendix – Chapter 4)*.

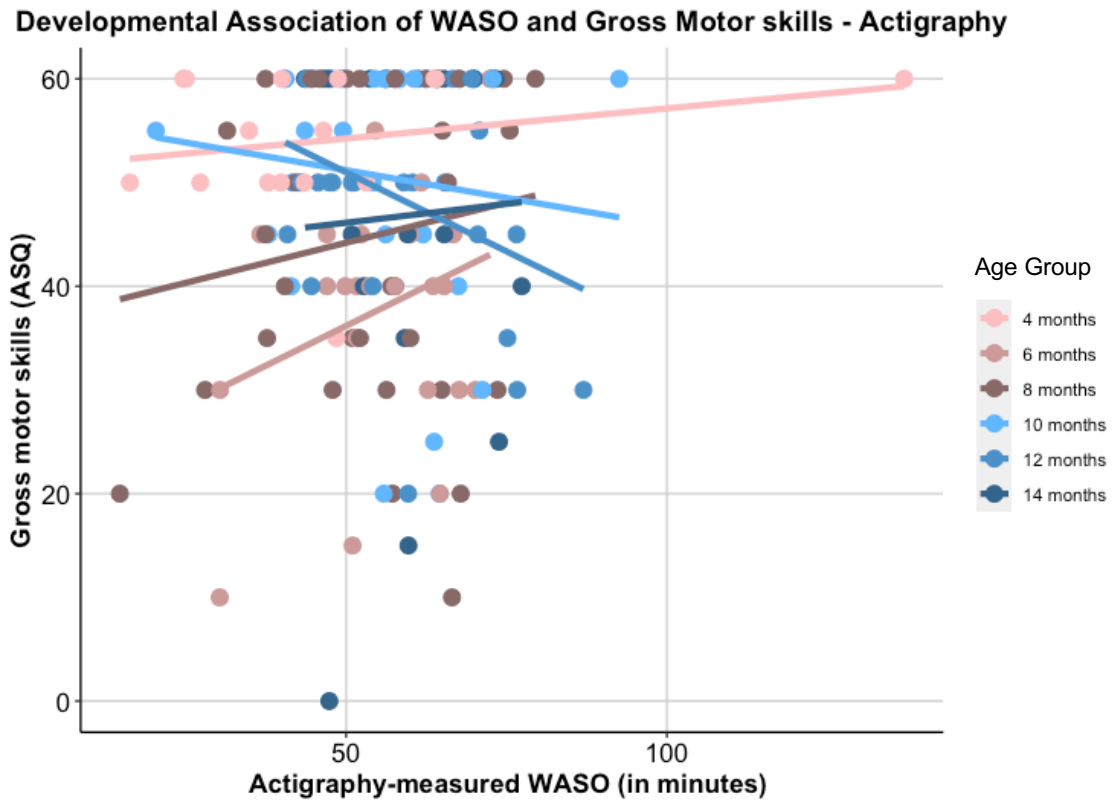


Figure 4.3. Developmental association between Gross Motor skills (ASQ) and objectively measured WASO. Lines represent trendlines of the association between gross-motor skills and WASO in each age group respectively.

Night Wakening Number. For diary-measured Night Wakening Number only an association with fine motor skills was found. There was a significant interaction for age group by Night Wakening Number [$F(5,118) = 2.44$, $p = .038$], where more night wakenings were associated with lower fine motor skills in age groups 4, 6, and 14 months of age, with no relationship at 8 months of age and a positive relationship at 10 and 12 months of age. There were no associations between BISQ-measured or actigraphy-measured Night Wakening Number on any of the subscales of ASQ (all p's >.05; see *Appendix – Chapter 4)*.

Night Sleep Duration. For objectively measured Night Sleep Duration only an association with the social subscale was found. There was a significant interaction for age group by Night Sleep Duration [$F(5,125) = 2.84$, $p = .018$]. There was a positive association between night sleep and social subscale score in the 6 months and the 10 months age group and a negative association between night sleep and social subscale in the 12-months age group. There did not seem to be an association in any of the other age groups. There were no associations between subjectively measured

Night Sleep Duration and any of the subscales of ASQ (all p's >.05; see *Appendix – Chapter 4)*.

Day Sleep Duration. For the actigraphy-measured Day Sleep Duration there was a main effect on the fine motor subscale [$F(1,133) = 6.16$, $p = .014$] with the association of more day sleep and lower fine motor skills. There were significant interaction effects of Day Sleep Duration by age group for problem-solving subscales for BISQ-measured [$F(5,125) = 2.70$, $p = .024$, diary-measured [$F(5,123) = 2.54$, $p = .032$] and actigraphy-measured [$F(5,128) = 4.03$, $p = .002$] Day Sleep Duration. See *Figure 4.4*. for illustration. For diary and BISQ the patterns emerging are mirroring patterns of the fine motor scales with age groups of 10, 12, and 14-months old there was a negative relationship between Day Sleep Duration and problem-solving subscale with more day sleep being associated with lower problem-solving skills. For actigraphy generally there was a trend of lower problem-solving skills and higher Day Sleep Duration except for the 12-months-old age group where the inverse relationship was true. Though from the plot it appears that the 12-months effect might be driven by one data point. There were no effects for communication and social subscales for subjectively measured Day Sleep Duration (all p's >.05; see *Appendix – Chapter 4)*.

There was a significant interaction of group by actigraphy-measured Day Sleep Duration for the communication [$F(5,132) = 3.83$, $p = .003$] and a main effect for actigraphy-measured Day Sleep Duration for the social subscale [$F(1,137) = 4.24$, $p = .041$] with lower social skills being associated with more Day Sleep Duration. There were no associations of actigraphy-measured and BISQ-measured Day Sleep Duration and gross motor scales (all p's >.05; see *Appendix – Chapter 4*). There was an interaction effect for age group by diary-measured Day Sleep Duration [$F(5,96) = 3.38$, $p = .007$] for gross motor skills with 14-months old infants showing lower gross motor skills with more day sleep duration. There were significant interaction effects for the fine motor subscales for BISQ-measured day sleep duration: age group by Day Sleep Duration [$F(5,125) = 2.70$, $p = .024$]; and for diary-measured age group by Day Sleep Duration [$F(5,113) = 2.29$, $p = .051$]. With both showing patterns where in the age groups of 10 months, 12 months, and 14 months old there was a negative relationship between Day Sleep Duration and fine motor skills with more day sleep leading to lower scores on the fine motor scales. In the younger age groups this association was not as clear cut.

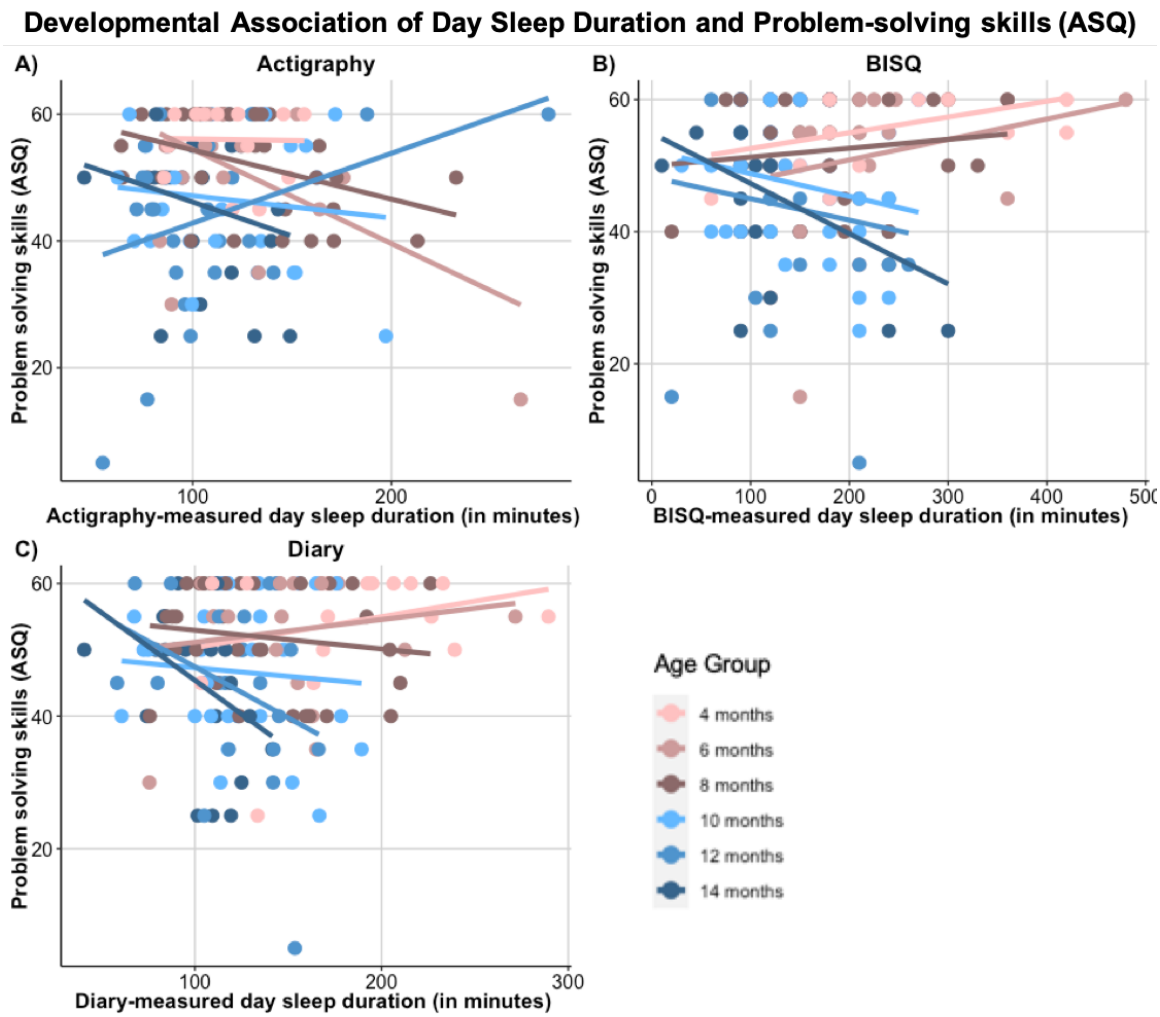


Figure 4.4. Illustration of the developmental changes in the association between objectively (A) and subjectively (B – C) measured day sleep and parent-reported problem-solving skills. Lines represent trendlines of the association between problem-solving skills and Day Sleep Duration in each age group respectively.

4.6.4.3 Infant temperament

Key Findings: More subjectively measured sleep fragmentation was associated with higher negativity scores. There were developmental changes in the association of objectively measured Night Sleep Duration with the Surgency subscale. Day Sleep Duration showed no association at all with infant temperament.

WASO. There was an a main effect of BISQ-measured WASO on negativity scale scores [$F(1,122) = 5.55$, $p = .020$]. There was a positive association between negativity score and BISQ-measured WASO for all age groups except age group 4 months old. There were no associations between IBQ-R subscales and actigraphy-measured WASO or diary-

measured WASO and no effects for surgency and regulatory subscales BISQ-measured WASO (all p's >.05; see *Appendix – Chapter 4*).

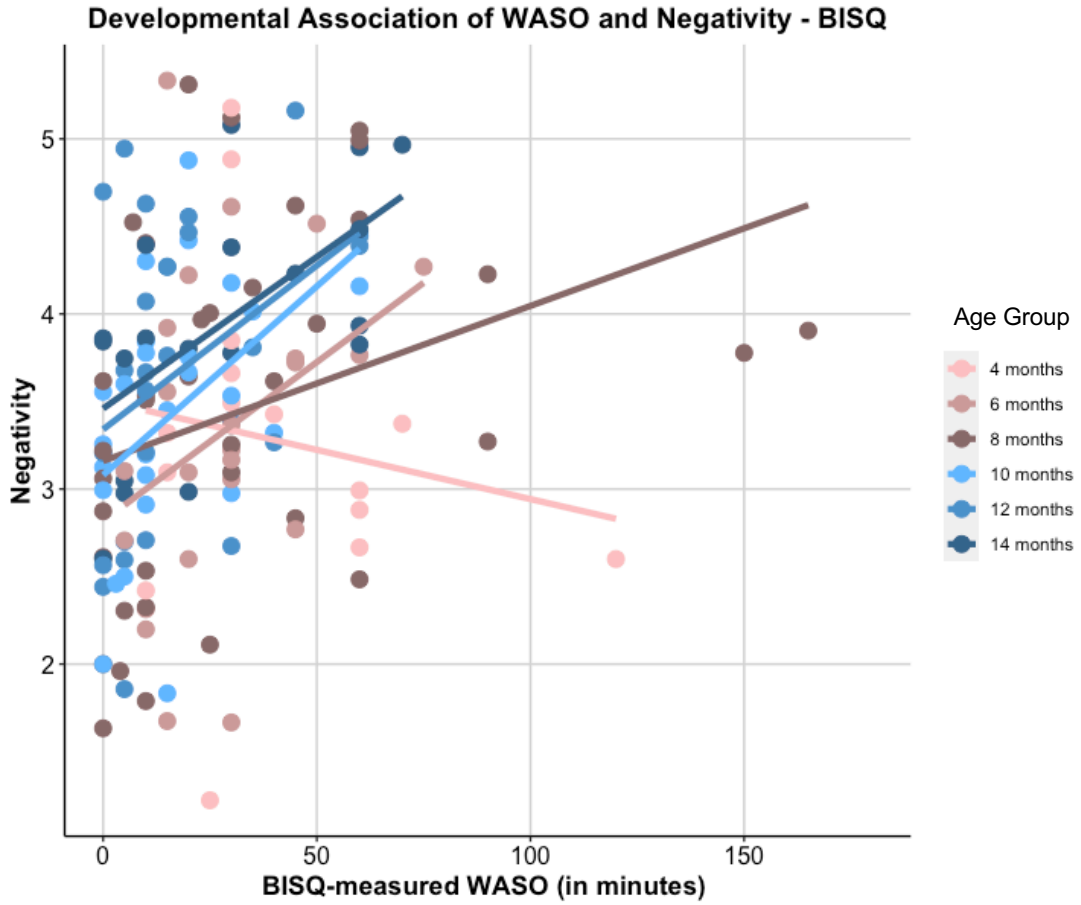


Figure 4.5. Illustration of the developmental changes in the association between BISQ-measured WASO and negativity/ negative emotionality dimension of the IBQ-R.

Night Wakening Number. There were significant main effects for both diary-measured Night Wakening Number [$F(1,119) = 13.86$, $p<.001$] and for BISQ-measured Night Wakening Number [$F(1,141) = 5.65$, $p = .019$] for the negativity dimensions. There was a positive association between negativity score and BISQ-measured Night Wakening Number for all age groups except the 4-months olds. These results match results from the WASO analyses above. Results for diary-measured Night Wakening Number showed a positive relationship between Night Wakening Number and negativity subscale for all age groups. There were no associations for any of the IBQ-R dimensions for actigraphy-measured Night Wakening Number. There were no effects for surgency and regulatory subscales of BISQ-measured and diary-measured Night Wakening Number (all p's >.05; see *Appendix – Chapter 4*).

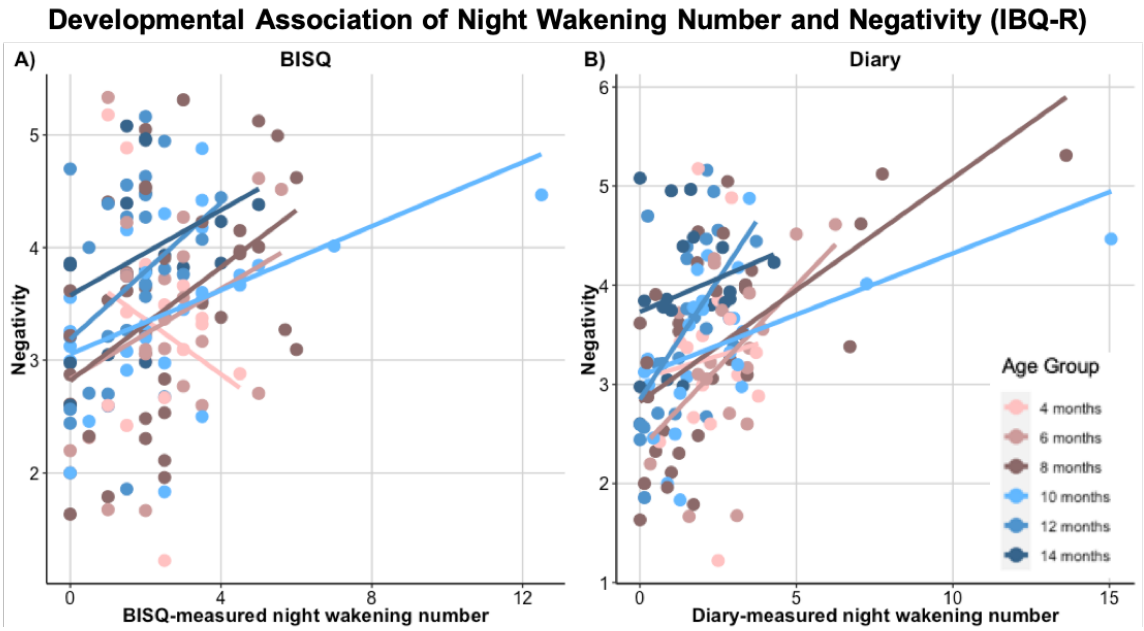


Figure 4.6. Association between subjectively measured (A) BISQ and B) diary) Night Wakening Number and IBQ-R Negativity dimension. Lines represent trendlines of the association between negativity and Night Wakening Number in each age group respectively.

Night Sleep Duration. There was a group by Night Sleep Duration interaction effect for the surgency subscale [$F(5,96) = 2.66$, $p = .027$] for the actigraphy measure. The relationship between Night Sleep Duration and surgency dimension was positive between ages 4 months to 8 months and slightly negative/constant in the older age ranges (10 months to 14 months). There were no associations between IBQ-R subscales for subjectively measured night sleep duration. There were no effects for regulation or negativity dimensions on actigraphy-measured Night Sleep Duration (all p's >.05; see *Appendix – Chapter 4*).

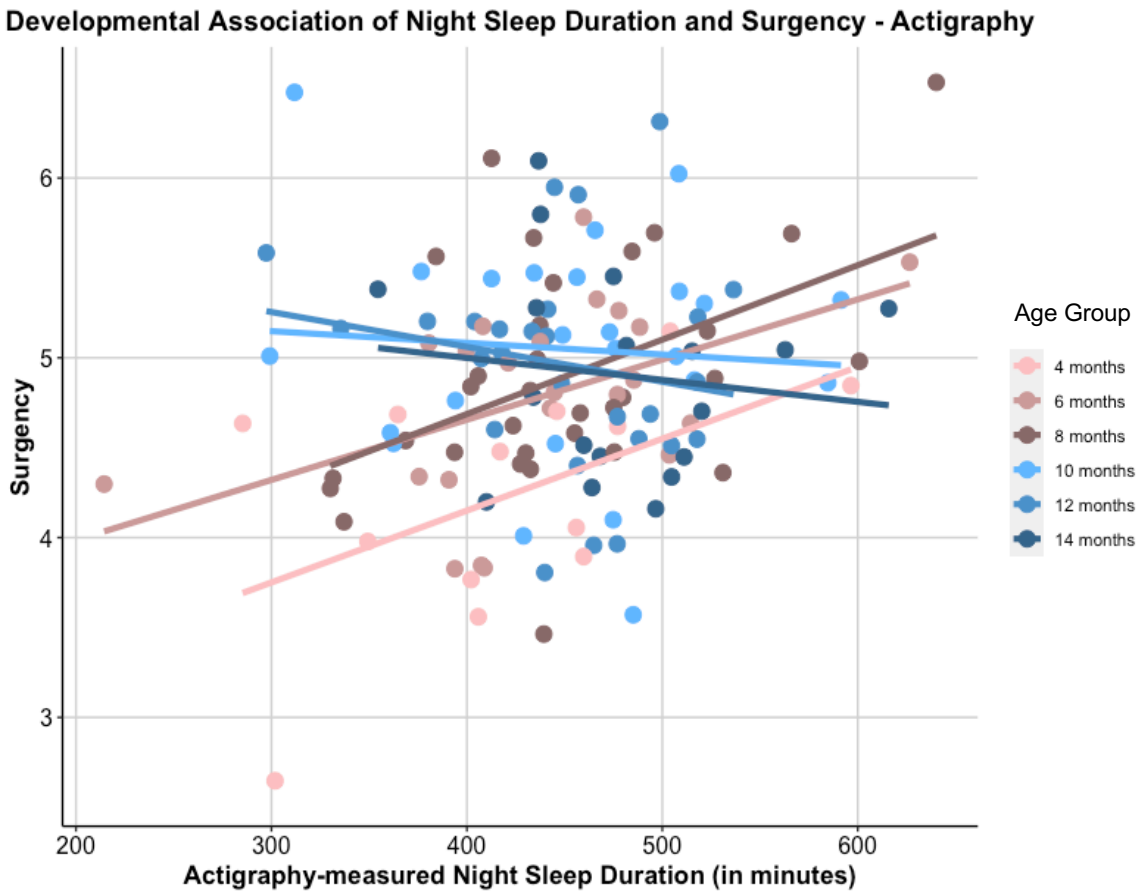


Figure 4.7. Illustration of the developmental changes in the association between objectively measured Night Sleep Duration and surgency/ positive emotionality dimension of the IBQ-R. Lines represent trendlines of the association between surgency and Night Sleep Duration in each age group respectively.

Day Sleep Duration. There were no effects of either objectively or subjectively measured Day Sleep Duration on any of the IBQ-R dimensions (all p's >.05; see *Appendix – Chapter 4)*.

4.6.4.4 Number of bedtime rituals

Key Findings: There were some associations between subjective sleep parameters and number of bedtime rituals, however no consistent pattern emerged. There were no associations with objectively measured sleep parameters.

WASO. There was a significant interaction effect of age group by BISQ-measured WASO on sleep ritual number [$F(5,125) = 2.85$, $p=.018$]. However, age group comparisons did not survive corrections for multiple comparisons using the Bonferroni

method. There were no associations between diary-measured or actigraphy-measured WASO on sleep ritual number (all p's >.05; see *Appendix – Chapter 4)*.

Night Wakening Number. There were no associations between either objectively or subjectively measured Night Wakening Number and sleep ritual number (all p's >.05; see *Appendix – Chapter 4)*.

Night Sleep Duration. There was a main effect of diary-measured Night Sleep Duration [$F(1,96) = 7.09$, $p = .009$] with a positive relationship between sleep ritual number and Night Sleep Duration. There were no effects for actigraphy-measured or BISQ-measured Night Sleep Duration on sleep ritual number (all p's >.05; see *Appendix – Chapter 4)*.

Day Sleep Duration. Diary-measured Day Sleep Duration interaction of age group by Day Sleep Duration [$F(5,103) = 2.62$, $p = .029$]. However, age group comparisons did not survive multiple comparisons. There were no effects for actigraphy-measured or BISQ-measured Day Sleep Duration on sleep ritual number (all p's >.05; see *Appendix – Chapter 4)*.

4.6.5 Maternal education as predictor for continuous sleep parameters

Results of the LMMs that did not show a predictive effect of maternal education on continuous sleep parameters (Night and Day Sleep Duration, Night Wakening Number, WASO) as measured by actigraphy or diary (all p's >.05). There was a significant effect of maternal education on BISQ-measured WASO [$F(2,61) = 5.42$, $p = .006$] with mothers with a university degree having on average higher WASO than mother without a university degree.

Table 4.4. Summary of results Chapter 4

		IBQ-R			ASQ					Stress	Maternal education	Sleep rituals
		SUR	**NEG**	**REG**	**COM**	**FM**	**GM**	**PS**	**SOC**			
Sleep quality	A											
	D		° did not survive multiple comparison									° did not survive multiple comparison
	B	day sleepers > adult-like sleepers		Day sleepers > poor sleepers								
Night Waken-ing number (NW)	A											
	D		↑NW↑Negativity			4m:↑NW ↓FM 6m:↑NW ↓FM 8m: - 10m:↑NW ↑FM 12m:↑NW ↑FM 14m:↑NW ↓FM						
	B		↑NW↑Negativity (except 4-months olds)									
WASO	A						4m:↑WASO ↑GM 6m:↑WASO ↑GM					

							8m: ↑WASO ↑GM 10m: ↑WASO ↓GM 12m: ↑WASO ↓GM 14m: ↑WASO ↑GM					
	D								4m: - 6m: - 8m: ↑WASO ↓ SOC 10m: ↑WASO ↓ SOC 12m: - 14m: ↑WASO ↓ SOC			
	B		↑Negativity ↑WASO (except age group 4 months old)							↑stress ↑WASO	mothers with university degree: ↑ WASO	4m: ↑WASO ↑ sleep ritual number 6-14 m: no association
Night sleep duration	A	4-8 m: ↑night sleep ↑SUR 10 – 14 m: ↑night							4m: - 6 m: ↑night sleep ↑ SOC 8 m: -			

		sleep ↓ SUR or no association							10 m: ↑ night sleep ↑ SOC 12 m: ↑ night sleep ↓SOC 14 m: -			
	D											↑sleep ritual number ↑night sleep duration.
	B											
Day Sleep Duration	A				4 m: - 6 m: ↑day sleep ↓COM 8 m: ↑day sleep ↑COM 10 m:↑day sleep ↓COM 12 – 14 m: ↑day sleep ↑COM	↑day sleep ↓ FM		↑day sleep ↓PS (except 12 months olds: inverse relationship)	↑day sleep ↓ SOC (exception: 12m	4-8 m: ↑ day sleep ↓ stress 12 m: ↑ day sleep ↓ stress 10, 14 m: ↑day sleep ↑ stress		
	D					4-8 m: association not clear 10 m: ↑day sleep ↓ FM	4 m: - 6 m: ↑day sleep ↓GM 8 m: - 10 m: ↑day sleep ↓GM 12 m: -	4m: ↑ day sleep ↑ PS 6 m: ↑ day sleep ↑ PS 8 m: -				4-6 m: ↑day sleep ↑sleep ritual number

						12 m: ↑day sleep ↓FM 14 m: ↑day sleep ↓ FM	14 m: ↑day sleep ↓GM	10 m: ↓ day sleep ↑PS 12 m: ↓ day sleep ↑PS 14 m: ↓ day sleep ↑ PS				8-14 months: ↑day ↓sleep ritual number
	B					4-8 m: association not clear 10 m: ↑day sleep ↓ FM 12 m: ↑day sleep ↓FM 14 m: ↑day sleep ↓ FM		4m: ↑ day sleep ↑ PS 6 m: ↑ day sleep ↑ PS 8 m: ↑ day sleep ↑ PS 10 m: ↓ day sleep ↑PS 12 m: ↓ day sleep ↑PS 14 m: ↓day sleep ↑ PS				

Note. ↑ increase in, ↓ decrease in, ° did not survive multiple comparison, m = months, COM=Communication subscale PS = Problem-solving subscale, GM = Gross motor subscale, FM = Fine motor subscale, SOC = social subscale, NEG = negativity dimension IBQ-R, SUR = surgency dimension IBQ-R, REG =regulation dimension IBQ-R, D = Diary, A = Actigraphy, B = BISQ, blue = developmental changes in the association between sleep parameter and questionnaire measure, red = negative association between sleep parameter and questionnaire measure, green = positive association between sleep parameter and questionnaire measure.

4.7 Discussion

The overarching goal of this chapter was to identify associations between infant sleep (using objective and subjective measures of infant sleep quality and sleep parameters) and measures of infant temperament, infant general development and maternal mental health. Furthermore, bedtime rituals and maternal education were examined.

Results from *Chapter 3* suggested that some cross-method inconsistencies were to be expected. Nonetheless, common themes were expected, especially with regard to sleep fragmentation measures and between subjective measures (both parent-report) or between diary and actigraphy (both estimating one week of sleep).

4.7.1 Developmental changes of questionnaire measures

Stress levels. Developmental changes were not apparent in number of sleep routines or in maternal stress levels. Prior research has also not shown a relationship between maternal stress and anxiety and infant age. This can likely be interpreted as maternal anxiety being more an individual maternal characteristic rather than dependent on infant age.

Infant temperament. There were some developmental changes in negativity and surgency scales of the IBQ-R but not in the regulatory scale. For example, the relationship between objectively measured Night Sleep Duration and surgency dimension was positive between ages 4 months to 8 months and slightly negative/constant in the older age ranges (10 months to 14 months). Prior research has cited moderate continuity for the different subscales, though Carranza, González-Salinas and Ato (2013) mention that the regulation subscale was stable (Carranza et al., 2013). This somewhat matches the present results. While some age-related changes in temperament occur in the emotionality subscales, the regulation subscale shows individual stability across the first year of life. It is important to acknowledge that the IBQ-R was used also in the 14-months old group, even though the questionnaire is only intended to be used until age 12 months.

4.7.2 Stress measures and their relation to sleep

This chapter focused on identifying the relationship between objectively /subjectively measured sleep quality (as identified by data-driven clusters) and objectively /subjectively measured continuous sleep parameters and self-reported measures of maternal stress. Results from *Chapter 3* suggested that some cross-method

inconsistencies were to be expected. Nonetheless, common themes were expected especially with regard to sleep fragmentation measures and between subjective measures (both parent-report) or between diary and actigraphy (both estimating one week of sleep).

There were no relationships between sleep quality, as measured by the sleep clusters, and maternal stress composite score. This finding aligns to some degree with the research by Sinai and Tikotzky (2012), who only found an association between sleep and maternal anxiety in mothers on maternity leave. The sample in this study contained both mothers on maternity leave and working mothers. Unfortunately, detailed information on maternity leave was not recorded, so there was no way to examine those subgroups in the present study.

Additional analyses with continuous sleep parameters revealed 1) an association between BISQ-measured WASO and maternal stress and 2) actigraphy-measured day sleep and maternal stress, with higher stress for more day sleep in older children and lower stress for higher day sleep in younger children. The first finding is in line with prior research showing that the more time infants spend awake at night, the higher the mothers' stress level (Goldberg et al., 2013). Interestingly, there was no association in objectively measured WASO. It is possible that maternal perception (i.e., BISQ-measured) of night waking led to higher stress levels, even though the underlying (true) night wakening might not be different in high- versus low-stress mothers. It could also be that mothers who are woken up by their infant at night are more stressed by the experience of their own disrupted sleep. Given the discrepancy between measures, it is also possible that stressed parents perceive sleep fundamentally differently. To clarify the causal relationship between infant sleep and maternal stress, one would need to use a gold standard sleep measure such as polysomnography to obtain information about underlying true infant sleep patterns. Of course, mothers who were more stressed could also have worse sleep themselves (Åkerstedt et al., 2007), spending more time awake at night and therefore taking note of their child's awakenings. Similarly, some mothers might not have known when their infant was awake, whereas actigraphy would have captured it, leading to differences in objectively and subjectively reported night wakening.

The second finding of an association of actigraphy-measured day sleep and maternal stress, with higher stress for more day sleep in older children and lower stress for higher day sleep in younger children, accentuates the findings described in *Chapter 3*. As reminder, these showed that cross-method agreement was associated with both infant age and maternal stress. While this relationship has not been described in the literature

yet, it hints towards developmental changes that were also discussed by Sordono and Reeb-Sutherland (2015). One explanation for this result is that parents expect younger infants to sleep during the day and are thus less stressed by their infant's day sleep. Additionally, one may easily take a 6-month-old infant out of the house in their stroller while they are sleeping. However, older infants rarely sleep in a stroller, meaning that parents have to stay at home with their child and wait until they are awake. Lastly, while day sleep in younger infants is a developmental characteristic of their sleep, day sleep should reduce in older infants. Increased day sleep in older infants could also be associated with more night wakening and less night sleep, so as to compensate for missed sleep. This naturally means that parents sleep less during the night and are therefore more tired and stressed. However, follow-up analyses of the present study showed that there was no consistent association between WASO/Night Wakening Number/Night Sleep Duration and Day Sleep Duration when controlled for age.

In summary, while maternal stress was related to objectively measured day sleep and subjectively measured WASO, the results were not consistent across methods.

4.7.3 General development and relation to sleep

Furthermore, I explored the relationship between objectively /subjectively measured sleep quality (as identified by data-driven clusters) and objectively /subjectively measured continuous sleep parameters and parent-reported measures of general development. Effects were found for continuous sleep parameters but not for sleep quality measures. There were no effects of sleep quality (as assessed by data-driven sleep clusters) on the measures of general development (ASQ subscales). This is in line with prior research that does not show a relationship between sleep quality and developmental scores (e.g., Camerota et al., 2020; Spruyt et al., 2008).

However, after the additional analyses with objectively and subjectively measured continuous sleep parameters, several findings stood out. First of all, results for night sleep parameters differed across methods. There were no effects for BISQ-measured parameters for subjective sleep measures. For diary-measured parameters, associations showed different relationships between ASQ social subscale and WASO depending on age, where especially in the older age group (8-, 10- and 14-months) higher WASO was associated with lower social ASQ scores. This finding might indicate that older infants who spent more time awake at night had worse social skills according to parent-report. It could be that infants who spent more time awake at night were more tired during the day, and therefore moodier and less sociable. However, there could also be a difference in parental

perception. Infants who were more awake at night were more likely to have stressed mothers (see above), which could have altered the parent-child interaction, thereby impacting either the parent-report of infant social skills or the social skills themselves. Future research should try and consider mother-child interactions when studying sleep, maternal stress and infant social skills.

With respect to fine motor skills, diary-measured Night Wakening Number showed similar patterns in age groups 4-, 6-, and 14-months olds (i.e., a negative relationship), but there was a positive association in age groups 10 and 12 months between night wakening and fine motor subscale scores. There were no effects for Night Sleep Duration. These findings are not consistent across the two parameters that are closely linked (WASO and Night Wakening Number) or across the two subjective measures. *Chapter 3* has shown consistency across sleep measures is subpar, perhaps explaining why there were no cross-method consistent results here. However, within diary measures, the same patterns should be apparent as infants who wake up more at night ordinarily have higher WASO values. This finding is puzzling. It is possible that the findings are spurious, and caution should be taken when drawing conclusions. Of course, it might be that frequent, short sleep disruptions are worse for development than one long awakening, even if the total amount awake at night equals the same amount. These findings do seem to indicate that there are age-related changes in the relationship between parent-reported social skills and fine motor skills and parent-reported night sleep parameters. This possibly suggests the presence of critical periods in the relationship between sleep and development, such that certain patterns of sleep might be beneficial at certain ages for certain skills.

With regard to the objective sleep measure, the different age groups showed distinct patterns for the relationship between gross motor skills and WASO. More WASO was associated with higher gross motor scores at age 6, 8, and 14 months, but higher WASO was associated with *lower* gross motor scores at 10 and 12 months of age. This could mean that there are certain critical periods where an infant might benefit from night wakenings and other periods where they do not. The period between 10 and 12 months is usually when infants start to walk, a gross motor skill. It is possible that continuous sleep and low WASO is relevant in that period of intense motor learning, but not so much earlier and later in development. This theory could mean that critical periods in development are accompanied and even perhaps facilitated by certain sleep patterns. It is impossible to tell from the present data whether this is the case, but future studies should look into gross motor development and patterns of sleep and perhaps even

investigate the impact of sleep interventions in gross motor learning. However, this pattern was not apparent in the night wakening.

Most notable are the findings regarding Day Sleep Duration which were consistent across both objective and subjective sleep measures. Critically, fine motor and problem-solving scales were related to Day Sleep Duration, where higher parent-reported day sleep was associated with lower scores on fine motor and problems solving, especially in older infants. Objectively measured sleep showed the same pattern across all age groups for fine motor skills. For problem-solving skills, the same patterns emerged as for subjective measures except for the 12-months age group where the inverse was true. Other subscales on the ASQ (i.e., the gross motor or social) also showed the same patterns of lower scores with higher sleep duration. Day Sleep Duration is not as commonly studied as night sleep parameters; however, according to my findings, this might be an important variable to consider when studying the relationship between sleep and development. Studies so far have indicated a positive relationship between day sleep and measures of development. For example, Horvath et al. (2016) showed that Day Sleep Duration was associated with vocabulary growth later in childhood. There are also many studies showing an association of the benefits of naps on memory. Only one study so far has shown that there was an association between problem solving and napping. Berger and Scher (2017) showed that infants who napped were actually better at a motor problem-solving task. These results seem contrary to Berger and Scher (2017). The present results could mean that while daytime napping is beneficial for infants, perhaps there is a dose-response relationship where too much daytime sleep is detrimental to general development, in particular to problem-solving and fine-motor skills.

In summary, the association between ASQ measures and sleep patterns corroborate the claim that sleep might have a general relation to neurocognitive development. Moreover, this relationship seemed to change with infant age and depending on the sleep assessment method and parameter used. However, a key limitation has to be noted here. The assessment of general development is based on parent-report of infant skill level. While this approach was appropriate in order to compare this study's results to prior research that employed such measures (e.g., Pisch, 2015), parent-report is potentially biased. It might be important to investigate the role of day sleep on general development specifically, where general development is assessed by a researcher, such as via the Mullen Scales of Early Learning. Future research should therefore aim incorporate such measures into the study design.

4.7.4 Infant temperament and sleep

In addition to maternal stress and anxiety measures, I explored the relationship between objectively /subjectively measured sleep quality (as identified by data-driven clusters) and objectively /subjectively measured continuous sleep parameters and parent-reported measures of infant temperament. There were no effects of objectively measured sleep quality on any subscales of the IBQ-R. However, negativity differed between diary clusters, and surgency differed between BISQ clusters. The diary clusters did not survive multiple comparison, so they are not further discussed. Infants in the BISQ-defined group of day sleepers had higher scores on both regulatory and surgency subscales. Both of these subscales, especially surgency, have been associated with later self-regulation abilities (Putnam et al., 2008). This could suggest that day sleep is related to later self-regulation abilities. Contrary to Spruyt et al. (2008), there was no association between Day Sleep Duration and negativity score, but the association between easy temperament and higher Day Sleep Duration matches the above findings (Spruyt et al., 2008). However, I did not find a similar pattern for diary measures. These differences between the subjective measures might be explained by the systematic differences between the two measures that were previously found (see *Chapter 3*). Nonetheless, further studies are required.

With regard to continuous sleep parameters, higher indices of BISQ-measured sleep fragmentation (i.e., higher Night Wakening Number and higher WASO) were associated with higher negativity scores. A similar pattern was found for diary-measured parameters. The temperament trait of negativity/negative affect may be related to increased sensory sensitivity (Dunn, 2001). It could be possible that infants with increased sensory sensitivity exhibit higher negativity-related behaviours during the day and are more sensitive to surrounding environment and potential disrupting stimuli during sleep. This could in turn mean they are more likely to wake up at night and have greater difficulty maintaining sleep. This theory should be studied further by administering sensory sensitivity measures in addition to sleep and temperament measures to determine a potential causal relationship or by investigating the fine-grained subscales instead of the overarching dimensions of the IBQ-R in more detail. Secondly, as suggested above, it may also be that infants who wake up a lot at night are moodier during the day, resulting in higher parent-reported negativity. Given the role of sleep in emotion regulation, as proposed by some sleep function theories (see *Chapter 1*), this could be important to study in future studies.

As the link between fragmentation and negativity was only apparent in the subjective measures, one has to consider the impact parental perception has on reporting

an infant's behaviour. For instance, it may be possible that parents who spend more time awake at night due to their infants' increased night wakening are more tired, and thus systematically report more negatively on their infant's temperament. This should be further examined by taking objective measures of infant temperament.

Interestingly, objectively measured Night Sleep Duration was associated with the surgency/positive emotionality dimension. Younger ages (4 to 8 months) had higher surgency scores with more night sleep and older infants (10 to 14 months) had slightly lower surgency scores for higher Night Sleep Duration. However, the subjective measures did not show any effect of sleep duration. The findings hint towards a potential developmental change in the relationship between sleep and temperament such as reported by Sordono and Reeb-Sutherland (2015), though the pattern in the present study is different. As reported above, the surgency subscale scores in infancy have been shown to be associated with better toddler effortful control (Putnam et al., 2008). The developmental changes could again mean that, at different times in the first year of life, certain sleep patterns benefit different aspects of temperament, paralleling the above-discussed developmental changes in infant general development and sleep.

Moreover, there was no direct relationship between objectively measured Day Sleep Duration and IBQ-R measures, which is puzzling given the results on sleep quality mentioned above. It underscores the importance of investigating different aspects of day sleep. The sleep quality measures contained information on the longest sleep period during the day and the number of naps, which was not studied here. Thus, a more fine-grained look into the role of day sleep may be required.

4.7.5 Maternal education and sleep

There did not seem to be a relationship between maternal education and sleep parameters in this study. While there was a significant relationship between education and BISQ-measured WASO, this effect was not apparent in other sleep measures nor in other sleep parameters measured by the BISQ (e.g., Night Wakening Number). The categories of maternal education in the present study were quite broad (only three distinct categories) and the sample, though diverse in terms of apprenticeship vs. university degree, was not well represented in the high-school only education category. Moreover, it might have been better to record number of years in education or use a composite score of SES rather than to use only one measure. While this limits the generalisability of the findings to a certain extent, it also means that SES/maternal

education did not confound the other associations found in the study, as the sample was fairly homogenous.

4.7.6 Bedtime rituals and parental perception of sleep

Results of sleep rituals and parental perception of sleep problems analysis showed that about 35 % of the parents reported some form of infant sleep problems. This matches prior research in which parents reported about 15 to 30 % of sleep problems in samples of comparable age (Byars et al., 2012; Meltzer & Mindell, 2006). Sleep problems are problematic insofar as that they can cause cascading problems on many aspects of development (Byars et al., 2012).

Given that parental bedtime rituals influence infant sleep substantially, one of the research aims was to investigate whether the number of different sleep rituals might be related to infant sleep quality. While there were no effects for actigraphy- or BISQ-measured sleep quality on sleep ritual number, diary-measured sleep clusters were different for sleep ritual number.

4-month-old infants who were exposed to more sleep rituals at night also spent more time awake at night. While the 4-months age group was small in comparison to the other groups, this finding could suggest that, in younger ages, more sleep rituals are arousing rather than soothing for the infant. This would be crucial to consider when designing sleep interventions for infant sleep problems. Conversely, it is also possible that parents of poor sleepers try many different rituals at night in order to try and improve their infant's sleep.

Interestingly, the number of sleep rituals was also associated with overall Night Sleep Duration. It could therefore also mean that infants were simply sleeping longer and thus had a higher chance of waking up at night and thus having higher WASO. Moreover, there was a positive association between number of sleep rituals and diary-measured Day Sleep Duration in the 4- and 6-months age groups, no association between sleep ritual number and Day Sleep Duration in age groups 8- and 10-months of age, and a negative relationship between sleep ritual numbers and Day Sleep Duration in the age groups of 12 and 14 months. Again, this hints towards possible differences in the effectiveness of sleep rituals on infant sleep depending on the infant's age.

These findings could be integrated with findings above. The association between night sleep ritual/routine number and day sleep might actually be related to the impact of sleep ritual number on Night Sleep Duration. Lower or higher Night Sleep Duration could then impact Day Sleep Duration. This could mean that, in younger infants, more

rituals at night are arousing, leading to less night sleep and consequently more day sleep. It may be that in older infants, more rituals at night lead to longer night sleep and consequently shorter day sleep. Future research, perhaps using moderation/mediation or latent variable analyses, should investigate whether sleep ritual number mediates the relationship between day sleep and night sleep.

4.7.7 Future directions and conclusions

Much like prior research, the results presented here paint a mixed picture with regard to the relationships amongst sleep parameters and questionnaire measures. However, this study highlights the importance of measuring sleep subjectively and objectively, as results show occasionally diverging findings for those two sleep methods. The results also highlight the importance of studying night and day sleep parameters, as well as their influence on general infant development and temperament. Lastly, it appears that certain types of sleep might be beneficial for different aspects of development or temperament at certain ages but not at others. This means that potentially critical periods in development are accompanied and even perhaps facilitated by certain sleep patterns.

One recently emerging approach to studying sleep and development has centred on the idea to consider variables that mediate/moderate the relationship and also to considering sleep as a moderator in other relationships commonly studied in infancy. For instance, the relationship between maternal and infant characteristics. Recently, Camerota et al. (2020) showed that infant sleep quality can be a moderator in the relationship between maternal education and infant attention, as well as between maternal sleep quality and infant general cognition (Camerota et al., 2020). These studies shift the focus to sleep as a contributing factor rather than a key causal one. Of course, this is slightly out of the scope of this work, as it focusses on infant sleep specifically. Nonetheless, the role of sleep as a moderator/mediator in development is crucial to consider in future studies. Recent research has demonstrated the importance of considering variables such as cultural background or maternity leave as moderators in the relationship between infant sleep and aspects of infant development, too (Goldberg et al., 2013; Sinai & Tikotzky, 2012).

These are just a few examples that illustrate that the relationship between infant sleep and aspects of their development could be influenced by a myriad of environmental, parental and infant characteristics, and even by aspects of sleep quality itself. When studying infant sleep and neurocognitive development, research should aim to take those into account to disentangle contributing factors. Unfortunately, the nature of the

accelerated design of the present study and the high number of missing (longitudinal) data means that mediation/moderation analyses are not a valid option to investigate the present dataset. While the present data did not suggest a relation of sleep with maternal education, it is worth considering such approaches in future studies. The aim should be to collect a larger, more diverse sample that would allow us to understand the role of environment on infant sleep and the myriad of factors interacting with each other.

Emerging evidence suggests that real-world models of infant sleep should integrate both external and internal characteristics of infant sleep. Moreover, as infants sleep is also closely associated with maternal sleep before, during and after pregnancy (Nakahara et al., 2020), future research should also include maternal sleep as a control variable.

Lastly, a few recent studies highlight the importance of collecting information on socio-cultural background and the significance that culture plays in the sleep practices/routines of infants. For example, Mindell and colleagues (2010) report cross-cultural differences in sleep duration and parent-reported sleep problems (Mindell et al., 2010). These differences in sleep duration are likely related to cross-cultural differences in *how* infants are put to sleep and availability of parents at bedtime and at night. Studies found that Brazilian infants and toddlers and children from Asian countries had systematically later bedtimes (by almost 2 hours) than were reported in European/US samples (Mindell et al., 2010; Netsi et al., 2017). Moreover, a review of 836 papers showed that co-sleeping depends on parents' values and cultural beliefs (Baddock et al., 2019). In turn, co-sleeping has been shown to significantly impact sleep patterns of infants, with co-sleeping infants presenting with shorter sleep and more night wakenings (e.g., MacKinnon et al., 2020).

These results show that sleep patterns differ substantially across cultures and likely the influences of cross-cultural sleep on development as well. Thus, any interventions and claims made in any given piece of research are only specific to each culture. Of the limited data that is available on infant sleep and development, much originates in high income countries and western society i.e., Europe and the USA. In the future, it is crucial to study different populations (Netsi et al., 2017) with high and low SES, as well as different cultures, using comparisons of objective vs. subjective sleep measures.

In summary, this chapter highlighted the strength of measuring sleep subjectively and objectively, as this way the occasionally diverging results findings for those two sleep methods are revealed. Overall, while some relations of infant sleep and aspects of infant development and temperament emerged, there was a lack of a strong cross-method consistent picture. However, in this chapter only parent-report measures of infant

development were investigated. As described previously, parent-report is subjective, potentially not lending a true representation of infant developmental status. Therefore, there is need to integrate objective measures to understand infant cognition rather than just parent-report. This will be the focus of subsequent *Chapters 5* and *6*.

CHAPTER 5 - Studying early visual attention and sleep using eye-tracking and objective and subjective measures of sleep

The following chapter investigates the relationship between the sleep clusters as described in Chapter 3 and the eye-tracking attention measures of Study 1, described in the methodology section. Moreover, additional analyses on the sleep data of Study 1 are presented.

5.1 Definition and development of visual attention

Attention is fundamental to development. It determines what in our environment we pay regard and thus lays the foundation for learning. Attention can be defined as a cognitive function that enables selection of specific stimuli over other stimuli against a background of environmental noise and other secondary stimuli (Amso & Scerif, 2015; Scerif, 2010). The present chapter focuses on a particular expression of attention, namely attention expressed through the visual modality.

Visual attention rapidly develops over the first year, concurrent and dependent on brain maturation and more specifically on the development of the sensory system (Johnson & De Haan, 2015). As control over eye-movements develops earlier than control over hand movements or language, studying eye-movement and thus visual attention gives researchers insight into how infants learn about their environment. Changes in the (visual) attention systems take place throughout infancy and childhood but last all the way through adolescence (Amso & Scerif, 2015; Reynolds & Romano, 2016; Scerif, 2010).

The classic division of attentional systems describes three subsystems: alerting, orienting and executive attention (Posner & Petersen, 1990). Alerting refers to the maintenance of an alert or vigilant state, orienting refers to the orientation to sensory events for processing of sensory information and executive attention is described as goal-directing attention processing. These systems develop at different rates in the first year of life and depend fundamentally on brain maturation of underlying structures involved in the (widespread) attention network. These include fronto-parietal regions as well as subcortical regions such as the thalamus. In addition to the attentional subsystems, researchers also distinguish between exogenous attention (automatic allocation of

attention to the environment) and endogenous attention (controlled allocation of attention to the environment through internal volition of the person/participant) (Amso & Scerif, 2015; Scerif, 2010).

The three attentional subsystems develop at different rates throughout development. However, rather than representing entirely separate entities their underlying, anatomical structures form an interrelated network where each system performs a function to result in a human's ability to pay attention to their surroundings (Posner & Petersen, 1990). Research has shown that alerting is the first capacity present already at birth (Amso & Scerif, 2015; Reynolds & Romano, 2016; Scerif, 2010). Newborns are able to attend to their environment and react to changes in stimuli. Usually young infants are only able to attend to and track a single target but are unable to predict trajectories of movement. Infants in the first few weeks after birth also show great difficulty disengaging their attention from a stimulus in order to attend to a competing stimulus (also called "sticky fixation" / "obligatory attention"; Johnson & de Haan, 2014; Johnson et al., 1991; Johnson & De Haan, 2015). However, at 2 months of age, they are able to track objects/stimuli with their gaze smoothly and a month later even able to predict trajectories of moving objects (Johnson & de Haan, 2014). Evidence for orienting and an early form of executive attention emerges at 4 to 6 months of age (Amso & Scerif, 2015; Reynolds & Romano, 2016; Scerif, 2010). Infants are able to shift attention and gain the ability to suppress distracting information to disengaging from a stimulus presented to them (Johnson & de Haan, 2014). In the course of the second half of the first year of life infants gradually become more proficient at disengagement and learn how to sustain attention for longer periods of time. Endogenous attention is apparent at around 8-12 months of age (Colombo, 2001; Courage et al., 2006; Holmboe et al., 2018). In general, infants rely on the orienting network for controlling their attention with executive attention developing more specifically during the second year of life (Holmboe et al., 2018).

5.1.1 Studying visual attention via looking patterns / methodological aspects

Development of visual attention in the first year of life has been traditionally studied by investigating look direction and look durations towards stimuli in an infant's environment (Colombo, 2001, 2002; Richards, 2010). Looking behaviours in the first year of life tell researchers about underlying attentional processes taking place (Johnson et al., 1991).

Researchers can use these shifts of attention and looking patterns to make inferences about how humans learn new information. This is particularly useful in pre-verbal infant populations that are unable to report on their learning and are not able to use traditional button-press tasks that are commonly used in the adult attention research. Early studies coded looking behaviour of infants using head motion, examining where infants looked preferably (Colombo, 2002, Holmqvist, 2011). However, with the invention of sophisticated eye-tracking methodology (see *Chapter 2* for details), eye-tracking based looking paradigms have become a staple in developmental research. Many if not all of the above studies refer to eye-tracking studies. Eye-tracking enables measurement of attention covertly by measuring gaze direction. It offers an objective way, unbiased by experimenter bias, to study attention (Holmqvist et al., 2011). Key variables that are commonly examined in eye-tracking are: look duration towards stimuli, reaction time of gaze shifts, fixations vs. saccades (for definitions of saccades and fixations refer to *Chapter 2*).

For example, systematic changes in look duration, such as decrease or increase of looking towards novel stimuli, correspond to development of attentional abilities. Colombo (2002) describes an increase in look duration in the first 2 months, that is postulated to be related to the emergence of the alerting subsystem. Afterwards until 6 months of age look durations typically decline (Courage et al., 2006; Richards, 2010). This may be related to the development of disengagement, the ability to voluntarily shift attention, but could also just indicate improved processing speed. Starting around 7 months, look durations level off and may even increase, which researchers link to the development of sustained attention and the gradual development of the ability for endogenous control of attention (Courage et al., 2006; Holmboe et al., 2018; Richards, 2010). A key age in attention has been highlighted to be 9 months of age, attentional abilities at this age were predictive of attentional control in toddlerhood and childhood (Holmboe et al., 2018).

However, studies report high interindividual variability in attention performance with these individual differences staying stable across testing sessions (Colombo et al., 1987). This implies that some infants categorically looked faster or slower than their peers. This has been viewed as support for the hypothesis that looking behaviour may reflect inherent differences in developmental status and information processing by serving as a behavioural measure of attentional abilities (Colombo, 2002; Cuevas & Bell, 2014; Holmboe et al., 2018). Several studies show that measures of visual attention in the first years of life were predictive of cognitive functioning in childhood. For example,

shorter infants' look durations to e.g., static images (= habituation) were often associated with better cognitive functioning in childhood (Holmboe et al., 2018). Though one study did not find any relations of infant attention abilities at 7 / 12 months and at 11 years of age (Rose et al., 2012). Camerota (2018) found concurrent associations of looking times during an attention task with higher general developmental scores (Camerota, 2018).

In summary, it is possible for researchers to study visual attention to understand the processes by which infants learn about the world surrounding them.

5.2 Sleep and visual attention

The ability to pay attention has been shown to be affected by several factors in adults, such as mood or stress level (Jiang et al., 2011; Sänger et al., 2014). However, one of the biggest impediments to attention is lack of sleep. In adults, sleep deprivation has a substantial influence on sustained attention. In a meta-analysis, Lim and Dinges (2010) found the largest effect size for simple attention and vigilance tasks for sleep deprivation studies, noting that vigilance/ sustained attention was most notably affected by sleep deprivation. However, complex attention tasks were only moderately affected (Lim & Dinges, 2010). The authors reason that this is due to the fact that executive attention abilities required for complex attention tasks might necessitate additional resources beyond simple attention capabilities. Moreover, one study (Bastien et al., 2003) found that better performance on the attention task digit span was associated with better habitual sleep quality and efficiency in older adults. This is mirrored by findings of an association of subjective sleep quality, as assessed by the Pittsburgh Sleep Quality Index with better performance on attention measures (Benitez & Gunstad, 2012) and by findings linking habitual sleep patterns to impaired sustained attention (Van Dongen & Dinges, 2005), to name a few examples. These findings are further underscored by neuroimaging studies that show sleep disturbances lead to impairments in the fronto-parietal attention networks. Underlying brain structures, in addition to behaviour, seem suffer from sleep abnormalities (Chee & Tan, 2010; Krause et al., 2017). However, some studies report no association between (subjective) sleep measures and attention tasks (Miyata et al., 2013). To date it is not entirely clear how this relationship plays out during development, though many new studies are rapidly emerging.

5.2.1 Sleep and attention in development

It is crucial to understand the relationship between sleep and attention in the first year of life given that there are fewer confounding factors so early in development. For example, older children with attention problems might find it harder to resist bedtime activities that potentially disrupt sleep. Nonetheless, much more research thus far has focused on school-age children than on infants.

5.2.1.1 School-age Children

Sleep has been associated with attention abilities in school-age children. The ability to pay attention is crucial for school-age children as it is fundamental for good academic performance (Stevens & Bavelier, 2012). This is also illustrated by looking at a disorder that affects attention systems, attention deficit hyperactivity disorder (ADHD). It has been suggested that sleep problems in infancy predict a diagnosis of ADHD at a later age (Thunström, 2007; Williams & Sciberras, 2016). In turn, children with sleep disorders tend to experience a disproportionate amount of attentional problems (Beebe, 2006; Gottlieb et al., 2004). However, especially in typically developing children, not all aspects of attention seem to be equally affected by sleep, and results of studies are somewhat mixed. For example, Astill (2012)'s meta-analysis of 86 studies found no effect of Night Sleep Duration or of sleep efficiency on sustained attention among 5 – 12-year-olds. Contrary to Astill (2012), Lam et al. (2011) found a positive association between Night Sleep Duration (i.e., a sleep pattern corresponding to more mature sleep) and auditory attention in pre-schoolers (Lam et al., 2011). Similarly, children with many daytime naps had greater attentional control problems, though this was potentially associated with a decreased need for night sleep that follows from more day sleep (Lam et al., 2011). In addition to concurrent relationships with attentional abilities, sleep problems in childhood may also be associated with later attention problems. For example, another study found that parent-reported lower sleep duration in childhood (4 – 16-year-olds) correlated with self-reported attention problems in adulthood (18 - 32 years; Gregory et al., 2008).

In summary, studies into children show an association of some sleep parameters and attentional abilities, though these findings are mixed.

5.2.1.2 Infants and toddlers

Attention measures are less well-studied in toddlers and infants than in school-age children, especially in typically developing populations. This is likely because

disentangling different aspects of attention is harder in infancy due to the underlying confounding abilities such as processing speed. Research using objective measures of attention as well as sleep is still lacking.

Potential effects of early sleep patterns on later attentional abilities. Some studies have found that sleep patterns early on in life, e.g., in newborns, predict attentional abilities later on. Geva et al. (2016) found that premature infants who exhibited better sleep efficiency as newborns showed shorter first gaze durations in a visual recognition memory task at 4 months of age and in a divided attention condition at 18 months of age. Poor sleepers in this study showed greater difficulty disengaging from distracting stimuli. Another large-scale study testing over 7000 children, found that less sleep at age 6 months was associated with attention problems at age 5 for boys and girls and for age 14 for girls. Even occasional sleep problems in toddlers were reliably associated with attentional problems in adolescence (O'Callaghan et al., 2010).

Sadeh and colleagues (2015) found that infant sleep patterns at 12 months of age, better sleep quality, (i.e., sleep percent and Night Wakening Number) were predictive of better performance on the Stroop task 2 to 3 years later (Sadeh et al., 2015). Interestingly, this executive attentional control was not related to concurrent childhood sleep patterns. Another recent longitudinal study found that sleep disturbances (i.e., lower sleep duration, more night wakenings) as early as 3-months-old was associated with more symptoms of inattentiveness at age 5 (Huhdanpää et al., 2019).

These studies could hint towards a cascading effect of early sleep patterns in infancy on the development of attentional abilities later in life. Most studies did not follow infants from birth nor did they follow infants across the first year of life. It is hard to assess whether changes in attention abilities derive directly from sleep patterns or whether environmental factors could be at play that potentially interact with sleep patterns as suggested previously (Camerota et al., 2019).

Concurrent associations of sleep and attention. Compared to studies looking into the relationship between sleep and memory abilities, studies on the relationship between attentional abilities and sleep in the first year of life are scarce.

One study tracked attentional abilities and sleep longitudinally using the gap-overlap task in infants from 4 to 10 months of age (Pisch, 2015). Pisch (2015) did not find an association between either saccadic reaction time or attention disengagement and a variety of sleep parameters including sleep duration and sleep efficiency. A study looking at social attention using an eye-tracking based preferential looking paradigm found that infants with longer parent-reported (BISQ) sleep durations favoured human

faces over non-human faces (Sun et al., 2016). This effect was not as strong for children with shorter sleep durations (Sun et al., 2016). However, they did not find an association between sleep quality and looking patterns. Another aspect research has shown to be related to sustained attention was sleep regulation. Infants with better sleep regulation of well-educated mothers showed the best levels of sustained attention (Camerota, 2018). Lastly, preliminary evidence also suggests sleep microstructural differences during a nap, such as sleep spindle density was negatively associated with habituation time (Horváth et al., 2018). Of note, sleep spindle density is a sleep EEG marker that has previously been linked to cognitive ability and information processing (Hoedlmoser, 2020).

However, only one of these studies is longitudinal (Pisch, 2015), two studies do not include objective measures of sleep (Camerota, 2018; Sun et al., 2016) and the study by Horvath et al. (2018) cannot explain potential influences of habitual sleep on attention abilities. Thus, there is a need to combine both objective measures of sleep and attention into a longitudinal design.

5.2.2 A potential mechanistic link between sleep and attention

In general, the cascading effect of early sleep patterns on attention is poorly understood. Geva et al. (2016) suggest that early sleep-wake organization (before exposure to SES and environment at home and parental interaction) might serve as a gating mechanism to direct gaze towards relevant targets in a complex environment. It could be that the neurobiological structures underlying the sleep and arousal networks are influencing both attention and sleep simultaneously (see *Chapter 1*).

For example, the ascending reticular activating system (ARAS) with the reticular formation in the brain stem, has been shown to play a crucial role in sleep-wake maintenance/control (see *Chapter 1*). Geva and colleagues (2016) suggest that the involvement of ARAS in attention gating and consequently selective attention could explain the close association of attention and sleep found in the studies described above. Research showing that sleep deprivation can hinder development of attentional systems (e.g., O'Callaghan, 2010) provide additional support for this hypothesis. Sleep regulation and attention regulation could be closely related; studies showing a relationship between mature/"adult-like" sleep patterns and attention, such as the study by Lam and colleagues (2011) mentioned above, provide tentative support for this notion. This would imply that infants with less regulated sleep-wake rhythms might have more difficulties in gaze regulation, and it may be important to look at these two patterns. This highlights the importance of potential investigating variability in eye-tracking parameters in addition to

mean parameters that are commonly used in the literature. Variability measures also could potentially provide information about individual differences in development that mean measures are not capturing (Frick et al., 1999). As such, high variability in task performance could signify low consistency across trials and no presence of learning. On the other hand, it could also be suggestive of an exploration of different attention techniques to optimize how they pay attention. In particular, it is pertinent to study the association of variability in eye-tracking measures and measures of sleep-wake regulation such as sleep fragmentation.

5.3 Research aim and current study

Research above shows that there are some associations between sleep and measures of attention in infancy that are concurrent to those found in adulthood; however, many important questions remain.

First, as is common in sleep research, there is a reliance on subjective parent-reports. Objective measures of both attention and of sleep are lacking. Moreover, though some studies looked at infant sleep patterns in relation to later attentional outcomes, studies tracking both attention and sleep continuously are scarce, especially in the age range of the first year of life. Many studies focus on one aspect of attention whereas it would be useful to track different aspects of attention over the first year of life to see whether sleep plays a part in the emergence and development of different types of attention.

To sum up, studies have not yet looked at longitudinal measures of attention as well as objective and subjective measures of sleep in the first year of life and lack comparison between different measures of attention (i.e., orienting attention, social selective attention, habituation).

This study addresses this gap in the literature by studying how habitual sleep is related to three measures of attention, i.e., social selective attention, habituation and orienting/disengagement of attention in the first year of life. See below for a discussion of the task parameters chosen and which domain of attention they represent. Moreover, research so far has not used objective ways to classify sleep into types of sleepers and investigate how they are related to attention. The research aims for this study are thus as follows:

- Investigate how different measures of attention (orienting attention, social selective attention, habituation) change across the first year of life to replicate prior findings.
- Investigate how different measures of attention (orienting attention, social selective attention, habituation) are related to objective (i.e., actigraphy) and subjective (sleep questionnaire and sleep diary) measures of sleep.

5.3.1 Eye-tracking tasks and parameters used in the present study

Eye-tracking tasks and parameters were chosen based on two important considerations. First, the aim was to use tasks already available and already validated within the CBCD and affiliated institutes to facilitate cross-study comparison (e.g., Elsabbagh et al., 2009; Gliga et al., 2009; Hendry et al., 2018; Powell et al., 2016; Wass et al., 2015). Given that data was collected in a different location than the CBCD, using the same tasks as were used across site in the EU-AIMS trials was essential. These tasks are designed to be used and validated by different research groups across Europe using different eye-trackers. Secondly, tasks chosen were tasks that assessed orienting and shifts of attention (gap-overlap task), social attention and sustained attention (face pop-out task / novelty habituation paradigm). These aspects of attention undergo significant changes in the first year of life and the aim (as stated above) is to investigate if these changes could be related to sleep patterns.

Table 5.1. Eye-tracking parameters tested and associated cognitive/attentional domain

Task	**Dependent variables tested**	**Cognitive/attentional domain**
Gap-overlap task	○ Mean saccadic reaction time in - Baseline condition - Gap condition - Overlap condition ○ Variability in saccadic reaction time - Baseline condition ○ Facilitation & disengagement	Orienting Disengagement/ shift of attention Potentially (underlying: processing speed
Face pop out task	○ 1st face look proportion ○ Peak look to face ° ○ Proportion face AOI *	Orienting Sustained attention
Habituation task	○ Keyboard measured look duration (Interesting vs. Boring slides)	Selective attention Information processing Executive attention Disengagement

Note. Information for tasks and attentional/cognitive domain taken from Hendry et al., 2019, Holmboe et al., 2018 & Johnson & de Haan, 2014; ° = longest, continuous look towards the face, * = how long the infants looked towards the face across the entire time looking at the array

5.4 Methods

This chapter describes the eye-tracking portion of Study 1.

5.4.1 Experimental Set-up

The experimental set-up of Study 1 is described in detail in *Chapter 2*. In summary, an accelerated longitudinal study was conducted, measuring sleep and indices of neurocognitive development in the first year of life using objective and subjective methods. The study was comprised of up to 4 visits per infant at which eye-tracking and

EEG was performed. After each lab visit, parents used actigraphy, sleep diary and questionnaires to record their infants sleep for a week in their home.

5.4.2 Participants

Participants were infants aged 4 to 14 months tested at up to 4 visits (see *Chapter 2*). Eye-tracking data from ~110 visits was included in the final analysis; however, the number of valid data points differed per task. Drop-out rate for the eye-tracking portion of the experiments was higher in younger than in older infants and higher than for EEG data. This was because the EEG session was performed before the eye-tracking session during each visit.

5.4.3 Eye-tracking

The eye-tracker used was a TX120 (Tobii, Sweden). The eye-tracking battery was composed of 7 different tasks, whose trial presentations were interspersed to keep the infant's interest. Here, three of the seven tasks are presented, namely: the gap-overlap task (Cousijn et al., 2017; Elsabbagh, Gliga, et al., 2013; Hood & Atkinson, 1993), face-pop-out task (Gliga et al., 2009) and a novelty habituation paradigm (Powell et al., 2016). These tasks were chosen as they are commonly used in other populations within the CBCD and there is information available on what typical response patterns look like. This allowed me to focus on their association with sleep rather than having to validate that my eye-tracking tasks work prior to investigating their associations with development. All tasks were run as part of a 25-minute-long eye-tracking test battery. The majority of subjects participated in the eye-tracking tasks after the EEG session described in *Chapter 2* and after a short break. Infants over 6-8 months of age and with parental permission were kept engaged with the use of rice cakes. Infants were seated in a car seat that was held by their caregivers on their caregivers' lap approximately 50 cm from the eye-tracker.

Gap-overlap task. The gap-overlap task is a visual orienting task with three conditions: baseline, gap and overlap condition (Hood & Atkinson, 1993). Here a version adapted from Elsabbagh (Elsabbagh et al., 2009, 2013) was used, currently also used in the STAARS and EU-AIMS projects (https://www.staars.org/staars-project / https://www.eu-aims.eu/). For an illustration of the gap-overlap task see *Figures 4.1* and *Figure 4.2*. A central stimulus (a clock, for example) is presented on a computer screen on a pink background accompanied by a sound and that oscillates in size slightly as soon as the infant's attention fixates on the central stimulus. A peripheral stimulus (a cloud or a star, for example) appears to the left or right of the central stimulus at the edge of the

screen (order = randomized). The onset of peripheral stimulus presentation is manipulated to create the baseline, gap and overlap conditions. The peripheral stimulus appears 200 ms after the central stimulus disappeared in the *gap* condition, while the central stimulus still appeared on the screen during the *overlap* condition, and precisely as the central stimulus disappeared in the *baseline* condition. The speed of the trials is dictated by the participants' speed of attention to the stimuli. The speed by which an infant orients/pays attention to the peripheral stimulus is taken as a reaction time measure for each condition. When an infant successfully fixated on the peripheral stimulus an audio-visual reward was played. An effect that is commonly observed during the gap-overlap task is that individuals are faster to shift their attention from the central stimulus to the peripheral stimulus in the gap condition than in the overlap condition (Wass et al., 2011). Other variables that are commonly investigated using the gap overlap are as follows: facilitation score (gap reaction time – baseline reaction time) and the target disengagement (overlap – baseline) score. Four to five blocks were presented, depending on number of valid trials. Each block had 12 trials.

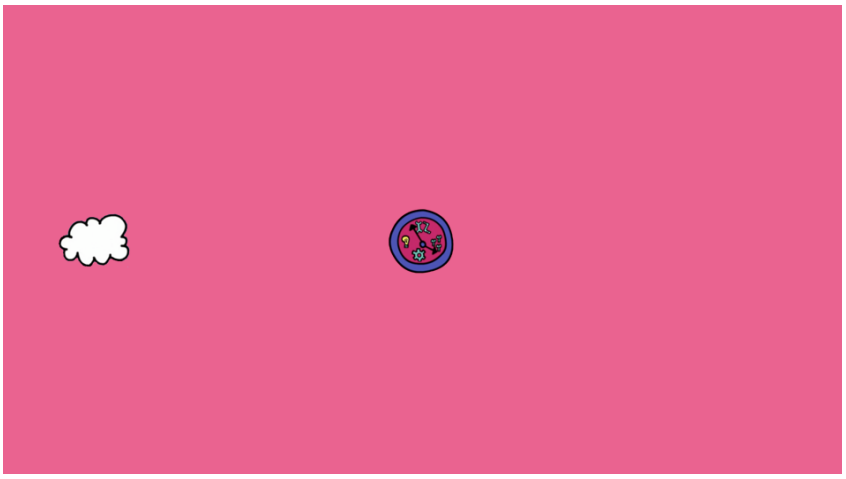


Figure 5.1. Example of gap overlap task stimuli (screenshot from task)

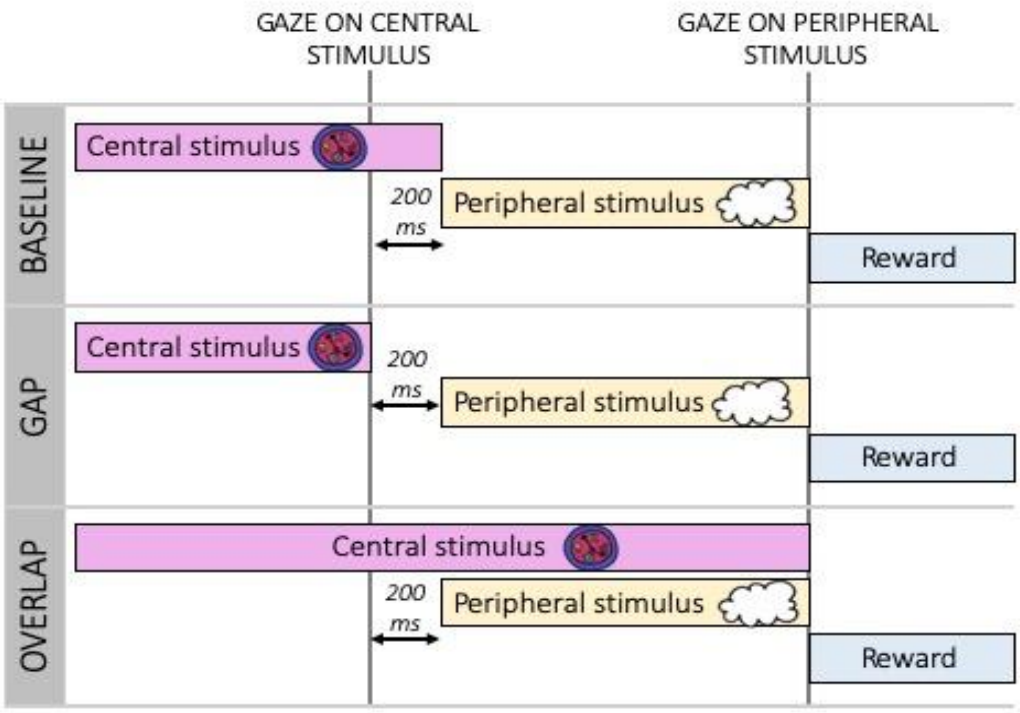


Figure 5.2. Presentation of stimuli for gap-overlap task. Adapted from L. Mason.

Face pop-out task. The second task used was the face pop-out task (Gliga et al., 2009; Hendry et al., 2018). An array with social stimuli – a face (10 different faces, 5 female, a variety of ethnicities), and a scrambled face (= noise) and some non-socials stimuli (bird, car, phone, 10 different versions of each) ordered in a circular fashion on a computer screen is presented. The noise image was generated using a scrambled version of the faces stimuli while ensuring that colour was kept constant (Halit et al., 2004). Music accompanied presentation of the array. Location of the stimuli in the array was randomized. Each array was presented for 12 seconds. These arrays have been used in prior studies (Elsabbagh, Gliga, et al., 2013; Klerk et al., 2014; Wass et al., 2015). Prior to presentation of the array on the screen the infants gaze was directed towards the middle of the presentation screen using a small animation. Key dependent variables were as follows: face peak look (i.e., longest continuous look to the face), 1st look towards face proportion (i.e., proportion of times that infants first looked towards the face), and total face look proportion (i.e., total proportion looking at faces across the entire array).

Figure 5.3. Example array of social and non-social stimuli for the face pop-out task.

Novelty habituation paradigm. The novelty habituation paradigm measures how fast an infant habituates/loses interest when exposed to a novel stimulus. Here a task was used that was described by Wass and colleagues (Wass et al., 2015). Four different slides are presented to the infant, after a brief fixation period to make sure they are looking at the screen. Music accompanied presentation of the respective slide. Slides consisted of two boring (a cross and an array of dots) and two interesting (an underwater scene and a flower/meadow scene) slides (see *Figure 5.4.* for details). Each slide is presented 5 times to the infant and each time the infant looks away an attention grabber is played until the infant looks towards the screen again. Using this task, individual epochs of attention can be measured. Moreover, in addition to recording the eye-tracking measures of look duration the (trained) researcher records look durations of the infant towards the screen by pressing down the space bar for the duration of the look. Here only button press data was used, to reduce the amount of data handled. The two variables that were investigated were time to habituate to boring and interesting conditions respectively.

A)

B)

Figure 5.4. A) Interesting conditions of the novelty habituation paradigm. B) Boring conditions of the novelty habituation paradigm.

5.4.4 Sleep assessment

As sleep indices for this chapter, the sleep clusters identified in *Chapter 3* by k-means cluster analysis. These were as follows: poor, adult-like and day sleepers for actigraphy and Brief Infant Sleep Questionnaire (BISQ) and poor, adult-like, day and mixed sleepers for sleep diary. Additional analyses were performed with four main continuous sleep parameters (Night and Day Sleep Duration, wake after sleep onset (WASO) and Night Wakening Number (sleep fragmentation).

5.4.5 Experimental procedure

Infants were placed 50 centimetres in front of a monitor underneath which a Tobii X120 was placed. Infants were strapped into a baby car seat that was held in position by parents to ensure stillness. For non-compliant infants/ infants who refused to be strapped into the car seat, parents held them on their lap. Gaze data was recorded at 120 Hz. *Chapter 2* shows an illustration of the eye-tracking set-up. A video camera was used for

experimenters to monitor infants' in-session behaviour and to record keyboard-measured look durations for the button press section of the habituation novelty paradigm.

5.4.6 Analysis Plan

Pre-processing of eye-tracking data. Data was pre-processed using the lab-based task engine pre-processing method (developed and performed by Dr. Luke Mason, CBCD). These were as follows. Pre-processing was performed with Matlab 2019. The reaction time was calculated as the time between when the peripheral stimulus appeared and the infants gaze entering the Area of Interest (AOI) surrounding the peripheral stimulus for the gap (9° box around the stimulus). For the face pop-out task these AOI were defined around the different array images. Exclusion criteria for the gap-overlap task were as follows. Data was excluded when > 60 ms of continuous data loss occurred, if infants did not fixate on the central stimulus when the peripheral stimulus was presented, and if infants did not perform a saccade to the peripheral stimuli within 2 seconds of the stimulus onset. Furthermore, trials were excluded when reactions times were <100ms or >1200ms, as determined in previous literature (Elsabbagh et al., 2013).

Exclusion criteria for the face-pop out task were as follows. Fixations with <50ms were removed, as in prior literature (Gui et al., 2020). Raw data was assigned to the AOIs. If data was missing (<200ms) within one AOI, all of the data was assigned to that AOI. Otherwise, data was counted as missing. If there was less than 5 seconds trial length that pop-out trial was excluded. For the novelty habituation paradigm no data was specifically excluded, as researcher button-press data was used as indicator for look duration. The only data excluded was the data not recorded due to fussy infants.

Pre-processing of sleep data. For details on actigraphy data pre-processing, refer to *Chapter 2* and *Chapter 3*. The sleep quality clusters identified in *Chapter 3* through k-means cluster analysis were used. These were as follows: poor, adult-like and day sleepers for actigraphy and BISQ and poor, adult-like, day and mixed sleepers for sleep diary. Sleep clusters (i.e., adult-like, poor and day sleepers/ mixed sleepers) identified in *Chapter 3* were used to identify a relationship between sleep quality and development. Additional analyses were performed on sleep parameters commonly used in the literature, i.e., Night and Day Sleep Duration, Night Wakening Number and wake after sleep onset (WASO), this was done because the broad sleep clusters might miss more fine-grained aspects of sleep/more specific relationships. For the actigraphy clusters of poor and day sleepers were merged as there were only nine participants in clusters for day sleep. For diary clusters, clusters of mixed and day sleepers were merged again due to the limited

number of participants in the day sleep cluster. No clusters were merged for the BISQ as cluster sizes were roughly equal.

***Analysis of tasks*.** Linear mixed effects modelling (LMMs) was used to analyse the data. For details with regard to different models tested and rationale for analysis choice see *Chapter 2*. Below the full linear mixed models (LMMs) tested are specified. Each analysis was performed three times for each sleep method once. Eye-tracking parameters, such as baseline reaction time in the gap-overlap task or the proportion of first look towards the face in the face pop-out and look duration towards interesting or boring stimuli in the novelty habituation paradigm were the dependent variables. For eye-tracking parameters that were tested see *Table 5.1*. and see above for detailed description of tasks.

The full LMMs tested are as follows:

1. The **baseline model** is the developmental change model assessing how the eye-tracking (ET) parameters changes over time.

Baseline: ET parameter = random intercept for participant + age group

2. **Model 1** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameters) on the eye-tracking parameters are assessed.

Model 1 (M1): ET parameter **=** random intercept for participant + age groups + sleep variable

3. **Model 2** describes a model where main effects of age group as sleep variable (sleep quality as well as continuous sleep parameters) and an interaction effect of age group by sleep variable on the eye-tracking parameters are assessed.

Model 2 (M2): ET parameter = random intercept for participant + age groups + sleep variable + age group by sleep variable interaction

4. **Model 3** describes a model where main effects of age group as sleep variable (sleep quality as well as continuous sleep parameters) and gender and potentially an interaction effect of age group by sleep variable on the eye-tracking parameter are assessed.

Model 3 (M3): ET parameter = random intercept for participant + age groups + sleep variable + (age group by sleep variable interaction) + gender

5.5 Results

Below results from the LMM's conducted are described. For a summary of the results refer to *Table 5.2*.

5.5.1 Developmental changes in eye-tracking tasks

The baseline model of the LMMs assessed potential age group differences in the different eye-tracking measures. For detailed statistics always refer to *Appendix – Chapter 5*. Overall, gap-overlap and pop-out tasks but not the novelty habituation paradigm showed significant developmental changes across the first year of life.

5.5.1.1 Gap-overlap task

There were developmental changes for gap [$F(5,57) = 5.25$, $p < .001$], overlap [$F(5,88) = 6.14$, $p < .001$] and baseline [$F(5,38) = 8.54$, $p < .001$] conditions, where reaction times decreased with age. Gap condition reaction times were significantly different between 6 and 10 ($MD = 55.74$, $p = .01$), 6 and 12 ($MD = 70.76$, $p = .001$), and 6 and 14 ($MD = 69.91$, $p = .001$) months of age. Baseline condition reaction times were significantly different between 6 and 10 ($MD = 69.34$, $p = .003$), 6 and 12 ($MD = 92.45$, $p < .001$), 6 and 14 ($MD = 97.70$, $p < .001$) months of age. Overlap condition reaction times were significantly different between 4 and 12 ($MD = 155.11$, $p = .008$) 4 and 14 ($MD = 152.45$, $p = .01$) and 6 and 12 ($MD = 107.14$, $p < .001$), 6 and 14 ($MD = 104.49$, $p < .001$) months. There were no significant developmental changes in the facilitation or the disengagement conditions or in baseline reaction time variability as measured by the baseline model of the LMMs (all p's >.05 see *Appendix – Chapter 5*). For an illustration see *Figure 5.5A-B*.

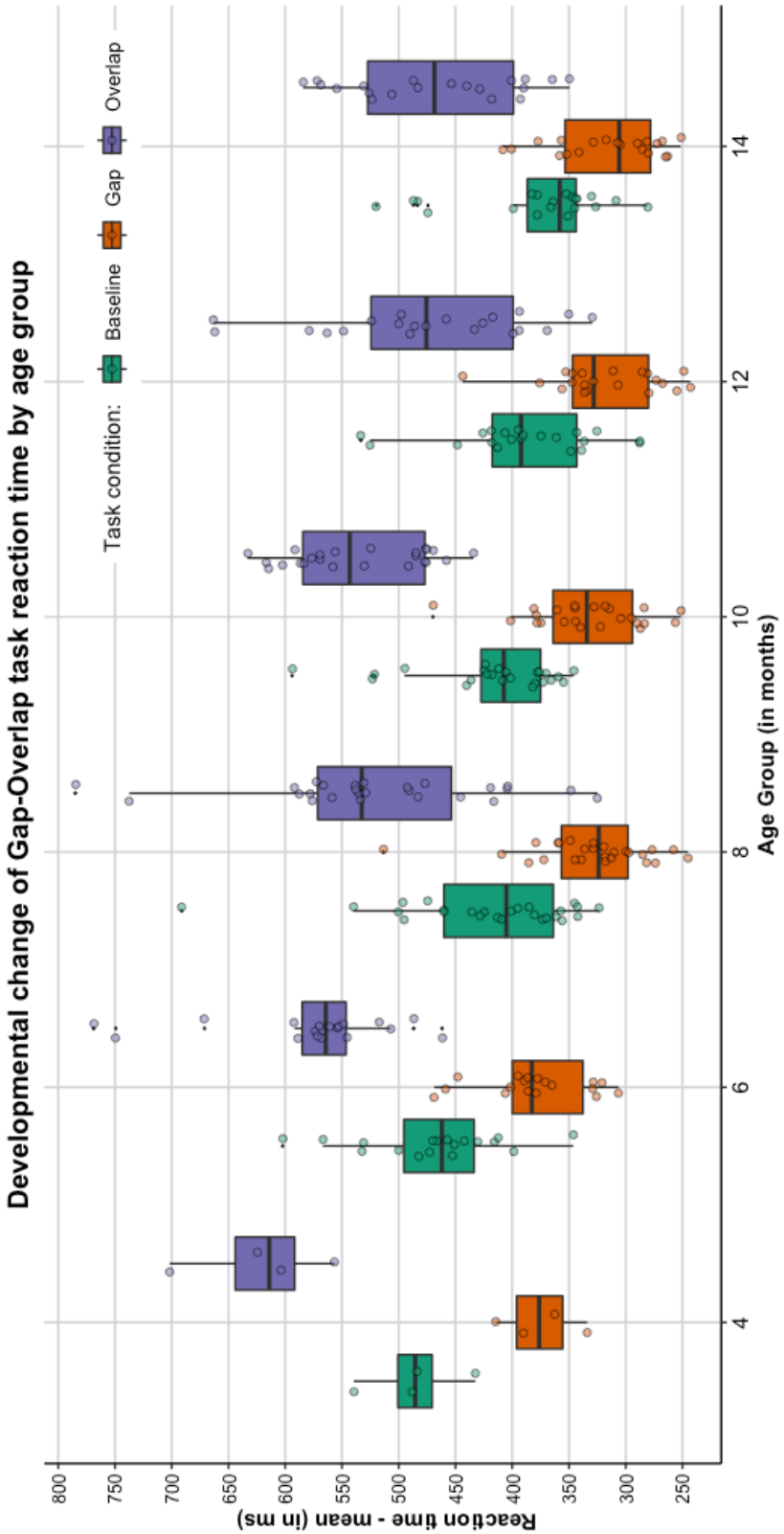


Figure 5.5A. Developmental change of the gap-overlap task for conditions baseline, gap and overlap.

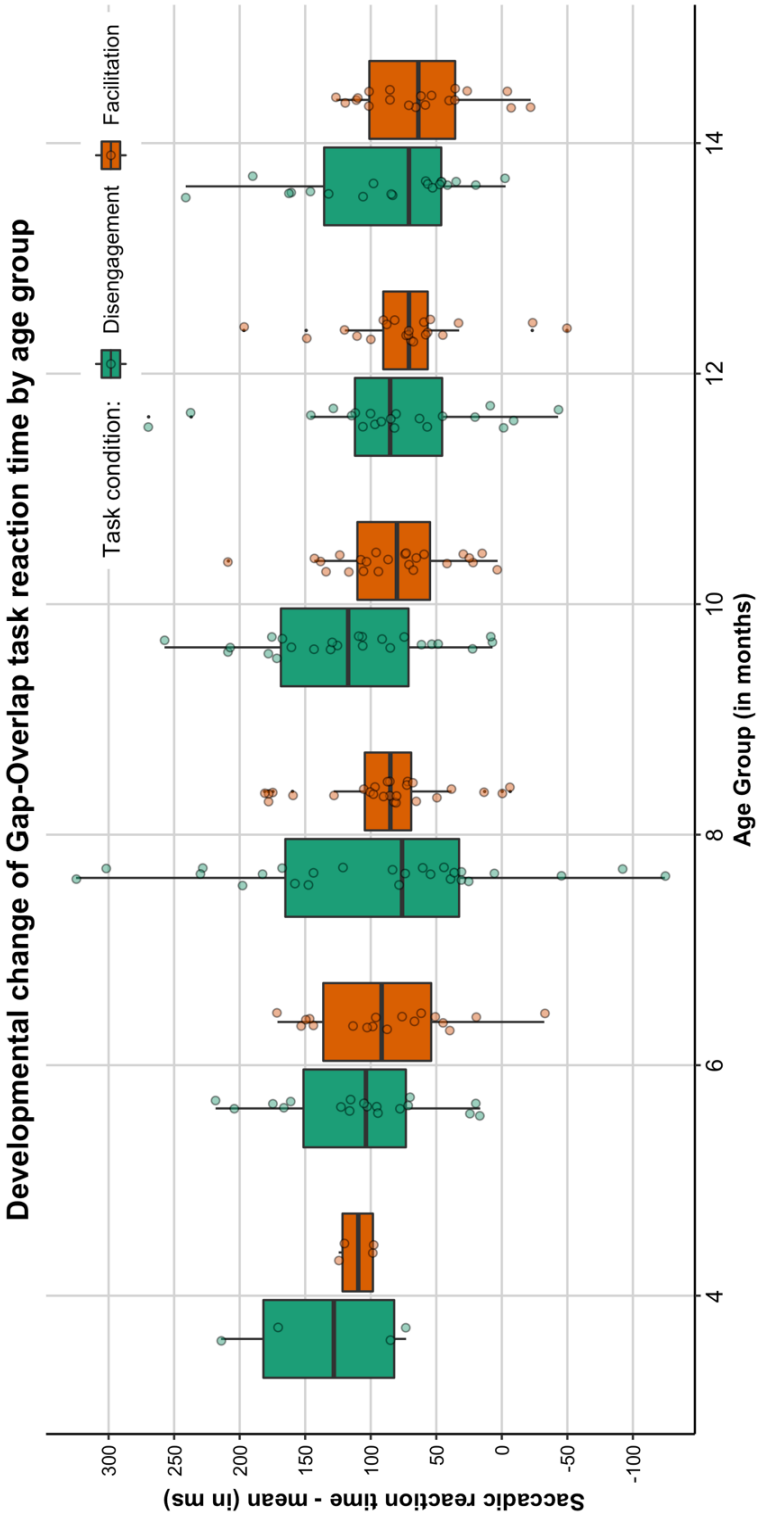


Figure 5.5B. Developmental change of the gap-overlap task facilitation and disengagement conditions.

5.5.1.2 Face pop-out task

For analysis of the pop-out task, three categories were can be examined: social (face) stimuli, noise (scrambled face) and an object category (pooled: bird, car, phone). However, for the purpose of this chapter, the focus will be on looking to the face, i.e.,1st look proportion of face, face peak look (= longest continuous look towards face) and face proportion AOI (= how long the infants looked towards the face across the entire time looking at the array) in order to reduce the amount of data included.

There were developmental changes for first look proportion of face [$F(5,112) = 4.82$, $p = .001$]. Follow-up analyses showed that age group differences were significant between 6 and 8 ($MD = -0.20$, $p = .01$), 6 and 10 ($MD = -0.28$, $p < .001$), and 6 and 12 ($MD = -0.19$, $p = .04$) months of age for first look proportion of face. 1st face look proportion was lower for 4 months and 6 months and it increased after 6 months of age. Multiple comparison correction was conducted using the Bonferroni-method.

There were also developmental changes in face peak look [$F(5,74) = 2.83$, $p = .004$]. Follow-up analyses showed that face peak look decreased with age with significant group differences between the following age groups: 6 and 12 months ($MD = 1.01$, p = .006) and 6 and 14 months ($MD = 0.93$, p = .02).

Lastly, there were developmental changes in total looking towards face (face proportion AOI; $F(5,97) = 5.57$, $p < .001$). Follow-up analyses showed there were age group differences between 4 months and 6 months ($MD = -0.18$, p =.05), 4 and 8 months ($MD = -0.23$, p =.001), 4 and 10 months ($MD = -0.22$, p = .003) and between 8 months and 12 months ($MD = 0.13$, p = .35), increasing after 4 months and decreasing slightly after 8 months. For illustration see *Figure 5.6*.

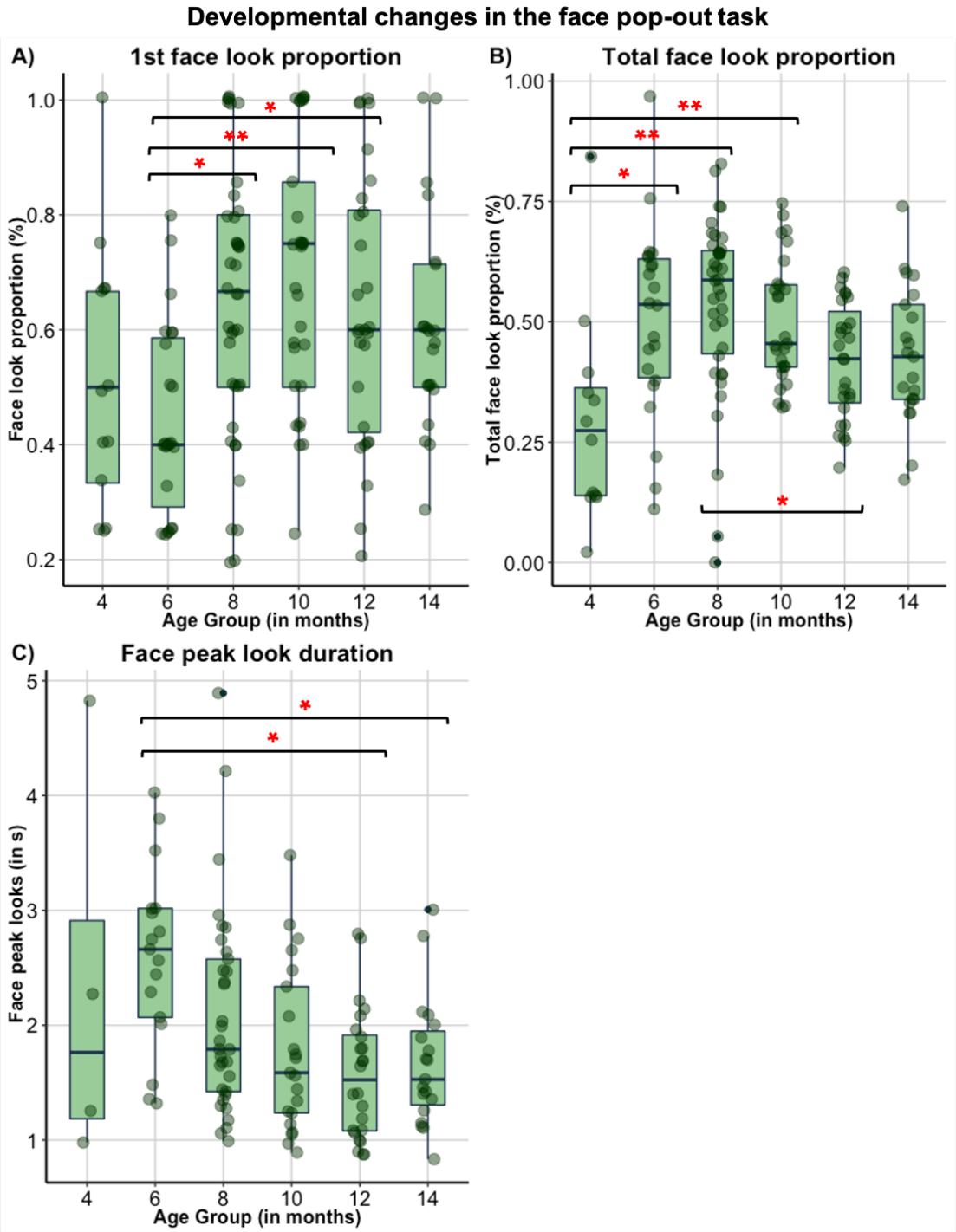


Figure 5.6. Developmental changes in face look parameters of the face pop-out task.

5.5.1.3 Novelty habituation paradigm

Results revealed no significant developmental changes in the look durations towards boring or interesting conditions of the novelty habituation paradigm in the

present sample as assessed by the baseline model of the LMMs (p >.10; see *Appendix – Chapter 5*).

Paired t-tests were also performed to compare whether Boring and Interesting look durations differed significantly from each other. Results showed that infants looked significantly longer towards the Interesting stimuli than the boring stimuli [$t(146) = 5.91$, $p < .001$].

5.5.2 Infant sleep quality and eye-tracking measures of infant attention

Below, the relation between the gap-overlap task, face pop-out task and the novelty habituation paradigm in relation to infant sleep quality is examined. Sleep quality is denoted here by sleep cluster membership that was identified in *Chapter 3*. LMMs were performed for actigraphy-, diary- and BISQ-measured sleep clusters and each parameter separately. All significant results are summarised in *Table 5.2*.

5.5.2.1 Gap-overlap task

Key findings: Overall, there were no cross-method consistent associations between gap-overlap parameters and objectively and subjectively measured sleep quality. Fragmented findings were as follows. There were associations of subjective sleep quality with mean gap condition reaction time and facilitation score. There were associations of objective sleep quality with variability in baseline condition reaction time and age-related changes in the association of objective sleep quality and disengagement.

For the sleep diary, sleep quality was significantly associated mean gap saccadic reaction time [$F(2, 79) = 5.02$, $p = .009$]. Post-hoc testing showed a difference between the adult-like and the mixed/day sleepers group where adult sleepers (369.9 ± 10.89) showed significantly higher mean gap reaction time than mixed/day sleepers (324 ± 9.19; $MD_{adult\text{-}like\ -\ mixed/day\ sleepers} = 45.85 \pm 14.81$, $p = .008$). There were no associations between objectively measured or subjectively measured sleep quality and baseline saccadic reaction time. There were no associations between objectively measured or BISQ-measured sleep quality and gap or overlap saccadic reaction time (all p's >.05; see *Appendix – Chapter 5)*.

Objectively measured sleep quality was significantly associated with variability of baseline saccadic reaction time [$F(1,95) = 4.60$, $p = .04$]. Post-hoc testing showed that variability in baseline saccadic reaction time was lower in poor and day sleepers (95.83 ± 8.21) than in adult-like sleepers (119.56 ± 9.73; $MD_{adult\text{-}like\ -\ mixed/day\ sleepers} = -23.73 \pm 11.07$, $p = .04$). There was no association between subjectively measured variability of

baseline saccadic reaction (all p's >.05; see *Appendix – Chapter 5*). There was an association between BISQ-measured sleep quality and facilitation score [$F(2,75) = 8.98$, $p = <.001$] with a significant difference between adult-like/mature sleepers (77.5 ± 7.46) and day sleepers (113.7 ± 8.72*;* $MD_{adult\text{-}like - day\ sleepers} = -36.25 \pm 10.00$, $p = .002$) and day sleepers and poor sleepers (62.96 ± 11.63; $MD_{day\ sleepers - poor\ sleepers} = -50.75 \pm 13.85$, $p = .001$). The day sleepers had higher facilitation scores than both adult-like and poor sleepers. There was no association between diary-measured or objectively measured sleep quality and facilitation condition (all p's >.05; see *Appendix – Chapter 5*). There was an interaction effect of age group by actigraphy cluster [$F(5,78) = 2.25$, $p = .05$] and a main effect of gender for disengagement [$F(1,48) = 4.44$, $p = .04$] (best model = model 3). This indicated age-related changes in the relationship between objectively measured sleep quality and disengagement. For illustration of this pattern see *Figure 5.7*. Of note are the large variability in each age group, as indicated by the error bars. Caution should therefore be warranted in the interpretation and extrapolation of the findings.

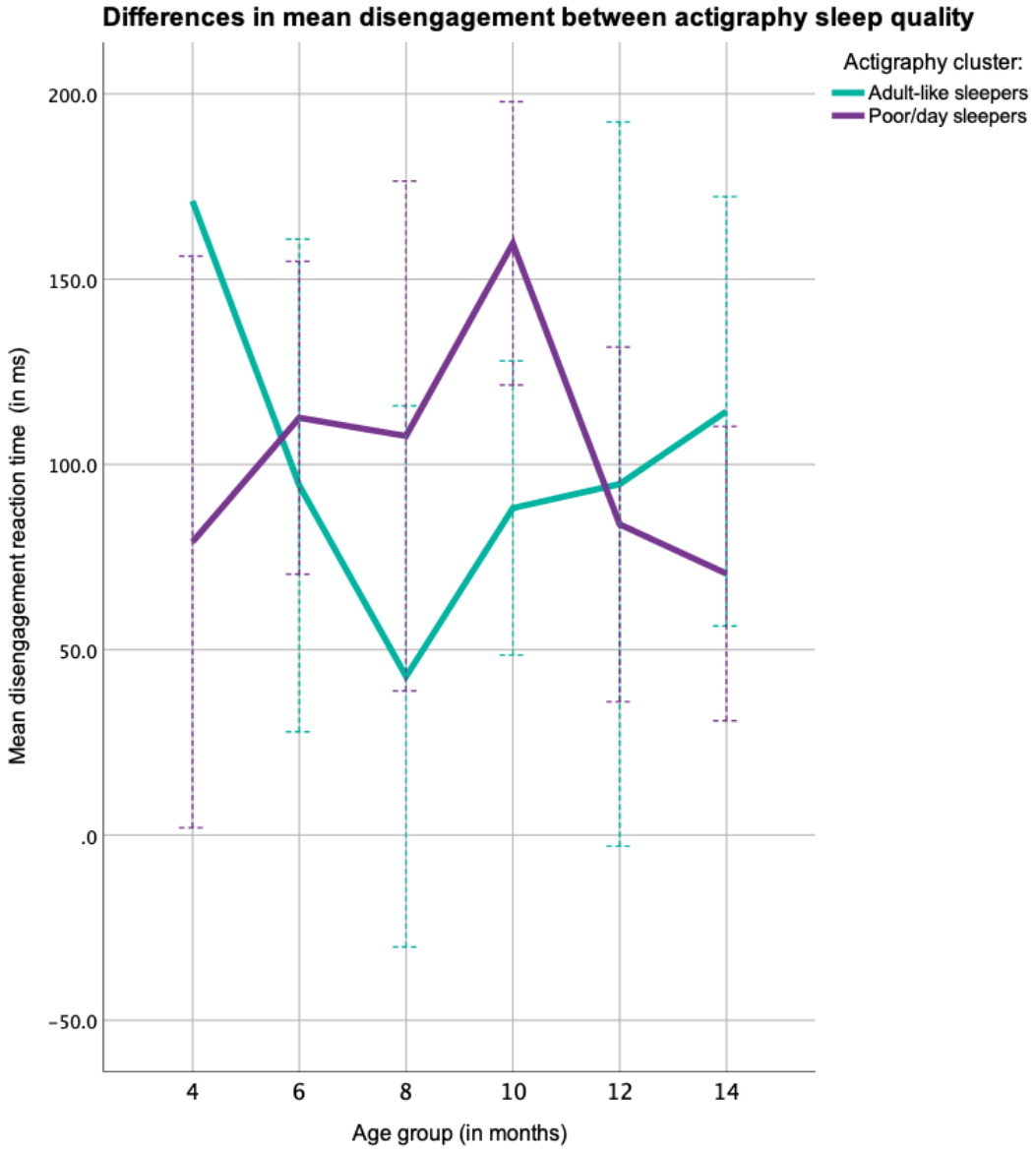


Figure 5.7. Illustration of the age group by actigraphy cluster interaction effect on mean disengagement in the gap-overlap task.

5.5.2.2 Infant sleep quality and face pop-out task

There were no significant associations between of objectively (actigraphy) or subjectively measured (BISQ or diary) infant sleep quality (as measured by data-driven cluster membership) and any face look parameters of the face pop-out task (all p's >.05; see *Appendix – Chapter 5)*.

5.5.2.3 Novelty habituation paradigm

There was an interaction effect of age group by BISQ cluster and look duration of the boring condition [$F(5, 101) = 2.38$, $p = .017$]. Visual inspection of the graph showed missing data for 10-month-olds in the poor sleeper's condition and few data points in the 4-month-olds. These patterns seemed to drive the group differences and therefore this association is not further discussed. There were no associations between objectively and diary-measured infant sleep quality as measured by data-driven clusters and the look duration for either boring or interesting conditions in the novelty habituation paradigm (all p's >.05; see *Appendix – Chapter 5)*.

Results from cluster analyses show some effects with regard to eye-tracking parameters; however, there was no clear patterns across methods. Most association were found with regard to patterns from the gap overlap task.

5.5.3 Continuous sleep parameters and eye-tracking measures of infant attention

After running LMMs on the sleep clusters, additional analyses were conducted on sleep parameters commonly assessed in the literature such as Sleep Duration (Day and Night), Night Wakening Number and wake after sleep onset (WASO) as independent variable instead of the sleep quality clusters. These variables were previously identified in the sleep literature as relevant to neurocognitive development. For detailed statistics refer to *Appendix – Chapter 5*.

5.5.3.1 Gap-overlap task

Key findings: Similarly to sleep quality there were no cross-method consistent associations between the different continuous sleep parameters and the gap-overlap task parameters. Developmental changes were evident in some of the associations, but these were also not consistent across different sleep measures.

WASO. Baseline saccadic reaction time variability was significantly associated with objectively measured WASO [$F(1,97) = 5.34$, $p = .023$]; however, a closer look showed that this effect was likely driven only by the 4 months age group an rather constant in the rest of the age groups. There was an association with diary-measured WASO [$F(1,79)=5.94$, $p = .017$], where more WASO was associated with lower variability in baseline reaction time. There were no associations between BISQ-measured WASO and the variability parameter (p >.05; see *Appendix – Chapter 5)*.

There were developmental changes in the association between diary-measured WASO [$F(5,80) = 3.43$, $p = .007$] and mean overlap reaction time. In the 4-, 8-, and 10-month-olds, there was a positive association between WASO and mean reaction time in the overlap condition. In the 6-, 12-, and 14-month-olds there was a negative association between WASO and mean reaction time in the overlap condition. There were developmental changes in the association between diary-measured WASO [$F(5,76) = 2.42$, $p = .043$] and disengagement. In the 4- and 10-months olds there was a positive association between WASO and disengagement. In the 6-, 8- 12-, and 14-month-olds there was no association. There were no association between actigraphy or BISQ-measured WASO with any other gap overlap parameters (all p's >.05; see *Appendix – Chapter 5)*.

Night Wakening Number. There were developmental changes in the association of objectively and diary-measured Night Wakening Number and disengagement as evidenced by an interaction effect [objective: $F(5,83) = 4.51$, $p = .001$ / diary: $F(8,75) = 3.01$, $p = .016$]. Group differences did not survive multiple comparisons for the objective sleep measure. Visual inspection of patterns in objective measure showed a negative association where lower night wakening was associated with higher disengagement in 4 months and 14 months, higher night wakening was associated with higher disengagement in 8- and 10-month-olds and the association was constant in the 6- and the 12-month-old. Visual inspection of patterns in the diary measure did not yield the same results as patterns in the objective measures. Diary measures showed a positive association with higher night wakening and higher mean disengagement in the 4-month-olds. In 6-, 12- and 14-month-olds, lower night wakening was associated with higher disengagement and but there was no association in the 8- and 10-month-olds. In the same model (objectively measured Night Wakening Number and disengagement) there was also a significant main effect of gender [$F(1,51) = 5.04$, $p = .029$]. This gender effect was also seen in the BISQ data [$F(1,57) = 5.59$, $p = .021$]. There were no associations of BISQ-measured Night Wakening Number and gap-overlap parameters (all p's >.05; see *Appendix – Chapter 5)*.

Night Sleep Duration. BISQ-measured Night Sleep Duration showed a positive association with baseline saccadic reaction time [$F(1,98) = 7.03$, $p = .009$] and gap saccadic reaction time [$F(1,86) = 4.10$, $p = .046$]. There were developmental changes in the association of diary-measured Night Sleep Duration and mean gap saccadic reaction [$F(5,92) = 2.62$, $p = .029$]. In the 4- and 8-month-olds, there was a negative association between Night Sleep Duration and gap reaction time. In the 6-, and 12-month-olds, there

was a positive association between Night Sleep Duration and gap reaction time. There was no association in the 10- and 14-month-olds. There were developmental changes in the association of diary-measured Night Sleep Duration and disengagement [$F(5,74) = 3.21$, $p = .011$]. There were positive associations in the younger age groups with the relationship between Night Sleep Duration and disengagement becoming negative in the 12- and 14-month-olds. There were no associations of actigraphy-measured Night Sleep Duration and gap-overlap parameters gap-overlap parameters (all p's >.05; see *Appendix – Chapter 5)*.

Day Sleep Duration. Objectively measured Day Sleep Duration was associated with disengagement [$F(1,98) = 4.41$, $p = .038$] where more day sleep was associated with slower disengagement. BISQ-measured Day Sleep Duration was associated with gap saccadic reaction time [$F(1,108) = 7.28$, $p = .008$] where higher Day Sleep Duration was associated with lower gap saccadic reaction time. BISQ-measured Day Sleep Duration was also associated with mean facilitation saccadic reaction time [$F(1,111) = 4.51$, $p = .036$] where higher Day Sleep Duration was associated with slower facilitation.

In general, disengagement saccadic reaction time showed a gender main effect for all models with all sleep parameters tested (all p's<.05 for details see *Appendix - Chapter 5*).

5.5.3.2 Face pop-out task

Key findings. <u>In face look parameters some cross-method consistencies emerged, however fragmented findings were also evident. There were developmental changes in the association of diary- and actigraphy-measured WASO and face looking.</u>

WASO. There were developmental changes in the association of objectively-measured WASO and face peak look [$F(5,97) = 4.13$, $p = .002$], where there was a positive association between face peak look and WASO in the 4-, 6-, and 8-month-olds, though the association was weak for the 6-month-olds. There was a slightly negative association between face peak look and WASO in the 10- and 12-months age groups. There was no association in the 14-month-olds. There were developmental changes in the association of diary-measured WASO and total looking towards face proportion [$F(5,106) = 2.38$, $p = 0.04$]. There was no association in the 4-month-olds, and a positive association between total looking towards face proportion and WASO in the 6-month, and 10-month-olds and a negative association between 8-, 12-, and 14 months of age.

There were no association between BISQ-measured WASO with any of the face look parameters.

Night Wakening Number . There were developmental changes in the association of objectively-measured Night Wakening Number and face peak look [$F(5,83)=5.06$, $p<.001$] with a negative association between face peak look and Night Wakening Number in the 4-month-, 6-month-, and 12-month-olds and a positive association between Face peak look and Night Wakening Number in the 8-month-, 10-month-, and 14-month-olds.

There was no association between subjectively measured Night Wakening Number with any of the face look parameters (all p's<.05 for details see *Appendix - Chapter 5*).

Night Sleep Duration. There were developmental changes in the association of BISQ-measured Night Sleep Duration and face peak look [$F(5,100) = 2.52$, $p = .034$]. There was a negative association in the 4-months, 10-months, and 14-month-olds and a positive association between face peak look and Night Sleep Duration in the 8-months, 6-months, and 12-month-olds. There were developmental changes in the association of BISQ-measured Night Sleep Duration and total looking towards face proportion ($F(5,136) = 3.27$, $p = .008$). There was a negative association in the 4-months, and 14-months olds and a positive association between total looking towards face proportion and Night Sleep Duration in the 6-months, 10-months, and 12-month-olds. There was a no association in the 8-month-olds.

Day Sleep Duration. Face peak look was associated with an effect of BISQ-measured Day Sleep Duration ($F(5,111) = 10.93$, $p = .001$) with lower face peak looks for more day sleep. There was no association between diary-measured or actigraphy-measured Day Sleep Duration with any of the face look parameters (all p's<.05 for details see *Appendix - Chapter 5*).

5.5.3.3 Novelty habituation task

Key findings: Only the BISQ-measured parameters showed an association with parameters of the novelty habituation paradigm. Diary and actigraphy measures showed no associations. More time spent awake at night and overall lower night sleep was associated with longer look duration in the boring condition.

WASO. There was a significant association between BISQ-measured WASO and look duration in the boring condition [$F(1,130) = 4.25$, $p = .041$] where more WASO was associated with higher look durations in the boring condition. There were no associations of either objectively or diary-measured WASO with look duration in the boring or interesting condition (all p's >.05; see *Appendix – Chapter 5)*.

Night Wakening Number. There were no association of either objectively or subjectively measured Night Wakening Number with look duration in the boring or interesting condition (all p's >.05; see *Appendix – Chapter 5)*.

Night Sleep Duration. There was a significant effect of BISQ-measured Night Sleep Duration for look duration in the boring condition [$F(1,140) = 7.20$, $p = .008$] where more night sleep was associated with lower look durations in the boring condition. There were no associations of either objectively or diary-measured Night Sleep Duration with look duration in the boring or interesting condition (all p's >.05; see *Appendix – Chapter 5)*.

Day Sleep Duration. There were no association of either objectively or subjectively measured Day Sleep Duration with look duration in the boring or interesting condition (all p's >.05; see *Appendix – Chapter 5)*.

Table 5.2. Summary of results of Chapter 5

		Gap overlap task						Face pop-out task			Novelty Habituation paradigm	
		Baseline SRT mean	**Gap SRT mean**	**Overlap SRT mean**	**FAC SRT mean**	**DIS SRT mean**	**Baseline SRT variability**	**1st Look proportion face**	**Total face look proportion**	**Face peak look**	**Boring look duration**	**Interesting look duration**
Sleep quality	A					Developmental changes in mean disengagement between adult-like and poor/day sleepers	Adult-like sleepers > poor and day sleepers					
	D		Adult-like sleepers > mixed and day sleepers									
	B				adult-like sleepers < day sleeper poor sleepers < day sleepers							
Night wakening number (NW)	A					4m: ↑NW ↓DIS 6m: - 8m: ↑ NW>DIS 10m: - 12m: ↑NW↑DIS 14m: ↑ NW ↓DIS						
	D					4m: ↑ NW ↑DIS 6m: ↑NW ↓DIS 8m: - 10m: - 12m: ↑NW ↓DIS						

						14m: ↑ NW ↓DIS						
	B									4m: ↑ NW↓ peak look 6m: ↑ NW ↓peak look 8m: ↑ NW ↑peak look 10m: ↑ NW↓peak look 12m: ↑ NW↓ peak look 14m: ↑ NW> peak look		
WASO	A						4m only: ↑WASO↓variability			4m: ↑WASO↑ peak look 6m: -/↑ WASO↑ peak look 8m: ↑ WASO↑peak look 10m: ↑ WASO ↓peak look 12 m : ↑WASO↓ peak look 14m: -		
	D		4m: ↓night sleep ↑ gap 6m: ↑night sleep ↑ gap 8m: ↓night sleep ↑gap 10m: - 12m: ↑night sleep ↑ gap		4m: ↑ WASO↑overlap 6m: ↑ WASO↓overlap 8m: ↑WASO↑overlap 10m: ↑WASO↑overlap 12m: ↑ WASO↓overlap 14m: ↑WASO↓overlap	4m: ↑WASO ↑ DIS 6m: - 8m: - 10m: - 12m: - 14m: ↑ WASO ↑ DIS	↑WASO ↓variability		4m: - 6m: ↑WASO ↑total face 8m: ↑WASO ↓ total face 10m: ↑WASO ↑total face 12m: ↑WASO ↓total face 14m: ↑WASO ↓total face			

			14m: -									
	B										↑WASO↑longer looks	
Night sleep duration	A											
	D					4m: ↑night sleep ↑ DIS 6m: ↑night sleep ↑ DIS 8m: ↑night sleep ↑ DIS 10m: ↑night sleep ↑ DIS 12m: ↓night sleep ↑ DIS 14m: ↓night sleep ↑ DIS						
	B	↑night sleep ↑ gap	↑night sleep ↑ gap							4m: ↑night sleep ↓ face peak 6m: ↑night sleep ↑face peak 8m: ↑night sleep ↑ face peak 10m: ↑night sleep ↓ face peak 12m: ↑night sleep ↑ face peak 14m: ↑night sleep ↓face peak	↑night sleep ↓look duration	
Day Sleep Duration	A											

	D											
	B		↑day sleep ↓ gap							↑day sleep ↓ face peak		

Notes. ↑increase in, ↓ decrease in, A = Actigraphy, B = BISQ, D = Diary, DIS = Disengagement, FAC = Facilitation, NW = Night Wakening Number , m = months, SRT = Saccadic Reaction Time, , blue = developmental changes in the association between sleep parameter and questionnaire measure, red = negative association between sleep parameter and questionnaire measure, green = positive association between sleep parameter and questionnaire measure.

5.6 Discussion

This study aimed to investigate how habitual sleep (as measured by actigraphy, sleep questionnaire and diary) is related to different measures of attention, i.e., social selective attention, habituation and orienting/disengagement of attention in the first year of life as measured by three eye-tracking tasks: gap-overlap task, the face pop-out task and the novelty habituation paradigm. The strengths of this study constitute in the relatively big sample and the use of objective and subjective sleep quality and parameter assessment. Overall results showed many cross-method inconsistencies in the association between infant sleep and attention.

5.6.1 Developmental changes in eye-tracking parameters

First, developmental changes apparent in the eye-tracking tasks were examined. Results showed that there was a developmental decline in saccadic reaction time during several conditions of the *gap-overlap task* with 6 months of age marking the difference between the first and second half of the first year of life. This pattern matches prior findings by Pisch (2015) who also observed a decrease in saccadic reaction time with increased age. As with prior studies, the fastest saccadic reaction time of this study was in the gap and slowest in the overlap condition (Holmboe et al., 2018; Hood & Atkinson, 1993; Pisch, 2015). This reduction in reaction time is often attributed to the development of the ability to shift/ disengage attention more readily and thus react faster, a skill that is developed in the second half of the first year of life (Colombo, 2001; Matsuzawa & Shimojo, 1997). Another reason for the developmental changes observed in the gap-overlap task might be maturation of the visual system (Hendry et al., 2019). Infants are faster in the gap condition because the disappearance of the central stimulus serves as a cue to refocus their attention and become aware of subsequent changes (Hendry et al., 2019). However, the effect described above has not been replicated quite as robustly as previously thought. For example, Nakagawa and Sukigara (2019) actually find that 12-month-olds perform slower than 6-month-olds in the overlap condition of the gap-overlap task (Nakagawa & Sukigara, 2019).

The present study did not replicate developmental changes in the facilitation effect or disengagement effect. As reminder, facilitation effect is calculated gap reaction time - baseline reaction time and the target disengagement is calculated overlap reaction time - baseline reaction time. Of note is emerging evidence that facilitation is an early onset phenomenon (Hendry et al., 2019; Xie & Richards, 2017). For example, facilitation effects

were observed in 3-months-old infants but no changes occurred in the facilitation effect later 5 months of age (Ross-Sheehy et al., 2015). Thus, it is possible developmental changes in the effect were not captured appropriately with my sample, as the present sample was already too old. Especially as overall there were faster reaction times in the gap condition than in the baseline condition in the present sample. Moreover, there were no developmental changes in variability of any of the parameters, which matches prior findings (Colombo, 2002) stating that although inter-individual variability is high and individual differences in reaction time are prevalent, intra-individual variability in reaction times remain relatively stable across the first year of life. Results from investigating developmental changes in the face pop-out tasks mirrored results from the gap-overlap task. Changes in the first look proportion for face declined with age.

Younger infants in particular seemed to look for the majority of time towards the face as seen by the age group differences in various face look parameters. This could be because while infants generally looked first towards faces over other stimuli (Johnson et al., 1991; Gliga et al., 2009), younger infants were unable to disengage their attention from the first stimulus while older infants were able to shift their attention and examine other parts of the complex array presented to them. Another reason could be that the shorter looks with increased age are related to developmentally driven increases in processing speed (Cuevas & Bell, 2014; Rose et al., 2012).

Interestingly, there were no significant developmental changes in look duration of the novelty habituation task. This finding is to a certain extent in line with Colombo et al. (2004)'s findings that look duration towards static stimuli do not change much in the second half of the first year of life. However, the expected differences between younger (4 - 6 months of age) and older (8 - 14 months of age) participants were not found (Colombo et al., 2004).

Overall developmental pattern matched prior research especially in the gap-overlap task (Wass et al, 2015). This provided a good starting point to investigate how these patterns might be related to sleep in the first year of life.

5.6.2 Sleep and eye-tracking parameters

This chapter focused on identifying the relationship between objectively /subjectively measured sleep quality (as identified by data-driven clusters) and objectively /subjectively measured continuous sleep parameters and eye-tracking measures of attention. Results from *Chapter 3* suggested that some cross-method inconsistencies were to be expected. Nonetheless, common themes were expected

especially with regard to sleep fragmentation measures and between subjective measures (both parent-report) or between diary and actigraphy (both estimating one week of sleep).

5.6.3 The gap-overlap task and infant sleep

5.6.3.1 Sleep quality

Sleep quality analyses revealed no consistent pattern across sleep methods for the gap-overlap task. While most sleep quality clusters were not associated with gap overlap parameters, some results showed significant associations. That some effects with sleep type were found is contrary to Pisch (2015), though Pisch examined individual sleep variables and not as here clustered measures of sleep quality, which could explain some of the differences. Furthermore, the findings from the gap-overlap task are not consistent across sleep assessment methods. To find out more about this theory, four sleep variables were investigated into more details: Day and Night Sleep Duration, Night Wakening Number and WASO. Variables that had previously been identified in the sleep research literature as relevant to cognitive development (e.g., Pisch et al., 2019). Contrary to the investigations on sleep quality revealed some associations between sleep parameters and eye-tracking task parameters.

There was a significant association between objectively measured sleep quality for variability in baseline saccadic reaction time with the cluster that combined poor and day sleepers showing lower variability than the adult-like/mature sleepers cluster. This means that adult-like/mature sleepers were less consistent in reaction time. However, as follow-up analyses were performed with variability in the other conditions, this pattern did not emerge across the gap or the overlap condition as would be expected (Hood & Atkinson, 1993; Pisch, 2015) so future research should focus on determining the reliability of this finding. Diary-measured sleep quality were only significantly associated with mean saccadic reaction time during the gap condition with adult-like sleepers being slower than day/mixed sleepers on the gap mean condition. The finding from the diary clusters is comparable to the pattern of the baseline condition results of the actigraphy clusters. Again, the pattern was not consistent across conditions and thus its reliability needs to be determined in future studies.

Additionally, actigraphy-measured sleep quality showed developmental differences for the two clusters in association with disengagement. This could hint towards distinctive disengagement trajectories in different types of sleepers. Infants in the adult-like sleep cluster showed the typical decrease in disengagement reaction time score with the fastest

disengagement being around 8 months of age and then slightly increasing (as suggested by Colombo, 2001, 2002). Infants in the poor/day sleepers cluster actually showed a different pattern with an initial increase and then a peak of disengagement scores at around 10 months of age and then a drop in mean scores. Sleep in the poor/day sleep cluster was not as regulated as in the adult/mature sleep cluster. Disengagement/attention orienting has been linked to aspects of attentional control (Hendry, Jones, & Charman, 2016). The atypical trajectory of disengagement in the poor/day sleep cluster could potentially reflect underdeveloped neuroanatomical structures that cause both impaired self-regulation in sleep-wake maintenance and in attentional control, much along the lines of Geva et al. (2016). However, it has to be acknowledged that this relationship was only found for the actigraphy-based clusters, so it should be treated with caution until it can be replicated.

BISQ-measured sleep quality was related to facilitation score with day sleepers having a significantly higher facilitation score than poor sleepers or adult-like/mature sleepers. Higher facilitation scores are indicative of a stronger effect of the cue, thus are better the higher. Apart from systematic differences between sleep clusters, this finding could also be explained by the fact that day sleepers were more refreshed during the day when the testing took place. Parents were asked to make sure that infants were well rested when they attended testing sessions, so it could be that day sleepers were likely to come well-rested, whereas other sleepers would not have napped prior to testing. However, if this was the case, this effect should have been seen across different variables for the BISQ-measured day sleepers.

In summary, while the findings are not consistent across conditions or across methods, sleep quality findings suggest a potential impact of sleep quality on consistency in the performance on the gap-overlap reaction times. Future research should investigate this claim further in addition to studying both objective and subjective measures.

5.6.3.2 Continuous sleep parameters

Investigation of the variability measures in relation to continuous parameters show variability in task reaction time was related to objectively measured WASO and night sleep duration. That is, infants who were awake longer at night had more variability in reaction time than did children who were awake for less time at night. Children with longer Night Sleep Duration also had more variability in reaction time. These findings could mean that infants who had a more dysregulated sleeping pattern (i.e., more time awake at night) also had a more dysregulated attention system, as suggested by higher

variability in reaction time. While there were also significant associations between the subjectively measured sleep variables and variability measures, these differed from the actigraphy-measured parameters, similarly to the patterns of the cluster-based analysis above.

While more variability on baseline reaction time was associated with more WASO in the actigraphy parameters, more variability was actually associated with lower WASO as measured by diary. These opposing results are puzzling but may possibly be explained by the systematic differences that were found between actigraphy and diary (see *Chapter 3*). For example, parents may sometimes underestimate how long infants are awake at night, especially in older infants that are able to self-soothe to sleep. These inherent difference between objective and subjective measures might have led to the contradictory results. BISQ-measured sleep parameters showed associations that differed to actigraphy or diary measures. There was an association of Night Sleep Duration with baseline and gap mean reaction time, this means that infants with longer sleep duration at night had slightly longer reaction times on those two conditions, though the effect was not very strong. In addition, there were no significant association of variability measures for the BISQ.

Interestingly, Day Sleep Duration was related to disengagement, such that children who sleep longer during the day showed higher mean disengagement scores. This finding could potentially be linked back to the findings of the actigraphy sleep quality, where poor/day sleepers, a sleep quality cluster defined by longer day sleep, showed an atypical increase in disengagement. Furthermore, children who commonly sleep during the day might be tired and thus perform worse on attention tasks (as indicated by higher disengagement scores). Other diary-measured night sleep parameters showed interaction effects with age group with mean reaction time of gap, overlap and disengagement conditions. However, there did not seem to be a clear pattern with regard to the results. The facilitation results of the sleep quality analysis are mirrored by the finding that higher BISQ-measured Day Sleep Duration was associated with higher facilitation scores. The latter results match the findings of the sleep quality analysis where day sleepers showed higher facilitation scores, with a potential explanation being that day sleepers were more alert during the day, when the testing took place, due to their recent nap.

Overall, it has to be acknowledged that while patterns observed in the association of sleep and gap-overlap task are interpretable; the lack of cross-method consistency warrants that these findings should be treated with caution.

5.6.4 The face pop-out task and infant sleep

There were no associations between sleep quality (as identified by data-driven clusters) and face pop-out task parameters. It is possible that attention towards faces does not depend on sleep contrary to Sun et al. (2016)'s study's conclusion. Looking towards faces is a universal phenomenon, especially in typically developing infants. Sleep might not have an impact on socially driven attention. However, although Sun et al. (2016) found association with individual sleep parameters, the associations with sleep quality indices were actually not significant. As the sleep clusters are the attempt at classifying sleep quality in a data-driven way, these findings are actually in line with Sun et al. (2016).

Analogously to the gap-overlap task, four sleep variables were investigated in more depth: Day and Night Sleep Duration, Night Wakening Number and WASO. These variables have previously been identified in sleep research as relevant to cognitive development (e.g., Pisch et al., 2019). Contrary to the investigations on sleep quality, these analyses revealed some associations between sleep parameters and eye-tracking task parameters.

All significant sleep parameters interacted with age group in their association with face pop-out parameters. For actigraphy-measured sleep variables, infants in the 10-month and 12-month age groups had higher longest looks towards the face the less time they spend awake at night. Infants in the age groups of 4 and 6 months of age showed lower face peak looks with more night wakenings. These findings together hint towards developmental differences in face looking in relation to sleep.

There were developmental changes in the associations of BISQ-measured Night Sleep Duration and BISQ-measured Day Sleep Duration with face peak look. 4- and 14-month-olds had more face peak looks when they sleep less at night, while 6- and 8-month-olds showed the opposite patterns of longer face peak looks with more sleep at night. The 10- and 12-month-olds fell right in the middle of these patterns with no strong associations between face peak looks and amount of sleep. In general, less day sleep was associated with longer duration of the longest face look, except for the 12-month-olds. Infants age 4-months and 14-months old looked proportionally longer towards faces the longer they slept at night, while the 6- and 12-month-olds showing the reverse pattern. Infants 8- and 10-months old showed no strong relation between night sleep and face look proportion. There were developmental association between diary-measured WASO for total look time towards face during the trials. Infants aged 6- and 10-months old

showed more looking towards faces with higher WASO, infants aged 8-, 12-, and 14-months old showed the opposing pattern.

These results are somewhat contrary to prior research. Several studies found that face looking generally levelled off in the second half of the first year of life and that this decrease was associated with better effortful control and better language scores in older infants and toddlers (Colombo et al., 2004; Courage et al., 2006; Hendry et al., 2018). Research has also shown that longer mean fixations to stimuli in the age ranges of 4 to 10 months were related to better effortful control (Papageorgiou et al., 2014). However, Though, the latter finding did not study face stimuli, such as the other studies.

It is unclear how sleep can impact the development of looking towards face, especially because sleep parameters were related to face parameters in different ways. The results suggest broadly that sleep patterns can interact with age in the effect of looking towards face in a complex array. Due to the cross-method inconsistencies it is unclear whether data from the objective of subjective sleep assessment methods should be interpreted. Moreover, it is not clear which sleep parameter is most relevant. Generally, it is possible that certain ages might benefit especially from a certain type of sleep, e.g., longer sleep duration at night and no night wakenings is especially useful in 14-month-olds, but not so important for younger infants. To verify these hypotheses, one would have to track the same infants for the entire duration of the first year of life on attention as well as sleep measures.

5.6.5 The novelty habituation paradigm and infant sleep

There were no effects of sleep quality for most parameters of the habituation task except for developmental differences in the BISQ sleep quality clusters for the look duration in the boring condition. Analyses showed a potentially different trajectory of look duration for the poor sleepers, with poor sleepers showing longer look durations than mature or day sleepers; however, the sample size for the 4-month-olds was very limited and thus this result has to be viewed with caution. In line with these findings, the additional analysis of the continuous sleep parameters also did not show any associations between objectively and diary-measured sleep parameters and look duration at interesting or boring stimuli.

For the BISQ-measured variables, Night Sleep Duration and WASO were both associated with look duration in the boring condition, such that higher Night Sleep Duration was associated with lower boring look durations and higher WASO with longer look durations towards boring stimuli. As shorter look durations suggest more efficient

information processing (Colombo et al., 2004), this finding could mean that infants who slept longer at night had more efficient processing speed and infants who spent more time awake at night had less efficient processing.

Overall, there were no strong patterns evident in the association of the novelty habituation paradigm and infant habitual sleep, as two out of three sleep measures showed no association on any sleep parameters.

5.6.6 Summary and concluding remarks

In general, though some of the eye-tracking measures were related to certain types of sleepers, there was no consistent pattern overall, and results differed across sleep assessment methods. The fact that there were no association between sleep clusters and many of the eye-tracking measures matches Pisch's (2015) results of no associations between several sleep parameters (habitual sleep) and the gap-overlap task. One explanation for this finding is that there is no association between (fine-grained) measures of attention and habitual sleep in the age range that was tested here. Given that the sparse prior research on infant sleep and attention is mixed, it is possible that sleep patterns are not related to selective social attention, habituation and/or orienting/disengagement. As suggested recently (e.g., Camerota et al., 2019), it is possible that sleep is only related to general development and not to measures such as attention. Rather, the effect of sleep on individual measures such as attention, processing speed or emotion regulation is small but over time a cumulative effect leads to an impact on general development. However, the findings from *Chapter 4* do not entirely support this notion. While associations with aspects of general development were found, the association was not as clear cut.

Another possibility is that the sleep clusters identified in *Chapter 3* are actually not an adequate way to classify sleep and are thus obscuring other patterns in the sleep data. For example, it is possible that certain individual sleep variables are more important than the composite sleep cluster that were formed. It could be that aggregating all sleep variables together led to the loss of crucial information. Some of the continuous sleep parameters that were investigated in addition to sleep quality clusters did show associations that are potentially informative, e.g., the results from the face pop-out task.

Overall, several key points stand out from the above analyses. First, developmental patterns in the data match prior research, lending credibility to the quality of the dataset and contributing to the knowledge base on attention development in typically developing infants. Second, there are indeed certain sleep parameters that might impact an infant's

attention. For instance, sleep fragmentation measures, that showed developmental changes in association with face look parameters.

What, however, are the mechanisms behind it? One explanation of how sleep can influence attention could lie in the SHY (see *Chapter 1*). It could be that sleep is directly involved in improving neuronal functioning as suggested by Tononi and others. Infants with better sleep (e.g., longer sleep duration, less night wakenings) could have better synaptic plasticity and, consequently, better developed attention networks (Tononi & Cirelli, 2003).

Another concept to consider is the role of sleep as a mediator. For example, Bernier et al. (2014) showed that, in children with longer night sleep duration, there was a relationship between maternal sensitivity and measures such as infant executive functioning (Bernier et al., 2014). This hypothesis is supported by Camerota (2018)'s study showing that children with good sleep regulation and well-educated mothers showed the best levels of sustained attention. Lastly, following Geva et al. (2016)'s argument, the underlying systems of sleep and arousal and thus attention are the same. Therefore, if the neuronal circuits underlying attention are not well-developed, sleep patterns may also be more irregular and more immature. This supports a stream of sleep research mainly focused on self-regulation and the importance that self-regulation plays in successful sleep wake maintenance. In this line of thinking, it seems as though poor sleep quality could simply serve as an indicator of brain maturation, where poor sleep and poor attention just incidentally occur together. Though, it has to be acknowledged that associations in the present study were relatively fragmented and showed cross-method inconsistencies. Thereby, perhaps only lending tentative support for this theory. Nonetheless, it should be investigated in future studies. Based on this study, attention parameters potentially relevant to investigate in relation to sleep are parameters that concern variability in reaction time (as evidenced by gap-overlap task findings) and parameters that concern maintenance of attention (as evidenced by peak look and boring look duration).

Moreover, the discrepancy between subjective and objectively measured sleep clusters and individual sleep parameters in terms of effect on eye-tracking parameters is interesting, as it emphasizes the conclusion of *Chapter 3*. The choice of sleep assessment method and the way in which sleep quality parameters are defined can dictate if and how associations are found. Researchers should therefore carefully choose, justify and define choice of sleep variables and methods prior to study initiation.

5.6.7 Limitations and future directions

First, as can be discerned by *Table 5.1.* it is hard to disentangle different aspects of attention in these tasks (see Hendry et al., 2019 for discussion). Thus, the tasks selected are not necessarily a "pure" measure of the aspects of attention. Moreover, attention task performance might be influenced by underlying processing speed abilities, which makes it hard to make a statement about the definite influence of sleep on attention. This is however an inherent drawback of eye-tracking technology. Using brain measures could provide additional information.

Second, as infants always performed the eye-tracking session after only a short break, their performance may have been hindered by being tired. There could be a bias towards babies that were alert and not tired, introducing an inherent bias in sleep differences. Thankfully, the number of infants dropped from the study were not particularly high. However, it meant I could not examine whether there were systematic differences in sleep patterns in babies dropped from the sample due to non-completion of the eye-tracking session. As not that many infants dropped out this is likely to not be an issue.

Third, there was no information on sleep-wake patterns at birth and in the crucial first months after birth. Prior research has shown those have the potential to have cascading influence on later attention and sleep patterns (Geva et al., 2016). Thus, future work should include measurement of attention abilities starting also at birth throughout the entire period of the first year of life to account for potential early changes in sleep-wake patterns.

In summary, this chapter highlighted the usefulness of using objective and subjective measures of sleep. There were fragmented associations between attention measures and sleep measures, that suggest some association between attention and sleep in the first year of life. Moreover, this relationship seemed to show age-related changes across. However, results were also marked by cross-method differences in the directionality of those patterns. While eye-tracking is a more objective measure to assess development than parent-report questionnaires (used in *Chapter 4*), there are some drawbacks including the difficulty in disentangling aspects of attention (see above). Another way to objectively investigate development is by looking at the brain in infancy. This is the goal of *Chapter 6* where I will explore the association between infant sleep and wake infant brain activity using the sample of Study 1.

CHAPTER 6 - Theta power, theta power change, and sleep in the first year of life

Thus far, questionnaire-based and behavioural assessments of developmental markers have been discussed; while both are good proxy measures of neurocognitive development, they can be confounded by for example, parental bias or be blurred by motor limitations, underlying attentional/processing speed abilities (e.g., as discussed in *Chapter 3, 4* and *5*). Occasionally the brain can reveal additional information that can extend and/or clarify findings of behavioural measures, such as eye-tracking or questionnaires. The brain can provide fine-grained information about individual differences above and beyond the so far mentioned methods.

6.1 Waking EEG markers of (neurocognitive) development

Brain measures of neurocognitive development can be obtained by various methods, e.g., functional magnetic resonance imaging (fMRI), functional near infra-red spectroscopy (fNIRS), magnetoencephalography (MEG) or electroencephalography (EEG) to name the most commonly used. For the longitudinal Study 1 EEG was selected for a number of reasons. Study 1 required a system that could easily be installed at a company, where no neuroimaging lab or infant testing facilities were already set up. The wireless ENOBIO EEG system (see *Chapter 2)* is portable, affordable and easily set-up. Its user-friendliness and non-invasive nature made it ideal for use in longitudinal studies, specifically in the case of paediatric populations. EEG has the ability to provide information about underlying neural activation patterns (see *Chapter 2*). Moreover, EEG is the only method to provide information about sleep microstructure, such as frequency decompositions or sleep stages during sleep. These tell researchers about the amount of deep sleep (using frequency/power) and other patterns in sleep (using oscillations). Similarly, to sleep science, developmental research often uses oscillations and power in frequency. However, in developmental science they have been used as indicators of EEG correlates of cognitive development.

Research has, thus far, clearly outlined that there are developmental changes in waking EEG power and oscillations. Investigating neural dynamics and oscillations have been shown to reflect underlying neural mechanisms and provide information about how different cognitive processes interact with each other. In general, frequencies in the lower range (i.e., theta; 3-6 Hz) decreased with age whereas higher-frequency EEG increased

with age (Anderson & Perone, 2018). Interestingly, this decrease in lower frequencies has been tentatively linked to synaptic pruning during development (Whitford et al., 2007). Apart from reflecting general patterns of brain maturation, developmental EEG oscillatory activity in various frequency bands has been linked to cognition/cognitive performance.

In general, higher frequency oscillations are said to be important for local integration of information whereas slower frequency oscillations are crucial for a more global integration of information (Buzsáki & Draguhn, 2004). Recently, theta band oscillations have been proposed to have potential as a unifying marker for general information processing in development (Jones et al., 2020; Meyer et al., 2019). Moreover, it is possibly predictive of later cognitive functioning (Jones et al., 2020), making it an important candidate to study development. Additionally, theta frequency has been related to aspects of sleep (for discussion see below), such as sleep propensity or the amount of slow wave activity during sleep. Therefore, it is possible that considering waking EEG patterns/brain activity, particularly waking theta oscillations in relation to sleep, has the potential to provide additional information on the relationship between sleep and development.

6.2 Theta power/theta power change as marker for development

The theta power band is emerging as being potentially relevant as an early marker for cognitive development and/or future cognitive function. While adult theta power has been linked mainly to top-down control mechanisms, memory consolidation and transmission of information between the hippocampus and cortex (Nyhus & Curran, 2010), the picture is less clear in development. The range of cognitive processes linked to theta is so broad that it has been proposed to reflect general information-processing and/or cognitive control and/or cognitive effort (Bosseler et al., 2013; Jones et al., 2020; Liu et al., 2014; Meyer et al., 2019) rather than a single individual process. Thus, theta modulation appears to reflect an integrated set of basic memory and attentional processes (bottom-up), as well as top-down control (Jones et al., 2020; Meyer et al., 2019). Whilst research examining theta activity has shown links with many cognitive processes, the underlying mechanisms through which theta power and cognitive markers/cognition are related are still debated.

In terms of the infant literature, theta power is higher in infancy than later in development (Orekhova et al., 2006). This is consistent with the above-mentioned decline in lower frequency ranges across development, that likely reflects synaptic pruning

processes. Of note, the theta power range, as all EEG band power ranges, is slightly lower in infant populations than in older children or adults with a range of 3 - 6 Hz (Jones et al., 2020; Saby & Marshall, 2012).

Below a number of studies on theta oscillations are briefly described to provide an overview of the range of cognitive domains to which theta has been linked.

6.2.1 Theta power

In developmental research, theta oscillations have been implicated in a wide range of emotional and cognitive processes. These include for example, exploration, attention, language processing or memory consolidation/learning (Begus & Bonawitz, 2020).

Object exploration/novelty detection. Early studies linked increases in frontal theta power (3.6 to 5.6 Hz) to exploration of novel toys in infants (7-12 months) and pre-schoolers (4-6 years) (Orekhova et al., 2006). Additionally, the amount of frontal theta, but not the duration of contact with the object, recorded from 11-months-old infants when they examined objects, predicted their memory for these objects later on (Begus et al., 2015).

Language processing. Another domain theta has been connected to is language**.** Research found that infant-directed speech elicited higher theta power compared to adult-directed speech in infants (Orekhova et al., 2006; Zhang et al., 2011). Similarly, theta was also linked to processing of familiar language cues in infants aged 6 and 12 months old and has also been linked to language learning in general (Bosseler et al., 2013).

Error monitoring. Infants also showed higher theta power during violation of expectation paradigms. In these paradigms' infants habituate towards a certain stimuli or sequences and then presented with another stimuli that is contrary to their expectation, leading to increased looking time. Results from these studies showed, for instance, that when looking at simple maths problems, infants displayed increased theta when their expectation of the outcome was violated (Berger et al., 2006). This study and others have linked theta power increases to error monitoring (e.g., Conejero et al., 2018; Meyer et al., 2019). Though the latter two studies looked at slightly older ages, i.e., toddlers and pre-schoolers. Meyer et al. (2019) also concluded that, rather than only error monitoring, theta is perhaps also crucial for task engagement.

Attention. Certainly, many of the above findings could also be explained in terms of attention, rather than language processing or error monitoring per se, as interpreted by the authors. Indeed, theta power during infancy has also been linked to maintenance of attention (Orekhova et al., 1999) and specifically to social attention (Jones et al., 2015;

Orekhova et al., 2006) in infants of varying ages in the first year of life. Infants aged 12-month-old, that played freely, fixated longer on certain toys when preceded by higher theta power, indicating an association between visual attention and theta power (Wass et al., 2018). Moreover, Xie and colleagues (2017) highlight the importance of theta power for sustained attention in 10- and 12-month-old infants (Xie et al., 2018). Lastly, theta power has been linked to executive attention (Bazhenova et al., 2007; Michel et al., 2015).

6.2.2 Theta change

Another way to think about theta power is in terms of continuous change across a longer period rather than in terms of absolute theta power during task condition compared to another task condition. One of the earliest studies on theta power also observed an increase in theta power at the end of infants watching an experimenter blow bubbles compared to the beginning of the session (Stroganova & Orekhova, 2007). A similar version of this theta change measure was used in two recent studies that looked at whether theta change might serve as an indicator of cognitive ability. Braithwaite et al. (2020) investigated changes in theta band power in response to watching a 60-second non-social video. The increase in theta power change at 6 months was predictive of non-verbal cognitive abilities (as measured by the Mullen scales of Early Learning) but not of executive functioning (as measured by an A-not-B/Freeze-Frame task) in 9-month old infants (Braithwaite et al., 2020). Theta power increase in the course of viewing a video was also found by Jones et al. (2020) in children at risk of autism. Theta changes in infancy were also related to concurrent, non-verbal cognitive ability and predicted non-verbal cognitive abilities later in development (at 3 years of age). These studies highlight the potential of theta change as a marker for cognitive ability that may even be predictive of childhood cognitive ability.

In summary, both theta and theta power change could serve as indicators of cognitive ability and/or cognitive development. Though research is still divided as to what theta power actually represents; sustained attention, error monitoring or the above-mentioned cognitive abilities, current research suggests that theta power is related to increased information processing and cognitive control. These are crucial skills for general development and skills that infants require in order to learn about their environment.

6.3 Theta power and sleep

Sleep research often highlights frequency in the theta range (3 - 6 Hz in infancy) primarily as of importance in indicating the transition from waking to sleeping states. However, a number of studies have shown that sleep propensity (the need to sleep, see *Chapter 1*) is related to waking (task-related) theta power, with higher sleep propensity being associated with higher theta power. For example, Cajochen and colleagues (1995) showed that EEG power density increased in the 6 - 9 Hz range with prolonged (up to 36 hours) wakefulness in adults (Cajochen et al., 1995). Similar findings were reported by others (Aeschbach et al., 1997; Finelli et al., 2000). This suggests that theta oscillations in adults are affected by sleep propensity. Thus, theta power might also be seen as a homeostatic marker of sleep (drive) (see *Chapter 1* for explanation of process S). In agreement with this are findings that link increased frontal theta power to subjective reporting of the ”feeling of sleepiness” (Strijkstra et al., 2003).

This alternate role of theta as an indicator of sleep drive is seen not only in adults, but also during development. A recent study into adolescents by Feinberg & Campbell (2019) showed a generalized decrease in all waking EEG power ranges (including theta) in adolescents with lower sleep duration. This demonstrates that waking EEG patterns are indeed affected by sleep patterns. Though these results seem to be contradictory to results from adult studies (Feinberg & Campbell, 2019), potentially due to inherent developmental differences in the development of neural activity or in how sleep affects waking brain activity.

Studies reported thus far are so-called sleep deprivation studies, but their findings extend to sleep studies into children, where sleep deprivation is not induced. For example, one study showed that approximately 45% of theta activity increases as a natural cause of accumulation of sleep propensity (process S) during the day in 8- to 12-year-old children in particular in frontal and central regions (Fattinger et al., 2014). Typically developing children with sleep problems (as measured by the parent-reported Child Habit Sleep Questionnaire; Owens et al., 2000) had higher theta power than children without sleep problems (Winkelman et al., 2018).

A potential explanation for the increase in theta power with increased sleep drive is that theta power reflects so-called local sleep in the awake brain. Pioneering research carried out on rats has shown that after prolonged wake some local cortical neurons exhibited brief periods of “silence”, which in turn were associated with theta oscillations (Vyazovskiy, Cirelli, et al., 2011; Vyazovskiy, Olcese, et al., 2011). The authors argue that

these periods of silence associated with theta power are parts of the brain falling asleep during wakefulness. Hung et al. (2013) confirmed the existence of such local sleep in human adults (Hung et al., 2013).

Another possible explanation of increased theta with increased tiredness is the link to local sleep, i.e., the longer the animal (or human) is awake, the more frequently parts of the brain fall into local sleep. This is further supported by evidence demonstrating that the increased theta activity observed during wake is associated with an increase in NREM SWA activity in the same brain regions (Finelli et al., 2000).

Moreover, Fattinger et al. (2017) and Vyazovskiy et al. (2011) relate these local sleep occurrences (as measured by theta activity) to cognitive performance. Local regions of the brain are falling asleep and consequently impair cognitive performance. In line with this theory, Fattinger and colleagues (2017) showed that following a period of theta activity, performance was slower on an oddball paradigm (an attention task) in children. Moreover, when theta activity was measured during the oddball paradigm periods, reaction times were longer than during periods without theta activity. Lastly, children with more theta events in waking EEG performed slower overall. Research is sparse with regard to determining the role of waking theta power in relation to sleep, in particular in developmental samples.

While there waking theta has not been examined in association with habitual sleep in infancy directly yet the above research highlights that this topic is important to further investigate.

6.4 Theta in relation to sleep vs. theta in relation to development

Research examining theta oscillations has demonstrated that it is difficult to determine the exact function of this neural process. At first glance, it seems that theta in relation to cognitive development and theta in relation to sleep have opposing roles. However, one can conclude that theta power and/or theta power change can potentially serve 1) as markers of development and 2) of sleep (drive). However, thus far, there is no research that has examined the relationship of theta activity during wake and sleep in infancy.

Given different populations were studied and the knowledge that sleep as well as development differs fundamentally in infants compared to older children or adolescents/adults, these diverging findings on theta and sleep may not be entirely surprising. One of the aims of the present study is to shed light on the role of theta in

relation to habitual sleep. Due to the lack of research into theta and sleep in infancy, at this point it is only possible to provide conjecture on how the seemingly divergent findings might be unified. It is possible that theta underlies the same function but expresses itself differently depending on the context.

Supportive of the idea that theta has the same role but is simply interpreted differently depending on whether sleep researchers or developmental scientists study its role is the research by Vyazovskiy and colleagues (2011). They report that local sleep, as indicated by theta oscillations, were associated with more exploratory behaviours in the rats. This is in line with infant research described above that demonstrated increased theta was related to an increase in toy exploration (Begus et al., 2015). Albeit the researcher's interpretation of the results is different, i.e., one interpretation is local sleep (in the rat experiment) and the other one is task engagement (in the infants).

Secondly, the idea of theta being associated with sleep drive/local sleep could suggest overall higher 'baseline' theta power in infants who are more tired. However, theta change within a stimulus (i.e., the dynamic range of theta) is greater when infants are less tired, delivering a potential explanation as to why theta change is linked to better attention and memory. Studying the role of wake theta and sleep in infancy will shed some light on this curious dichotomy.

6.5 Research aim and current study

In this study the aim was to examine how theta power change and theta power may be related to habitual sleep patterns in infancy. It was hypothesised that better infant sleep (i.e., as indicated by infant sleep quality clusters; see *Chapter 3*) or e.g., longer sleep duration/less fragmentation) would be associated with less overall theta power in response to a video such as in prior studies. Secondly, I hypothesised that better infant sleep would be associated with increased theta change values.

6.6 Methods

6.6.1 Sleep measures

As sleep indices this chapter as for *Chapter 4* and *5*, the sleep clusters identified in *Chapter 3* by k-means cluster analysis were used. These were as follows: poor, adult-like and day sleepers for actigraphy and Brief Infant Sleep Questionnaire (BISQ) and poor, adult-like, day and mixed sleepers for sleep diary.

As with *Chapters 4* and *5* sleep clusters (i.e., adult-like, poor and day sleepers/ mixed sleepers) identified in *Chapter 3* were used to identify a relationship between sleep and development. Additional analyses were performed on sleep parameters commonly used in the literature, i.e., Night and Day Sleep Duration, wake after sleep onset (WASO) and Night Wakening Number (sleep fragmentation), this was done because the broad sleep clusters might miss more fine-grained aspects of sleep/more specific relationships. For the actigraphy data, clusters of poor and day sleepers were merged as there were only 9 participants in clusters for day sleep. For diary clusters, clusters of mixed and day sleepers were merged again due to the limited number of participants in the day sleep cluster. No clusters were merged for the BISQ as cluster sizes were approximately equal.

6.6.2 EEG measures

6.6.2.1 EEG system

For details of the EEG system and EEG recording see *Chapter 2*. The EEG system used in this study is a 20-channel, wireless Enobio System (Neuroelectrics, BCN, ES). Gel-based electrodes are embedded in a soft neoprene cap and connected to a Bluetooth transmitter. The sampling frequency was 500Hz. References were placed on the right mastoid. The EEG set-up covered the whole head. Channel configurations see *Figure 6.1*.

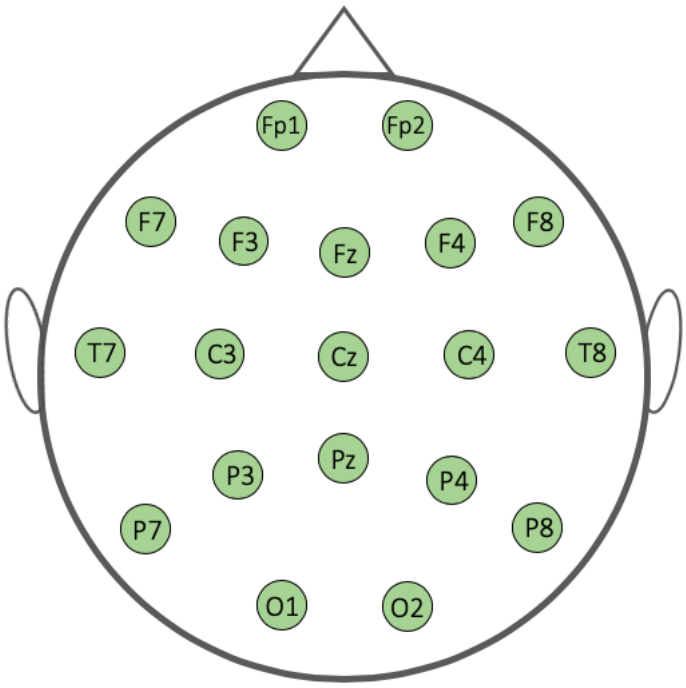


Figure 6.1. Channel figuration for the 20-channel ENOBIO.

6.6.2.2 EEG task

Data for three different tasks was collected. However, for this chapter only social videos were analysed. These were 1-minute videos of women singing different nursery rhymes, with corresponding hand gestures, in Swedish (see *Figure 6.2*). Swedish was selected, so not to bias the participants of different ages and thus different language experiences and expertise. Social videos were chosen as they had elicited the strongest theta response in prior studies compared to other videos (Jones et al., 2015). The videos were presented up to three times, interspersed with other tasks. The total time needed to present all of the EEG tasks was approximately 15-20 minutes.

Figure 6.2. Screenshot of social videos used in the present study.

6.6.3 Analysis Plan

6.6.3.1 EEG pre-processing

EEG data pre-processing was done using EEGlab version 19.1 and custom-written MATLAB scripts (by LG) using Matlab version 2019a. Details of the pre-processing steps can be found in *Figure 6.3*. Data was bandpass filtered at 0.1 - 48 Hz. Data was segmented into 60 1-second-epochs for each video and artefact rejection was performed. Data sets were only included if at least 15 epochs per each half of the social video were valid (according to Braithwaite et al., 2020; for pre-registration and details of analyses see: https://osf.io/v5xrw). No re-referencing was performed due to the low number of channels. Re-referencing is not strictly necessary as mastoid references were used during acquisition. Bad channels were excluded on a subject-by-subject basis, but at least 4 frontal channels were required for inclusion of the data set. Only the first social video was used for theta change analysis and the first and second video for theta power calculation. Only approximately 25 EEG visits had completed all three videos, hence only the first two

videos were used in order to maximize the amount of complete data. After segmentation and artefact rejection the datasets were Fourier transformed (Matlab 2019a function fft) to obtain theta power (defined as 3 - 6 Hz, as in Jones et al., 2020; Braithwaite et al., 2020) of each 1-second segment as well as across the entire number of valid segments of the video. Overall theta power was obtained by averaging theta power across all valid segments of social video 1 and 2 across all available frontal channels. Theta power change was calculated as follows. The theta power value of each segment was correlated with the segment numbers resulting in a correlation value that was interpreted as the theta change value. Here, spearman's rho correlations were used to account for the fact that some datasets had more data in either half of the video resulting in slightly skewed segment numbers. In linear distributions spearman rho and pearson r correlation are almost equal, therefore it was considered better practice to use spearman rho, in order to not introduce systematic bias. Theta power change was calculated as in Braithwaite et al. (2020) (also see https://osf.io/v5xrw, description Index b) in order to facilitate cross-study comparison.

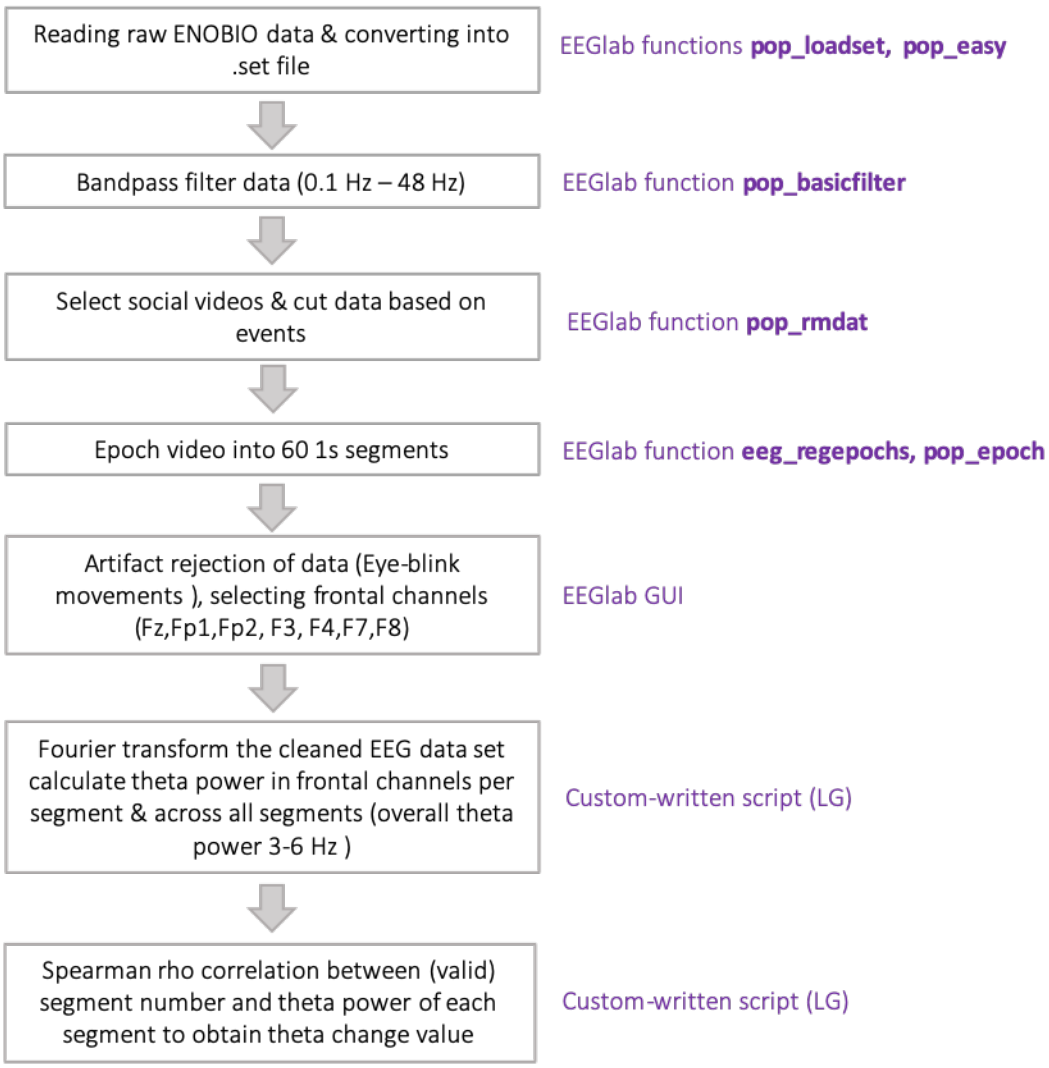


Figure 6.3. Illustration of EEG pre-processing pipeline.

Table 6.1 shows the excluded data of the social video analysis and *Table 6.2.* shows the percentage of included participant demographics for EEG data.

Table 6.1. EEG data exclusion

	No EEG data collected	**EEG data excluded due to noisy data** (HR, electrode pops, eye movement artefacts etc.)	**Experimenter/equipment error / event file error**
Data excluded (out of 166)	N = 25	N = 30	N = 15
Notes	due to baby fussing out/ parents not feeling comfortable with the EEG	HR artefacts were prominent in younger populations as mastoid reference placement was harder due to limited space	Occurred primarily in the beginning of testing for study 1

Table 6.2. Percentage of included participant demographics for EEG

		Included	**Excluded**
Age group	4 m	64.7 %	35.3 %
	6 m	41.7 %	58.3 %
	8 m	53.5 %	46.5 %
	10 m	69.7 %	30.3 %
	12 m	50.0 %	50.0 %
	14 m	47.6 %	52.4 %
Gender	Female	61.6 %	38.4 %
	Male	55.9 %	44.1 %
Visit	1	52.6 %	47.4 %
	2	52.3 %	47.7 %
	3	63.0 %	37.0 %
	4	57.9 %	42.1 %

Notes. m = months

6.6.3.2 Statistical analysis

Linear mixed effects modelling (LMMs) was used to analyse the data. For details with regard to different models tested and rationale for analysis choice see *Chapter 2*. Below the full linear mixed models (LMMs) tested are specified. Each analysis was performed three times for each sleep method once. Overall theta power and theta power change were the dependent variables. The full LMMs tested are as follows:

1. The **baseline model** is the developmental change model assessing how the theta parameters change over time.

Baseline: EEG parameter = random intercept for participant + age group

2. **Model 1** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameter) on overall theta power / theta change are assessed.

Model 1 (M1): EEG parameter **=** random intercept for participant + age groups + sleep variable

3. **Model 2** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameter) and an interaction effect of age group by sleep variable on overall theta power / theta change are assessed.

Model 2 (M2): EEG parameter = random intercept for participant + age groups + sleep variable + age group by sleep variable interaction

4. **Model 3** describes a model where main effects of age group as well as sleep variable (sleep quality as well as continuous sleep parameter) and gender an interaction effect of age group by sleep cluster and gender on overall theta power / theta change are assessed.

Model 3 (M3): EEG parameter = random intercept for participant + age groups + sleep variable + (age group by sleep variable interaction) + gender

6.7 Results

6.7.1 Descriptive Statistics

Table 6.3. shows the descriptive statistics for theta power and theta power change. T-tests showed absolute theta power was significantly different from video 1 to video 2 [t (56) = -3.13, p = .003] with video 2 showing higher theta power than video 1. There was no difference in theta change between video 1 and 2 [t (57) = -1.52, p = .14].

Table 6.3. Descriptive statistics overall theta power and theta power change

	Minimum	Maximum	Mean	SD
Theta power video 1	2.38	3.98	3.08	0.35
Theta power video 2	2.33	4.06	3.16	0.37
Overall theta power	2.36	4.00	3.12	0.35
Theta power change video 1	-0.31	0.44	0.06	0.16
Theta power change video 2	-0.17	0.49	0.11	0.16

Note. SD = Standard deviation

6.7.2 Developmental changes in theta power and theta change

Developmental changes were only observed in overall theta power [$F(5,57) = 7.61$, $p < .001$] but not with theta power change [$F(5,73) = 0.63$, $p = .67$]. Follow-up analyses for overall theta power showed that age group differences were significant between 4 and 8 (MD = -0.48, $p < .001$), 4 and 10 (MD = -0.41, $p = .003$), 4 and 12 (MD = -0.46, $p = .002$), and 4 and 14 (MD = -0.42, $p = .03$) months of age. Group differences were also significant between 6 and 8 (MD = -0.39, $p = .001$), 6 and 10 (MD = -0.32, $p = .01$), and 6 and 12 (MD = -0.37, $p = .01$) months of age. Multiple comparison correction was conducted using the Bonferroni-method. For detailed statistical results refer to *Appendix – Chapter* 6 and for illustration see *Figure 6.4A-B.*

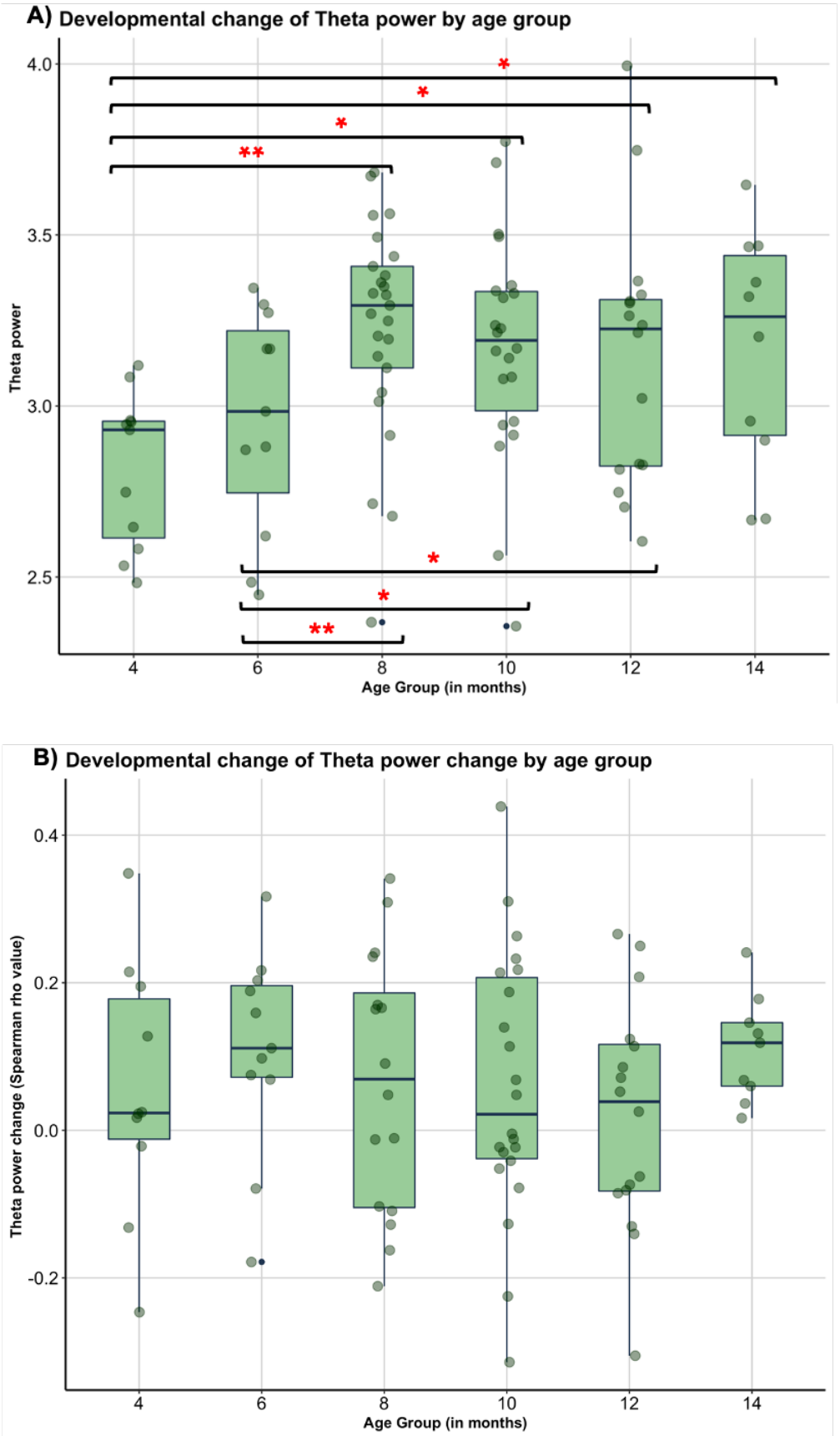


Figure 6.4. A) Developmental change of theta power, B) developmental change of theta power change, * p <.05, ** p <.001.

6.7.3 Infant sleep quality and overall theta power and theta change

Theta power. There were no actigraphy-measured, diary-measured or BISQ-measured cross-cluster differences with regard to overall theta power. This indicates no effect of sleep quality on overall theta power in response to the watching of social videos (all p's > .05, see *Appendix – Chapter* 6).

Theta power change. No actigraphy-measured cross-cluster differences with regard to theta power change, at the $p = .05$ level, though $p = 0.07$ were observed for actigraphy cluster differences which suggest that the poor sleepers showed lower theta power change [$F(1,69) = 3.35$, $p = .07$]. There were no diary-measured or BISQ-measured cross-cluster differences with regard to theta power change (all p's > .20, see *Appendix – Chapter* 6).

6.7.4 Continuous sleep parameters and overall theta power and theta power change

Below the results of the LMM's of continuous sleep parameters in association with theta power and theta power change are discussed. Detailed statistical results can be found in *Appendix – Chapter 6.*

6.7.4.1 Theta power

WASO. There was no significant relationship between actigraphy-measured, diary-measured or BISQ-measured WASO and overall theta power (all p's > .05, see *Appendix – Chapter* 6).

Night Wakening Number. There were significant interaction effects for diary-measured Night Wakening Number by age group ($F(5,27) = 3.25$, $p = .02$) and actigraphy-measured Night Wakening Number by age group ($F(5,21) = 4.24$, $p = .008$). For illustration of actigraphy-measured developmental changes in the relationship between theta power and night wakening see *Figure 6.5*. Diary-measured developmental changes were similar though not identical. There was a significant effect of BISQ-measured Night Wakening Number [$F(1,59) = 10.32$, $p = .002$; best model = M3]. However, as can be seen in *Figure 6.6.* one data point showed more night wakenings than the others and appears to maybe have affected the association. Therefore, I ran some correlational analyses between BISQ-measured Night Wakening Number and overall theta power to investigate this further. Moreover, I reran for the BISQ model excluding the potential outlier, this indeed yielded non-significant results in the association between BISQ-measured Night Wakening Number and overall theta power [$F(1,31) = 0.45$, $p =$

.51; best model = M1]. This indicates that caution is warranted in the interpretation of the BISQ finding. However, due to the large variability of sleep in the first year of life (Bathory & Tomopoulos, 2017), I believe there was not sufficient theoretical grounds for removing the potential outlier from the data completely.

Night sleep duration. There was no significant relationship between actigraphy-measured, diary-measured or BISQ-measured Night Sleep Duration and overall theta power (all p's > .05, see *Appendix – Chapter* 6).

Day sleep duration. There was no significant relationship between actigraphy-measured, diary-measured or BISQ-measured Day Sleep Duration and overall theta power (all p's > .05, see *Appendix – Chapter* 6).

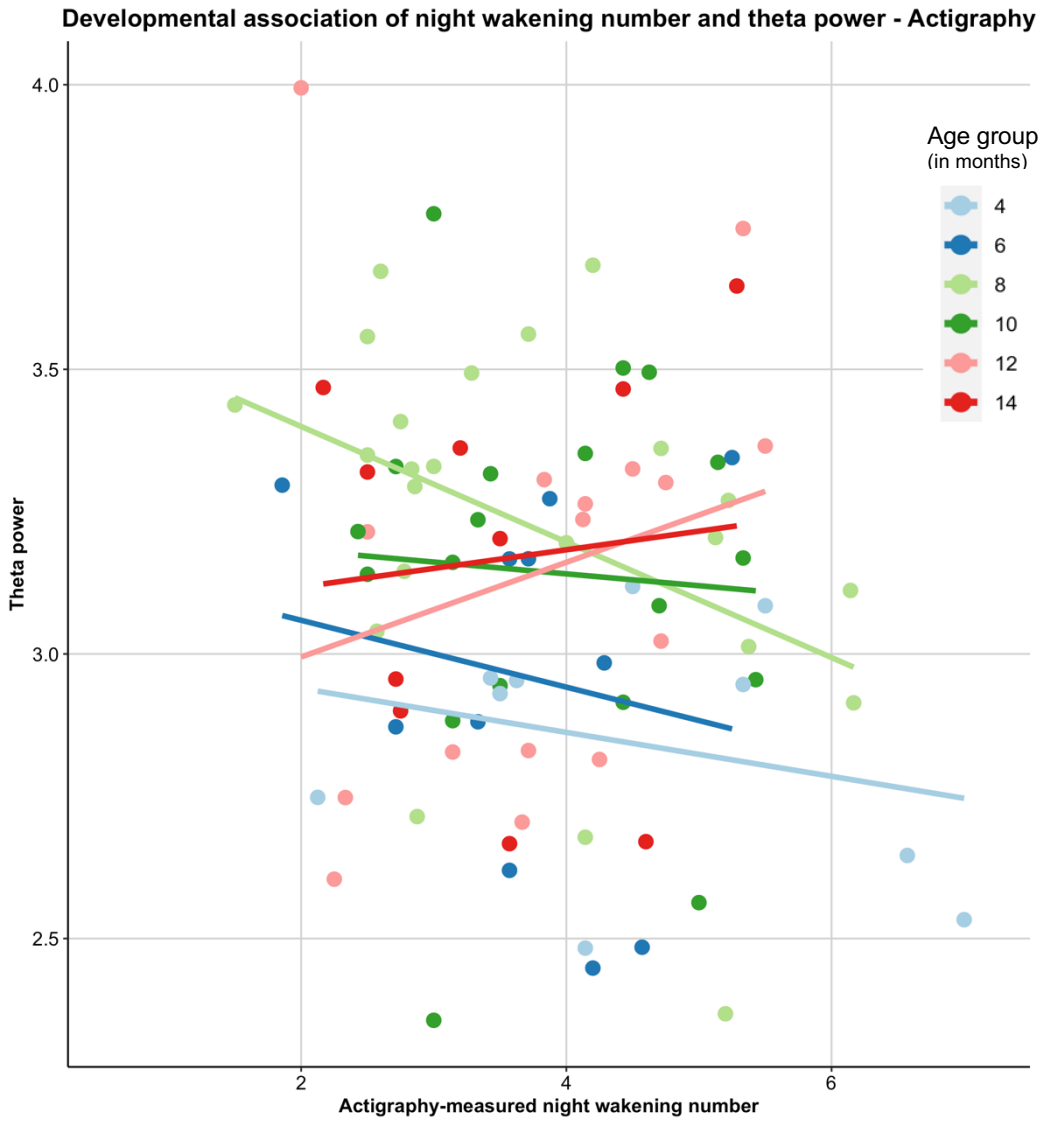


Figure 6.5. Developmental changes in the relationship between objectively measured night wakening and overall theta power.

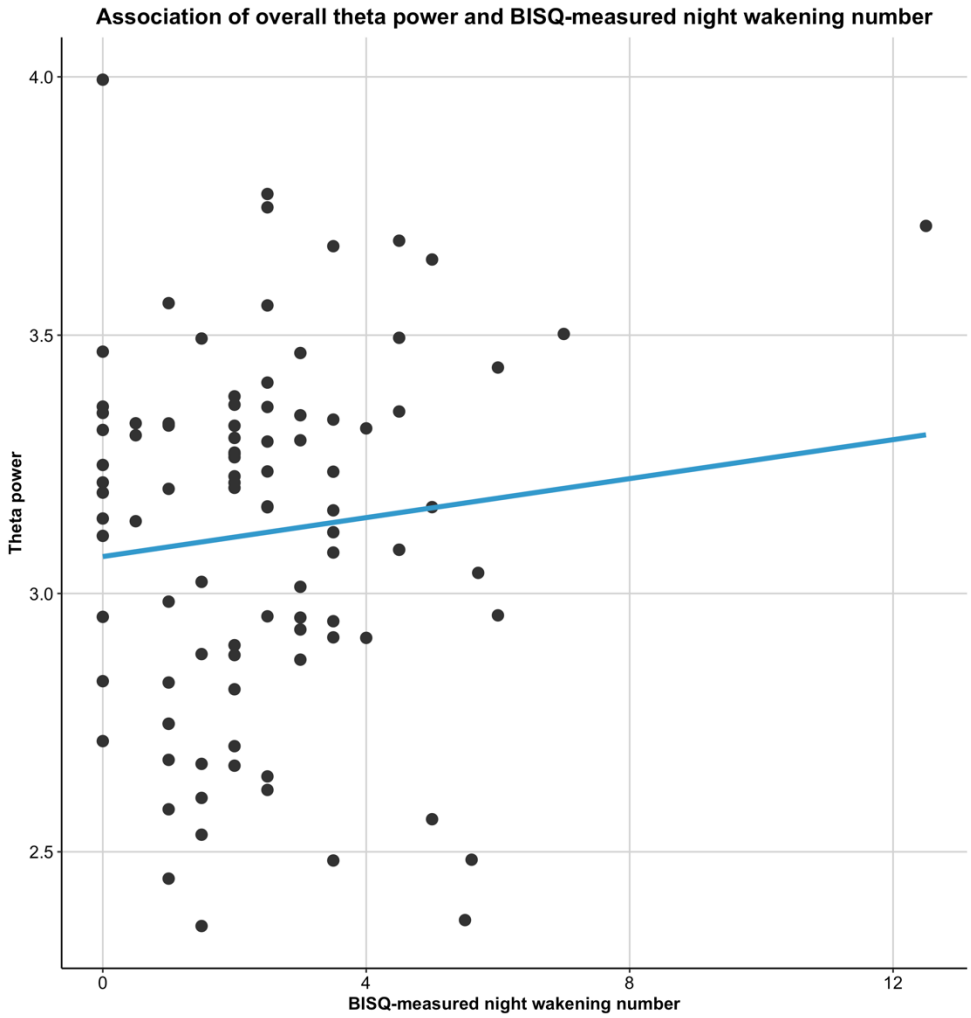


Figure 6.6. Relation of BISQ-measured Night Wakening Number and overall theta power.

In summary, The above results hint towards an importance of Night Wakening Number for overall theta power. Habitual Night/Day Sleep Duration or the amount spent awake at night (i.e., WASO) did not have a large impact overall theta power.

6.7.4.2 Theta change

WASO. There was no significant relationship between actigraphy-measured or diary-measured WASO and theta power change. There was a significant effect of BISQ-measured WASO ($F(1,79) = 4.40$, $p = .04$), with increased WASO being associated with lower theta change. See *Figure 6.8* for illustration.

Night Wakening Number. There was a significant effect for actigraphy-measured Night Wakening Number [$F(1,65) = 5.49$, $p = .02$] and a significant effect of diary-

measured Night Wakening Number ($F(1,76) = 4.37$, $p = .04$]. For both measures there was theta change decreased for increased night wakening. For illustration see *Figure 6.7*.

Night sleep duration. There was no significant relationship between actigraphy-measured, diary-measured or BISQ-measured Night Sleep Duration and theta power change (all p's > .05, see *Appendix – Chapter* 6).

Day sleep duration. There was no significant relationship between actigraphy-measured, diary-measured or BISQ-measured Day Sleep Duration and theta power change (all p's > .05, see *Appendix – Chapter* 6).

In summary, these results show that increased Night Wakening Number was associated with lower theta change values in the present sample.

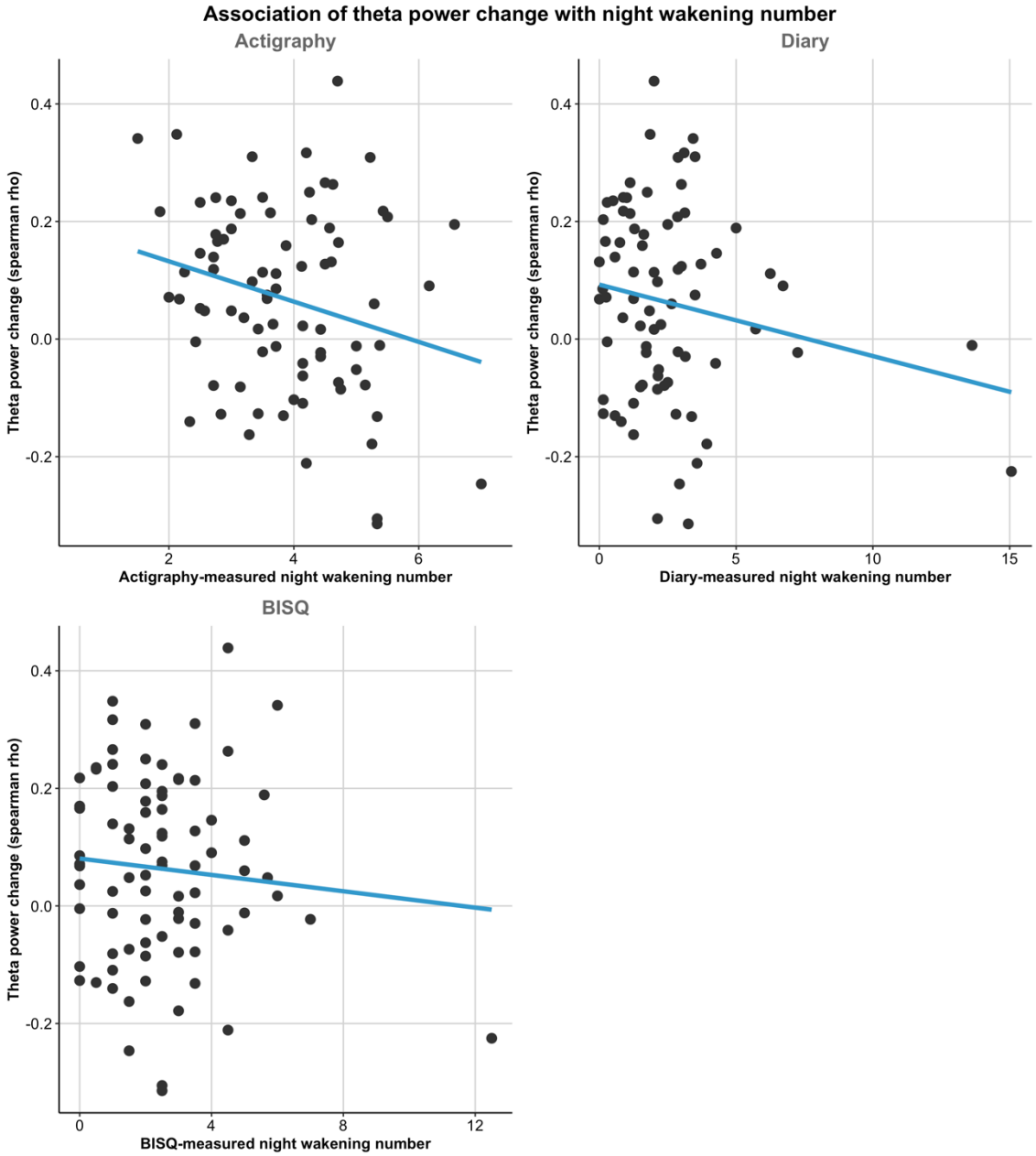


Figure 6.7. Illustration of the negative relationship between Night Wakening Number (objective and subjective sleep measures) and theta change.

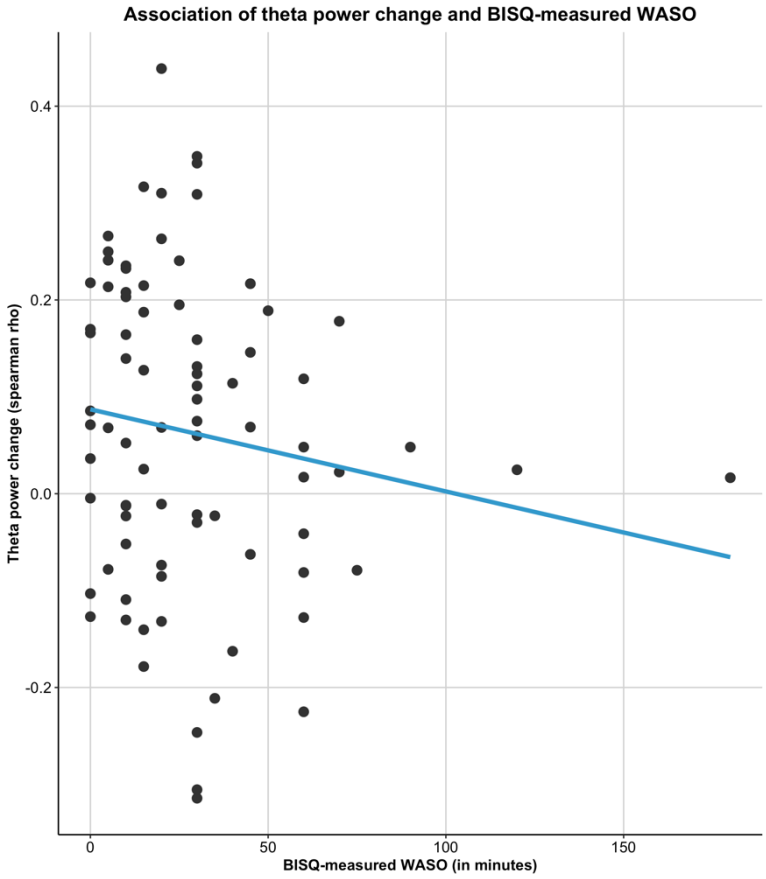


Figure 6.8. Illustration of the negative relationship between BISQ-measured WASO and theta change.

6.8 Discussion

This chapter aimed at investigating the impact of sleep quality and continuous sleep parameters on overall theta power and theta power change. Longitudinal EEG data was collected from infants aged 4- to 14-months old while they watched 1-minute videos of social stimuli. Overall theta power in response to watching the social video and theta power change across the video was measured. I hypothesised that better infant sleep (i.e., as indicated by infant sleep quality clusters or e.g., longer sleep duration/less fragmentation would be associated with less overall theta power whilst infants viewed social stimuli. Secondly, I hypothesised that better infant sleep (i.e., as indicated by infant sleep quality clusters (*Chapter 3*) or e.g., longer sleep duration/less fragmentation would be associated with higher theta change values. Results from this study highlighted an importance of sleep fragmentation measures for theta power and theta power change.

Below I present details of the results from the study. Additionally, I present interpretation of these results within the context of the current literature.

6.8.1 Developmental change of theta power and theta change

Theta power increased significantly from video 1 to video 2 in our sample, but there were no differences in theta power change across the two videos. This is in line with research that shows that theta power increases with task duration (e.g., Orekhova et al., 1999; Wass et al., 2018). This is often interpreted as increased engagement with a task. However, another explanation could be that rather than engagement, increases in theta power could be a marker of cognitive effort, such as proposed by Liu & colleagues (Liu et al., 2014). If one is sleepy, there is an increased effort to attend to the stimuli. This then leads to an increase in theta power. This point will be further discussed below.

Results showed developmental changes of overall theta power with an increase of theta power with age, though this change was only significant between 4 - 6 months of age and the older age groups. Changes were not significant between 8 to 14 months of age. This seems to indicate that theta power levelled off after 8 months. As theta has been proposed to be related to attention (Michel et al., 2015) this finding could be a reflection of the underlying development of attentional abilities. It could also be a reflection of underlying changes in brain maturation that occur in the first year of life (Anderson & Perone, 2018; Whitford et al., 2007).

There were no developmental changes in theta power change. This matches the prior research by Jones et al. (2020) and Braithwaite et al. (2020), where theta change was found to predict individual non-verbal, cognitive ability and is thus a marker for individual developmental status rather than overall group related developmental change.

Overall, these results are therefore in line with prior research and do not raise concern about the validity of the data. This study therefore also contributes to the understanding of theta change in the first year of life. However, more studies are needed, in particular longitudinal ones and studies investigating theta change during video viewing in order to truly draw a conclusion about theta power and theta power related underlying developmental changes during the first year of life.

6.8.2 Sleep quality and overall theta power and theta power change

Sleep quality was expected to be related to both theta power change and overall theta power, however results revealed no association amongst aspects of theta power and sleep quality.

6.8.2.1 Overall theta power

Sleep quality (as measured by the clusters defined in *Chapter 3*) in the present study did not relate to overall theta power. This was true for objectively, as well as subjectively, measured sleep quality. This finding does not correspond with the one developmental study by Winkelmann et al. (2018) that reported that children with sleep problems (i.e., with poorer sleep quality), showed higher levels of theta activity.

On the one hand, this could mean that there is indeed no association between objective or subjectively measured sleep quality and theta power. Theta power could be related to fine-grained aspects of sleep, such as duration or fragmentation rather than broad sleep profiles that are identified by the sleep quality measures. Past research (Aeschbach et al., 1997; Cajochen et al., 1995; Finelli et al., 2000) cite theta power as a marker of sleep propensity. Based on the literature, higher sleep propensity is associated with lower sleep duration but not necessarily to reported sleep quality.

On the other hand, as mentioned in other sections in this thesis (see *Chapter 4 and 5*), it could be that the data-driven classification of sleep clusters as a proxy for sleep quality is not an optimal way to sort infants into different sleep quality categories and does not actually reflect underlying true sleep quality. The findings with regard to continuous sleep parameters support this notion (further discussed below). In the present study, parent-reported sleep problems in infancy were not related to the theta parameters. One way to look at sleep quality in the future would be to look at parent-reported incidence of infant sleep problems, similarly to the Winkelman et al. (2018) study. One reason why findings of the present study are not in line with Winkelmann et al. (2018) could of course be that the present study investigated infants and not children. The age group (4- to 14-month-olds) that was measured here has never been assessed before in relation to sleep. Extrapolating results from research into other age groups is perhaps not appropriate. This is due to the fact that there are fundamental differences between infancy and childhood in sleep patterns/composition/structure (e.g., Iglowstein et al., 2003) and waking theta power (Anderson & Perone, 2018). Therefore, directly comparing those findings might lead to drawing erroneous conclusions. This study serves as a good point of reference for future studies investigating the relationship between waking theta power and sleep quality.

6.8.2.2 Theta power change

In general, sleep quality was not associated with theta power change in the present study. As theta power change is thought to be a marker for cognitive ability, the null

relationship could be taken as evidence that there was no association between cognitive ability as measured by theta change and sleep quality. These findings are contrary to findings from other research, which reports a positive relationship between sleep efficiency (which can be taken as a measure of sleep quality), problem-solving skills and general development respectively (Gibson et al., 2012; Scher et al., 2008).

However, when I examined the impact of actigraphy-measured sleep quality in more detail, results approached the $p = .05$ level, where poorer sleepers (as classified by actigraphy clusters) showed lower theta change than infants in the adult-like/mature cluster. While this should obviously be interpreted with caution, it could also indicate a trend in the hypothesised direction where poor sleep quality is related to poorer cognitive abilities as indexed by lower theta change values.

In summary, neither theta power nor theta power change showed an association with sleep quality measures in the present study. These findings could be interpreted as evidence for the lack of an association between theta and sleep quality. It is possible that theta power rather relates to fine-grained aspects of sleep, i.e., the subcomponents that underlie sleep quality, such as sleep duration or fragmentation than the broad classification of sleep quality. On the other hand, it is possible that the metric of sleep quality is not appropriate, as postulated in other parts of this thesis.

6.8.3 Continuous sleep parameters and overall theta power and theta power change

The closer investigation of individual sleep parameters showed that the approach of investigating fine-grained aspects of sleep reveals a more nuanced picture than the broad sleep quality associations.

6.8.3.1 Overall theta power

Results of the LMMs showed no effects of WASO, Day or Night Sleep Duration on overall theta power change. These results did not differ between objective and subjective sleep assessment methods.

The adult sleep research literature has shown that theta power increases with sleep deprivation, it was expected that there would be an association between theta power and Night Sleep Duration. It had been hypothesised that lower habitual Night Sleep Duration would be related to higher theta power in infants, suggesting a perpetual state of latent sleep deprivation. Instead, the findings from the current study indicate that habitual sleep duration during infancy does not impact overall wake theta power. It may of course be

possible that theta power is only influenced by prior night's sleep/ sleep close to the testing date and not the habitual sleep that was assessed in our study.

Interestingly, all three sleep measures show that the number of night awakenings predicted overall theta power. BISQ-measured Night Wakening Number showed a positive association with theta power, with infants that reported more Night Wakening Number having higher overall theta power. However, this finding turned non-significant when a potential outlier was removed, therefore caution is warranted when interpreting it. Further investigation of the other measures showed that there were developmental changes in both actigraphy- and diary-measured Night Wakening Number in relation to theta power, though the findings were more fragmented for the diary data. Actigraphy-measured Night Wakening Number was negatively associated with the younger age groups but for age groups 12 and 14 months the association was positive. Cross-method differences between sleep methods in terms of results may be explained by the inherent cross-method differences in sleep measures that were described in *Chapter 3*. As both actigraphy and diary capture a more detailed and fine-grained picture of infant sleep it could be that they manage to capture the developmental changes better than perhaps the one-time-assessment of the BISQ could. Considering the impact that the maternal stress and anxiety measure had on cross-method agreement, it is interesting that both diary and actigraphy show similar associations. This underscores perhaps the argument made at an earlier point in this work that a strong association between sleep neurocognitive measure should be captured by different sleep assessment methods regardless of underlying influences on cross-method agreement.

Night Wakening Number (or sleep fragmentation, as called in the following) is sometimes taken as an indicator for poor sleep. Fragmented sleep is not as restorative as uninterrupted sleep. This may lead to more daytime sleepiness and, thus, increased theta overall. Sleep fragmentation has been linked to less slow wave sleep (Bonnet, 1985), which is crucial for memory formation and synaptic plasticity and therefore learning (see *Chapter 1* for details). Interestingly, adult insomniacs (a disorder characterized by poor, often fragmented, sleep) exhibited lower theta power during wakeful periods, which the authors interpreted as lower sleep drive (Wołyńczyk-Gmaj & Szelenberger, 2011).

Theta power could also serve as a marker of cognitive effort in infants, rather than a marker of attentional abilities. This would connect research lines from both the sleep research community and from developmental science. A sleepy person has to exert more cognitive effort during any task than a person who is alert. In this study, infants with more night wakening may have needed to work harder to stay focused on the video

presented. As such, higher theta power was observed in those that slept worse (as indicated by higher sleep fragmentation). In addition, the developmental differences may potentially be explained by the fact that younger infants simply stopped exerting effort to pay attention or may have stopped paying attention when they are watching the video when they were tired (as a consequence of their increased sleep fragmentation) and therefore exhibited lower theta power. In turn, the older infants might still try to pay attention and therefore require more cognitive resources resulting in higher theta power.

Another way in which excess theta power is interpreted could be as a marker for delayed maturation. Higher sleep fragmentation is common in younger infants and a sign of more immature sleep consolidation. It could be that underlying immature brain anatomy affects both sleep, as well as theta power expression. In line with this interpretation of theta power are findings that show that theta power is higher in children that suffered adversity (Marshall & Fox, 2004) and in children with ADHD (Barry et al., 2003).

6.8.3.2 Theta power change

Interestingly, night wakenings on all three sleep measures predicted theta power change. Prior research has shown that less theta change is indicative and/or predictive of poorer cognitive abilities. This matches research that links sleep fragmentation to poorer performance on cognitive tasks (e.g., Pisch et al., 2018). Less theta change in infants with higher sleep fragmentation also fits the above hypothesis regarding developmental changes in the actigraphy data. Younger infants show less theta power for more night wakening, perhaps indicating that they have stopped paying attention and therefore also do not show a response of change to the video. Similarly, infants with high Night Wakening Number already show a higher amount of theta at the start of the video and therefore will not exhibit a stronger response of change to the video.

There were no associations of theta change with Day or Night Sleep Duration in any of the measures. Further, there was no association of theta change with actigraphy- or diary-measured WASO. WASO measures the duration that the infant was awake at night in total, whereas Night Wakening Number measures the number of times the infant woke up. It could be that theta is most influenced by the number of disruptions of sleep rather than the duration of the disruption. By that metric being awake once a night for 30 minutes would not be as bad for cognitive performance/development as waking up many times a night for 3 or 4 minutes at a time.

This suggests that sleep fragmentation, rather than duration, is important for theta activity. Overall, it could mean that duration of sleep is not as important for development as sleeping continuously through the night.

6.8.4 Integration of the findings and potential mechanistic explanations

In summary, this study highlights that theta power is indeed related to one aspect of sleep: sleep fragmentation. This is illustrated by relationship between sleep fragmentation and theta power and theta power change. Moreover, this study underscores the potential importance of sleep fragmentation for neurocognitive development.

The underlying mechanism through which sleep might influence theta oscillations, and therefore cognition, could be explained by the restorative properties of (slow wave) sleep and via the synaptic homeostasis hypothesis. The latter proposes that slow wave sleep particularly is needed for "resetting synapses" after a day of learning new information (see *Chapter 1* for an explanation of the SYH). Interrupting slow wave sleep with many night wakenings might disrupt this process, that is especially relevant in infants.

Nonetheless, the lack of consensus as to what (frontal) theta power during wake in infants actually represents must be acknowledged. Is frontal theta power an indicator for sleep propensity, a neurocognitive marker for attention, language or information processing or cognitive control? Future studies should try and disentangle the role of theta during wake and its direct connection to subsequent infant sleep. One possible way to tackle this could be to measure theta power across different times of the day (similar to Fattinger et al. (2017)) to see if infants also show the same homeostatic accumulation of theta power as adults do. In the present study, theta power was not associated with habitual Day Sleep Duration but based on the literature theta could be a marker of day-to-day sleep propensity rather than habitual sleep propensity. Moreover, future studies should combine measuring theta power and theta power change during wake with polysomnography measurements to identify whether slow wave sleep differs depending on individual theta power, as found in prior literature of other age groups.

Importantly, if theta power is indeed a marker for development that is sensitive to sleep, it may be possible to manipulate it and therefore constitute a target for interventions. As prior findings show theta power differs in children with neurodevelopmental disorders and in infants at risk for neurodevelopmental disorders (Jones et al., 2020) and given theta powers role in general information processing,

targeting it via sleep intervention could be promising. As such, sleep fragmentation may be targeted with sleep interventions in order to reduce the frequency of awakenings. One such method that has been used is to adjust a child's sleeping environment (temperature, noise levels, …). Future studies could potentially include an intervention targeting sleep fragmentation with the aim to manipulate theta power. Should theta power (and theta power change) be responsive to manipulations of night wakening frequency, this would provide further evidence for the importance that night wakening has on wake theta power.

In conclusion, these results hint towards the fact that night sleep parameters, and in particular measures of sleep fragmentation, could be of investigative value when examining wake theta oscillations and their associations with sleep. Here, a negative relationship between Night Wakening Number and theta power change was demonstrated. Moreover, there were age-related changes in the relationship between overall theta power and habitual Night Wakening Number; where habitual Night Wakening Number was negatively associated with the younger age groups but for age groups 12 and 14 months the association was positive. Notably, contrary to results from eye-tracking and parent report measures, EEG results converged better across methods. This potentially underscores the benefit of investigating the brain when examining sleep. Thus far, the focus has been on examining habitual sleep and its relation to development, i.e., examining general sleep timing and patterns/schedules. However, it is entirely possible that while two babies sleep the exact amount, the actual quality of their sleep in terms of underlying brain functioning is fundamentally different. This would then have a differential effect on development even though the two infants exhibited the same broad sleeping patterns. Therefore, in addition to understanding when infants sleep habitually, we need to understand how they sleep in terms of what happens in their brain while they are sleeping. This latter approach is the focus of the second study, described in *Chapter 7*.

CHAPTER 7 - Studying the sleeping infant's brain using combined NIRS-EEG

Thus far the discussion of the relationship between sleep and development in this thesis has relied on investigating habitual sleep patterns. Results of Study 1 show disparities in the concordance between sleep measures but also in the association between subjective and objective sleep measures and developmental measures respectively. Prior work in this thesis focused on how infants usually sleep, i.e., duration and frequency of sleep-wake. An essential part of studying the relationship between sleep and development however is to look what happens in the brain during sleep. This might provide complimentary information that could potentially shed light on the method disparities found when investigating macrostructural habitual sleep. One of the most direct ways to study the impact of sleep on the developing brain is to study what happens in the brain during sleep directly. Below Study 2 is described where the infant brain was studied while they were sleeping. Of note, this study had to be terminated prematurely before data collection was complete in line with UK government regulation with regards to the COVID-19 pandemic.

7.1 Studying the sleeping infants' brain

One of the most direct ways to investigate the impact of sleep on cognition and/or consequently development is to study the brain while the infant sleeping. These studies are sometimes done using overnight polysomnography (PSG; see *Chapter 2*). Much of this research is conducted into/on vulnerable populations (prematurely born infants or infants with severe sleep problems or epilepsy), as they are very time-consuming and require placement of much technical equipment on the infant. Thus, parents need a good reason to participate in such experiments. In addition, the sleep itself is likely modified due to the changes in environment and as such not a natural representation of sleep.

Most commonly, polysomnography is employed during a nap. These nap studies are used to study the impact that sleep has on cognition in typically developing infants. These studies are fundamentally different to the study of habitual sleep that was described in the prior chapters, as they usually are conducted once and require the infant to sleep in the lab while wearing PSG equipment. As briefly discussed in the introduction of this thesis (see *Chapter 1*) it is most common to study learning in relation to naps/short-term sleep cross-sectionally.

Researchers use investigations of presence of so-called sleep spindles and amount of slow wave activity (SWA) as sleep markers of development. These studies revealed a benefit of napping after an experimental task for learning artificial languages and language in general (Friedrich et al., 2017; Gómez et al., 2006; Horváth et al., 2015; Hupbach et al., 2009), generalisation of learned information (Friedrich et al., 2015, 2019), or performance on a motor (memory) task (Berger & Scher, 2017; Rovee-Collier et al., 1980) to name a few examples. Researchers conclude that a nap after learning new information is essential for infants to commit information into short- (Horváth et al., 2018) as well as long-term memory (Konrad et al., 2016; Seehagen et al., 2015). Of note, this is also true for adults who have been shown to also benefit from a nap after learning new information (Scullin et al., 2017). These studies show a benefit of napping for memory and learning, which are absolutely crucial skills for development. Overall, these studies also show the importance that studying the brain during sleep has. This research has provided fundamental insight into the role of sleep for development, for example, sleep benefits memory consolidation which in turn has cascading effects on development by influencing skill acquisition.

7.2 Functional connectivity as a way to study infant development

Another way of thinking about developmental status/development is in terms of how different parts of the brain interact with each other. Rather than solely thinking about different brain areas independently, research has recognised that in order to understand complicated cognitive processes that take place in a complex system such as the brain, one has to study the interaction between different areas of the brain globally and locally between different groups of neurons rather than individual parts in isolation. This has been termed brain connectivity. Brain connectivity and the interaction of different networks is a crucial part of development. In the course of development connectivity patterns are indicative of developmental status. In general, the pattern that arises across development from infancy to adulthood is one of local connectivity, i.e., spatially close neuronal groups, to global, i.e., spatially distant neuronal groups, pattern (Bruchhage et al., 2020). Brain plasticity, the brain's ability to forge new connections and prune unnecessary connections, is integral in forming connectivity in development. As proposed by major theories in sleep research, e.g., the SHY, plasticity is crucially dependent on sleep. To date it is not clear how brain plasticity is related to sleep in the first year of life.

Connectivity in the brain can refer to both structural and functional connectivity. *Structural connectivity* refers to the underlying anatomical connections present in the brain, i.e., axons, synapses and larger fiber bundles such as the corpus callosum. While these connections can be modified to a certain extent by brain plasticity changes over time and are crucial to development (see below), changes in structural connectivity do not occur in response to immediate external conditions (Sporns, 2010). The brain forms a crucial amount of neural connections via myelination or synaptic pruning in the first year of life (Ouyang et al., 2019). This growth of neural connections is fundamental also for the functional connectivity that is described below. Structural connectivity can be measured using Diffusion Tensor Imaging (DTI).

Functional connectivity refers to a "(…) pattern of statistical dependencies between distributed and neural elements. (…) " (Sporns, 2010; p. 328). Researchers use correlational measures (time domain) or coherence measures (frequency domain) or multiresolution domains (wavelet coherence) to understand whether certain brain areas are showing similar changes in activation patterns even if they are potentially distant in the brain (Sporns, 2010). Functional connectivity can be manipulated during experiments and by external circumstances. Recently, a way to look at functional connectivity without experimental task or external stimuli has become of interest in particular with regard to development, it is called *resting-state functional connectivity*, i.e., functional connectivity in absence of a task or particular stimulation (Betzel et al., 2014; Biswal et al., 1995).

Structural connections shape the functional connections to a certain extent, but functional connectivity can occasionally change underlying brain structure by inducing neuronal activity-dependent changes (Sporns, 2010). But while structural connectivity leads to functional connectivity, high functional connectivity can be present without direct underlying anatomical connectivity (Betzel et al., 2014; Koch et al., 2002; Sporns, 2010). Of course, underlying indirect anatomical connections are always necessary.

As stated above, the emergence of functional brain networks and their interaction with each other are a critical aspect of development (Bruchhage et al., 2020; Marrus et al., 2018). The local to global connectivity changes are also found in the functional networks. For example, Damaraju and colleagues (2014) show in an fMRI study that from the age range of 4 - 9 months short range connections decrease, likely a reflection of synaptic pruning. Long range connection appeared primarily around the first year of life (Damaraju et al., 2014).

Cao et al. (2017) interpret this finding (shift from local to global) in the literature as the brain becoming more optimized/organised at information processing, enabling simultaneous integration of information from different regions (Cao et al., 2017).

In addition to a local to global shift, different functional networks develop at different rates and in a different order (Cao et al., 2017; Gao et al., 2017; Gao, Alcauter, Elton, et al., 2015; Gao, Alcauter, Smith, et al., 2015). Sensorimotor, visual and auditory networks develop first pre-natally and in the first months after birth, after which attention networks develop around 6 months of age with the higher-order executive control networks exhibiting the majority of changes towards the end of the first year of life (Gao, Alcauter, Elton, et al., 2015; Gao, Alcauter, Smith, et al., 2015).

Perhaps not surprisingly, the development of brain functional networks also parallels the general behavioural development of a child's abilities, this was found in an exhaustive study investigating the relationship between functional connectivity (using rs-fMRI) and various aspects of cognitive development in a large samples ages 6 months to 6 years (Bruchhage et al., 2020). Moreover, there is individual variability in the functional connectivity patterns in infancy and these individual differences have been shown to predict later cognitive development in some studies (Cao et al., 2017). Similarly, functional connectivity has been shown to be altered in preterm infants (Gozdas et al., 2018; Kwon et al., 2016) and children with neurodevelopmental disorders such as Autism Spectrum Disorder (Di Martino et al., 2014; Keehn et al., 2013) compared to typically developing children. Interestingly, there were also effects of socio-economic status on development of functional connectivity (Gao, Alcauter, Elton, et al., 2015).

Given the importance the key feature that functional brain networks have in development it appears to be a good candidate feature to investigate in relation to sleep in development. Research that shows sleep's importance for brain plasticity further underscores the need to study functional connectivity changes during sleep. Moreover, measuring functional connectivity during sleep has a number of practical advantages. For example, one can record functional connectivity for an extended amount of time which is not easily done in infants that are awake and infants do not have to be sedated in order to keep still.

7.3 Methods for analysing functional connectivity

Methods commonly used for assessment of functional connectivity include EEG (e.g., Orekhova et al., 2014) and functional magnetic resonance imaging (fMRI; see above

studies). However, there are some drawbacks to fMRI and EEG. EEG requires many channels to reliably identify spatial components and is quite sensitive to movement. fMRI is the gold standard for functional connectivity studies as it has the ability to image cortical and subcortical brain regions. Most of the studies cited above refer to fMRI studies of functional connectivity. However, some drawbacks in fMRI methodology show its limitation when used with infants. fMRI is very sensitive to head motion, even small movements reduce accurate estimation of connectivity patterns (Friston et al., 1996). When conducting connectivity studies into infant populations it is virtually impossible to avoid these movements. Researchers circumvented this in the past by only imaging sleeping infants using fMRI. This is in fact an advantage for me in the present thesis, however, researchers interpret the findings as though infants were awake for scanning. The assumption that the sleeping brain behaves as the awake brain is not correct. Some sparse research has shown that wake and sleep affect connectivity patterns differently (Mitra et al., 2017; Tagliazucchi & Laufs, 2014). Often infants that are scanned using fMRI are sedated in order to keep them asleep in the (noisy) scanner.

A further limitation is that combining fMRI with other methods, such as EEG, is very difficult to do. For the purpose of specifically investigating functional connectivity patterns in relation to sleep, this limitation is crucial. Several sleep markers of development can only be identified with EEG, that is essential for sleep stage assessment. Therefore, for adequate sleep studies and sleep stage identification, EEG measurements are a necessity. However, EEG has poorer spatial localization making it a difficult tool to use for studying functional connectivity. Thus, an alternative is using fMRI due to its high spatial resolution. The combination of EEG with fMRI would give information on sleep stages and functional connectivity with high temporal and spatial precision. However, fMRI's limitation includes disruptive scanner noise in fMRI studies and the fact that fMRI does not allow parents to soothe their baby back to sleep should the infant wake up in the middle of a sleep study potentially interrupting a data collection session.

However, recent studies have shown that the novel neuroimaging technique *Near-infrared spectroscopy (NIRS)* can offer a good, more infant-friendly technique to measure cortical connectivity patterns (Bulgarelli et al., 2019) with studies showing the potential for fNIRS to investigate connectivity patterns as early as 2009 (White et al., 2009). fNIRS measures changes in cerebral blood oxygenation by shining light in the near-infrared range onto the brain. As discussed in *Chapter 2*, fNIRS has many advantages compared to other neuroimaging techniques, its robustness to movement artifacts being its primary one and its portability. This potentially allows for more accurate measurement of long-

range connectivity (Friston et al., 1999). Secondly, contrary to fMRI when investigating connectivity patterns in sleeping infants, infants can stay close to their parents and can fall asleep being held or being cuddled by their parents. Moreover, fNIRS does not have the same noise issues as fMRI scanning does and fNIRS can possibly be used for an extended amount of time. Compared to EEG, fNIRS primary advantage is its better spatial resolution, an important feature for connectivity studies. Lastly and perhaps most importantly for the present study, fNIRS has the ability to potentially be combined with other methods, namely EEG. As discussed above a number of sleep EEG markers for development can be found in a nap, the only way in which sleep stages may be identified currently are using sleep EEG. One drawback included that fNIRS can only measure at a cortical level and therefore connectivity analyses are limited to the investigation of cortical connectivity patterns.

7.4 Combining fNIRS with EEG for sleep measurements

Combining fNIRS with EEG is most often done for hospital settings and in newborns. In one of the earliest studies, Roche-Labarbe and colleagues (2007) combined measurement of 8 electrodes and temporal cortex NIRS measurements in a small sample (10 prematurely born neonates). They found that spontaneous neuronal activity in quiet sleep was associated/accompanied by an initial HbR increase, followed by a stronger increase in HbO_2. This early combined study of NIRS-EEG in sleeping infants proved that it is possible to record both methods at the same time in infants (Roche-Labarbe et al., 2007).

The first study investigating functional connectivity using fNIRS and EEG during sleep states was conducted into adults and revealed that with deeper sleep (stage N2 compared to N1 sleep) network connectivity decreased, which the authors explain as mirroring the reduced response of the sleeping adult to their environment (Nguyen et al., 2018). Lee et al. (2020) showed that there was more interhemispheric connectivity during active sleep than during quiet sleep in newborns and more intra-hemispheric connectivity during quiet sleep than during active sleep (Lee et al., 2020).

The results of these two studies employing fNIRS for connectivity research suggest that both groups, adults and newborns, show differences in EEG connectivity depending on sleep states. These results are supported by prior research that suggest that certain sleep states, such as SWS, potentially facilitate memory consolidation by inducing cross-regional brain connectivity changes (Berkers et al., 2018) in adults. Furthermore, sleep

deprivation alters functional connectivity as measured by EEG and fMRI during subsequent sleep (Kaufmann et al., 2006; Verweij et al., 2014). These studies imply that brain functional connectivity is fundamentally different depending on the sleep state. Therefore, investigating functional connectivity changes in the brain could even circumvent traditional classifications of sleep stages using EEG.

The two fNIRS-EEG studies described above suggest that it is possible to combine fNIRS with EEG for sleep measurements, that connectivity patterns fluctuate across the duration of a sleep in newborns and in adults and that those fluctuations might reveal more and map onto underlying sleep stages. Moreover, prior research suggests that measurement of fNIRS and EEG could potentially reveal important information about how investigating connectivity during sleep could provide insight into the relationship between sleep and development. The next step then is to understand how known sleep markers of development (i.e., sleep spindles and SWA) might be related to connectivity patterns during sleep.

However, to date there are no studies that investigate how sleep markers of development are related to connectivity patterns. Most importantly, method development using fNIRS-EEG for sleep research is still in its infancy. Therefore, before functional connectivity can be investigated in relation to sleep marker there is need for a feasibility study that aims to lay the foundation for widespread use of this innovative technology for sleep research.

7.5 The current study

Currently there are no studies that use simultaneous fNIRS-EEG during sleep with the aim of understanding the relationship between sleep and development. However, as mentioned above fNIRS-derived functional connectivity has the potential to be an important marker for development. Moreover, measuring connectivity patterns during sleep could provide important information about how sleep and development are related. In addition, understanding how different sleep stages could be related to connectivity patterns in infants and how they relate to wake cognition and general development could shed light onto how these two interact. I propose that studying hemodynamic changes during sleep and how they relate to neuronal electrical activity of the brain will provide a more insightful picture of the sleeping infant brain.

However, to date, there are no studies into infants that investigate this. The only two studies looking at fNIRS-measured functional connectivity in combination with EEG,

studied adults and newborns. Studying older infants might result in methodological challenges, such as getting the infant to sleep in the lab while wearing both EEG and fNIRS sensors.

This approach has the potential to provide an objective way to measure the relationship between sleep and development rather than relying on parental reports that may be biased or actigraphy data, that has its own drawbacks (see *Chapter 2* for details) and both of which are unlikely to reflect true underlying sleep.

However, as this relationship has not been studied yet in older infants, the first step is to develop the methodology to measure fNIRS and EEG simultaneously and to ensure an adequate environment for infant sleep studies.

7.5.1 Research goals

The main aim of the chapter is to conduct a proof-of-concept sleep study to investigate the feasibility of using a combined NIRS-EEG headgear to measure sleep EEG markers as well as functional connectivity during a nap to provide a novel way to understand the ways in which sleep and development are related. Accordingly, the first goal was to prove that measuring NIRS during sleep as well as EEG simultaneously is possible especially for a longer period of time. Proving feasibility of this study will aid in addressing additional scientific questions about the role of sleep in development in infancy, such as whether the functional connectivity markers extracted from fNIRS data can unveil new information or how they might be related to known sleep microstructure. The goal of this chapter is first and foremost to assess feasibility.

Below, first the development of the NIRS-EEG headgear is described first. This has been a substantial part of the present study, which served first and primarily as a feasibility study. Thereafter, the study and its results are described.

In this study habitual sleep using actigraphy, sleep questionnaire and diary, parent-report questionnaires from *Chapter 4* as well as the eye-tracking tasks from *Chapter 5* were administered. However, the focus of this chapter is the proof of feasibility of using NIRS-EEG and therefore the additional data collected is not further discussed.

7.6 Methods

7.6.1 Development of a NIRS-EEG headgear

The following chapter/section discusses the development of an integrated fNIRS-EEG headgear for sleep research and that was designed for Study 2.

7.6.1.1 Existing neuroimaging headgear at the CBCD and requirements for infant fNIRS-EEG headgear

The Centre for Brain and Cognitive Development (School of Psychology; Birkbeck, University of London) and the Department of Medical Physics and Bioengineering (University College London) centre were one of the first research facilities developing infant-friendly NIRS headgear. Many years of research have been invested into optimising NIRS headgear for use with infant populations. When designing infant NIRS headgear a number of aspects need to be taken into consideration and certain requirements need to be satisfied (Lloyd-Fox et al., 2010).

1) The headgear needs to be comfortable for the infant to wear.
2) The heavy fibre optic cables need to be attached safely and in a stable manner.
3) The optodes need to be comfortable for the infant and ensure a good optical coupling with the scalp.
4) A standardised way needs to be developed to place the headgear/optodes in a reliable way across all participants to be sure that each fNIRS channel would probe the same brain region across the cohort.
5) Make headgear stable so it doesn't move during testing.

These requirements enable researchers to minimize the large drop-out rate in infants NIRS studies and provide optimal data quality. Over the past two decades the design of the array used at the CBCD as well as the optodes changed to the design illustrated below in *Figure 7.1*. always with the goal of satisfying the above criteria**.** These continuous improvements resulted in better signal quality and lower drop-out rates (Lloyd-Fox et al., 2010). For a detailed review of the changes and improvements made to the CBCD headgear please refer to Lloyd-Fox et al. (2010). This design is currently used in all awake infant studies at the CBCD. The CBCD headgear illustrated in *Figure 7.1*. is made of silicon which is fixed on infants' head using velcro stripes. The optode holders are using a flat tip to minimize discomfort. Occasionally a chin strip is used to prevent the headgear from moving during testing. While this solution works very well in awake infants and is successfully used in current studies it does not allow EEG integration and the placement of electrodes around the head.

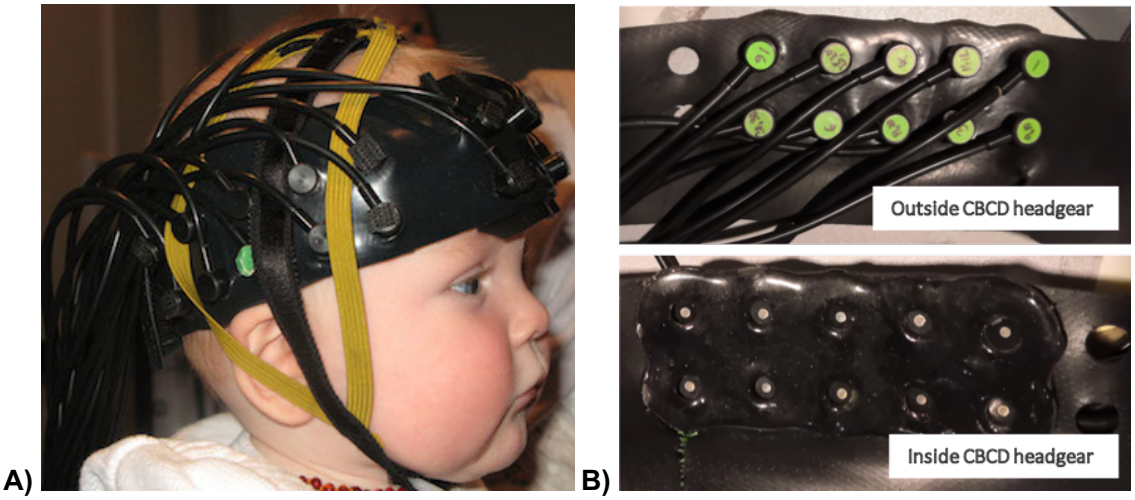


Figure 7.1. Illustration of the headgear as it is currently used at the CBCD for studies with awake infants A) illustration of CBCD headgear on an infant – picture reproduced from cbcd.ac.uk/NIRS B) illustration of the array (inside and outside).

Traditionally either EEG or NIRS is used in developmental studies, but the integration of the two systems presents some methodological and theoretical (in terms of task design) difficulties. There are a number of hardware challenges. While theoretically easy to integrate EEG and fNIRS, as EEG electrodes can be placed between fNIRS optodes, the cap becomes easily overcrowded and heavy. In terms of analyses fNIRS and EEG signals have very different time scales, so their integrations during the analysis is difficult and requires careful experimental design, due to the differing temporal resolutions.

However, with the development of wireless systems, combining NIRS and EEG measurements is becoming attainable. Measuring both EEG and NIRS has a number of advantages, e.g., in addition to learning about temporal properties of brain activation (EEG), more accurate information about spatial localization of brain activation can be collected (NIRS).

Approaches to combining NIRS and EEG range from creating custom-merged EEG and NIRS electrode-optodes such as by Wallois (for image of the custom EEG-NIRS electrode see Wallois et al., 2012). However, the more cost-effective approach especially for non-engineering focused labs is to use two separate systems and synchronize them subsequently or for data collection such as reported in e.g., Güven et al. (2019) or in Shin et al. (2018) (Güven et al., 2020; Shin et al., 2018). With Shin et al. (2018) integrating both NIRS optodes and EEG electrodes from two systems into a single stretchy EASYCAP (Shin et al., 2018).

The latter approach was followed also by Dr. Siddiqui at the CBCD who worked on integrating NIRS and EEG and created a customised NIRS-EEG headgear for that purpose (see *Figure 7.2.)*. While a different NIRS system was used (Broadband NIRS system, UCL), the EEG system (ENOBIO, Neuroelectrics, BCN, ES) was the same that was used in the present study and in Study 1 of this PhD project. Similarly, to the fNIRS-only headgear the inside of the cap features a non-slip silicone layer. Much of the work in this chapter on the sleep-based customised NIRS-EEG headgear is based on the prior work by researchers at the CBCD and particularly by Dr. Siddiqui.

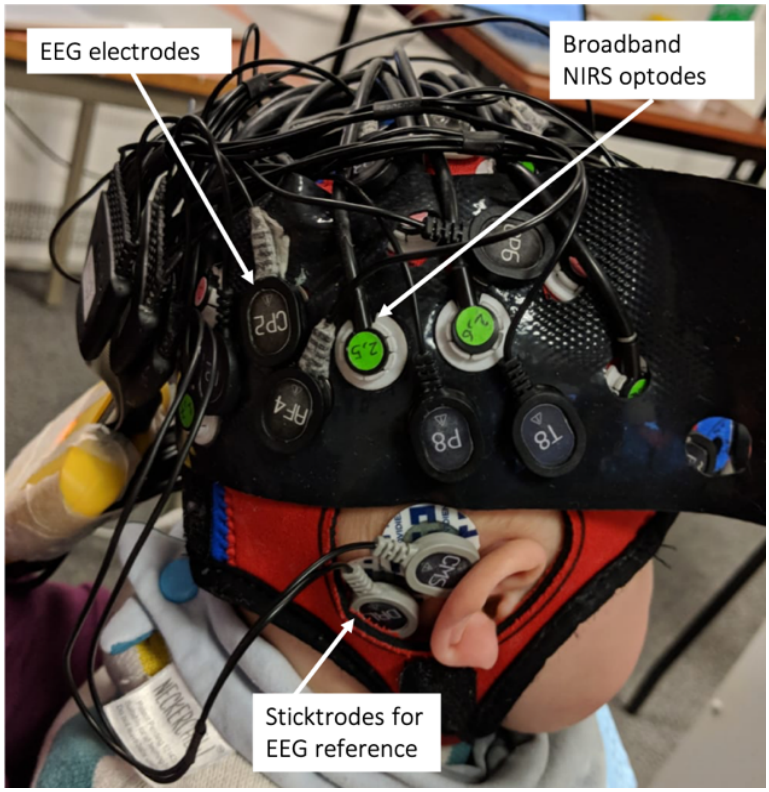


Figure 7.2. Illustration of Dr. Siddiqui's development of an integrated NIRS-EEG array headgear (Pictures courtesy of Dr. Siddiqui).

7.6.1.2 Requirements and challenges of an integrated fNIRS-EEG headgear for sleep research

The work done on fNIRS headgear design/integrated fNIRS-EEG headgear design at the CBCD is specifically for awake infants and toddlers. Demands for a sleep-based headgear are slightly different for a number of reasons. The particular fNIRS-EEG headgear of the CBCD was not ideal for sleep studies (see below for discussion) and therefore a new headgear had to be designed.

Drawbacks of the current headgear include the following:

Challenge 1: The NIRS optodes' pressure on the skin is too much for long studies.

Challenge 2: The CBCD headgear does not allow measurement of the midline, thus optode and electrode placement needed to be changed.

Challenge 3: The CBCD optode holder design can cause the leaking of the EEG gel onto the NIRS optodes.

Challenge 4: Non-breathable-silicone headband: The non-breathable silicone headband causes the infant to sweat and become very warm if worn for longer durations.

fNIRS probes are commonly not very comfortable to wear for an extended period of time due to the optode ends being uncomfortable and the optical fibre bundles being very heavy. However, for the purpose of studying sleep the primary goal should be comfort during wear time. This is of utmost importance especially as the infant might wear the headgear for the entire duration of a nap that could last up to two hours in contrast to the ~20 minutes of typical awake studies with infants. Thus, identifying a way to reduce the amount of pressure that optodes as well as EEG electrodes put on the infant's skin is the first goal of the development of the headgear. This is one of the reasons why the current headgear used in awake infants could not be used with sleeping infants. The non-breathable silicone headband would cause the infant to sweat and become very warm if worn for longer durations. Therefore, an alternative solution should be sought.

Additionally, the headgear should enable the placement of EEG electrodes alongside the NIRS electrodes as measurement of EEG activity to identify sleep stages and sleep stage markers such as sleep spindles. Placement of electrodes on the midline is essential in accordance with common PSG placement to identify e.g., sleep spindles (D'Atri et al., 2018). Sleep spindles occur frequently along the midline and are most easily identified there in PSG recordings, necessitation placement of electrodes there (Grigg-Damberger et al., 2007). However, this placement is not possible with the available headgear designs at the CBCD. The cap should thus be designed to cover as widespread an area as possible using the NIRS optodes, so functional connectivity analyses are possible while also allowing for accurate EEG recording to enable sleep stage classification.

This leads to the other problem, that concerns the accidental leaking of EEG gel onto the NIRS optodes while wearing the headgear, in the worst case corrupting the optodes and in the best case leading to bad data quality. This is more a concern for sleep studies again as the infant will likely wear the cap for and extended amount of time, increasing the risk of the gel from the EEG electrodes to warm and leak across the scalp.

The non-breathable-silicone headband and the silicone-lining in the current CBCD headgear designs can cause the infants to sweat and become very warm if worn for longer durations, such as in the case of naps. Ideally the headgear should also allow for some movement of the infant while they are sleeping and ideally even allow for parents to pick up the infant and soothe them should they wake up during the nap.

Another aspect regards the source-detector separation, this is not a unique problem to sleep studies but still essential to consider when this headgear is designed.

Below a summary of the problems that need to be addressed when designing a fNIRS-EEG headgear (Figure 7.3).

Box 7.1. A NIRS-EEG headgear for sleep needs to:

- Be comfortable for sleeping for an extended amount of time.
- Accommodate both EEG electrodes to assess sleep stages/markers and NIRS optodes to assess functional connectivity.
- Ensure adequate separation between optodes (source detector separation) and between electrodes and optodes.

Figure 7.3. Requirements for a NIRS-EEG headgear for infant sleep research.

7.6.1.3 Development of a new fNIRS-EEG headgear

A detailed description of the available equipment at the CBCD including which NIRS and which EEG system can be found in *Chapter 2*. Illustrations of the ENOBIO electrode and the NIRS optodes used in the current sleep study can also be found in the methodology chapter. The design of the headgear was thus further constrained by the availability of the system in the lab (i.e., wireless EEG system and stationary NIRS system). It was decided modifying the existing neoprene EEG caps to also work for a NIRS-headgear would be the best way forward. Holes were cut into the neoprene cap

were the NIRS optodes would sit (for details on location, see below section 7.2.1.4.3.). This allowed the solution of Challenge 2.

Initially the ideas included placing the EEG electrode in between the NIRS optodes, as commonly done in adult NIRS-EEG studies. This approach has the advantage of measuring the hemodynamic signal in the same area as the electrical activity of the brain. However, this method did not work for infant studies. It would lead to too large a source-detector separation for infants (3.2 cm vs. the typical 2 cm), which would not allow for accurate measurements. The second idea was taking an existing optode holder (see *Figure 7.4A*.) and attaching it to the neoprene cap by gluing it onto the cap. This was discarded as 1) gluing neoprene was difficult and 2) it would have made the cap very inflexible and therefore hard and uncomfortable for sleeping. These are a few of the most relevant ideas though others were considered and discarded. One of the early pilot designs for optode holders from Dr Siddiqui included a clip-in optode holder, that could potentially be fit into the neoprene cap without having to be glued to the cap. This optode holder was created using AutoCAD (Autodesk, USA) by Siddiqui, 2019, as earlier versions for her integrated fNIRS-EEG headgear (see *Figure 7.4B*.). This potentially solved Challenge 3.

However, the 3-D printed optode holder has the disadvantage of being very uncomfortable, which did not solve Challenge 1. Moreover, it was not possible to add a silicon pad on the inside of the headgear cap (as done by Dr. Siddiqui) to keep source detector separation constant and to keep the 3-D printed plastic from touching the sensitive infant skin, because the silicone pad would disproportionately increase sweating in the infant (Challenge 4). Due to the higher number of channels required for connectivity, a silicon pad on the inside of the cap would significantly reduce breathability. In addition, the infants were wearing the cap for a longer duration than awake infants and a certain level of breathability of the cap was key.

The solution to both Challenges 1 and 4 was in sewing neoprene cloth rings to the inside of the headgear where the sources and detectors were sitting. Specifically, the plastic ring of the optode holder would be covered by an additional layer of cloth while the detector/source still made good contact with the scalp of the infants (see *Figures 7.5 A & B* and *7.6.* for photos of the cap and an illustration of the positioning of the sources and detectors inside the cloth ring). An adhesive bandage was wrapped around the entire headgear after placement to avoid infants pulling on the cables or getting caught in the optode holders.

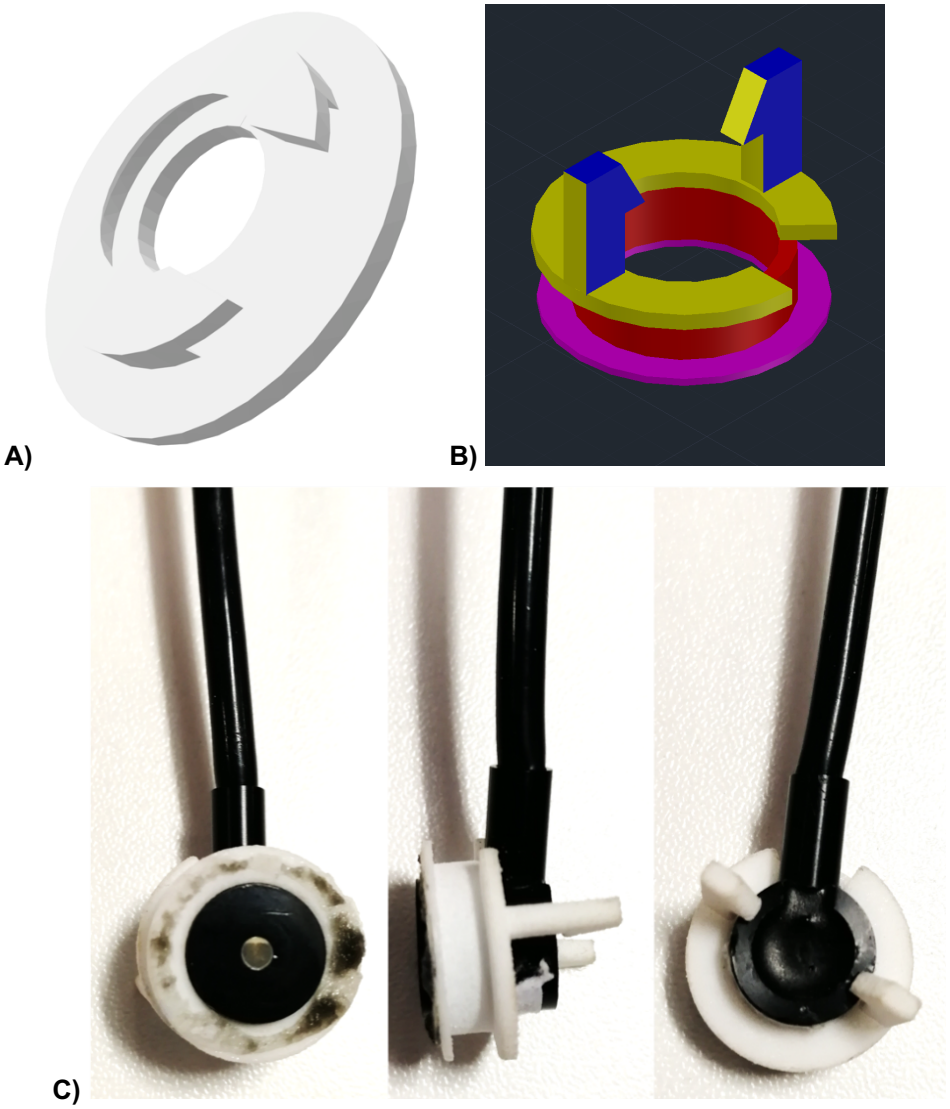


Figure 7.4. A) BRIGHT project optode holder design B*)* Image of the final optode holder with hooks to clip in NIRS NTS optodes, designed by Dr. Siddiqui. C*)* Image of the final optode holder and the optode.

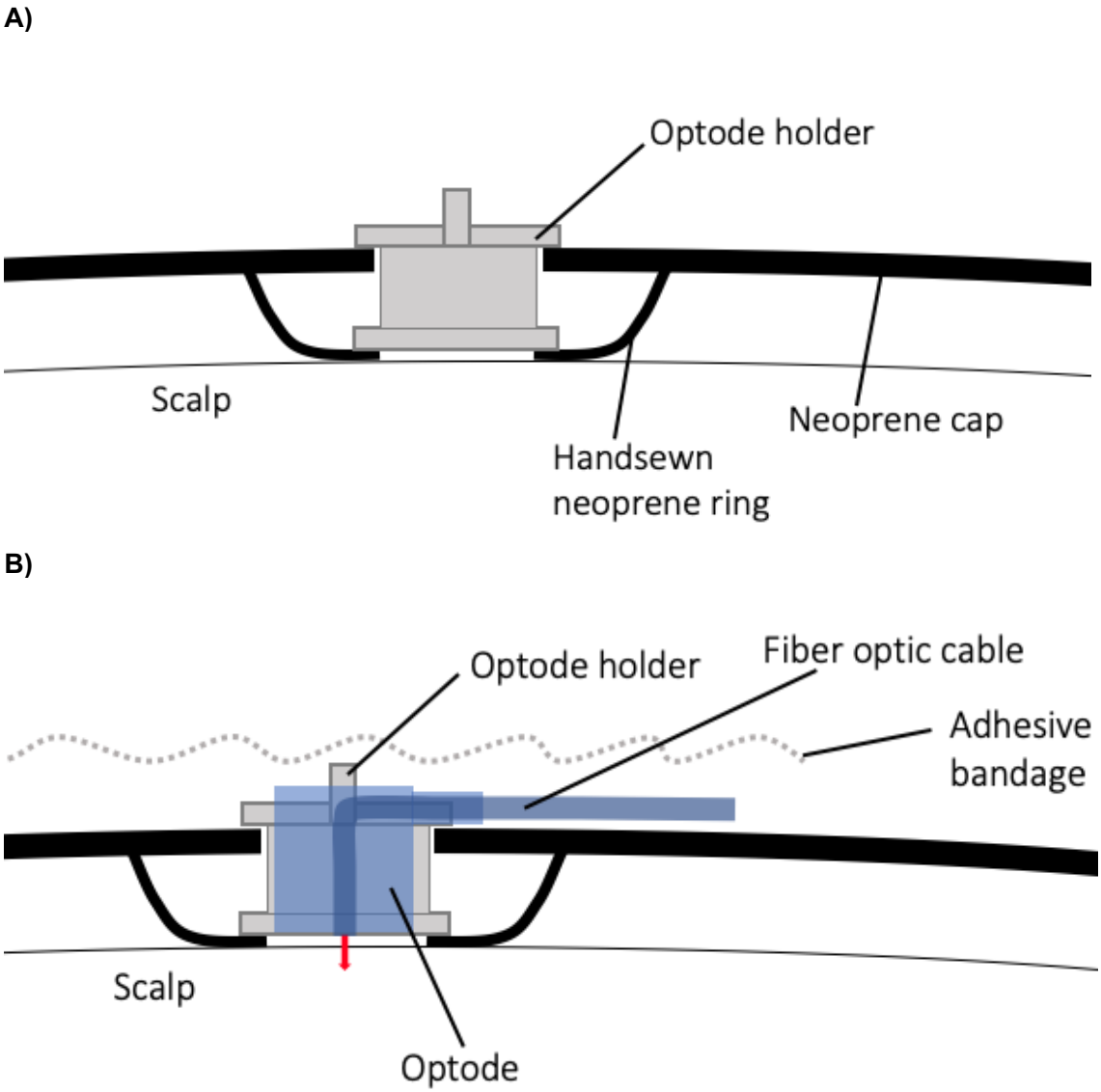


Figure 7.5. A) Illustration of the optodes holder sitting in the hand sewn neoprene ring. B) Illustration of the optode holder and the optode sitting in the hand sewn neoprene ring.

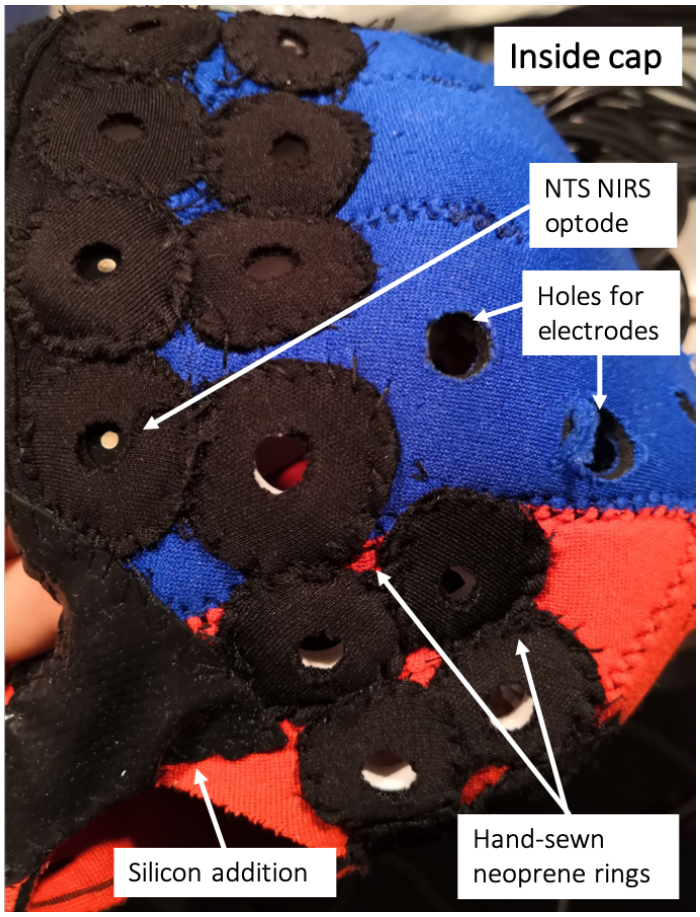


Figure 7.6. Inside of final NIRS-EEG headgear, including the non-slip silicone piece attached to the temples of the cap.

7.6.1.3.1 Placement of EEG electrodes and NIRS optodes on the head

The placement of the NIRS optodes and the EEG electrodes was driven by two considerations: 1) The importance of measurement of sleep stages and sleep markers of development using EEG and the measurement of functional connectivity using NIRS and 2) making sure to place NIRS optodes in accordance with known underlying anatomical regions. For point 1 placing EEG electrodes along the midline was important (see above). Moreover, the goal was to distribute as many NIRS optodes as possible around the head, while leaving the back of the head free so that infants could be lying on their back and not be uncomfortable. The latter point coincided with the accurate anatomical placement of the optodes on the head and the selection of the source-detector separation. For the purpose of knowing which anatomical features were measured and to enable cross-study comparison source-detector separation and array placement was based on Lloyd-Fox and colleagues (2014). The researchers coregistered a fronto-temporo-parietal array design

with MRI scans to determine which optodes and corresponding channels were associated with which underlying anatomical brain regions. Age range was similar to the present study (Lloyd-Fox et al., 2014). For the final array design see *Figure 7.7.* and for the final headgear see *Figure 7.8.*

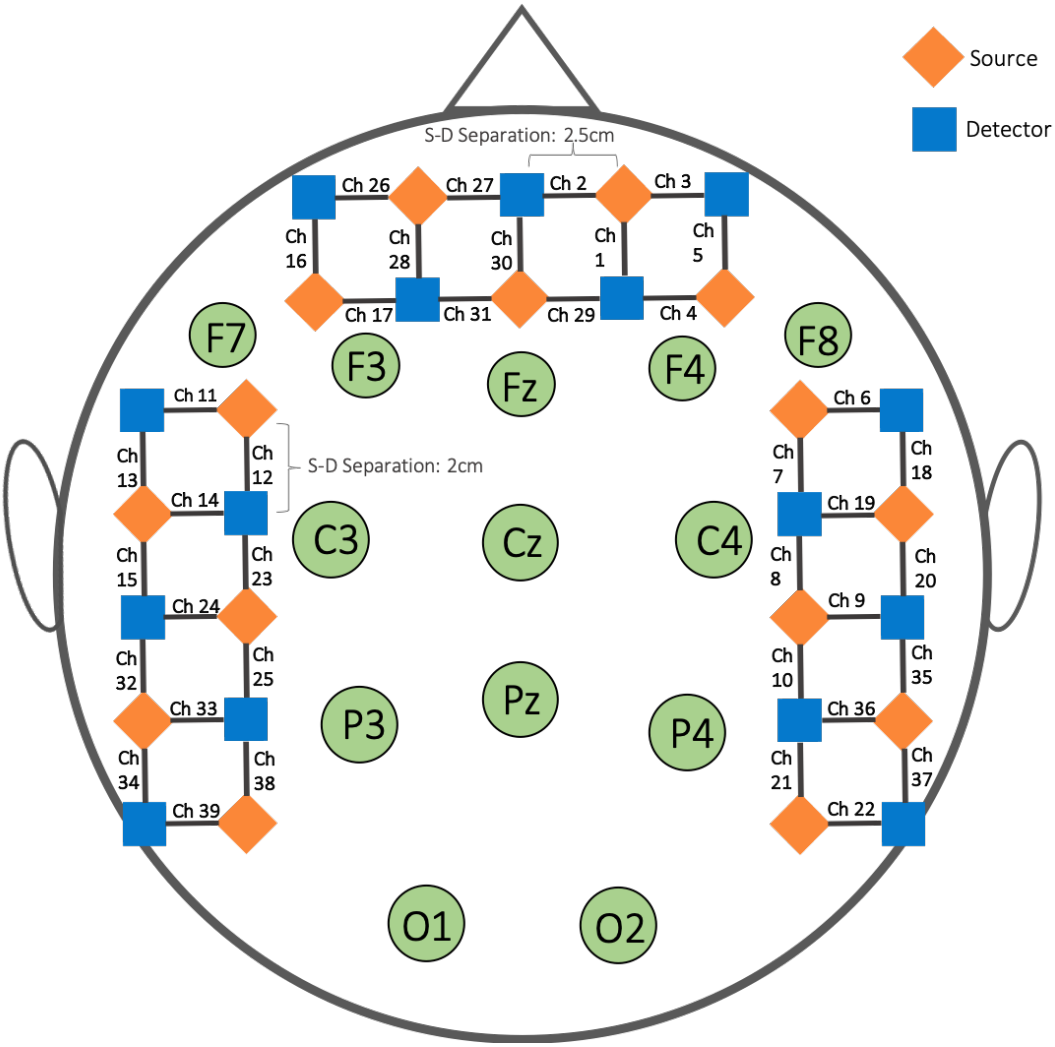


Figure 7.7. Array design for combined NIRS-EEG.

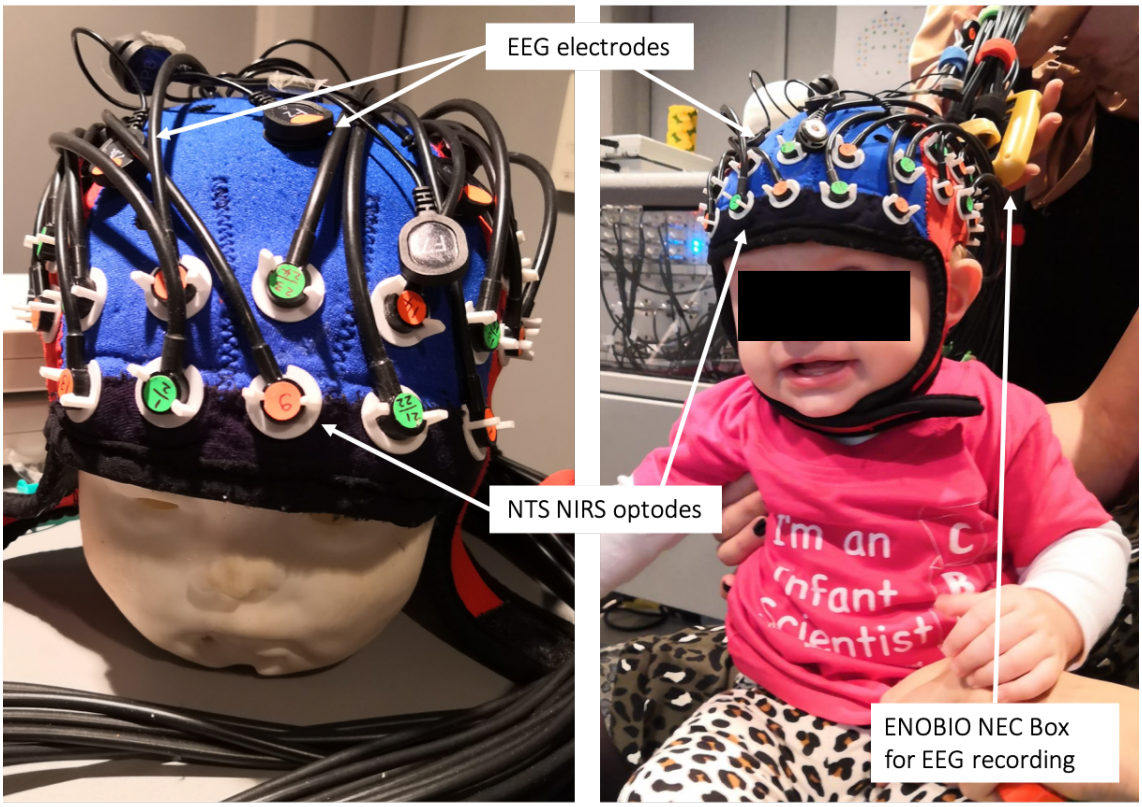


Figure 7.8. Final NIRS-EEG cap on head model (left) and infant (right).

7.6.1.4 CBCD sleep environment: creation of pram environment

One key aspect to making the customised NIRS-EEG headgear to work in practice during sleep and take on the challenge of getting babies to sleep in a lab environment that was not designed for sleep studies was to establish specific conditions for testing. Testing took place in a quiet room where usually NIRS experiments are conducted, as this was where the stationary NIRS system was located. However, the room was not equipped with a cot or a place for putting infants to sleep, an EEG system, a comfortable chair for parents or other amenities that are key components in a sleep lab. Usually infants sit on their parent's lap and spend only a limited amount of time in the room. However, for this study the room had to be modified to make sure it was appropriate for sleep studies.

Parents were asked to bring any sleeping clothes or blankets/sleeping bags the infants were familiar with as well as familiar songs and toys. For the purpose of the recording a modified pram (see *Figure 7.9.*) was used. The headend of the pram was cushioned specifically for the study with foam pads on either side to a) reduce the pressure of electrodes on the back of the head on the infants' skin and b) to prevent the infant's head from moving a lot during sleep. Infants were put down awake after attachment of the headgear and the lights in the room were dimmed to facilitate falling

asleep. Unless parents specified that the baby was used to sleeping in quiet either white noise was played or a song chosen by the parent. In some cases, the infant was used to sleeping in their parents' arms. In those cases, the infant was allowed to sleep in the parents' arms and a researcher held the fibre optic cables for the duration of the nap so that pressure was reduced on the infants head. For illustration see *Figure 7.10*.

Figure 7.9. Sleeping environment for Study 2.

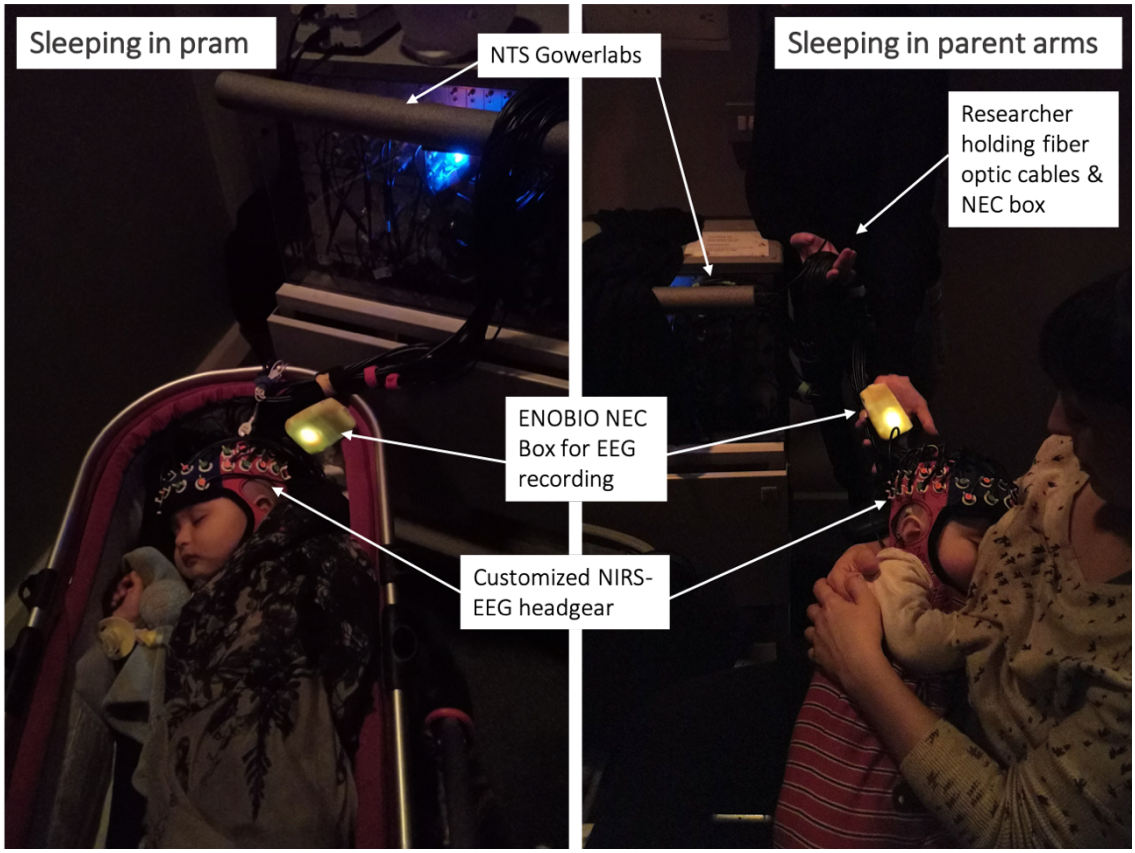


Figure 7.10. Illustration of how infants slept in respective environments (Pram vs. parent's arms).

In summary, after several months of trialling several versions of the headgear and sewing the final versions, pilot participants showed promising results with 3/5 sleeping with the headgear on, one with the entire NIRS optodes and two with only the frontal optodes. The initial two participants were tested with only the frontal array to ascertain the headgear did not disturb the infant. Then I started testing for the second study and deemed the customised headgear ready for use with our participants. NIRS-EEG data was synchronized via button press.

7.6.2 Study 2 Participants

Participants were 26 typically developing infants with no (family) history of neurodevelopmental or sleep disorders in the age range of 5 to 8 months (mean age: 6 months, 12 female). 10 infants did not sleep at all in the lab, 2 infants slept without the headgear on, 11 slept with the NIRS-EEG headgear on and 3 participants slept with an

alternative version of the headgear on (see below for discussion of wireless NIRS-EEG headgear). Participants were recruited from the Birkbeck Babylab's participant data base.

7.6.3 Study 2 procedure

The second study involved an initial phone screening interview and a study visit (see chart *Chapter 2*) at the Birkbeck Babylab. The initial phone screening served to schedule visits and assess the infants habitual sleeping patterns, including potential nap times and routines surrounding the nap. The visit was scheduled approximately 45 minutes before the infant's regular nap time and was set to take between 1 and 3 hours depending on whether the infant slept or not. After welcoming the baby and the caregiver, they were accompanied to the room, where the stroller and the PSG equipment (including customised NIRS-EEG headgear) was located. Regular pre-nap routines were replicated in the lab environment as closely as possible e.g., caregivers bring their infants blanket/sleeping bag, familiar toys or plush animals as well as familiar music/ lullabies. After putting the PSG equipment (NIRS, EEG, respiratory belt, EMG electrode) on the infant, he/she was put into the stroller. If the infant usually slept in the caregiver's arms, infants were held for the duration of their nap by their parent. Thereafter the researcher waited until the infants woke up again, recording the duration of the sleep. Thereafter the same eye-tracking battery as in Study 1 was administered. However, eye-tracking tasks were administered regardless of whether the infant slept or not. If it became apparent that baby would not sleep, usually the decision was to wait 30 minutes and proceed to the eye-tracking without the baby having slept. The infants sat on the parent's lap, while the stimuli were presented.

After the lab visit 7 days of in-home actigraphy and sleep diary were performed (similarly to Study 1) and parents filled out the same questionnaires as in Study 1 (maternal stress and anxiety measures, SES and demographics, infant development, temperament and sleep questionnaires (BISQ & SSQ)). Afterwards they returned the questionnaires and actigraph to the lab via post.

7.6.4 Study 2 methods

As mentioned above the focus of this chapter is the method development and the study of the feasibility of using NIRS-EEG for sleep measurements. Therefore eye-tracking, questionnaire measures and habitual sleep recordings are not further discussed at this point.

7.6.4.1 Sleep recording

For sleep recording the customised (above described) headgear was used. It featured the NTS Gowerlabs NIRS system and the ENOBIO EEG system (Neuroelectrics, ES), resulting in 39 fNIRS channels and 13 electrodes (see *Chapter 2* for details of systems).

7.6.5 Study 2 Analysis Plan

7.6.5.1 Pre-processing steps of fNIRS data

Pre-processing was performed using opensource Matlab-based toolbox Homer2 (MGH Martinos Center for Biomedical imaging, Huppert et al., 2009). Homer2 is commonly used in the fNIRS research community to pre-process and analyze fNIRS data collected from a variety of systems. As it requires a file format called .nirs prior to initiating pre-processing steps with Homer2, a custom in-house script was used to convert the NTS output file into a .nirs file. In addition, my own custom-written scripts were used to segment the data into sleep and wake periods. *Figure 7.11* describes the steps in the Homer2 pipeline as well as parameters that were chosen. These parameters and pre-processing pipeline were developed in careful consideration of prior studies conducted at the CBCD with infants and toddlers, e.g., for the motion artifact rejection by channel. I also consulted prior research, leading to the decision of using a combination of spline and wavelet motion correction (Di Lorenzo et al., 2019). In addition, to Homer2 pre-processing, channels with a low Signal to Noise Ratio (SNR) were identified in two ways. The first was a visual inspection using Homer2 and custom-written visual inspection scripts by Dr. Pinti (Senior Lab Developer Birkbeck Toddlerlab). Checks were performed for identification of the heartbeat component in the raw data, signal intensity for both wavelengths and other irregular patterns. Heartbeat is a viewed as good indicator for fNIRS data as it signifies the accurate measurement of hemodynamic changes. However, in order to reduce the amount of bias that comes with checking and excluding NIRS channels manually (subject to experimenter bias), an additional way to check data quality and identify bad channels was employed. This was done using a novel tool called *QT-NIRS* ("Quality Testing of Near Infrared Scans"; an extension of the software package PHOEBE; Pollonini et al., 2016). Developed by Dr. Pollonini and his lab at the University of Houston (Hernandez & Pollonini, 2020)). *Table 7.1* shows channels excluded per participant *QT-NIRS* exclusion. *Appendix – Chapter 7* shows channels excluded manually as well as with *QT-NIRS*. *QT-NIRS* excludes channels based on insufficient correlation between the two wavelengths and the absence of a clear heart rate. Recently, Bulgarelli

et al. (2020) also showed that this approach yielded significantly better SNR than previously used methods (Bulgarelli et al., 2020). In the end channels were excluded based on *QT-NIRS*, as an objective exclusion was deemed more appropriate than a (potentially) biased assessment of one researcher. *Appendix – Chapter 7* shows an example of poor and good NIRS data quality as based on visual data inspection.

Figure 7.11. NIRS data pre-processing pipeline using Homer2 and custom Matlab scripts.

7.6.5.2 Functional connectivity analysis

Functional connectivity analysis was performed using a custom written script using MATLAB R2019a. Hereafter, the procedure of the functional connectivity analysis is described, the procedure was performed two times, once each for HbO_2 and HbR changes. Results will be reported separately for each chromophore. This was done as it has been shown that HbO_2 and HbR have the potential to reveal slightly different information (Nguyen et al., 2018) and increase the reliability of the results (Tachtsidis & Scholkmann, 2016). After pre-processing the NIRS data each sleep data set was segmented into 120 seconds non-overlapping epochs in line with previously reported epoch durations of resting state fNIRS data in infants (Bulgarelli et al., 2019, 2020). Afterwards, Spearman rho correlations for channel-by-channel pairs within each epoch were computed as a measure of connectivity, this led to a correlation matrix/epoch. Spearman rho was computed instead of Pearson's correlation to account potential nonlinearity in the data. Afterwards bad channels for each participant identified in the pre-processing were set to missing values. After concatenating all correlation matrices into a of all participants into a single data frame, channels that were of poor quality (as determined in pre-processing steps, see above) in at least 50% of the whole group of participants were excluded from the analysis. For channels with less than 50 % missing values, missing values were imputed with the channel mean across all epochs. Thereafter correlation values of less than 0.2 were set to 0 to reduce data complexity. Overview of the analysis steps can be found in *Figure 7.12*.

7.6.5.3 Cluster analysis on connectivity data

After the functional connectivity analysis was performed, a K-means cluster analysis was performed similarly to the one performed in *Chapter 3* on the sleep data. This was done in accordance with prior fMRI research that used cluster analysis to classify recurring patterns of connectivity (Kahnt et al., 2012).

K-means is an iterative algorithm that determines clusters of data points so that the variation within each cluster is minimized and the distances to other clusters maximized. It works by determining a k number of cluster centres (so called centroids) randomly from the data and then assigning each data point to the cluster centres based on their distance to the centroid. K-means requires the number of clusters to be pre-specified. In order to obtain a clearer idea of how many clusters were the ideal fit for the present data set, several iterations of the algorithms using various different k number of clusters values was conducted. A scree plot was obtained, displaying the total within sum of square of

the cluster variation (WSS) by number of clusters (k). This allowed us to determine the ideal number of clusters. In order to increase validity in the selection of number of clusters, the data set was randomly split into a training set and a test set. 80% of the data were assigned to the training set. K-means was run 50 times on the training set using different numbers of k (1-10) and each time a total WSS value was obtained. In the end the minimum value of total WSS was selected as the interest was in selecting the optimal model.

In order to determine the optimal cluster/centroid values and number of participants in each cluster k means was run 100 times and the cluster model with the best total within sum of squares was selected. Cluster analysis was run separately on connectivity matrices of HbO_2 and HBR changes. *Figures 7.13.* shows the screeplots identifying the k-values chosen. The k-value ultimately chosen was k = 5.

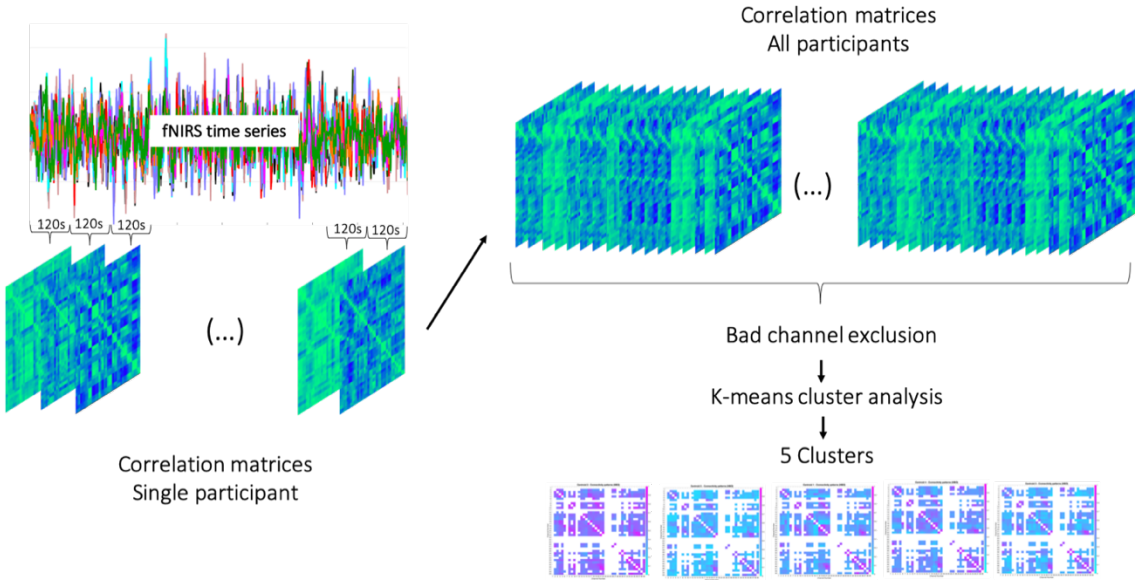


Figure 7.12. Illustration of analysis steps.

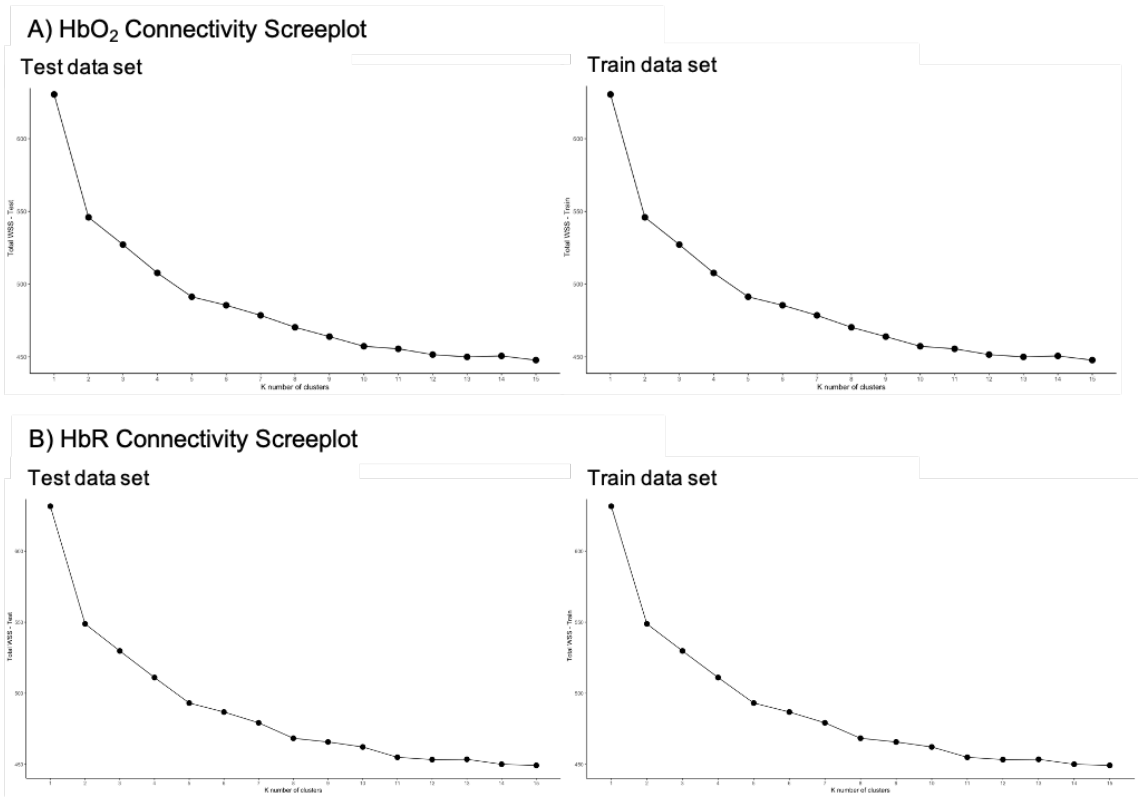


Figure 7.13. Scree plots for k-means selection for A) HbO_2 connectivity and B) HbR connectivity (test and train data sets).

Due to the data quality of the EEG data (further explanation see below) and premature termination of the study, only results from NIRS analysis are presented. Therefore, the results and subsequent discussion focus on debating the feasibility of using NIRS-EEG for sleep assessment and to investigate if measuring fNIRS functional connectivity during sleep has the potential to contribute valuable information to the fields of developmental neuroscience and sleep science.

7.7 Results

7.7.1 Data quality and pre-processing of fNIRS data

42 % (11/26) of participants (7 girls) tested slept in the lab with the customised headgear and provided good NIRS data (details see *Table 7.1*.). EEG data quality was worse than NIRS data quality, of those 42 % with good NIRS data about half (5/11) had good EEG data. Infants nap duration varied from 23 to 63 minutes (mean: 39.64 minutes, SD = 13.96 minutes) providing varied epoch numbers per participant (8 - 37 epochs). 64 % of those who slept (7/11) slept in the pram. During NIRS-processing quite a few

channels were identified as poor quality/noisy, though some subjects had more than others. See further details in *Table 7.1*.

Table 7.1. Sleep study summary

Parti-cipant	**Nap (in min)**	**Age *(in months at testing)***	**Poor quality channels NIRS – QT-NIRS**	**Valid epochs (120s/ epoch)**	**EEG data**	**Activities before sleep**	**Location of sleep**	**Cap size**
P05 (f)	58 min	8 mo 14 d	11, 12, 23, 28, 29,30, 31, 32, 34	29	poor quality EEG (drift in data, no sufficient contact of most electrodes)	Playing, feeding	Pram	46
2002 (f)	27 min	5 mo 21 d	6, 7, 8, 9, 10,11, 21, 24, 28, 29, 30, 31, 32, 35, 36, 37, 38	13	poor quality EEG (Loose reference - noisy data)	White noise, feeding	Pram	42
2004 (f)	31 min	6 mo 16 d	9, 10, 11, 21, 22 37	13	poor quality EEG (Cz no contact, drift in data)	Video watching, feeding, playing	Arms	42
2005 (m)	37 min	7 mo 11 d	1, 2, 6, 7, 9, 11, 13, 14, 15, 23, 24, 25, 26, 27, 28, 31, 38	33	poor quality EEG (loose reference)	Playing, feeding	Pram	46
2013 (f)	44 min	7 mo 13 d	1,4, 6, 7, 8, 9, 10 11, 23, 24, 25, 26, 27, 28, 32, 33, 35, 36, 38	22	Good quality EEG	Playing	Pram	42
2015 (f)	62 min	6 mo 5 d	1, 7, 11, 23, 24, 25, 28, 29	37	Moderate quality EEG (some movement noise)	Video watching, feeding, playing rocking in pram, stroking	Pram	42
2019 (m)	31 min	5 mo 22 d	1, 2, 3, 6, 7, 11, 12, 23, 24, 25, 26, 27, 28, 38	15	Moderate quality EEG (some movement noise)	Feeding	Arms	42
2020 (f)	34 min	6 mo 27 d	8, 9, 10,11,12,17,21,22,23,24,25, 26, 27, 28, 35, 36, 37	14	Good quality EEG	Feeding, playing	Arms	42
2021 (m)	59 min	7 mo 14 d	4, 6, 7, 11, 12, 16, 17, 21, 32,33, 34, 35, 36	26	poor quality EEG (drift in data, no sufficient contact of most electrodes)	Feeding	Pram	46
2023 (m)	23 min	5 mo 9 d	8, 9, 11, 12, 15, 23, 24, 25, 26 ,27, 28, 39	8	poor quality EEG (drift in data, no sufficient contact of most electrodes)	Feeding, music	Arms	42
2024 (f)	30 min	5 mo 16 d	1, 2, 11, 16, 17, 26, 27, 28, 32, 33	14	Moderate quality EEG (some movement noise)	Bubbles, playing, white noise, rocking in pram	Pram	42

Note. F = female, m = male, min = minutes, mo = months, d = days

7.7.2 Cluster analysis on connectivity data

Connectivity matrices of every epoch/ subject showed differences in connectivity across the sleep period in every infant. For one example of the connectivity matrices of every epoch/infant see *Appendix – Chapter 7*. Below the patterns of connectivity/in each cluster for each chromophore are described.

7.7.2.1 HbO_2

Figure 7.16. shows the connectivity matrix (channel by channel correlation matrix) per cluster identified in the cluster analysis for HbO_2. These show that there are indeed differences in correlation strength between different channels and between cluster. Cluster 2 seems to show particularly strong correlations, while cluster 5 seems to show the weakest correlational strength. *Figure 7.17.* illustrates the 50 strongest correlation pairs in each cluster to give a better overview over which brain regions might be particularly connected. Due to the bad channels that were present primarily on the left hemisphere, definite conclusions about underlying brain networks will be avoided at this point. However, it seems as though e.g., cluster 2 showed a pattern that consisted of strong intraregional connectivity whereas cluster 4 showed inter-hemispheric connectivity (although slightly weaker). Cluster 1 has primarily right intra-hemispheric connectivity.

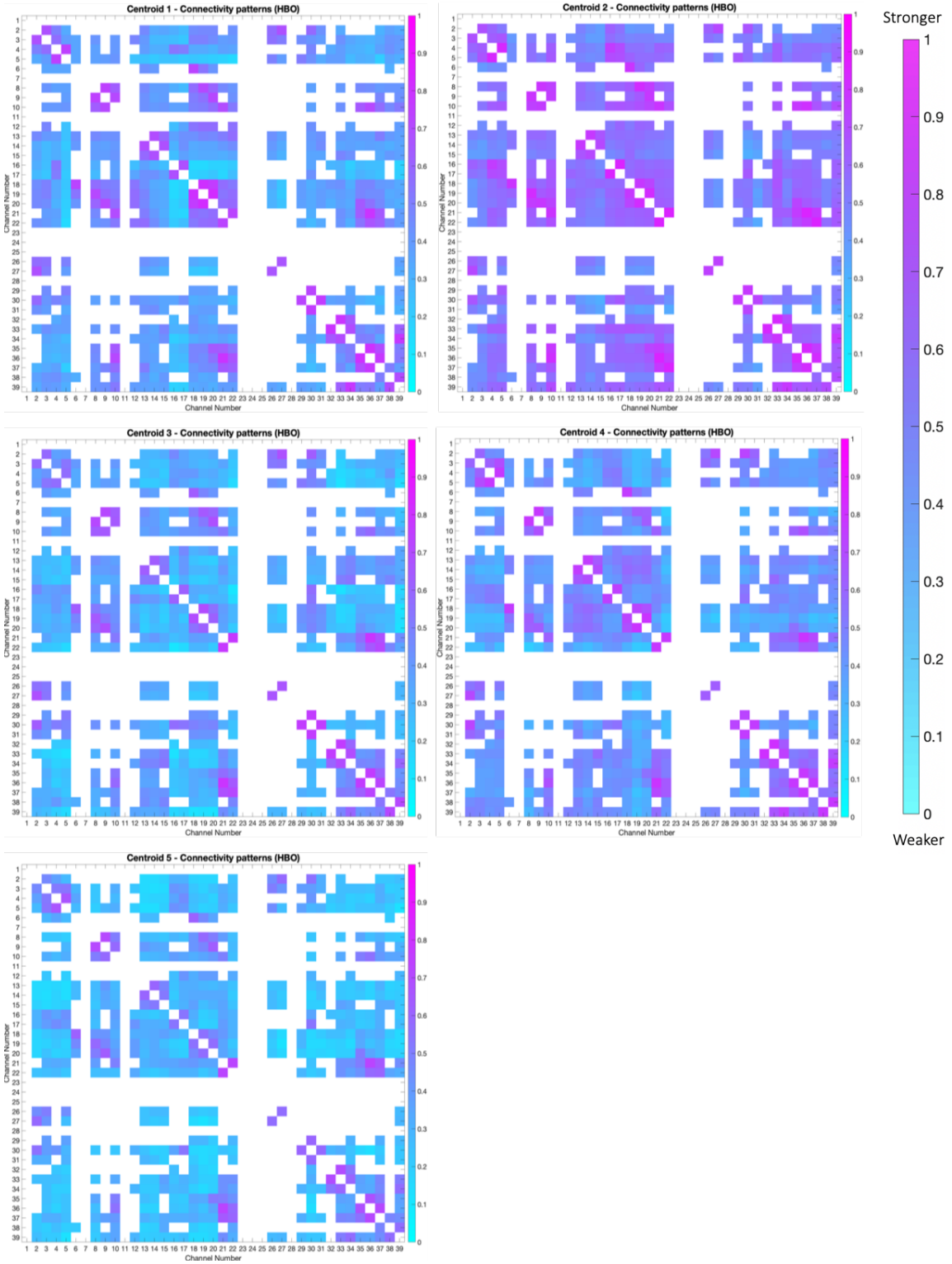


Figure 7.14. HbO_2 channel by channel correlation matrices (white = excluded channels; Pink = strong correlation; purple/dark blue = moderate correlations; light blue = weak correlations)

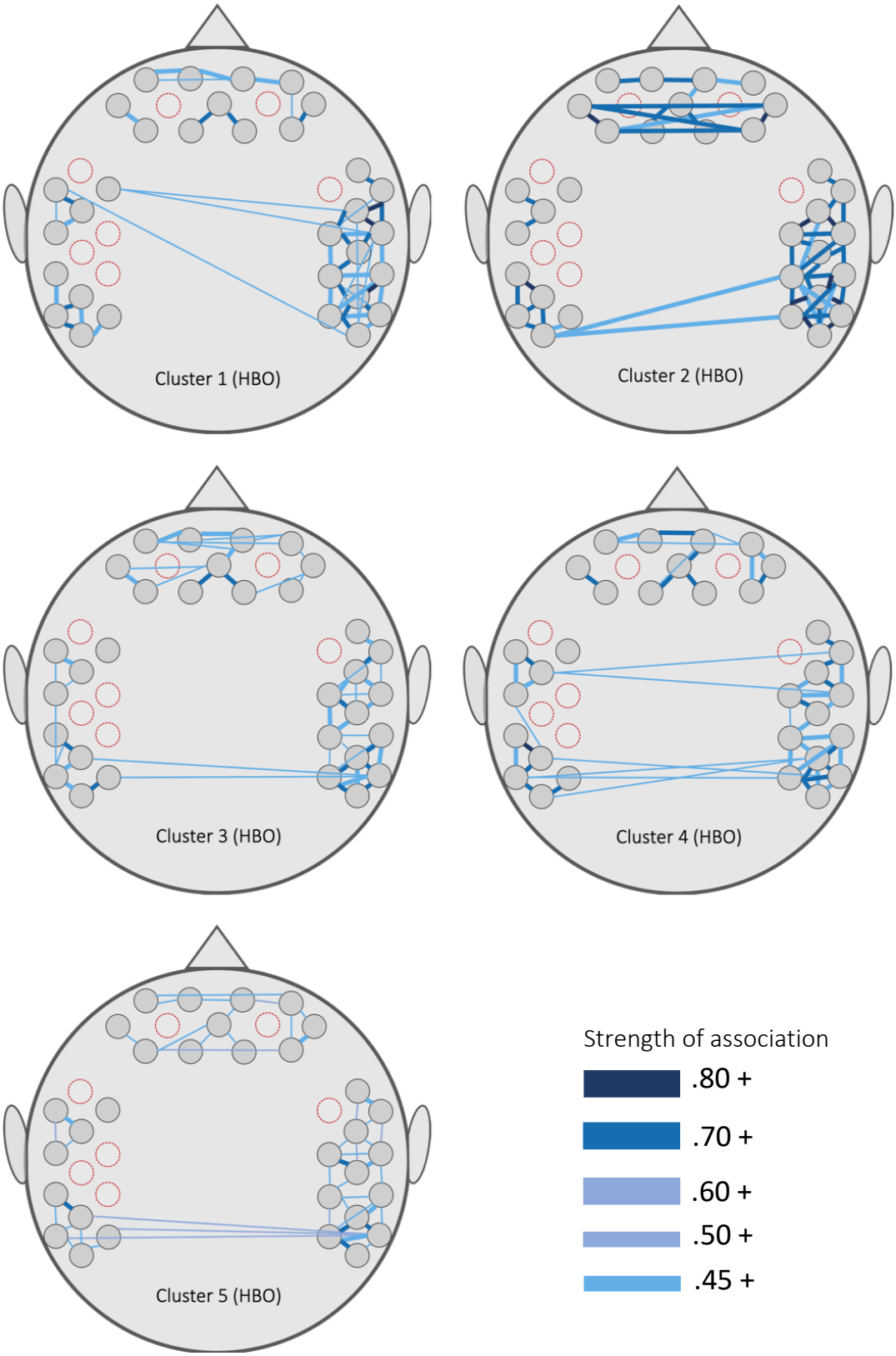


Figure 7.15. HbO_2 50 strongest correlations/cluster to illustrate the regions in which we observe connectivity patterns.

7.7.2.2 HbR

Figure 7.18. shows the connectivity matrix (channel by channel correlation matrix) per cluster identified in the cluster analysis for HbR. These show that there are indeed differences in correlation strength between different channels and between clusters. Cluster 2 seems to show slightly stronger correlations than other clusters. However, correlations are overall lower than for HbO_2, in line with reports from prior research (Nguyen et al., 2018). *Figure 7.19* illustrates the 50 strongest correlation pairs in each cluster to give a better overview over which brain regions might be particularly connected. Due to the bad channels that were present primarily on the left hemisphere, definite conclusions about underlying brain networks will be avoided at this point. However, it seems as though e.g., cluster 2 showed a pattern of inter-hemispheric connectivity whereas cluster 4 showed weak intra-hemispheric connectivity.

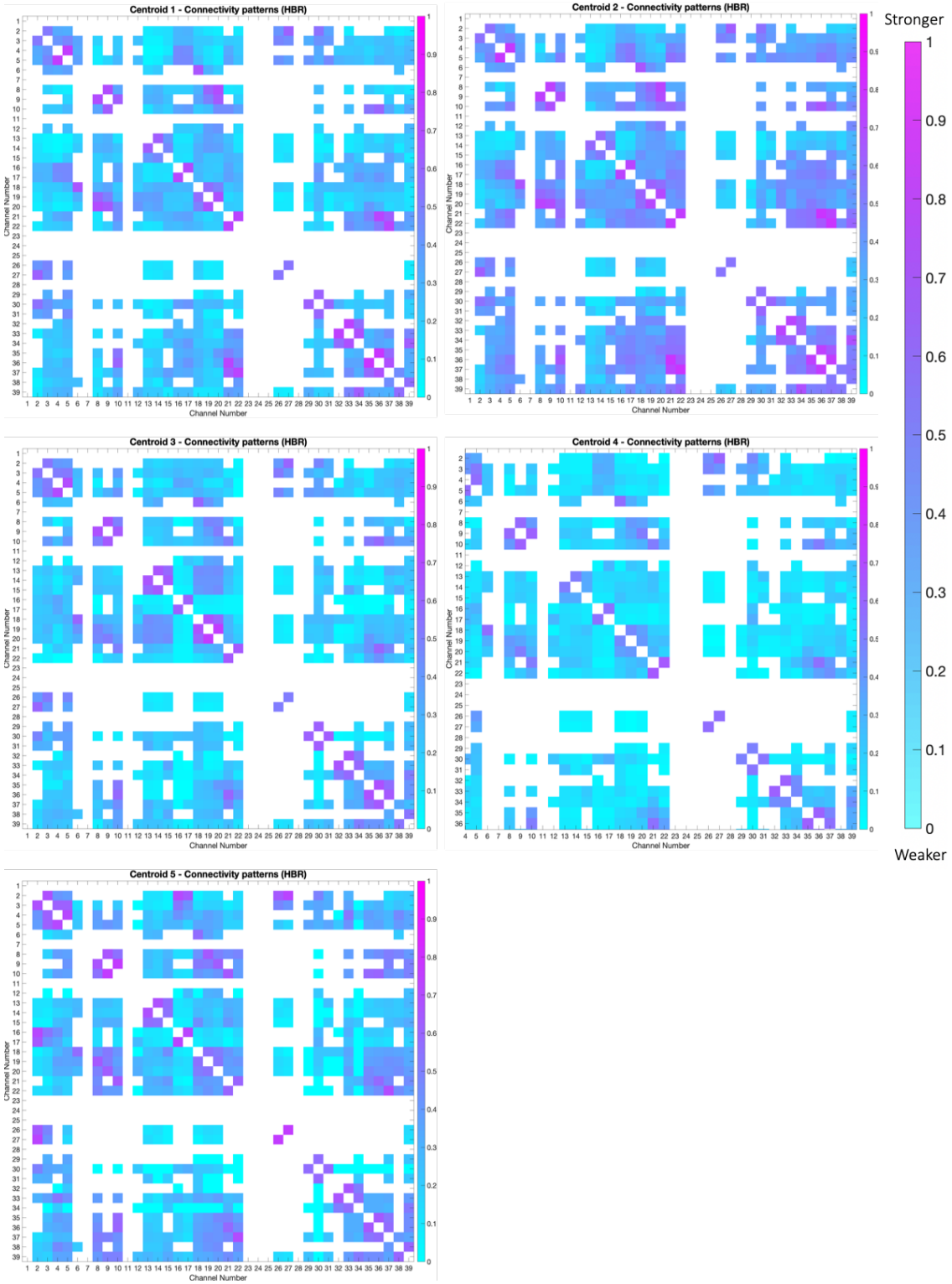


Figure 7.16. HbR channel by channel correlation matrices (white = excluded channels (white = excluded channels; Pink = strong correlation; purple/dark blue = moderate correlations; light blue = weak correlations)

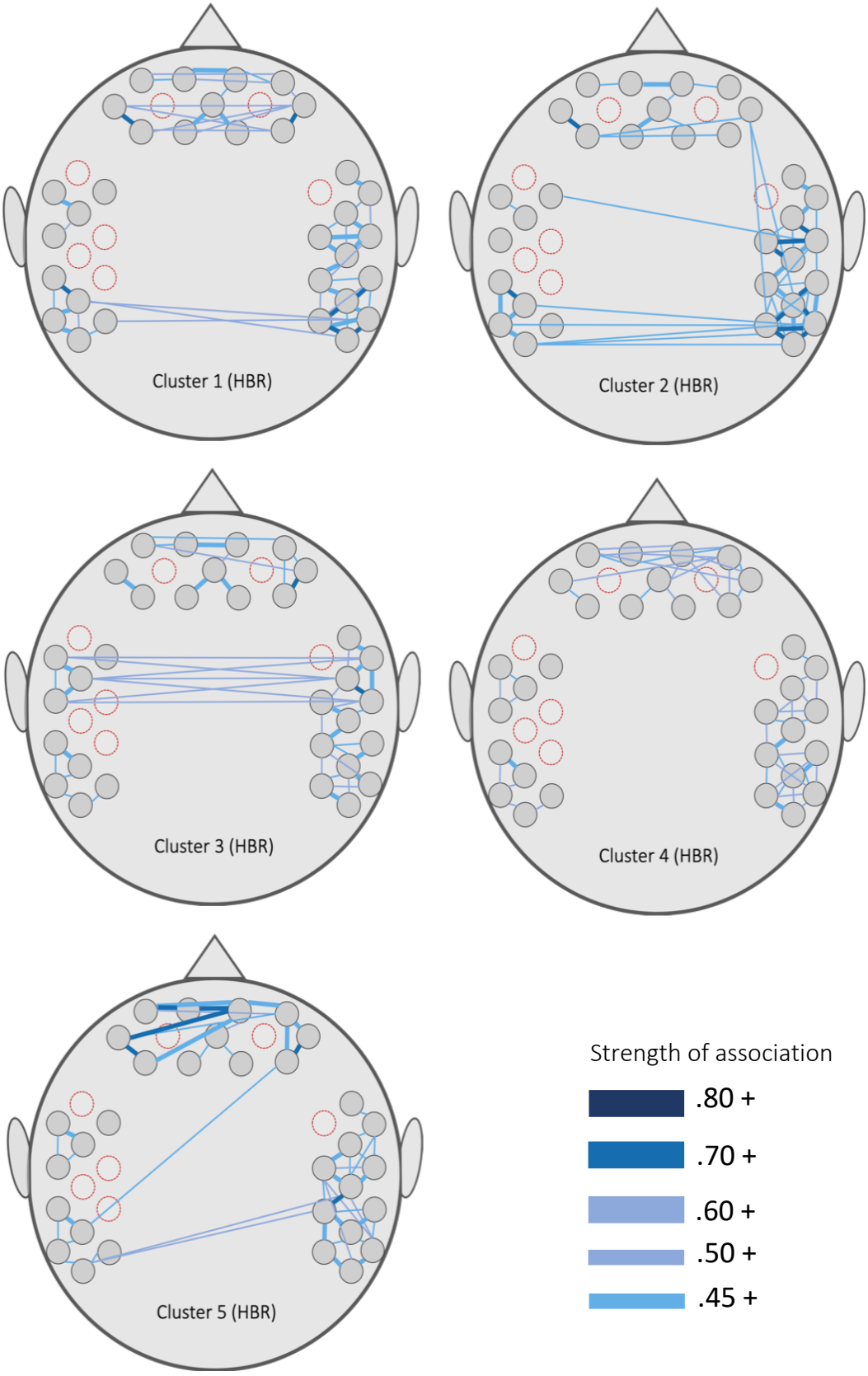


Figure 7.17. HbR 50 strongest correlations/cluster to illustrate the regions in which we observe connectivity patterns.

7.7.2.3 Occurrence of cluster

Tables 7.2 and *7.3.* show the percentage of clusters in each nap for every participant. Results show that overall occurrence of clusters differs across individual naps. This suggests individual differences in connectivity pattern occurrence during a nap in infants.

Table 7.2. Percentage of clusters in sleep segment/ participant – HbO_2

Participant	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
P05	3.5 %	6.9 %	37.9 %	6.9 %	44.8 %
2002	23.1 %	30.8 %	7.7 %	30.8 %	7.7 %
2004	7.7 %	69.2 %	15.4 %	7.7 %	0 %
2005	63.6 %	12.1 %	0 %	15.2 %	9.1 %
2013	0 %	22.7 %	18.2 %	40.9 %	18.2 %
2015	5.4 %	2.7 %	43.3%	27.0 %	21.6 %
2019	0 %	0 %	0 %	86.7 %	13.3 %
2020	7.1 %	0 %	0 %	50.0 %	42.9 %
2021	11.5 %	11.5 %	0 %	50.0 %	26.9 %
2023	12.5 %	87.5 %	0 %	0 %	0 %
2024	23.1 %	76.9 %	0 %	0 %	0 %
All participants	16.1 %	20.5 %	15.2 %	28.6 %	19.6 %

Table 7.3. Percentage of clusters in sleep segment/ participant - HbR

Participant	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
P05	10.3 %	0 %	10.4 %	79.3 %	0 %
2002	38.5 %	30.8 %	0 %	30.8 %	0 %
2004	53.9 %	23.1 %	0 %	23.0 %	0 %
2005	18.2 %	6.1 %	63.6 %	12.1 %	0 %
2013	36.4 %	63.6 %	0 %	0 %	0 %
2015	13.5 %	2.7 %	29.7 %	54.1 %	0 %
2019	0 %	0 %	100.0 %	0 %	0 %
2020	0 %	0 %	78.6 %	21.4 %	0 %
2021	0 %	0 %	42.3 %	50.0 %	7.7 %
2023	0 %	0 %	0 %	12.5 %	87.5 %
2024	0 %	0 %	7.2 %	21.4 %	71.4 %
All participants	15.2 %	10.7 %	32.6 %	33.0 %	8.5 %

7.8 Discussion

The aim of this chapter was primarily to design and ascertain the feasibility of a customised fNIRS-EEG headgear for sleep research in infants. Thus, the aims were a) designing a combined NIRS-EEG headgear for sleep measurements and b) collecting valid sleep data with this headgear. The long-term aim of this Study 2 would focus on an objective investigation of sleep and development by measuring functional connectivity using fNIRS and EEG markers of development during sleep.

7.8.1 Using customised NIRS-EEG headgear for sleep research: considerations surrounding data quality

Results from this chapter can be summarised as follows. First and primarily it was possible to use the customised NIRS-EEG headgear for sleep recording in infants 6- to 8-months-old. The rate of infants who slept in the study was around 40 %, something that is usual for infant sleep research and within the accepted time range (see Friedrich et al. 2017, 2018, 2019). Infants who slept with the headgear on usually had (parent-reported) no more trouble sleeping than normally and seem to tolerate it as well as similar caps are tolerated in infant populations. Some of infants who slept for a longer time showed some

pressure marks, which faded within half an hour after removal of the cap. Overall the instructions for parents to bring their child's familiar sleep environment worked well. It has to be acknowledged that the study was time consuming (five hours / participant) and required two researchers at all times. Moreover, the heavy fibre bundles that only allowed little movement of the NTS meant parents could not just pick up their infant when they were vocalizing or needed to be soothed during sleep. This made movement for parents breastfeeding their babies to sleep also more difficult and required a researcher to stand directly next to the parent. This could be remedied by only including bottle-fed babies and having all of them nap in the pram instead of in parents' arms. Though this could lead to a further biased sample of including only infants who are exceptional sleepers. The use of an artificial arm to hold up the NIRS fibres prior to capping could also be an advantage here.

Secondly, data quality from the study was somewhat mixed. In general, NIRS data quality was better than the EEG data quality. There were 11 children with good NIRS data and 5 infants with fair EEG data. The reasons for this were that placement of EEG mastoid references was harder with the combined cap resulting in the occasional misplaced reference reducing data quality. Moreover, all EEG electrodes were placed along the midline, in a neoprene cap it was possible that fit was looser towards the top of the head especially as the heavy fibres might have pulled up the cap occasionally reducing scalp contact of the electrodes. fNIRS data showed quite a large number of poor quality channels, though this is a common outcome in fNIRS infant studies. These could be again due to the fact that the fibres pulled the cap up a bit, reducing scalp contact of the optodes. Moreover, some infants were lying on the side in the pram which could have reduced data quality on one side particularly.

7.8.2 Consideration of biases surrounding data quality

As alluded to above, testing sessions using the customised NIRS-EEG headgear carried a number of (potential) biases that warrant discussion.

The first bias concerns the observation that some parents indicated their infants to be poor sleepers during the pre-study phone call. These infants to the majority indeed did not sleep in the lab. Interestingly, when the preliminary habitual BISQ sleep data was examined from the present study there were no differences in habitual sleep fragmentation or sleep duration (day or night) markers between infants who napped in the lab vs. infants who did not nap in the lab. This suggests that parental perception and potentially parental attitude might influence whether infants nap in lab-based sleep

studies. Future work will include 1) using a larger sample and 2) investigating whether sleepers and non-sleepers different in habitual sleep using actigraphy data rather than BISQ data, to account for the potential cross-method differences between actigraphy and BISQ. The issue of breastfeeding infants to sleep is an important bias to consider, too. These considerations become especially important when thinking about expanding the testing age range further beyond the first year of life. Infants who were breast-fed fell asleep more readily than infants who were not breastfed. This could introduce a systematic bias into the sample.

The future work should take a closer look at the role of biases that might affect the data collected.

7.8.3 Connectivity analysis

However, despite some complications with data quality, it is still an important insight that NIRS data was collected successfully and that the collected data was of good enough quality to be analysed. These additional connectivity analyses revealed that connectivity patterns varied across the duration of the sleep period in all infants. The cluster analysis confirmed that indeed certain patterns of connectivity were reoccurring when pooling the data across all infants. Five different patterns of connectivity were identified for HbO_2 and HbR. This finding could be interpreted in relation to prior data showing that infant connectivity patterns differ depending on the sleep stage (Lee et al., 2020). While it was not possible with the limited EEG data that was acquired to investigate sleep stage differences depending on the identified connectivity cluster, it is possible that some of the different connectivity clusters corresponded to a specific sleep stage. For example, it could be that the stronger more global connectivity patterns observed in e.g., Cluster 2 or 4 of the HbO_2 data were apparent in stage 2 sleep, such as in Nguyen et al.'s (2018) adults that exhibited stronger connectivity patterns in stage 2 sleep. This would be in line with research showing that sleep stage transitions to SWS as well as sleep spindle occurrence (in adults) are accompanied by an increase in hemodynamic activity (Schabus et al., 2007). Importantly, the connectivity patterns that were observed differed across infants. Some infants showed all five functional connectivity patterns that were identified in the cluster analysis, in the duration of their nap and some infants showed only a subset of connectivity patterns. This variability is of high importance as the end goal of this research was obviously to link the individual differences in connectivity patterns to neurocognitive markers of development.

7.8.4 Wireless NIRS-EEG headgear for sleep assessment

This study can be considered a successful first attempt at characterising infant sleep using NIRS-EEG and provided a key foundation for future studies. Several aspects need improvements before proceeding with this research line. Many of the above-reported caveats of the study that lead to reduced data quality or infants not sleeping, are rooted in the physicality of the heavy NTS NIRS system and their long, heavy fibre optic cables that made navigating the participant more difficult and reduced comfort of infant and parent. For infants sleeping in the pram and infants that were parent-reported easy sleepers/good sleepers, the NTS NIRS worked very well. Length of the fibers was only one meter and so it was not possible for parents to soothe their babies to sleep by walking around and carrying them. Moreover, feeding babies to sleep was difficult with the heavy headgear. However, recently a wireless NIRS system became available, the Artinis Brite 24 system, a 22-channel system. As the EEG system was already a wireless system the goal would was to try and integrate a wireless NIRS system in place of the stationary NTS system. Serendipitously, the *Artinis* optodes fit perfectly into the already designed optode holders and thus no modification of the customised cap was required. The wireless NIRS-EEG system (for an illustration see *Figure 7.18*) instead of the stationary NTS-NIRS system in combination with the wireless EEG system has numerous advantages. 1. The system is light-weight, replacing the heavy fibre optic cables of the NTS-NIRS system. 2. It is mobile. Thus, enabling the parent to feed the infant before napping (and during and move around with him/her), potentially even holding them while sleeping. 3. It has the potential to increase the number of infants sleeping, in particular in infants that are poor sleepers. Lastly, it has a wider range of application; in-home measurements are possible with a headgear like this and it enables researchers to reach a diverse range of socioeconomic backgrounds and different cultures. Furthermore, infants with poor sleep quality and older infants/toddlers might sleep better when sleep is measured in their homes. Drawbacks included lower number of channels so whole head coverage for functional connectivity analyses is not possible. Moreover, the channel design provided by the software currently is not as flexible as with the NTS.

Three proof-of-concept testing sessions were performed with the system in February 2020 before testing was suspended due to the COVID-19 pandemic. Parents were able to easily carry their baby around as well as feed them before and during sleep. The reduced amount of cables also meant that placing the headgear was easier and more comfortable for the baby. Data quality for the two sessions looked good for frontal channels and saturated for the temporal channels. This was, as the Artinis device was set to work with

older children so the light power was too much. However, the upgraded version of the Artinis Brite device will be adjusted to the working light power when testing resumes.

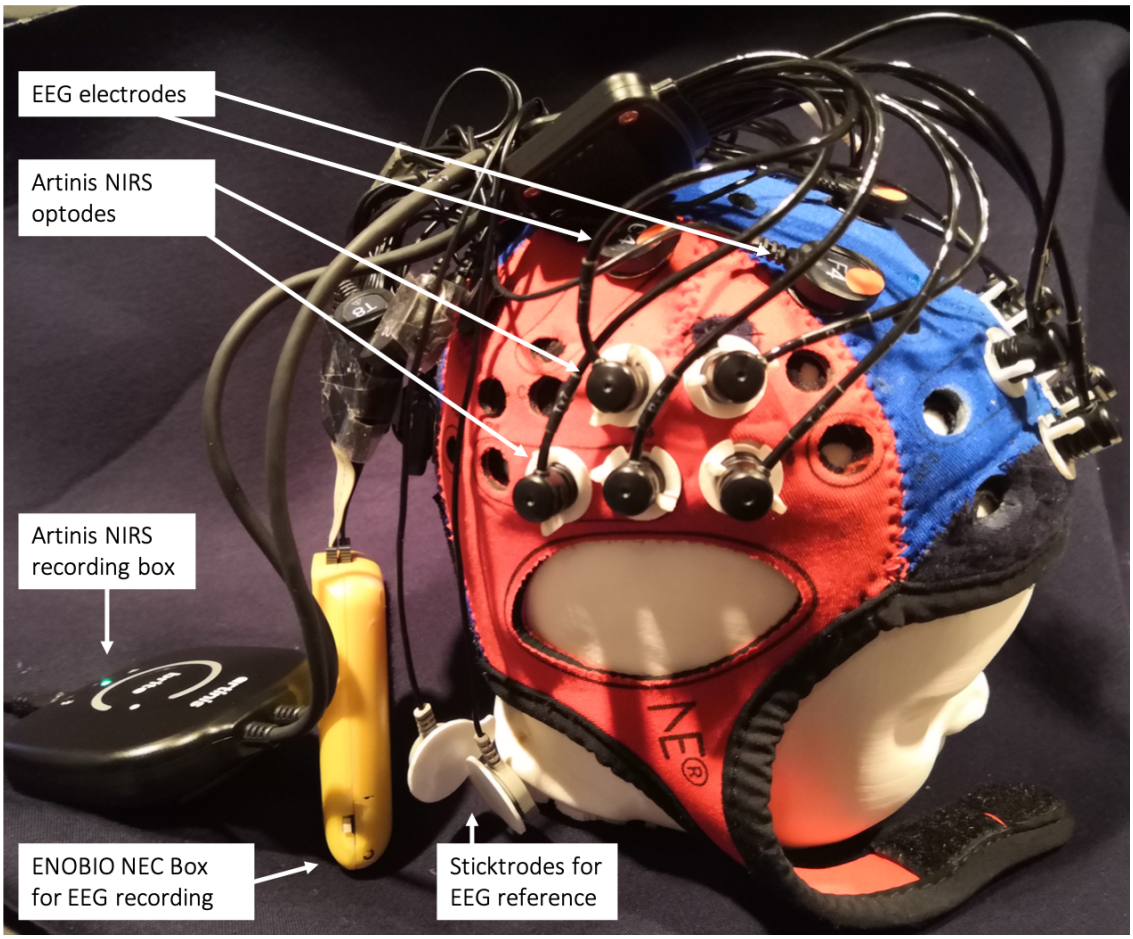


Figure 7.18. Wireless NIRS-EEG headgear setup.

7.8.5 Future directions

Results of this study showed individual differences in connectivity patterns across infants. This is but a first proof-of-concept step. It is conjectured that these patterns are associated with sleep EEG characteristics. One, they might map onto different sleep stages. Future research should compare within each sleep epoch each cluster with the corresponding sleep stage.

Past research has linked specific characteristics in an infant's / child's sleep (nap) EEG may serve as a marker of memory consolidation and also of development. One such marker are *sleep spindles*, that have now been well studied by scientists for their relation to memory, plasticity and cognitive development. As spindles are generated by thalamocortical structures, their occurrence is heavily tied to anatomical maturation (Gruber & Wise, 2016). Consistent with this their topographical occurrence and

characteristics (density, duration, frequency) show developmental changes with age, leading to their proposed value as markers of development (D'Atri et al., 2018; Gruber & Wise, 2016; Scholle et al., 2007). Research has shown that their occurrence is related to visual abilities and perceptual learning (Bang et al., 2014), aspects of IQ test performance (Gruber et al., 2013), (declarative) memory (Hoedlmoser et al., 2014; Kurdziel et al., 2013) or information encoding and processing in infants (Friedrich et al., 2017, 2018) to name a few. For detailed reviews see (Gruber & Wise, 2016; Hoedlmoser, 2020). In summary, sleep spindles are potentially a good marker for development, nonetheless it has to be acknowledged that directionality and strength of association show mixed findings across the literature. Another EEG marker of development that has emerged is slow wave activity (SWA). Generally, it is considered a marker of homeostatic sleep pressure (see *Chapter 1* for further explanation), though in recent years SWA has been also related to cognition e.g., by promoting widespread neuronal synchronisation (Vyazovskiy et al., 2007). Studies show, for instance, increases in SWA after learning. In a study comparing adults, adolescents and children (aged 9 – 11 years), the researchers found that learning of a visuomotor task prior to sleep increased SWA activity in the parietal lobe for all participants but especially so in children (Wilhelm et al., 2014). The authors interpret this increase in SWA with a post-learning increase in neuronal synchronisation and synaptogenesis. Other research shows that more SWA is associated with better cognitive performance in children (Möhring et al., 2019). These are just some examples of studies implicating SWA in development /learning. Paradoxically, larger SWA in response to sleep deprivation in children in posterior regions was also negatively associated with myelin content in temporoparietal regions (Kurth et al., 2016). General changes in SWA across infancy have also been observed, showing that synchronisation of neurons, as indicated by an increase in SWA from 2 to 9 months of age. In summary, both sleep spindles and SWA can serve as markers for development, perhaps reflecting underlying anatomical changes in the developing brain particularly in the thalamocortical circuits (Gorgoni et al., 2019). These are just some examples of two of the main markers of development in sleep EEG, though REM sleep has also been shown to be potentially relevant for aspects of development (Jenni et al., 2004; Roffwarg et al., 1966). For example, animal research has demonstrated that active sleep, can encourage connectivity, e.g., in a rat study Del Rio-Bermudez and Blumberg show that active sleep triggered widespread synchronized oscillatory activity in sensorimotor networks in rats (Del Rio-Bermudez & Blumberg, 2018). For an exhaustive review on the relationship of sleep EEG characteristics and developmental status refer to Gorgoni et al. (2019).

Future research should focus on relating the findings from the fNIRS connectivity analysis in a full sample to EEG sleep markers (such as spindles or SWA), to habitual sleep (actigraphy and parent-report) and to eye-tracking markers of development (see *Chapter 5* for details on which markers could be used). However, due to limited data, it is not feasible to investigate those relationships in a meaningful way in the current data available. The expectation would be that more SWA during a certain sleep epoch is associated with higher and more global connectivity patterns (given that both global patterns and higher SWA have been named as markers of development).

On the other hand, the connectivity patterns during sleep should also be associated with developmental markers during wake, e.g., information about visual attention abilities from the eye-tracking data that was collected upon waking from the infants, waking theta power and theta power change or parental questionnaires about general development. For example, higher theta change during wake could be linked to more global connectivity patterns during sleep and to higher occurrence of sleep spindles during the nap. It would also be interesting to see if the variability patterns observed in the gap-overlap task that was linked to habitual sleep patterns might be associated with a higher variety in connectivity patterns. This might represent a developmental type that is characterized by variability. Given that the present study investigates connectivity in social brain areas (Lloyd-Fox et al., 2014) linking connectivity patterns during sleep in those social brain areas to face look parameters of the face pop-out task might provide more information about the role of sleep connectivity for social attention.

Lastly, one important step would be to link the connectivity patterns during sleep (and sleep spindle occurrence) to the objective and subjective measures of habitual sleep and especially the sleep quality clusters that were identified. As discussed in other parts of this thesis, while two infants might exhibit the same habitual sleep patterns, their underlying quality of sleep could be fundamentally different, affecting how sleep impacts development. One of the aspects of an infant's sleep that differs could be the connectivity patterns during sleep. Thus, future work needs to focus on linking habitual sleep quality as identified by the data-driven clusters in *Chapter 3* to the connectivity patterns. The other parameters that emerged as relevant might be sleep fragmentation. As evidenced by results of Study 1 sleep fragmentation could be important for development. It might be that night wakenings disrupt beneficial/global connectivity patterns and consequently crucial learning and plasticity processes. Associations between habitual sleep quality and brain connectivity measures during sleep could provide a more definite answer to the question of how sleep impacts development.

7.8.6 Conclusion

In conclusion, this proof-of-concept study showed that we can successfully measure both brain oxygenation changes and neuronal activity using combined fNIRS-EEG in napping infants. It was possible to define a protocol that enabled successful data collection. Challenges to the measurement of simultaneous NIRS-EEG during sleep in infants were discussed and solutions to these challenges were implemented. The preliminary analyses showed that during a nap connectivity patterns in the brain varied. In the follow-up study that will be conducted I will take into considerations the insights from this feasibility study and use a wireless fNIRS-EEG device to investigate how these connectivity patterns could reflect individual differences in developmental status.

First steps towards objectively measuring both sleep and development have been taken and further method development will enable presentation of results that will help clarify the mixed findings with regard to sleep and development in the field.

CHAPTER 8 - General Discussion

The goal of the present thesis was to explore the relationship between sleep and neurocognitive development in the first year of life using both objective and subjective measures. The first aim was to contribute to the methodological issues surrounding the measurement of the relationship between sleep and development and the second aim was to contribute to the theoretical understanding of how sleep is related to neurocognitive development.

Two overarching studies were conducted in the context of this thesis. The first was a longitudinal study that employed actigraphy and parent-report measures (questionnaires and sleep diary) to assess habitual sleep and eye-tracking, EEG, and parent-report measures to assess development in infants ages 4 to 14 months. *Chapters 3, 4, 5,* and *6* analysed data from this longitudinal study. Specifically, *Chapter 3* examined agreement between different sleep measures and tested a data-driven approach to classifying habitual infant sleep quality. *Chapter 4* described the relationship between habitual infant sleep and parent-report measures of infant general development, infant sleep routines, infant temperament, and maternal characteristics. *Chapter 5* described the relationship between habitual infant sleep and eye-tracking-measured aspects of visual attention as a proxy for neurocognitive development. *Chapter 6* described the relationship between habitual infant sleep and aspects of waking theta power as a proxy for brain development. A second cross-sectional study was conducted to investigate the sleeping infant brain using a novel, customised NIRS-EEG headgear with the aim of measuring both sleep and brain activity. *Chapter 7* described proof-of-concept results and feasibility of the cross-sectional study including a discussion of the potential improvements of the headgear.

In the following, the main results from the studies conducted during this PhD project are discussed, as well as their limitations and implications for the research community and society. This work highlighted the importance of considering methodological issues in the study of sleep and development. There were areas of convergence and divergence across sleep measures and in relation to various developmental measures and parental characteristics were likely associated with cross-method agreement. Further, the development of the customised NIRS-EEG headgear is discussed and preliminary results of individual differences in sleep connectivity. Lastly, the potential of wearable technology for the assessment of sleep and development is considered.

8.1 Main findings in the multi-method exploration of infant sleep and development

8.1.1 Agreement of sleep measures

The first aim of this thesis was to examine the multiple ways in which sleep is measured. Cross-method agreement as well as characteristics that might influence this agreement were investigated. Here, I measured infants longitudinally (up to four visits) with multiple sleep assessment methods and *Chapter 3* focused on the investigation of the agreement between sleep measures.

Subjective measures (sleep diary and questionnaires) did not yield good agreement with each other or with the objective measure (actigraphy) across most sleep parameters. When investigating developmental changes in sleeping patterns in the sample, the sample largely showed results in line with prior literature (Peters, 2017; Gorgoni et al., 2019). A reduction in Day Sleep Duration, an increase in Night Sleep Duration and a general decline in Night Wakening Number was found across measures. However, objective and subjective measures showed inconsistent patterns. This finding emphasises how cross-method differences might dictate study results.

Overall, night wakening parameters yielded slightly better cross-method agreement than sleep duration assessments, though some discrepancies remained. This is likely because it might be easier for parents to remember how often their child woke up than to remember the actual duration of the sleep. The cross-method disparities have a number of implications for research and the conclusions that sleep research draws about sleep parameters. It might be prudent to treat studies that find effects with regard to sleep duration with caution, especially if only parent-report measures are used. Moreover, sleep parameter and method choice need to be carefully deliberated and rooted in theoretical reasoning. For instance, it may be possible that parental perception of infant sleep is particularly interesting to the overarching research question, in which case subjective measures should be chosen. In addition, direct cross-study comparisons should be undertaken only if similar methods were used (i.e., either objective or subjective).

It is also possible to use data-driven approaches to classify sleep clusters that map onto prior literature definitions of good/poor sleep quality. However, cluster membership differed across infants, such that the same infant did not appear consistently in the same cluster across methods, i.e., different methods identify slightly different clusters. This indicated that the data-driven approach to classify sleep quality needs more research and potentially more sophisticated data classification methods (see below for discussion on

automatic classification of sleep data). It could again highlight the fact that different sleep assessment methods measure different aspects of sleep. Another avenue could be to classify sleep quality multi-modally, i.e., using objective and subjective measures and create a combined index of sleep quality. Though a larger sample would be needed to capture the different contributions from different methods, and hence was not done in the scope of this project.

In summary, the question that arises is how infant sleep and infant sleep quality should be measured in future studies. Careful deliberation and justification of method choice is needed by considering research questions, available resources, sample and study design. For further discussion regarding method choice see below. Additional research is required to compare subjective and objective measures of sleep in detail in the first year of life, perhaps in comparison to a measure of true underlying sleep such as PSG.

8.1.2 Influence of confounding variables on agreement between sleep measures

The investigation of the cross-method agreement showed the potential presence of a bias in agreement across methods. Therefore, in *Chapter 3* I tried to understand what the confounding variables might be. Findings revealed that cross-method agreement was related to infant age as well as maternal stress and anxiety levels, e.g., mothers reporting higher stress and anxiety levels and those of younger infants showed better cross-method agreement on night wakening parameters. These results illustrate the importance of a holistic view of studying sleep and development, i.e., to study infant sleep considering an infant's age and potentially parental characteristics. This is a highly relevant finding for the sleep research in general. It suggests that studies using heterogenous samples to study group differences in terms of maternal stress could have inadvertently introduced an additional bias. In particular in developmental studies that investigate sleep differences between typically developing and infants with neurodevelopmental disorders, the component of maternal stress could affect sleep measurement, as there is evidence of higher parental stress in children with neurodevelopmental disorders (Hayes & Watson, 2015). This could mean, for example, that sleep reporting is more consistent in the high stress group (i.e., parents of children with neurodevelopmental disorders) resulting in potential group differences reported in sleep patterns when perhaps there is no underlying difference.

It also raises questions about longitudinal studies and the assumption that age-related changes in the association between sleep and cognition are solely due to changes

in that association and not due to methodological issues. Therefore, a longitudinal study might investigate age-related changes in sleep patterns using questionnaire measures. For instance, the reported Night Wakening Number will decrease, solely due to the fact that as infants learn self-soothing, parents will report less night wakening. Researchers might conclude the presence of age-related changes when in practice these only reflects the degree in which the child's behaviour is noticed by parents.

Interestingly, it was the cross-method agreement that was particularly affected. The LMMs in *Chapter 4* did not reveal an association between objectively or subjectively measured infant sleep quality or parameters with stress measures, except an association between BISQ-measured WASO and day sleep and stress; a similar association was not observed with diary or actigraphy. This highlights the cross-method disparities and underscores the need to carefully consider method choice in conducting and evaluating (developmental) sleep studies.

As both actigraphy and parent-report have their drawbacks (see *Chapter 1-3*), no definite recommendation can be made with regard to which method is "better": actigraphy or parent-report. However, *Figure 8.1.* represents an attempt to aid researchers in choosing a sleep measure for their study. Researchers selecting a sleep assessment method need to consider the following factors. First, the research question needs to be considered, i.e., is sleep the main question and which sleep parameters are of interest. For example, if parental perception of sleep is of interest, parent-report should be chosen instead of actigraphy. Secondly, available resources need to be considered. Actigraphy devices are more expensive than parent-report measures and pre-processing of actigraphy data is time-intensive. Other considerations centre around the sample and study design. For example, if the sample is likely to be heterogenous in terms of parental characteristics (e.g., comparing different SES) both parent-report and actigraphy should be used to account for cross-method differences driven by parental characteristics. Similarly, in longitudinal studies testing infants many times or in studies testing large age ranges, multiple measures should be used. In homogenous samples and narrow age groups this is likely less of an issue.

Choosing actigraphy vs. parent-report measures for studying infant sleep in the context of development ?

	YES	NO
1. Main research question concerns sleep		
2. Research questions concern sleep fragmentation		
3. Research questions concern sleep duration		
4. Research questions concern parental perception of sleep		
5. Resources (money to acquire devices /time to preprocess actigraphy, ...) available		
6. Longitudinal study		
7. Large age range		
8. Infants < 6 months old are studied		
8. Heterogenous sample (e.g., comparison of control group vs. infants with neurodevelopmental disorders, comparing poor sleepers with good sleepers, ...)		

Figure 8.1. Illustration of questions to consider when choosing actigraphy vs. parent-report measures. & = both actigraph and questionnaires can be chosen. / = either actigraph or parent-report can be chosen.

Future studies should aim to disentangle the bias in cross-method agreement and investigate influences beyond infant age and maternal stress, such as infant mood /temperament.

8.1.3 Influence of methodological choice on associations with general development

The above results posed the question of which method to use when assessing sleep in relation to development. As the results above suggested that different sleep assessment

methods measured sleep differently, all of the sleep methods were explored in association with development. A straight-forward method to understand an infant's development and to capture it across a broad range of contexts, is for parents to fill out a questionnaire about their child's developmental status. This also has the advantage of being less affected by infant state at a one-time lab observation. In *Chapter 4* I investigated how parent-reported general infant development was related to objective and subjective habitual sleep measures. There were cross-method differences in the association of night sleep with general parent-reported development. There were no effects for BISQ-measured night sleep parameters. Though, both diary and actigraphy showed developmental changes in the association between night wakening parameters and some subscales of the general developmental questionnaire. Higher parent-reported WASO was associated with lower parent-reported social skills in some age groups (8, 10, and 14 months of age) but not in the other age groups. Similarly, higher Night Wakening Number was associated with lower parent-reported fine motor skills in some age groups (4, 6, and 14 months) but better fine motor skills in others (10 and 12 months). However, results from Night Wakening Number and WASO did not show converging age-related patterns for the parent-report measures. Both Night Wakening Number and WASO are measures of time awake at night and therefore linked. The expectation would have been that they show comparable age-related changes. Higher actigraphy-measured WASO was associated with increased parent-reported gross-motor skills at 6-, 8-, and 14-months-old but with lower parent-reported gross motor skills at 10 months and 12 months of age. Age-related changes could suggest the presence of critical periods in development, for example, the age range of 10 and 12 months coincides with the onset of walking in most children. Possibly, increased WASO could hinder development of gross-motor skills. It might also be possible that as children learn new skills, they start to sleep less. Thus, infants who have not yet developed the skills in question (e.g., walking) wake up more compared to children who have already mastered them.

It is possible that some of the age-related changes that were observed are related to the method disparity results, too. That is, some methods may better reflect true underlying sleep at certain ages. The disparity analyses support this claim, showing better cross-method agreement for some ages in some parameters than for others, e.g., the cross-method agreement was better for WASO in the younger infants than in the older infants but worse for the younger infants than for the older infants for Day Sleep Duration.

Importantly, Day Sleep Duration showed cross-method consistency with higher day sleep being associated with lower parent-reported fine motor and problem-solving skills. It is possible that due to the shorter duration of day sleeps parents are able to keep better track of their infant's Day Sleep Duration. Day sleep might also show less variability than night sleep patterns and is often tied to an infant's feeding schedule. The results regarding Day Sleep Duration also underscore the need for the multi-method approach. When different measures provide consistency on a sleep parameter it indicates that a researcher can have greater confidence in its association with development. This is particularly important, as in this thesis many statistical analyses were performed which can lead to inflation of false positive rates (see *Chapter 2* and Limitation section below for further details/considerations). While I worked to adjust for the multiple comparison problem, convergence of patterns across different methods lends more confidence to the respective results. In general, the findings of the present study highlight the importance of looking at the role of day sleep in fine motor and problem-solving skills. The role of day sleep is further discussed below.

8.1.4 Influence of methodological choice on associations with temperament

Prior research showed some associations between sleep and temperament (e.g., Sordono & Reeb-Sutherland, 2015; Spruyt, 2008), though the mixed findings necessitated further research. Temperament refers to an infant's behavioural style, i.e., how they regulate their emotions and interact with the world around them (Rothbart, 1982; Weissbluth, 1981). The development of temperament is a key milestone in a child's development. In *Chapter 4*, the Infant Behaviour Questionnaire (IBQ-R) was used to look at temperament measures across three domains (surgency/positive emotionality, negativity/negative emotionality and regulation).

There was no association between any of the temperament subscales with objective sleep quality or with diary-measured sleep quality. BISQ-measured day sleepers showed higher regulatory and surgency scores but these effects were not found for diary or actigraphy sleep quality clusters.

Subjective Night Sleep Duration was not associated with parent-reported temperament subscales. Higher parent-report WASO and Night Wakening Number were associated with higher negativity scores. These association were not observed in the actigraphy data. This might suggest that parents who are more attuned to their infant's night wakening patterns could have more disrupted sleep themselves, influencing parental mood during the day (Meltzer & Mindell, 2007) and consequently view their

child more negatively during the day (Rigato et al., 2020). Alternatively, infants with more negative emotionality might cry more and are less able to self-soothe and are more likely to alert parents at night. Actigraphy provides information about the infants wake patterns but not how disruptive that might be for both infant and parent.

There were developmental changes in the relationship between objectively measured Night Sleep Duration and surgency subscales with younger infants (8 months and younger) showing higher surgency scores with higher Night Sleep Duration and older infants (10 months and older) showing lower surgency scores with higher Night Sleep Duration. Temperament is thought to be a relatively stable concept over the first year of life, whereas night sleep undergoes changes. These results could mean that very active infants sleep a lot during the night when they are young but less when they are older. Future research should investigate this further to understand these changes in association with each other. Of note, the surgency dimensions actually showed developmental changes in the present study, which might have driven the age-related change observed here. There were no associations of either subjective or objective Day Sleep Duration with any aspects of temperament.

Overall, there was little cross-method consistency for sleep quality, likely indicating that there were no strong associations between the measure of sleep quality and temperament indices. There was some cross-method consistency only for the subjective measures for the sleep parameters but strong conclusions should not be drawn. Actigraphy results indicate developmental changes in the association between Night Sleep Duration and positive emotionality. These developmental changes are seen in other parameters too (e.g., in general development) and are discussed further below.

8.1.5 Investigating the number of sleep rituals

Another question that arose when studying the context of a child's sleep was whether the number of bedtime rituals that infants were exposed to were associated with sleep (*Chapter 4*). The number of bedtime rituals was associated with diary-measured sleep quality but not with actigraphy- or BISQ-measured sleep quality, indicating little cross-method consistency for sleep quality. For diary-measured night sleep parameters, higher amount of WASO, Night Sleep Duration and Night Wakening Number were all associated with higher number of sleep rituals but only in the 4-month-old infants. Moreover, there were developmental changes in the association of Day Sleep Duration and sleep ritual number. In the younger infants (4 and 6 months) there was a positive association between sleep ritual number and Day Sleep Duration, while in the older

infants (12 and 14 months) there was a negative association between sleep ritual number and Day Sleep Duration with infant ages 8 to 10 months old being right in the middle. Similar to temperament and general development there were developmental changes in the association. As discussed in *Chapter 4,* the association between sleep ritual number and day sleep could be related to the impact of sleep ritual number on Night Sleep Duration. Lower or higher Night Sleep Duration could then impact Day Sleep Duration. Potentially, in younger infants, more rituals at night are arousing, leading to less night sleep and consequently more day sleep. It may be that in older infants, more rituals at night lead to longer night sleep and consequently shorter day sleep. These results also illustrate the challenges of correlational studies such as the one conducted here in terms of understanding the directionality of the associations. Future studies should consider conducting intervention studies targeting sleep rituals to determine if there is causal relationship and to make sure that associations found in this study are robust and replicable.

8.1.6 Relation between sleep and neurocognitive measures of visual attention

In order to reduce the potential bias introduced by parent-report the goal was to minimise the bias in the developmental assessment by using an objective measure. First, the attempt was to use eye-tracking-measured visual attention as a proxy for development. In older children and adults, visual attention has been shown to be linked to sleep patterns and to be predictive of later executive functioning (e.g., Bernier et al., 2014, Lim & Dinges, 2010). The main attention measures that were investigated were as follows: orienting/disengagement parameters, social sustained attention, and selective attention, that cover several important visual attention features that are developing in the first year of life. These were measured by three eye-tracking tasks: gap-overlap task, face pop-out task, and the novelty habituation paradigm.

A parameter that I thought is important to investigate due to Geva et al.'s (2016) proposition that regulation in attention is impaired following sleep problems, is variability in visual attention (Geva et al., 2016). The researchers propose that infants with less regulated sleep-wake rhythms might have more difficulties in gaze regulation. Early looking time research highlights the importance of studying variability measures, as it provides information about individual differences that are not captured by mean measures (Frick et al., 1999).

Behavioural eye-tracking results showed varied association of sleep parameters with measures of attention (*Chapter 5*). Sleep quality assessment showed that the objectively measured poor/day sleep cluster showed lower variability in reaction time in the gap-overlap task. The latter finding is in line with diary results showing lower variability in poorer sleepers as well as faster reaction times and adult-like sleepers showing slower reaction times and higher variability. These findings are relatively consistent across methods. While there is not much known about variability in attention measures, faster mean reaction times are thought to be reflective of a faster orienting response and easier disengagement, a skill learned in the course of the first year of life, and thus in theory indicative of more advanced development (Elsabbagh, Fernandes, et al., 2013; Wass et al., 2011). So far there is no research that indicates that sleep quality is associated with variability in attention. However, these findings suggest that variability in reaction time could be impacted by overall sleep profile. While sleep quality investigations show consistent patterns, closer investigation of the sleep parameters yielded inconsistent results. For objectively measured WASO and Night Sleep Duration, there was higher variability in reaction time; this is contrary to findings from subjective measures, where higher WASO was associated with lower variability. Effects for the other parameters were mixed and therefore not further discussed. Overall, despite the associations with variability, the further inconsistent results from the gap-overlap task, might suggest that while some associations between attention and sleep exist, a robust overarching theme is lacking. It is possible that sleep is perhaps not strongly related to measures of attention.

Some, but not all objective and subjective measures showed associations of night waking parameters with face looking. For social attention I looked at various parameters that described how infants looked towards faces in an array on a screen that also contained objects. Both diary- and actigraphy-measured night wakening parameters showed changes with development in association with some of the looking variables towards faces. While consistency here was not perfect (i.e., some changes were apparent in the actigraphy measure but not in the diary measures and vice versa), the overarching conclusion is that night wakening parameters in particular are related to face looking. Infants in the 10-month and 12-month age groups had longer continuous looks towards the face the less time they spent awake at night. Infants in the age groups of 4 and 6 months of age showed shorter continuous looks with more night wakenings. These findings together hint towards developmental differences in face looking in relation to

sleep. It is possible that certain ages might benefit especially from a certain type of sleep, e.g., no night wakenings is especially useful in older infants but not so important for younger infants. There were no effects observed for sleep quality on social attention (face pop-out task) or novelty habituation.

Findings with regard to BISQ-measured night sleep parameters were also mixed. Broadly, there were a number of developmental changes in the association of BISQ-measured Night Sleep Duration and face looking, but there were no such association with either actigraphy or diary. An association with Day Sleep Duration and face look parameters were only apparent in the BISQ data, with lower BISQ-measured Day Sleep Duration being associated with longer face looks. There was no association of actigraphy or diary-measured Day Sleep Duration with face parameters, again underlining the inconsistency of the findings. For the novelty habituation look durations, there were some associations of sleep parameters with BISQ but not for actigraphy and diary.

In summary, these results show the likely importance of night wakening parameters for visual attention, in particular for face looking measures. Moreover, age-related changes observed in this association highlights the importance of tracking this relationship across the duration of the first year of life and potentially beyond. However, it is crucial to acknowledge that there are many cross-method inconsistencies that have to be considered when interpreting and extrapolating from these findings. Since the cross-methods age-related changes do not map onto each other fully, it is still not possible to make a definite statement about how the relationship between visual attention and sleep fragmentation changes. These results can also be taken as evidence that sleep does not strongly relate to visual attention in general, with a potential exception of social attention. It is possible that lab-based attention measures are not strongly affected by habitual sleep, though the role of night wakening needs clarification in future studies. Future research should combine visual attention measures with brain measures of arousal regulation to disentangle the directionality of the association between night wakening parameters and visual attention. Lastly, it is important to acknowledge again, that analyses were correlational in nature and therefore necessitate further intervention studies and complex analyses methods (see Limitation section below) to be able to make definite statements about the associations discussed above.

8.1.7 Relation between habitual sleep and brain activity

While the behavioural measures and the parent-report measures revealed a substantial amount of inconsistency in terms of overarching emerging patterns, investigation of brain activity yielded some converging results. Investigation of brain activation patterns can reveal information above and beyond what behavioural measures and parent-report measures can provide. Analyses of frequency bands in relation to cognition have recently shown the theta band frequency to have potential as a unifying marker of general information processing (Jones et al., 2020; Meyer et al., 2019) and that is predictive of later non-verbal cognitive functioning in infants (Jones et al., 2020). Theta has also been linked tightly to sleep propensity and children with sleep problems reported higher theta power (Winkelman et al., 2018). However, sleep fragmentation relates to overall theta power differentially depending on infant age. Objectively measured Night Wakening Number was negatively associated with theta power in the younger age groups but for age groups 12 and 14 months the association was positive. Diary results showed similar patterns but BISQ results were not significant. Theta power change was predicted by Night Wakening Number of all three sleep measures. These findings suggest that sleep fragmentation, in particular Night Wakening Number is crucial for theta power and theta power change in the first year of life. Notably, these associations are consistent across sleep measures.

Results from *Chapter 6* showed that sleep quality (as identified by the data-driven clusters) did not predict theta power or theta power change. Further analyses showed that habitual sleep duration during infancy does not impact overall theta power. Although robust associations were noted with night wakening, there were no associations of theta change with Day or Night Sleep Duration in any of the measures and no association of theta change with actigraphy- or diary-measured WASO. This suggests that sleep fragmentation rather than duration is important for theta activity. Overall, it could mean that duration of sleep is not as important for development as sleeping continuously through the night. Considerations surrounding sleep fragmentation and their role in wake theta power are further discussed below.

8.1.8 Development of new methodology for measuring brain activity during sleep

Night wakening is also important to consider as it could disrupt brain activity changes during sleep. As discussed in the introduction of this thesis, crucial memory consolidation and plasticity processes appear to be happening in the brain during sleep. Night wakening could potentially disrupt this process. However, research investigating

brain activation changes during sleep in the first year of life and how those might link to habitual sleep, is still in its infancy. In a second study (*Chapter 7*), the infant's brain was studied during sleep in order to explore the relation between sleep and development from a different angle. More specifically, the goal was to develop the tools needed to investigate the brain during sleep in order to clarify whether perhaps sleep duration is less important than what actually happens in the brain during sleep. For this purpose, a customised NIRS-EEG headgear was developed. Study 2 yielded findings that were primarily of methodological insight. The feasibility study showed for the first time that it was possible to use the customised NIRS-EEG headgear for sleep recording in infants 5-months to 8-months-old. NIRS data quality was better than the EEG data quality. NIRS connectivity patterns varied across the duration of the sleep period in all infants. The cluster analysis confirmed that indeed certain patterns of connectivity were reoccurring when pooling the data across all infants and there were individual differences across infants in these connectivity patterns. It was conjectured that these individual differences might be related to underlying quality of sleep.

8.1.9 Overall summary of the empirical work

In summary, findings from the longitudinal study emphasised that broad classifications of sleep quality are not as informative with regard to neurocognitive development as individual sleep parameters. The study highlighted the importance of sleep fragmentation for various developmental measures. While duration measures were also informative, findings were more mixed here. The study also emphasised the importance of examining the relationship between sleep and development continuously as there was evidence for age-related changes in the association between sleep and development. This study also underlined the importance of methodological choices as well as method development. Many parameters showed cross-method inconsistencies that are crucial to consider and which may in part be related to the statistical analyses conducted in this thesis. Developing new methods to measure sleep and sleep quality could provide clarity as to which habitual sleep assessment methods could be used to study sleep and development.

8.2 Broader themes

The empirical work presented in this thesis yields two broad insights. The first insight is of theoretical consideration and concerns the findings that contribute to the

understanding of relationship between sleep and development. The second insight concerns the methodological aspects that surround the study of the relationship between sleep and development.

8.2.1 Key theme 1: methodology

Contributions of this thesis may be summarised under results with regard to methodology. Much of the work of this thesis has focused on investigating the way in which differences in sleep measurements might influence findings of the relationship between sleep and development.

8.2.1.1 Cross-method agreement

One of the key findings related to methodology is the finding that cross-method agreement between sleep measures is relatively poor and might be influenced by maternal and infant characteristics. To a certain extent, this is consistent with prior literature which also demonstrated discrepancies between actigraphy and parent-report measures. For example, studies showed an overestimation of Night Wakening Number from actigraphy when compared to the parental diary (Hall, 2015), poor cross-method agreement for BISQ and actigraphy (Tikotzky & Volkovich, 2019) and good agreement between actigraphy and diary on sleep duration measures (Camerota et al., 2018). Some cross-sectional studies find that there are relationships between actigraph (activity monitors) assessments but not parental reports of infant sleep and cognition respectively (Scher, 2005). Refer to *Chapter 1* or *Chapter 3* for further details on prior studies of cross-method agreement of sleep measures. Researchers have suggested that these disparities are rooted in the fact that actigraphy measures a slightly different aspect of sleep than does parent-reported sleep does.

The additional finding of the present study that the agreement between methods might be related to maternal and infant characteristics represent a novel contribution to the field. Tikotzky and Volkovich (2019) cite higher agreement for younger infants than for older infants, except for WASO which showed high agreement in the older infants as well. In the first study of this thesis there was higher agreement for younger infants than for older infants in night wakening parameters whereas for the day sleep parameters the reverse was true, providing a more fine-grained picture into cross-method agreement. These age differences in cross-methods agreement could be due to the fact that young infants sleep more often and more irregularly during the day, making it harder for parents to keep track of the naps and durations, whereas older infants usually only have one

consolidated nap at a regular time. Similarly, younger infants are likely to signal to their parents at night when they are awake whereas older infants are more likely to self-soothe back to sleep, which could lead to parents missing a night wakening. Further, this illustrates the importance of measuring particular sleep parameters using a specific method. On the other hand, the reader should remember the bias results that found that maternal characteristics influences cross-method agreement, indicating that in heterogenous samples that should be considered, too.

These findings have wide-range implications for the sleep research literature. The implication that follows is that choice of sleep assessment method and of sleep parameter investigated dictates the findings; especially if studies only include one sleep measure or one sleep parameter. In an additional consideration, the different sleep measures used in this PhD project (parent-report (questionnaire, diary) or objective (NIRS-EEG, actigraphy)) represent different aspects of sleep. Parent-report measures represent parental perception of infant sleep, actigraphy represents a day to day objective estimation of habitual infant sleep pattern to understand sleep timings and measurement of NIRS-EEG during sleep provides an insight into an infant's brain during sleep and the processes that happen while an infant is sleeping. Sleep is investigated from slightly different angles. These considerations are important when designing a study that includes sleep measurements. Researchers designing studies need to carefully consider infant age, maternal characteristics, feasibility of sleep method with regard to sample and many other factors.

It may also be possible that for sleep parameters parent-report might not show fine grained age-related changes (e.g., sleep fragmentation). Meanwhile actigraphy measures can identify age-related changes that are not captured by parent-report measures. It remains clear that the different measures have different strengths and weaknesses. Therefore, it is important to integrate multiple methods to understand where coherence occurs and where it does not. For example, here the theta power results of *Chapter 6* yielded converging results across methods, but eye-tracking results did not converge fully across methods.

8.2.1.2 Objective classification of sleep quality

Another result that pertains to the methodology related key theme is the fact that it was possible to identify clusters as an objective measure of sleep quality. The goal was to use data-driven approaches to classify habitual sleep quality. However, results show that these broad sleep quality classifications were not associated with many

neurocognitive parameters and did not show clear patterns. As discussed, it is possible that k-means cluster analysis is not the best approach to clustering data. Other ways in which sleep quality should be defined must be sought, especially in infancy. However, it is important to step away from biased approaches to data, that are using e.g., median split of sleep duration to determine good and poor sleep quality (e.g., compare Geva et al., 2016). In addition, it is possible that infants are not simply good or poor sleepers per se, but rather periodically experience episodes of better or worse sleep and therefore attempts to classify sleep quality yield unstable results. An interesting future direction of research would be incorporating the multi-method approaches into the data-driven classification, providing a more complete picture of infant sleep.

Data-driven approaches have one key advantage and that is that they can account better for sleep variability markers. Sleep research has thus far neglected to investigate variability in sleep duration or fragmentation specifically. Future research will focus on this aspect more.

8.2.1.3 Customised fNIRS-EEG for sleep assessment

Lastly, one major contribution of the present work is towards the method development of using NIRS-EEG for sleep assessment. Results from the first longitudinal study illustrated the pitfalls associated with the measurement of habitual sleep (see above). Given the many mixed findings from Study 1 on the association between sleep and development, the question was raised whether sleep quality might not be better assessed by a look into the brain rather than by patterns of sleep timings. The quality of the underlying sleep might differ fundamentally across infants. For example, memory consolidation (per 2-stage memory process model) or synaptic downscaling (per SHY) during sleep might function efficiently in one infant leading to a positive long-term effect in the association between sleep and development whereas in another infant these processes malfunction or work less efficiently. This also emphasises the importance of studying sleep quality by investigating the brain. This information would not be picked up by investigating broad habitual sleep patterns, but instead necessitates measurement of brain activity. The second study showed that using fNIRS to do this might prove fruitful. Results showed that there were individual differences in infant connectivity patterns in the brain. These different connectivity patterns could potentially represent alternating sleep quality during a nap. The small sample of the second study did not allow relating the connectivity patterns to measures of development, but future work that is conducted as a follow-up to this PhD, will include this important step.

On a related note, research has also made progress towards classifying sleep stages using data-driven algorithms. The optimisation of this procedure would allow more sleep researchers to use PSG as an objective tool to study the sleeping brain. Sleep staging is still done manually by one (or two) expert scorers and is very time-consuming. These approaches, together with the wireless NIRS-EEG system, improve PSG assessments and take a step towards enabling use for longitudinal studies and in larger, more diverse groups of people.

8.2.2 Key theme 2: sleep and development - theoretical insights

First, contributions of this thesis may be summarised under results that contribute to the understanding of the relationship between sleep and development.

8.2.2.1 Sleep fragmentation

Interestingly, in the longitudinal present study results converged across different sleep measures when investigating a specific sleep parameter, namely Night Wakening Number and Duration. These were related to several of the developmental markers. The nature of the correlational analyses conducted limits the ability to draw causal conclusions. However, I will nonetheless attempt to tie different findings together in an attempt to provide a starting point for future research. Some prior research has also shown that sleep fragmentation measures could be predictive of developmental status. Night wakenings in infancy predicted higher levels of inattentiveness/hyperactivity symptoms at age 5 years (Huhdanpää et al., 2019) and lower executive attention abilities in 3- to 4-year-olds (Sadeh, 2015). In addition to longitudinal associations between sleep fragmentation and developmental status in childhood, objectively measured WASO also predicted developmental trajectories within the first year of life (Pisch et al., 2019) and showed concurrent associations in 10-month-olds (Scher, 2005) with more objectively measured fragmented sleep patterns leading to lower scores on the mental developmental index. However, one study did not report differences between infants who woke up a lot and infants who slept through the night with mental or psychomotor development (Pennestri et al., 2018). Studies investigating this relationship between sleep fragmentation and developmental indices are still lacking and potentially suffer from publication bias as a result of null findings being rarely reported. The exact age of the infants is likely a crucial factor in interpreting cross-study consistency in addition to the differences in sleep measure methodology.

In *Chapter 6*, two associations were noteworthy. One, there was evidence that sleep fragmentation was associated with a marker that is predictive of general non-verbal development (theta power change), too. Theta power change describes continuous change in theta power across a longer period of time. Here 60-seconds videos were used. Two recent studies (Jones et al., 2020; Braithwaite et al., 2020) suggest that theta power change in response to a video relates to concurrent cognitive ability and predicted non-verbal cognitive abilities later in development (at 3 years of age). In *Chapter 6*, lower theta power change was predicted by higher Night Wakening Number across all sleep measures. This could represent a direct link between a sleep parameter and development. As described above, this is in line with some prior research (Sun et al. 2016; Scher, 2005) but contrary to other findings (Pennestri et al., 2018).

Secondly, another cross-method consistent association was between sleep fragmentation with a brain activity marker (overall theta power) for development. There were developmental changes in the association. Objectively measured Night Wakening Number was negatively associated with theta power with the younger age groups but for age groups 12 and 14 months the association was positive. In *Chapter 6* I conjectured that fragmented sleep would not be as restorative as uninterrupted sleep, leading to more daytime sleepiness and, thus, increased theta overall. In line with an interpretation of theta as a marker for cognitive effort infants with more night wakening may have needed to work harder to stay focused on the video presented. As such, higher theta power was observed in those that slept worse (as indicated by higher sleep fragmentation). In addition, the developmental differences may stem from the fact that younger infants simply stopped exerting effort to pay attention or stopped paying attention when they were tired (as a consequence of their increased sleep fragmentation) and therefore exhibited lower theta power. In turn, the older infants might still try to pay attention and therefore require more cognitive resources resulting in higher theta power. Another way in which I interpreted excess theta power is as a marker for delayed maturation. Higher sleep fragmentation is common in younger infants and a sign of more immature sleep consolidation. It could be that underlying immature brain anatomy affects both sleep, as well as theta power expression.

These findings on theta power potentially relate to results from the eye-tracking face-pop out task (social sustained attention, *Chapter 5*) where in younger infants (4 and 6 months) higher objectively measured Night Wakening Number was associated with shorter continuous looks to the face whereas in 14-month-olds higher objectively

measured Night Wakening Number was associated with longer continuous face looks. Typically, longer look duration towards faces are expected in the first half of the first year of life (Gliga et al., 2009), an effect that commonly decreases in the second half of the first year of life (Colombo et al., 2004; Courage et al., 2006; Hendry et al., 2018). It is possible that sleep fragmentation disrupts or delays this process in one way or another. However, the results of theta and face looking could be interpreted as analogous to each other, potentially reflecting a similar pattern in the effect of sleep fragmentation on development, or rather two aspects of development: social attention and general information processing. From this insight follow a number of considerations.

First, given that theta power has also been linked to attention (Begus & Bonawitz, 2020; Jones et al., 2015; Orekhova et al., 2006; Orekhova et al., 1999) it could be that sleep fragmentation, rather than being indicative of general infant development is actually linked to attentional processes. The patterns captured then reveal an underlying relationship between sleep fragmentation and attention processes, that reflects in both theta power and social attention. For instance, higher sleep fragmentation was associated with poorer attentional control as indexed by shorter look durations and higher theta. This fits some of the prior research that finds that early sleep fragmentation is linked to later attentional abilities (Huhdanpää et al., 2019; Sadeh et al., 2015). The developmental changes in the association that are described above might also partially be due to the many changes that the attention system undertakes in the first year of life.

One important remark here is the acknowledgement of the underlying arousal system that underlies both the sleep and the attention systems (Dahl, 1996; Geva et al., 2016). One possibility is, that both sleep fragmentation and attention patterns reflect an immaturity of the brain anatomy, making sleep fragmentation a mere indicator for brain development rather a causal factor in development. As discussed in *Chapter 5* Geva and colleagues (2016) conjecture that the ARAS' involvement in attention gating and consequently selective attention could provide a plausible explanation for the close association of attention and sleep that was found in some studies. Studies that show that sleep deprivation can hinder development of attentional systems (e.g., O'Callaghan, 2010) provide further support. Thus, one of the reasons why attention may be impacted by sleep and vice versa could be rooted in brain structures. Conversely, a second plausible hypothesis is that sleep fragmentation has a causal effect on development, perhaps via impacting these attentional abilities. Sleep fragmentation could disrupt brain plasticity processes in key attentional brain areas.

Without intervention studies, it is not possible to make a statement with regard to directionality or potential causal links identifying which of the above hypotheses is correct at this point. However, evidence from studies into sleep apnoea suggests that the link between sleep fragmentation and aspects of attention could indeed be causal. Sleep apnoea is a disorder that causes sleep disruption by micro (and occasionally) macro awakenings due to insufficient oxygen delivery. Studies have linked disrupted sleep in apnoea patients to attentional and other cognitive difficulties (e.g., Mazza et al., 2005). Those difficulties decrease when sleep apnoea and subsequent sleep fragmentation is treated (Marcus et al., 2012). Research with regard to this in infancy is lacking, however it provides a promising rationale for designing intervention-based studies to investigate the impact that improving sleep fragmentation may have on later neurocognitive development.

The second piece of evidence for a potential causal link between sleep fragmentation and subsequent development comes from recent animal research, which suggests that sleep fragmentation in neonatal rabbits leads to various behavioural problems that can be interpreted as cognitive impairments (Bertrand et al., 2020). The researchers manipulated sleep fragmentation in neonatal rabbits and measured their performance on novel object recognition and maze tasks. Those rabbits experiencing sleep fragmentation showed lasting changes in the hippocampus and cortex as well as impaired performance on the tasks. These findings persisted despite overall equivalent sleep architecture in control and fragmented sleep rabbits.

Mechanistically it might be possible that the interruption of continuous sleep by sleep fragmentation disrupts plasticity processes hypothesised to take place during REM sleep and NREM sleep as described in the SHY and the ontogenetic hypothesis (see *Chapter 1*). However, proving this hypothesis might prove tricky in infant populations. Perhaps intervention studies could provide interesting insights. For example, one could potentially disrupt infants' naps and investigate whether the interruption of the nap has any impact on the typically observed beneficial effects of naps on information consolidation, such as done by e.g., Friedrich et al. (2017, 2019). These studies showed a benefit of naps on learning information. On the other hand, intervention studies targeted to reduce sleep fragmentation and observe the impact on cognitive functioning could also be designed (see below for further discussion).

Links to social cognition. Another aspect to this relationship that might be of importance is the presence of social stimuli. Both the task for theta power (women singing

nursery rhymes) and the face pop-out task, are social tasks. It is possible that uninterrupted sleep (lower Night Wakening Number) is particularly important for processing social information. This is supported by research highlighting a higher amount of sleep fragmentation/sleep problems in individuals with autism, a disorder counting amongst its symptoms impaired social cognition (Levin & Scher, 2016). In infants only two studies I am aware of investigate social information in relation to sleep. One study showed that 6-month-old infants with longer sleep duration preferred looking to human faces where the researchers related infant sleep patterns to emotional face processing in 12-month-olds (Sun et al., 2018). The results showed that infants with lower WASO and lower variability in sleep patterns preferred to look to the eyes compared to other face regions. Infants with lower sleep duration looked less towards the eyes. Another study implicated the brain stem in social disengagement (Geva et al., 2013), a brain region also involved crucially in sleep-wake maintenance, which could link social cognition to sleep. It is possible that this association is particularly prevalent as social brain development is rapid in the age studied here and therefore simply the foremost/strongest emerging characteristic, whereas in other age groups a different link might emerge. Future studies could employ e.g., the customised NIRS-EEG headgear to specifically investigate the activation and cortical connectivity patterns in the social brain areas.

Implications for interventions. Importantly, sleep fragmentation can be targeted by intervention studies. Past research has shown that intervention studies may improve sleep problems in children (Field, 2017). Knowledge is vital in intervention, parents who knew more about sleep were also more likely to report that their child had healthy sleep habits (Mcdowall et al., 2017). Field (2017) described that 8 /11 sleep intervention studies showed a positive impact of parental sleep intervention on infant sleep. While this indicates mixed findings and the necessity for more research, it highlights the potential of sleep interventions. Importantly, many sleep interventions are low-cost behavioural interventions like following a certain routine at bedtime. These sleep interventions have also been shown to work in children with neurodevelopmental disorders (Rigney et al., 2018). Targeting sleep fragmentation by controlling for instance an infant's sleep environment, such as noise exposure or by implementing sleep training interventions (Mindell et al., 2011), could have positive downstream effects on development.

However, the present study could be interpreted as evidence that night wakening at certain ages could be beneficial. One parent-report measure was associated with sleep fragmentation and showed developmental changes. Higher actigraphy-measured WASO was associated with increased parent-reported gross-motor skills at 6, 8, and 14 months

but with lower parent-reported gross motor skills at 10 months and 12 months, ages that coincide with the onset of walking and crawling respectively. These developmental changes are somewhat in line with above hypotheses that sleep fragmentation could be beneficial at certain periods in the first year of life and detrimental during others. Therefore, when designing interventions targeting sleep fragmentation it may be important to consider a child's general developmental status.

8.2.2.2 Night Sleep Duration

Night Sleep Duration is one of the most commonly studied parameters in the infant sleep literature. Those studies show (for example) that 6-month-olds with habitually shorter sleep durations than their peers show a reduced preference for social stimuli (i.e., human face) compared to non-social stimuli (Sun et al., 2016). Night sleep in infancy was positively related to parent-reported problem-solving and fine motor skills at 12 months of age (Gibson et al., 2012) and to later higher order executive functioning (Bernier et al., 2010). Current research interprets these findings as higher sleep duration during night being beneficial to various aspects of neurocognitive development. An alternative interpretation is simply reflective of a more advanced neurodevelopmental status as older infants and children show longer night sleep durations.

The results from the longitudinal study suggest a lack of a cohesive picture with regard to Night Sleep Duration that does not fully conform to past research. There were some isolated relationships noted, for example developmental changes in the association between night sleep and positive temperament or with social sustained attention, but for many of the numerous relationships tested in this thesis Night Sleep Duration did not emerge as an important factor. Sleep parameters like sleep fragmentation (see above) or even Day Sleep Duration (see below) seem to be more associated with individual differences in development. This presents an interesting consideration for sleep research. It is possible that estimations of night sleep are not actually a true reflection of the infant's sleep. For example, Night Sleep Duration (even more so than Day Sleep Duration) showed low agreement across sleep methods in the current study. Inaccuracies in estimations of underlying sleep could have influenced the associations of sleep measures with developmental markers.

The relative lack of association between Night Sleep Duration and measures of development in the present study lends tentative support to the theory that has been brought up at other points in this thesis. Namely, that the key aspect to the relationship between sleep and development is not the amount of sleep infants get but rather what

happens in the brain when they are asleep that is critical. That is, sleep quality, rather than quantity, could be more important for development. Though, at the time of writing there is sparse evidence supporting or refuting this hypothesis. Evidence for this could be taken from the studies on sleep spindles in infants (Friedrich et al., 2015, 2017, 2019). For example, infants that exhibited specific characteristics of sleep spindles, i.e., density or occurrence during a nap, performed differently on memory tasks after the nap, even though sleep duration did not differ across the groups. This could be interpreted as evidence for the importance of studying the brain during sleep rather than looking only at duration, where there was no difference found. Future work on the brain activation patterns during sleep also in relation to habitual sleep should conclude if this hypothesis is correct. Linking this back to the effects that were seen in sleep fragmentation, it could be that night wakenings disrupt e.g., spindle occurrence and other processes crucial for neurocognitive development that take place during sleep, thereby initiating a cascading effect on neurocognitive development.

Another hypothesis is that sleep fragmentation is primarily biologically driven and not as susceptible to environmental influences as e.g., sleep duration. Yu et al. (2020) found that at 1-months-old sleep duration did not differ based on SES/ethnicity but at 6-months-old there were differences especially in Day Sleep Duration (longer) and Night Sleep Duration (shorter) for lower SES or Hispanic/Asian/Black ethnicities. Sleep fragmentation was not related to education. This could match the results in that parent-report measures were especially associated with duration measures and brain measures were associated with fragmentation (the latter of which are both biologically driven).

8.2.2.3 Day sleep

Recent studies have recognised the importance of studying habitual day sleep (Horvath & Plunkett, 2018). Day sleep in particular undergoes many fundamental changes in the first year of life (Gorgoni et al., 2019). Day sleep is also influenced by parental background, such as education. For example, at 6 months, infants of mothers with lower education levels showed higher Day Sleep Duration than infants of mothers with higher education levels (Yu et al., 2020).

Day sleep has primarily been studied in order to identify sleep microstructural compositions in a nap and to study the effect of learning on sleep rather than looking at habitual day sleep patterns (e.g., Friedrich et al., 2019; Horváth et al., 2018), partly because it is harder to have infants wear an actigraph device during the day. These nap

studies suggest a benefit of day sleep after learning for memory consolidation and even knowledge transfer.

Further, within studies that have looked at habitual day sleep, prior research has shown that more parent-reported day time naps at 7-months-old predict vocabulary growth in early childhood (Horváth & Plunkett, 2016). Infants whose parents indicated (using the BISQ) that they napped frequently, were better at generalising previously memorised information (Lukowski & Milojevich, 2013). Napping is also thought to be essential for committing learned information from short-term into long term memory, as evidenced by a number of studies (e.g., Horváth et al., 2017; Konrad et al., 2016; Seehagen et al., 2015). Although these associations indicate that looking at day sleep is important, it has to be acknowledged that day sleep assessment itself might be biased when using parent-report measures. For example, if a child is in childcare, parental estimation of Day Sleep Duration might not be accurate. Moreover, day sleep is conjectured to be different in participants with high vs. lower maternal education (Yu et al., 2020).

The present longitudinal study also highlighted the potential importance of day sleep when studying development. Accordingly, there were cross-method consistent associations where higher day sleep was associated with lower parent-reported fine motor and problem-solving skills. Interestingly, there was a developmental association observed. For younger age groups there was no association between Day Sleep Duration and fine motor skills but in older infants (10 - 14 months) there was a negative one. This is not consistent with some of the prior research that suggests that naps facilitate consolidation of information/learning or vocabulary learning in the long run.

It is not clear yet what properties of day sleep could hinder development. On the one hand it is possible that the occurrence of more day sleep later in development is associated with less mature, not yet consolidated sleep cycles in development reflecting an underlying immature brain anatomy. On the other hand, it is possible that infants who sleep more during the day sleep worse at night having both lower sleep quality at night and more sleep during the day. In this study there was no strong association between Night Wakening Number and Day Sleep Duration but underlying sleep quality might have been different. The developmental changes that were found also allude to the fact that while day sleeps might not be bad earlier in the first year of life they could pose a problem later in the first year of life. However, this cannot be assessed using the correlational analyses in the current dataset. Below some analyses methods are discussed that could shed light onto this in future studies.

Another aspect that has to be considered in this context is the role of the parents. For example, infants who sleep more during the day might have comparably less time to practice their fine motor skills/problem solving skills. Moreover, they might have less time to interact with parents or other people if they are sleeping during the day. To date, research lending support to one or the other hypothesis has not been conducted yet. Conversely, it is also possible that infants who are more advanced in their development sleep less during day and have better fine motor skills, both natural consequences of increased age. Another hypothesis it that infants who develop better fine motor skills do not need to consolidate as much information during the day, as they have learned a lot of information already. On the other hand, it is also possible that infants with inherent delays in development exhibit differences in day sleeps as a symptom, in much the same way in which younger infants sleep more during the day.

Finally, research showed that mothers with higher educational levels put their infant to sleep later at night, which could have a cascading effect on day sleep and potentially leading to more day sleep (Netsi et al., 2017). The importance that parents have is further illustrated by the findings on sleep rituals where in the younger infants (4 and 6 months) there was a positive association between sleep ritual number and Day Sleep Duration, while in the older infants (12 and 14 months) there was a negative association between sleep ritual number and Day Sleep Duration with infant age 8 to 10 months old being right in the middle. This association was not found for other sleep parameters. It is possible that day sleep is particularly modulated by parental characteristics. This could link back to the considerations on fine motor skills above.

The study findings here are somewhat contrary to prior research that find an advantageous role of day sleep. For example, more naps were better for vocabulary development (Horvath et al., 2016). Horvath & Plunkett's (2018) review of napping in infants provides a succinct summary of studies conducted on this topic. Interestingly, Bernier et al (2010) found results that map onto the present results to a certain extent. They investigated the proportion of Day Sleep Duration to Night Sleep Duration and found that 12-month-old infants who sleep more during the night than during the day have better expressive vocabulary skills 14 months later. A possibility is that the studies that have been conducted so far fail to capture all the fine-grained, age-related changes that occur in the relationship between day sleep and certain aspects of development. The present data could potentially hint to the fact that initially day sleeps are beneficial for aspects of development, but that in the course of the first year of life this shifts such that

day sleeps hinder development. Of course, more day sleep later in the first year of life could also be associated with less advanced development. Another possibility is that faster development requires more sleep to condense developmental milestones in a shorter period of time and therefore later developmental milestones do not require as much day sleep. These are merely hypotheses currently, and have yet to be examined further.

8.2.2.4 Sleep quality

A substantial part of this thesis was devoted to investigating the relationship of data-driven/automatically identified sleep quality clusters to various parameters of development. Here k-means analysis was used as an unsupervised machine learning algorithm to classify sleep quality clusters. Results from the longitudinal study suggest that it might be better to look at fine-grained aspects of sleep, i.e., sleep parameters rather than broad classifications of good and poor sleepers. Associations between sleep quality clusters and neurocognitive parameters did not show a clear overarching pattern. Several considerations follow from this. First, broad sleep quality identified by habitual sleep patterns might not be as informative as individual parameters. Possibly aggregating all sleep variables together led to the loss of crucial information. One study found no association between sleep quality and looking patterns but an association between parent-reported sleep duration and face looking (Sun et al., 2016). As discussed in *Chapter 1* studies' definition of sleep quality differ widely, and thus far, no consensus has been reached as to which parameters best assess infant sleep quality. Parameters used included: sleep efficiency measures, parental rating of sleep quality as poor, higher incidence of sleep fragmentation and the proportion of day to night sleep.

Sleep quality identified based on brain activity measures during sleep rather than habitual sleep patterns might provide a better and more unifying approach to looking at sleep quality. Using connectivity patterns could provide a promising avenue to identifying types of sleepers. Evidence for this is provided by studies showing that even across individuals with seemingly similar sleep duration, factors such as sleep stage composition and sleep microstructure might affect IQ and memory (Schabus et al., 2006).

In this line of thinking, the approach used in *Chapter 7* where individual differences in connectivity patterns were identified during sleep in infants. These might provide a different way to approach sleep quality classification. The future research that will follow on this project will show whether the individual connectivity patterns map onto habitual sleep patterns, such as sleep fragmentation.

Additionally, the clusters that were identified based on the k-means cluster analysis might not represent the most accurate way to classify the data. It might be better to use a different, more sophisticated machine learning approach or by combining unsupervised with supervised methods. It is likely that data-driven approaches can identify a more nuanced picture of sleep pattern classification.

8.2.3 Key theme 3: age-related changes

The unifying factor in both themes are the age-related changes that impact the relationship between sleep and development as well methodological/measurement considerations. The investigation of sleep and development longitudinally did provide useful information that to a certain extent fits with prior literature. Many of the parameters showed age-related changes, illustrating that not only do cognition and sleep individually change with development, but also their relationship changes over time. This fundamental insight that in order to study development one has to study it over time accounting for factors such as individual differences.

These age-related changes often show opposing cross-method patterns. In the following, the main age-related changes are briefly summarised. For instance, there were developmental changes in the association of objective and subjectively measured night sleep parameters and ASQ subscales. However, the directionality did not converge across methods/parameters. This non-convergence is evident in a number of the other developmental changes, e.g., younger infants (8 months and younger) showed higher surgency scores with higher Night Sleep Duration and older infants (10 months and older) showed lower surgency scores with higher Night Sleep Duration but only for actigraphy. In younger infants (4 and 6 months) there was also a positive association between sleep ritual number and Day Sleep Duration, while in the older infants (12 and 14 months) there was a negative association. For visual attention, there were some age-related changes across all eye-tracking parameters that assessed face looking in relation to different sleep parameters, but again the patterns did not fully converge across methods. However, for the theta power results actigraphy and diary showed largely similar results with older infants (12 – 14 months of age) showing more theta power for more night wakenings and the reverse pattern for younger age groups.

While the cross-method disparities need to be acknowledged, these age-related changes could also represent a concept that warrants further investigation in future research. They could indicate critical periods in the relationship between sleep and development. It is possible that certain types of sleep are detrimental at one age but

beneficial at another time in development. These findings emphasize the fact that the only way to study the association between sleep and development is by employing longitudinal designs. These critical periods might provide an opportunity for early intervention but they also yield the potential for development to go astray.

Longitudinal studies are also absolutely crucial in order to understand the individual differences in the relationship between sleep and development across infants. For example, memory consolidation (per 2-stage memory process model) or synaptic downscaling (per SHY) during sleep might function efficiently in one infant leading to a positive long-term effect in the association between sleep and development whereas in another infant these processes malfunction or work less efficiently.

Of note, the results from *Chapter 3* showed that cross-method agreement was related to infant age. Therefore, it is possible that some of the observed cross-method differences in the age-related changes of the association between sleep and neurocognitive development are at least partially driven by this effect.

In larger studies with bigger sample sizes different statistical analyses could be helpful in providing more information on the potential causal nature of the association between sleep and development as well as the age-related changes that are described above. These include e.g., structural equations models that allow for causal inferences of observational (longitudinal data), barring a few restrictions (for discussion see limitations section below).

In summary, the disparity in the results highlights the need for complete longitudinal studies with a large sample size. The present study highlighted the age-related changes that can potentially occur but also showed the necessity for taking account individual differences and the impact of method disparity across the first year of life.

8.3 This works contribution to the field and its limitations

Based on the review of key themes in the previous section the biggest contributions of this thesis to the field of sleep/developmental science are as follows.

One, sleep method choice matters and collecting multi-dimensional sleep data is paramount. In addition to measuring confounds, objective measures such as using the novel NIRS-EEG headgear for sleep measurement will provide a better picture of the role of infant sleep in development. Methodological differences might explain the discrepancies in the literature. A key drawback of the present work with regard to method

choice is that there was no longitudinal data that included brain activation changes during sleep across the first year of life. Thus, there was no information on the true underlying sleep in the infants. While actigraphy is a good proxy for estimating true sleep, at this point the limitations of this method should be acknowledged. Moreover, the premature termination of the second study did not allow for us to compare the results from Study 1 to Study 2 and to brain activation patterns during sleep. Combining these two approaches could provide more information on how habitual sleep was related to brain activation changes. Future work should integrate work that examines habitual sleep, neurocognitive markers of development as well as brain measures of sleep. Along those lines, the longitudinal study only included one objective sleep assessment method. I combined various subjective measures, but it might have been informative to include, for example, in-home videosomnography in addition to actigraphy; at least for night sleep to capture night wakenings more accurately (similarly to Camerota et al., 2019). This could be especially important to do given the importance that sleep fragmentation seemingly has for development. It could also help corroborate whether infants with higher actigraphy-identified measures of sleep fragmentation were indeed awake or simply exhibited more movement in sleep. Moreover, the longitudinal study is missing a more objective assessment of general developmental status (e.g., the Mullen Scales of Early Learning; Mullen, 1995). Originally this was planned but due to the already extensive study protocol it was removed. Future work should also compare the Ages & Stages Questionnaire vs. a researcher-based assessment of development in relation to sleep. Lastly, this study did not take a closer look at sleep variability parameters, however correlations seemed to indicate that this might be an important factor to investigate in the future.

Secondly, this work proved that studying sleep and development longitudinally is imperative. The age-related changes in the relationship between sleep and development could suggest that a certain type of sleep (e.g., day sleep) is beneficial at a particular age (e.g., in younger infants) but detrimental at another time in the first year of life. While this study was longitudinal in nature and included a range of measures and techniques, making it multi-disciplinary, this breadth also had its pitfalls. Few infants completed all four visits of the longitudinal study and due to the wide age range tested the amount of analyses I was able to do was limited. Ideally, it would have been beneficial to be able to use structural equation modelling or path models to image the interaction of all the different sleep and developmental parameters with each other over time. . Specifically, structural equation models and similar models (e.g., directed acyclic graphs, path models,

latent class models) would allow for drawing causal conclusions under certain circumstances (Rohrer, 2018). Using these approaches, observational data can be used as a basis for causal inferences also in exploratory datasets such as the current dataset. For example, model specification for future SEM studies into sleep and early neurocognitive development could include perhaps fixed paths for sleep fragmentation and social attention based on this PhD work. However, these models require a large sample size, especially when testing a large age range and as such could not be performed for the current data set.

Thirdly, sleep fragmentation is potentially important for neurocognitive development. However, the work in this thesis is exploratory and correlational in nature. While we are able to recognise that sleep fragmentation and development are related, we are limited in the ability to make strong causal inferences about, for instance, the directionality of the relationship between sleep and development. Open questions remain as to whether sleep impacts neurocognitive development or whether sleep and neurocognitive development are both influenced by a common underlying process.

Most importantly, it could simply be that sleep changes with age and therefore associations occur with factors such as cognitive or motor skills that also change with ageand maturation of underlying anatomical structures. This so-called third-variable problem is often a concern in developmental science especially in exploratory studies with many variables. Inclusion of age group as a variable in the models that were tested should control for this at least to a certain extent, though of course the same age does not always equate with the same underlying maturational status. Both cognition and sleep depend on the brain's maturation, but the question is whether individual differences in sleep are affecting cognition above and beyond what may be explained by maturation alone. Insights from the PhD with regard to which variables and aspects might be relevant to study in future studies combined with the above-mentioned statistical techniques could allow for clarification on this problem. Secondly, rather than posing the question of the importance of underlying brain changes and their impact on both cognition and sleep perhaps the question for future studies should be if by modifying sleep we can support maturational processes. For this sleep intervention studies and studies assessing underlying brain maturity objectively (via structural brain scans) are invaluable. This thesis can serve as a starting point for intervention studies that can bring more information on causal inferences.

Lastly, inferences about the relationship between sleep and neurocognitive development derived from this thesis need to be viewed against the backdrop of its

correlational and exploratory nature. In this thesis, I presented wide reaching suggestions and explanations for the associations observed in my exploratory studies. However, it is important to acknowledge that. In order to be able to make causal inferences about the directionality of the relationship between sleep and neurocognitive development, intervention studies are needed. The idea is that this work can serve as a starting point for further research. Additional insights could be brought forward by studying the role of sleep in neurodevelopmental disorders. Disordered sleep is a symptom in many of those disorders (Kamara & Beauchaine, 2020). For example, infants who later developed Autism Spectrum Disorder (ASD) showed more sleep onset problems at 6 to 12 months of age (MacDuffie et al., 2020). Large longitudinal studies employing sibling designs can shed more light on this relationship. In particular, there is preliminary evidence for the usefulness of sleep intervention to target sleep disturbances in some neurodevelopmental disorders (McLay et al., 2019; Rigney et al., 2018).

One neglected aspect in this study is the role of the environment and culture above and beyond maternal education and maternal stress and anxiety measures. The present studies were only comprised of middle to high income households. However, recent evidence suggests that the relationship between sleep and development is different in infants/children living in adversity/low socioeconomic status (El-Sheikh & Sadeh, 2015; Netsi et al., 2017). Infant sleep may also be impacted by factors such as noise levels in the home, as has been suggested by Grimes et al. (2019) or Strauch et al. (1993) or by parental work schedules such as suggested by Sinai & Tikotzky (2012). Future studies should further include these factors at least as confounds.

As per the *Transactional Model* (see *Chapter 1*) many factors interplay with each other. And in this study, I looked at subparts in this relationship, and future work should integrate the findings from this study with further work on the role of parental behaviour at nighttime and general environment. Extending this further would include studying sleep in different countries. Germany and UK are different countries but still western European, wealthy industrialised societies. Sleep research into different cultures is currently still lacking. Recent sleep research has recognised the importance that culture has on sleep, e.g., Mindell et al. (World Sleep Congress, 2019) show that infant sleep durations differ by up to 3 hours between Japan and New Zealand. This means that across different cultures the relationship between sleep and development could differ fundamentally. Extrapolating findings of this project onto other cultures is not valid, and therefore there is a need to study the relationship between sleep and development in

different societies. The development of the wireless NIRS-EEG headgear from this thesis might provide an important tool to study this relationship in the field in cultures where parent-report is not an option; in cultures that do not use of the westernised understanding of time or have a high rate of illiteracy, for example. Moreover, several cultures carry their infants on their back while working or moving, making actigraphy measurements invalid. In these cases, the methods developed in this work could prove extremely useful.

Along the same lines as the role of environment, is research that looks further into the role of the circadian system and how it might be influenced by the rapidly changing world, e.g., the increased use of technology and immittance of blue light. Research has shown the significant impact of light on sleep cycles in children (Lee et al., 2018) and of touch screen device use on sleep in infants and toddlers (Cheung et al., 2017). Akacem and colleagues (2018) suggest that the detrimental impact of blue light on sleep during development is rooted in a suppression of melatonin (Akacem et al., 2018). These studies indicate the importance of considering blue light exposure in studying sleep in infants, especially as touchscreen/screen use becomes more prevalent very early in development.

Study of the human genome could provide another fruitful avenue of research. By understanding the genetic underpinnings of certain sleep traits, scientist will better understand how sleep might be related to typical and atypical brain development. Early studies already showed that sleep EEG signature were more similar in monozygotic twins than in dizygotic twins (De Gennaro et al., 2008) and recent studies have highlighted the roles of sleep genes in a wide range of functions that are, for example, fundamental to cell functioning and metabolism (Webb & Fu, 2021). These genetics studies highlight sleep regulation in particular (Webb & Fu, 2021).

8.4 Relevance of the present project

The relevance of the present work can be viewed from different angles.

Relevance for the research community. The insight that sleep method choice can drive results regarding the relationship between sleep and development calls for a more careful identification of the method that is used in a particular study. It would be better to specifically distinguish between parent-reported infant sleep and a method-driven identification of sleep measures, due to their inherent measurement differences. While it might be very interesting to understand what influences parental perception of infant sleep, this is likely to be biased. In reading the scientific literature surrounding infant

sleep and development it would be important to understand the context in which each study is set rather than broadly classifying everything as infant sleep. This study has highlighted the potential importance of investigating day sleep patterns and sleep variability patterns especially as both undergo many significant changes in the first year of life. Moreover, I have developed a novel method that allows for the examination of sleep in a naturalistic setting in the future. This method can also be used by other researchers to study the brain during sleep in different age groups, different populations and different countries.

Relevance for society. More broadly, this research has implications for policy works, the general public, and parents. Misinformation surrounding infant sleep and its impact on development is still prevalent in society and providing evidence-based information is key. While there were associations of infant sleep with developmental markers in the present study, the relationship is certainly not as strong as often portrayed and only impacts aspects of development rather than having a broad impact. Additionally, the large normative database of sleep in typically developing infants collected in Study 1 can serve as a starting point for parents to understand if their infant suffers from sleep problems. Sleep problems have been shown to be persistent across development. Clinically disordered sleep can lead to developmental disadvantages in typically developing infants later on, especially in infants suffering from adversity. These developmental disadvantages can have cascading effects on educational and professional achievements which in turn has an impact on society as a whole, further widening inherent socio-economic gaps. At the same time sleep may be improved using interventions and can therefore constitute a cost-efficient way to improve outcome in children at risk for neurodevelopmental disorders or equalize chances for children living in adversity.

8.5 Conclusion

This thesis represented a multi-method exploration of the relationship between sleep and neurocognitive development in the first year of life. Objective and subjective measures of both development and sleep were combined. Until recently sleep has often been neglected in developmental science but in combination with previous research, this thesis further extends the evidence that sleep may be a crucial aspect of development where further research can enhance our understanding of the awake brain, of the sleeping brain and the relationship between the two.

This work provided insight into how sleep measurement choice can influence how the relationship between sleep and development is described. Agreement between different sleep measures varied depending on sleep parameters studied, infant age and maternal stress. These insights have crucial implications for new sleep research and also for the interpretation of past sleep research. Moreover, I contributed a new methodology to studying the relationship between sleep and development and sleep quality by designing a customised NIRS-EEG system that can be used for sleep assessment and has the potential to be fully portable. Findings from the longitudinal study emphasized that broad classifications of sleep quality are not as informative with regard to neurocognitive development as individual sleep parameters. The study highlighted the importance of sleep fragmentation for various developmental measures. While duration measures were also informative, findings were more mixed here. The study also underlined the need to study the relationship between sleep and development continuously as there was evidence for age-related changes in the association between sleep and development.

In conclusion, this work represents a valuable contribution to the field of developmental sleep research by uncovering the importance of method choice in studying the relationship between sleep and neurocognitive development. New avenues of research can follow from the pioneering, technological advances in methods development undertaken here (i.e., the customised NIRS-EEG system), such as the study of sleep outside of the lab and/or in previously inaccessible populations.

Bibliography

Acebo, C., Sadeh, A., Seifer, R., Tzischinsky, O., Hafer, A., & Carskadon, M. A. (2005). Sleep/wake patterns derived from activity monitoring and maternal report for healthy 1- to 5-year-old children. *Sleep*, *28*(12), 1568–1577. http://www.ncbi.nlm.nih.gov/pubmed/16408417

Adam, K., & Oswald, I. (1977). Sleep is for tissue restoration. *Journal of the Royal College of Physicians of London*, *11*(4), 376.

Addyman, C., & Mason, L. (2016). Researching cognitive development in infancy. *Practical Research with Children*, 3–23.

Aeschbach, D., Matthews, J. R., Postolache, T. T., Jackson, M. A., Giesen, H. A., & Wehr, T. A. (1997). Dynamics of the human EEG during prolonged wakefulness: Evidence for frequency-specific circadian and homeostatic influences. *Neuroscience Letters*, *239*(2–3), 121–124. https://doi.org/10.1016/S0304-3940(97)00904-X

Akacem, L. D., Wright, K. P., & LeBourgeois, M. K. (2018). Sensitivity of the circadian system to evening bright light in preschool-age children. *Physiological Reports*, *6*(5), e13617. https://doi.org/10.14814/phy2.13617

Åkerstedt, T., Kecklund, G., & Axelsson, J. (2007). Impaired sleep after bedtime stress and worries. *Biological Psychology*, *76*(3), 170–173. https://doi.org/10.1016/j.biopsycho.2007.07.010

Amso, D., & Scerif, G. (2015). The attentive brain: Insights from developmental cognitive neuroscience. In *Nature Reviews Neuroscience* (Vol. 16, Issue 10, pp. 606–619). Nature Publishing Group. https://doi.org/10.1038/nrn4025

Amzica, F., & Steriade, M. (1995). Short- and long-range neuronal synchronization of the slow (<1 Hz) cortical oscillation. *Journal of Neurophysiology*, *73*(1), 20–38. https://doi.org/10.1152/jn.1995.73.1.20

Ancoli-Israel, S., Cole, R., Alessi, C., Chambers, M., Moorcroft, W., & Pollak, C. P. (2003). The role of actigraphy in the study of sleep and circadian rhythms. *Sleep*, *26*(3), 342–392. http://www.ncbi.nlm.nih.gov/pubmed/12749557

Anders, T. F., & Keener, M. (1985). Developmental course of nighttime sleep-wake patterns in full-term and premature infants during the first year of life. I. *Sleep*, *8*(3), 173–192.

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 ….

Andersen, S. C., Gregersen, M. K., Nielsen, H. S., & Thomsen, M. K. (2020). Parent Involvement, Socioeconomic Status and Reading Performance. *Scandinavian Journal of Educational Research*. https://doi.org/10.1080/00313831.2020.1840429

Anderson, A. J., & Perone, S. (2018). Developmental change in the resting state electroencephalogram: Insights into cognition and the brain. *Brain and Cognition*, *126*, 40–52. https://doi.org/10.1016/j.bandc.2018.08.001

Asaka, Y., & Takada, S. (2011). Comparing sleep measures of infants derived from parental reports in sleep diaries and acceleration sensors. *Acta Paediatrica*, *100*(8), 1158–1163. https://doi.org/10.1111/j.1651-2227.2011.02204.x

Aserinsky, E., & Kleitman, N. (1953). Regularly occurring periods of eye motility, and concomitant phenomena, during sleep. *Science*, *118*(3062), 273–274.

Astill, R. G., Van der Heijden, K. B., Van IJzendoorn, M. H., & Van Someren, E. J. W.

(2012). Sleep, cognition, and behavioral problems in school-age children: A century of research meta-analyzed. *Psychological Bulletin*, *138*(6), 1109.

Baddock, S. A., Purnell, M. T., Blair, P. S., Pease, A., Elder, D., & Galland, B. C. (2019). The influence of bed-sharing on infant physiology, breastfeeding and behaviour: A systematic review. In *Sleep Medicine Reviews* (Vol. 43, pp. 106–117). W.B. Saunders Ltd. https://doi.org/10.1016/j.smrv.2018.10.007

Baker, W. B., Parthasarathy, A. B., Busch, D. R., Mesquita, R. C., Greenberg, J. H., & Yodh, A. G. (2014). Modified Beer-Lambert law for blood flow. *Biomedical Optics Express*, *5*(11), 4053–4075. https://doi.org/10.1364/BOE.5.004053

Bang, J. W., Khalilzadeh, O., Hämäläinen, M., Watanabe, T., & Sasaki, Y. (2014). Location specific sleep spindle activity in the early visual areas and perceptual learning. *Vision Research*, *99*, 162–171. https://doi.org/10.1016/j.visres.2013.12.014

Barreira, T. V., Redmond, J. G., Brutsaert, T. D., Schuna, J. M., Mire, E. F., Katzmarzyk, P. T., & Tudor-Locke, C. (2018). Can an automated sleep detection algorithm for waist-worn accelerometry replace sleep logs? *Applied Physiology, Nutrition, and Metabolism*, *43*(10), 1027–1032. https://doi.org/10.1139/apnm-2017-0860

Barry, R. J., Clarke, A. R., & Johnstone, S. J. (2003). A review of electrophysiology in attention-deficit/hyperactivity disorder: I. Qualitative and quantitative electroencephalography. *Clinical Neurophysiology*, *114*(2), 171–183.

Bastien, C. H., Fortier-Brochu, É., Rioux, I., LeBlanc, Mélanie, Daley, M., & Morin, C. M. (2003). Cognitive performance and sleep quality in the elderly suffering from chronic insomnia: Relationship between objective and subjective measures. *Journal of Psychosomatic Research*, *54*(1), 39–49. https://doi.org/10.1016/S0022-3999(02)00544-5

Bastien, L., Tétreault, É., & Bernier, A. (2020). Disentangling the Direction of Associations between Sleep and Temperament in Toddlers. *Behavioral Sleep Medicine*, *18*(4), 523–536. https://doi.org/10.1080/15402002.2019.1629442

Bathory, E., & Tomopoulos, S. (2017). Sleep Regulation, Physiology and Development, Sleep Duration and Patterns, and Sleep Hygiene in Infants, Toddlers, and Preschool-Age Children. *Current Problems in Pediatric and Adolescent Health Care*, *47*(2), 29–42. https://doi.org/10.1016/J.CPPEDS.2016.12.001

Bayley, N. (2009). *Bayley-III: Bayley Scales of infant and toddler development*. Giunti OS.

Bazhenova, O. V., Stroganova, T. A., Doussard-Roosevelt, J. A., Posikera, I. A., & Porges, S. W. (2007). Physiological responses of 5-month-old infants to smiling and blank faces. *International Journal of Psychophysiology*, *63*(1), 64–76. https://doi.org/10.1016/j.ijpsycho.2006.08.008

Beccuti, G., & Pannain, S. (2011). Sleep and obesity. In *Current Opinion in Clinical Nutrition and Metabolic Care* (Vol. 14, Issue 4, pp. 402–412). NIH Public Access. https://doi.org/10.1097/MCO.0b013e3283479109

Becker, P. T., & Thoman, E. B. (1981). Rapid eye movement storms in infants: rate of occurrence at 6 months predicts mental development at 1 year. *Science*, *212*(4501), 1415–1416.

Beebe, D. W. (2006). Neurobehavioral morbidity associated with disordered breathing during sleep in children: a comprehensive review. *Sleep*, *29*(9), 1115–1134.

Begus, K., Lloyd-Fox, S., Halliday, D., Papademetriou, M., Darboe, M. K., Prentice, A. M., Moore, S. E., & Elwell, C. E. (2016). *Using fNIRS to Study Working Memory of Infants in Rural Africa* (pp. 273–279). Springer, New York, NY. https://doi.org/10.1007/978-1-4939-3023-4_34

Begus, K., & Bonawitz, E. (2020). The rhythm of learning: Theta oscillations as an index of active learning in infancy. In *Developmental Cognitive Neuroscience* (Vol. 45, p. 100810). Elsevier Ltd. https://doi.org/10.1016/j.dcn.2020.100810

Begus, K., Southgate, V., & Gliga, T. (2015). Neural mechanisms of infant learning: differences in frontal theta activity during object exploration modulate subsequent object recognition. *Biology Letters*, *11*(5), 20150041.

Benitez, A., & Gunstad, J. (2012). Poor sleep quality diminishes cognitive functioning independent of depression and anxiety in healthy young adults. *Clinical Neuropsychologist*, *26*(2), 214–223. https://doi.org/10.1080/13854046.2012.658439

Bennet, L., Fyfe, K. L., Yiallourou, S. R., Merk, H., Wong, F. Y., & Horne, R. S. C. (2016). Discrimination of sleep states using continuous cerebral bedside monitoring (amplitude-integrated electroencephalography) compared to polysomnography in infants. *Acta Paediatrica*, *105*(12), e582–e587. https://doi.org/10.1111/apa.13602

Berger, A., Tzur, G., & Posner, M. I. (2006). Infant brains detect arithmetic errors. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(33), 12649–12653. https://doi.org/10.1073/pnas.0605350103

Berger, H. (1929). Über das elektroenkephalogramm des menschen. *Archiv Für Psychiatrie Und Nervenkrankheiten*, *87*(1), 527–570.

Berger, S. E., & Scher, A. (2017). Naps improve new walkers' locomotor problem solving. *Journal of Experimental Child Psychology*, *162*, 292–300. https://doi.org/10.1016/j.jecp.2017.04.021

Berkers, R. M. W. J., Ekman, M., van Dongen, E. V., Takashima, A., Barth, M., Paller, K. A., & Fernández, G. (2018). Cued reactivation during slow-wave sleep induces brain connectivity changes related to memory stabilization. *Scientific Reports*, *8*(1), 1–12. https://doi.org/10.1038/s41598-018-35287-6

Bernard, S., Gonze, D., Čajavec, B., Herzel, H., & Kramer, A. (2007). Synchronization-induced rhythmicity of circadian oscillators in the suprachiasmatic nucleus. *PLoS Computational Biology*, *3*(4), 667–679. https://doi.org/10.1371/journal.pcbi.0030068

Bernier, A., Beauchamp, M. H., Bouvette-Turcot, A. A., Carlson, S. M., & Carrier, J. (2013). Sleep and cognition in preschool years: Specific links to executive functioning. *Child Development*. https://doi.org/10.1111/cdev.12063

Bernier, A., Carlson, S. M., Bordeleau, S., & Carrier, J. (2010). Relations Between Physiological and Cognitive Regulatory Systems: Infant Sleep Regulation and Subsequent Executive Functioning. *Child Development*, *81*(6), 1739–1752. https://doi.org/10.1111/j.1467-8624.2010.01507.x

Bernier, A., Matte-Gagné, C., & Bouvette-Turcot, A.-A. (2014). Examining the Interface of Children's Sleep, Executive Functioning, and Caregiving Relationships. *Current Directions in Psychological Science*, *23*(4), 284–289. https://doi.org/10.1177/0963721414534852

Bertrand, S. J., Zhang, Z., Patel, R., O'Ferrell, C., Punjabi, N. M., Kudchadkar, S. R., & Kannan, S. (2020). Transient neonatal sleep fragmentation results in long-term neuroinflammation and cognitive impairment in a rabbit model. *Experimental Neurology*, *327*, 113212. https://doi.org/10.1016/j.expneurol.2020.113212

Betzel, R. F., Byrge, L., He, Y., Goñi, J., Zuo, X. N., & Sporns, O. (2014). Changes in structural and functional connectivity among resting-state networks across the human lifespan. *NeuroImage*, *102*(P2), 345–357. https://doi.org/10.1016/j.neuroimage.2014.07.067

Biswal, B., Zerrin Yetkin, F., Haughton, V. M., & Hyde, J. S. (1995). Functional connectivity in the motor cortex of resting human brain using echo-planar mri. *Magnetic Resonance in Medicine*, *34*(4), 537–541. https://doi.org/10.1002/mrm.1910340409

Bland, J. M., & Altman, D. (1986). Statistical methods for assessing agreement between

two methods of clinical measurement. *The Lancet*, *327*(8476), 307–310.
Bland, J. M., & Altman, D. G. (1999). Measuring agreement in method comparison studies. *Statistical Methods in Medical Research*, *8*(2), 135–160. https://doi.org/10.1177/096228029900800204
Bluestone, C., & Tamis-LeMonda, C. S. (1999). Correlates of parenting styles in predominantly working-and middle-class African American mothers. *Journal of Marriage and the Family*, 881–893.
Blumberg, M. S. (2010). Beyond dreams: do sleep-related movements contribute to brain development? *Frontiers in Neurology*, *1*, 140. https://doi.org/10.3389/fneur.2010.00140
Bonnet, M. H. (1985). Effect of sleep disruption on sleep, performance, and mood. *Sleep*, *8*(1), 11–19. https://doi.org/10.1093/sleep/8.1.11
Borb, A. A., & Achermann, P. (1999). Sleep Homeostasis and Models of Sleep Regulation. *Journal of Biological Rhythms*, *14*(6), 559–570. https://doi.org/10.1177/074873099129000894
Borbély, A. A. (1982). A two process model of sleep regulation. *Hum Neurobiol*, *1*(3), 195–204.
Borbély, A. A., Daan, S., Wirz-Justice, A., & Deboer, T. (2016). The two-process model of sleep regulation: a reappraisal. *Journal of Sleep Research*, *25*(2), 131–143. https://doi.org/10.1111/jsr.12371
Borbély, A. A., Rusterholz, T., & Achermann, P. (2017). Three decades of continuous wrist-activity recording: analysis of sleep duration. *Journal of Sleep Research*, *26*(2), 188–194. https://doi.org/10.1111/jsr.12492
Born, J., & Wilhelm, I. (2012). System consolidation of memory during sleep. In *Psychological Research*. https://doi.org/10.1007/s00426-011-0335-6
Bosseler, A. N., Taulu, S., Pihko, E., Mäkelä, J. P., Imada, T., Ahonen, A., & Kuhl, P. K. (2013). Theta brain rhythms index perceptual narrowing in infant speech perception. *Frontiers in Psychology*, *4*, 690. https://doi.org/10.3389/fpsyg.2013.00690
Boyd, S., & Vandenberghe, L. (2018). *Introduction to applied linear algebra: vectors, matrices, and least squares*. Cambridge university press.
Braithwaite, E. K., Jones, E. J. H., Johnson, M. H., & Holmboe, K. (2020). Dynamic modulation of frontal theta power predicts cognitive ability in infancy. *Developmental Cognitive Neuroscience*, *45*, 100818. https://doi.org/10.1016/j.dcn.2020.100818
Britton, J., Frey, L., Hopp, J., Korb, P., Koubeissi, M., Lievens, W., Pestana-Knight, E., & St., E. L. (2016). Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants. In *Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants*. American Epilepsy Society, Chicago. http://www.ncbi.nlm.nih.gov/pubmed/27748095
Brown, R. E., Basheer, R., McKenna, J. T., Strecker, R. E., & McCarley, R. W. (2012). Control of sleep and wakefulness. *Physiological Reviews*, *92*(3), 1087–1187.
Bruchhage, M. M. K., Ngo, G. C., Schneider, N., D'Sa, V., & Deoni, S. C. L. (2020). Functional connectivity correlates of infant and early childhood cognitive development. *Brain Structure and Function*, *225*(2), 669–681. https://doi.org/10.1007/s00429-020-02027-4
Bruni, O., Novelli, L., Miano, S., Parrino, L., Terzano, M. G., & Ferri, R. (2010). Cyclic alternating pattern: A window into pediatric sleep. In *Sleep Medicine*. https://doi.org/10.1016/j.sleep.2009.10.003
Bryant, P. A., Trinder, J., & Curtis, N. (2004). Sick and tired: does sleep have a vital role in the immune system? *Nature Reviews Immunology*, *4*(6), 457–467.

Buchmann, A., Ringli, M., Kurth, S., Schaerer, M., Geiger, A., Jenni, O. G., & Huber, R. (2011). EEG sleep slow-wave activity as a mirror of cortical maturation. *Cerebral Cortex*, *21*(3), 607–615.

Bulgarelli, C., Blasi, A., de Klerk, C. C. J. M., Richards, J. E., Hamilton, A., & Southgate, V. (2019). Fronto-temporoparietal connectivity and self-awareness in 18-month-olds: A resting state fNIRS study. *Developmental Cognitive Neuroscience*, *38*, 100676. https://doi.org/10.1016/j.dcn.2019.100676

Bulgarelli, C., Blasi, A., Pollonini, L., Lloyd-Fox, S., Pirazzoli, L., Perdue, K. L., Nelson, C. A., & Elwell, C. E. (2020). Standardising an infant fNIRS analysis pipeline to investigate neurodevelopment in global health. *Optics and the Brain*, BM2C-2.

Buzsáki, G. (1989). Two-stage model of memory trace formation: A role for "noisy" brain states. *Neuroscience*, *31*(3), 551–570. https://doi.org/10.1016/0306-4522(89)90423-5

Buzsáki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, *304*(5679), 1926–1929.

Byars, K. C., Yolton, K., Rausch, J., Lanphear, B., & Beebe, D. W. (2012). Prevalence, patterns, and persistence of sleep problems in the first 3 years of life. *Pediatrics*, *129*(2), e276–e284. https://doi.org/10.1542/peds.2011-0372

Cajochen, C., Brunner, D. P., Krauchi, K., Graw, P., & Wirz-Justice, A. (1995). Power density in theta/alpha frequencies of the waking EEG progressively increases during sustained wakefulness. *Sleep*, *18*(10), 890–894. https://doi.org/10.1093/sleep/18.10.890

Camerota, M., Gueron-Sela, N., Grimes, M., & Propper, C. B. (2020). Longitudinal links between maternal factors and infant cognition: Moderation by infant sleep. *Infancy*, *25*(2), 128–150. https://doi.org/10.1111/infa.12321

Camerota, M., Propper, C. B., & Teti, D. M. (2019). Intrinsic and extrinsic factors predicting infant sleep: Moving beyond main effects. *Developmental Review*, *53*, 100871. https://doi.org/10.1016/J.DR.2019.100871

Camerota, M., Tully, K. P., Grimes, M., Gueron-Sela, N., & Propper, C. B. (2018a). Assessment of infant sleep: how well do multiple methods compare? *Sleep*, *41*(10). https://doi.org/10.1093/sleep/zsy146

Camerota, M., Tully, K. P., Grimes, M., Gueron-Sela, N., & Propper, C. B. (2018b). Assessment of infant sleep: how well do multiple methods compare? *Sleep*, *41*(10). https://doi.org/10.1093/sleep/zsy146

Cao, M., Huang, H., & He, Y. (2017). Developmental Connectomics from Infancy through Early Childhood. In *Trends in Neurosciences* (Vol. 40, Issue 8, pp. 494–506). Elsevier Ltd. https://doi.org/10.1016/j.tins.2017.06.003

Carranza, J. A., González-Salinas, C., & Ato, E. (2013). A longitudinal study of temperament continuity through IBQ, TBAQ and CBQ. *Infant Behavior and Development*, *36*(4), 749–761. https://doi.org/10.1016/j.infbeh.2013.08.002

Cassanello, P., Díez-Izquierdo, A., Gorina, N., Matilla-Santander, N., Martínez-Sanchez, J. M., & Balaguer, A. (2018). Adaptation and study of the measurement properties of a sleep questionnaire for infants and pre-school children. *Anales de Pediatría (English Edition)*, *89*(4), 230–237. https://doi.org/10.1016/J.ANPEDE.2017.12.007

Cellini, N., Buman, M. P., Mcdevitt, E. A., Ricker, A. A., & Mednick, S. C. (2013). Direct comparison of two actigraphy devices with polysomnographically recorded naps in healthy young adults. *Chronobiology International*, *30*(5), 691–698. https://doi.org/10.3109/07420528.2013.782312

Chee, M. W. L., & Tan, J. C. (2010). Lapsing when sleep deprived: Neural activation characteristics of resistant and vulnerable individuals. *NeuroImage*, *51*(2), 835–843. https://doi.org/10.1016/j.neuroimage.2010.02.031

Cheour, M., Martynova, O., Näätänen, R., Erkkola, R., Sillanpää, M., Kero, P., Raz, A., Kaipio, M.-L., Hiltunen, J., Aaltonen, O., Savela, J., & Hämäläinen, H. (2002). Psychobiology: Speech sounds learned by sleeping newborns. *Nature*, *415*(6872), 599–600. https://doi.org/10.1038/415599b

Cheung, C. H. M., Bedford, R., Saez De Urabain, I. R., Karmiloff-Smith, A., & Smith, T. J. (2017). Daily touchscreen use in infants and toddlers is associated with reduced sleep and delayed sleep onset. *Scientific Reports*, *7*(1), 1–7. https://doi.org/10.1038/srep46104

Cirelli, C., & Tononi, G. (2008). Is sleep essential? In *PLoS Biology* (Vol. 6, Issue 8, pp. 1605–1611). Public Library of Science. https://doi.org/10.1371/journal.pbio.0060216

Cohen, M. X. (2014). *Analyzing neural time series data: theory and practice*. MIT press.

Cohen, S., Kamarck, T., & Mermelstein, R. (1994). Perceived stress scale. *Measuring Stress: A Guide for Health and Social Scientists*.

Cole, R. J., Kripke, D. F., Gruen, W., Mullaney, D. J., & Gillin, J. C. (1992). Automatic Sleep/Wake Identification From Wrist Activity. *Sleep*, *15*(5), 461–469. https://doi.org/10.1093/sleep/15.5.461

Colombo, J. (2001). The development of visual attention in infancy. *Annual Review of Psychology*, *52*(1), 337–367.

Colombo, J. (2002). Infant Attention Grows Up: The Emergence of a Developmental Cognitive Neuroscience Perspective. *Current Directions in Psychological Science*, *11*(6), 196–200. https://doi.org/10.1111/1467-8721.00199

Colombo, J., Mitchell, D. W., O'Brien, M., & Horowitz, F. D. (1987). The stability of visual habituation during the first year of life. *Child Development*, 474–487.

Colombo, J., Shaddy, D. J., Richman, W. A., Maikranz, J. M., & Blaga, O. M. (2004). The Developmental Course of Habituation in Infancy and Preschool Outcome. *Infancy*, *5*(1), 1–38. https://doi.org/10.1207/s15327078in0501_1

Conejero, Á., Guerra, S., Abundis-Gutiérrez, A., & Rueda, M. R. (2018). Frontal theta activation associated with error detection in toddlers: influence of familial socioeconomic status. *Developmental Science*, *21*(1), e12494.

Cope, M., & Delpy, D. T. (1988). System for long-term measurement of cerebral blood and tissue oxygenation on newborn infants by near infra-red transillumination. *Medical & Biological Engineering & Computing*, *26*(3), 289–294. https://doi.org/10.1007/BF02447083

Courage, M. L., Reynolds, G. D., & Richards, J. E. (2006). Infants' attention to patterned stimuli: Developmental change from 3 to 12 months of age. *Child Development*, *77*(3), 680–695. https://doi.org/10.1111/j.1467-8624.2006.00897.x

Cousijn, J., Hessels, R. S., Van der Stigchel, S., & Kemner, C. (2017). Evaluation of the Psychometric Properties of the Gap-Overlap Task in 10-Month-Old Infants. *Infancy*, *22*(4), 571–579. https://doi.org/10.1111/infa.12185

Cox, J. L., Chapman, G., Murray, D., & Jones, P. (1996). Validation of the Edinburgh Postnatal Depression Scale (EPDS) in non-postnatal women. *Journal of Affective Disorders*, *39*(3), 185–189.

Cox, J. L., Holden, J. M., & Sagovsky, R. (1987). Detection of postnatal depression: development of the 10-item Edinburgh Postnatal Depression Scale. *The British Journal of Psychiatry*, *150*(6), 782–786.

Cuevas, K., & Bell, M. A. (2014). Infant Attention and Early Childhood Executive Function. *Child Development*, *85*(2), 397–404. https://doi.org/10.1111/cdev.12126

Cui, X., Bray, S., Bryant, D. M., Glover, G. H., & Reiss, A. L. (2011). A quantitative comparison of NIRS and fMRI across multiple cognitive tasks. *NeuroImage*, *54*(4), 2808–2821. https://doi.org/10.1016/J.NEUROIMAGE.2010.10.069

Cui, X., Bryant, D. M., & Reiss, A. L. (2012). NIRS-based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation. *NeuroImage*, *59*(3), 2430–2437. https://doi.org/10.1016/J.NEUROIMAGE.2011.09.003

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve Frequently Asked Questions About Growth Curve Modeling. *Journal of Cognition and Development : Official Journal of the Cognitive Development Society*, *11*(2), 121–136. https://doi.org/10.1080/15248371003699969

D'Atri, A., Novelli, L., Ferrara, M., Bruni, O., & De Gennaro, L. (2018). Different maturational changes of fast and slow sleep spindles in the first four years of life. *Sleep Medicine*, *42*, 73–82. https://doi.org/10.1016/j.sleep.2017.11.1138

Damaraju, E., Caprihan, A., Lowe, J. R., Allen, E. A., Calhoun, V. D., & Phillips, J. P. (2014). Functional connectivity in the developing brain: A longitudinal study from 4 to 9months of age. *NeuroImage*, *84*, 169–180. https://doi.org/10.1016/j.neuroimage.2013.08.038

Datta, D. (2017). blandr: a bland-altman method comparison package for R. *<DOI:10.5281/Zenodo.824514> Https://Github.Com/Deepankardatta/Blandr*, *10*.

Davis, K. F., Parker, K. P., & Montgomery, G. L. (2004). Sleep in infants and young children - Part one: Normal sleep. *Journal of Pediatric Health Care*, *18*(2), 65–71. https://doi.org/10.1016/S0891-5245(03)00149-4

De Gennaro, L., Marzano, C., Fratello, F., Moroni, F., Pellicciari, M. C., Ferlazzo, F., Costa, S., Couyoumdjian, A., Curcio, G., Sforza, E., Malafosse, A., Finelli, L. A., Pasqualetti, P., Ferrara, M., Bertini, M., & Rossini, P. M. (2008). The electroencephalographic fingerprint of sleep is genetically determined: A twin study. *Annals of Neurology*, *64*(4), 455–460. https://doi.org/10.1002/ana.21434

De Marcas, G. S., Soffer-Dudek, N., Dollberg, S., Bar-Haim, Y., & Sadeh, A. (2015). IV. Reactivity and sleep in infants: a longitudinal objective assessment. *Monographs of the Society for Research in Child Development*, *80*(1), 49–69.

Del Rio-Bermudez, C., & Blumberg, M. S. (2018). Active Sleep Promotes Functional Connectivity in Developing Sensorimotor Networks. *BioEssays*, *40*(4), 1700234. https://doi.org/10.1002/bies.201700234

DeLeon, C. W., & Karraker, K. H. (2007). Intrinsic and extrinsic factors associated with night waking in 9-month-old infants. *Infant Behavior and Development*. https://doi.org/10.1016/j.infbeh.2007.03.009

Delisle Nyström, C., Pomeroy, J., Henriksson, P., Forsum, E., Ortega, F. B., Maddison, R., Migueles, J. H., & Löf, M. (2017). Evaluation of the wrist-worn ActiGraph wGT3x-BT for estimating activity energy expenditure in preschool children. *European Journal of Clinical Nutrition*, *71*(10), 1212–1217. https://doi.org/10.1038/ejcn.2017.114

Dement, W., & Kleitman, N. (1957). Cyclic variations in EEG during sleep and their relation to eye movements, body motility, and dreaming. Electroencephalography and Clinical Neurophysiology, 9(4), 673–690.

Diekelmann, S., Wilhelm, I., & Born, J. (2009). The whats and whens of sleep-dependent memory consolidation. Sleep medicine reviews, 13(5), 309-321.

Di Lorenzo, R., Pirazzoli, L., Blasi, A., Bulgarelli, C., Hakuno, Y., Minagawa, Y., & Brigadoi, S. (2019). Recommendations for motion correction of infant fNIRS data applicable to multiple data sets and acquisition systems. *NeuroImage*, *200*, 511–527. https://doi.org/10.1016/j.neuroimage.2019.06.056

Di Martino, A., Yan, C. G., Li, Q., Denio, E., Castellanos, F. X., Alaerts, K., Anderson, J. S., Assaf, M., Bookheimer, S. Y., Dapretto, M., Deen, B., Delmonte, S., Dinstein, I., Ertl-Wagner, B., Fair, D. A., Gallagher, L., Kennedy, D. P., Keown, C. L., Keysers, C., … Milham, M. P. (2014). The autism brain imaging data exchange: Towards a

large-scale evaluation of the intrinsic brain architecture in autism. *Molecular Psychiatry*, *19*(6), 659–667. https://doi.org/10.1038/mp.2013.78

Dias, C. C., Figueiredo, B., Rocha, M., & Field, T. (2018). Reference values and changes in infant sleep-wake behaviour during the first 12 months of life: a systematic review. *Journal of Sleep Research*, *27*(5), e12654. https://doi.org/10.1111/jsr.12654

Dijk, D. J., & Czeisler, C. A. (1995). Contribution of the circadian pacemaker and the sleep homeostat to sleep propensity, sleep structure, electroencephalographic slow waves, and sleep spindle activity in humans. *Journal of Neuroscience*, *15*(5 I), 3526–3538. https://doi.org/10.1523/jneurosci.15-05-03526.1995

Dørheim, S. K., Bondevik, G. T., Eberhard-Gran, M., & Bjorvatn, B. (2009). Sleep and Depression in Postpartum Women: A Population-Based Study. *Sleep*, *32*(7), 847–855. https://doi.org/10.1093/sleep/32.7.847

Dunn, W. (2001). The sensations of everyday life: Empirical, theoretical, and pragmatic considerations. *American Journal of Occupational Therapy*, *55*(6), 608–620.

Ednick, M., Cohen, A. P., McPhail, G. L., Beebe, D., Simakajornboon, N., & Amin, R. S. (2009). A review of the effects of sleep during the first year of life on cognitive, psychomotor, and temperament development. *Sleep*, *32*(11), 1449–1458.

El-Sheikh, M., & Sadeh, A. (2015). I. SLEEP AND DEVELOPMENT: INTRODUCTION TO THE MONOGRAPH. *Monographs of the Society for Research in Child Development*, *80*(1), 1–14. https://doi.org/10.1111/mono.12141

Elsabbagh, M., Fernandes, J., Webb, S. J., Dawson, G., Charman, T., Johnson, M. H., & British Autism Study of Infant Siblings Team, T. B. A. S. of I. S. (2013). Disengagement of visual attention in infancy is associated with emerging autism in toddlerhood. *Biological Psychiatry*, *74*(3), 189–194. https://doi.org/10.1016/j.biopsych.2012.11.030

Elsabbagh, M., Gliga, T., Pickles, A., Hudry, K., Charman, T., & Johnson, M. H. (2013). The development of face orienting mechanisms in infants at-risk for autism. *Behavioural Brain Research*, *251*, 147–154. https://doi.org/10.1016/J.BBR.2012.07.030

Elsabbagh, M., Volein, A., Holmboe, K., Tucker, L., Csibra, G., Baron-Cohen, S., Bolton, P., Charman, T., Baird, G., & Johnson, M. H. (2009). Visual orienting in the early broader autism phenotype: Disengagement and facilitation. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *50*(5), 637–642. https://doi.org/10.1111/j.1469-7610.2008.02051.x

Elwell, C. E., Cope, M., Edwards, A. D., Wyatt, J. S., Delpy, D. T., & Reynolds, E. O. (1994). Quantification of adult cerebral hemodynamics by near-infrared spectroscopy. *Journal of Applied Physiology*, *77*(6), 2753–2760.

Everdell, N. L., Gibson, A. P., Tullis, I. D. C., Vaithianathan, T., Hebden, J. C., & Delpy, D. T. (2005). A frequency multiplexed near-infrared topography system for imaging functional activation in the brain. *Review of Scientific Instruments*, *76*(9), 93705.

Fattinger, S., Jenni, O. G., Schmitt, B., Achermann, P., & Huber, R. (2014). Overnight Changes in the Slope of Sleep Slow Waves during Infancy. *Sleep*, *37*(2), 245–253. https://doi.org/10.5665/sleep.3390

Feinberg, I., & Campbell, I. G. (2019). Shorter sleep durations in adolescents reduce power density in a wide range of waking electroencephalogram frequencies. *PLOS ONE*, *14*(1), e0210649. https://doi.org/10.1371/journal.pone.0210649

Ferrari, M., Mottola, L., & Quaresima, V. (2004). Principles, techniques, and limitations of near infrared spectroscopy. *Canadian Journal of Applied Physiology = Revue Canadienne de Physiologie Appliquee*, *29*(4), 463–487. http://www.ncbi.nlm.nih.gov/pubmed/15328595

Ferrari, M., & Quaresima, V. (2012). A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application. *NeuroImage*, *63*(2), 921–935. https://doi.org/10.1016/J.NEUROIMAGE.2012.03.049

Field, T., Diego, M., Hernandez-Reif, M., Figueiredo, B., Schanberg, S., & Kuhn, C. (2007). Sleep disturbances in depressed pregnant women and their newborns. *Infant Behavior and Development*, *30*(1), 127–133. https://doi.org/10.1016/j.infbeh.2006.08.002

Fields, A. (2005). Discovering statistics using SPSS. *Beverly Hills: Sage Publications*, *541*.

Finelli, L. A., Baumann, H., Borbély, A. A., & Achermann, P. (2000). Dual electroencephalogram markers of human sleep homeostasis: Correlation between theta activity in waking and slow-wave activity in sleep. *Neuroscience*, *101*(3), 523–529. https://doi.org/10.1016/S0306-4522(00)00409-7

Frank, Marcos G, Issa, N. P., & Stryker, M. P. (2001). Sleep enhances plasticity in the developing visual cortex. *Neuron*, *30*(1), 275–287.

Frank, Marcos Gabriel. (2011). Sleep and developmental plasticity: Not just for kids. In *Progress in Brain Research* (Vol. 193, pp. 221–232). Elsevier B.V. https://doi.org/10.1016/B978-0-444-53839-0.00014-4

Freudigman, K. A., & Thoman, E. B. (1993). Infant sleep during the first postnatal day: an opportunity for assessment of vulnerability. *Pediatrics*, *92*(3), 373–379.

Frick, J. E., Colombo, J., & Saxon, T. F. (1999). Individual and Developmental Differences in Disengagement of Fixation in Early Infancy. *Child Development*, *70*(3), 537–548. https://doi.org/10.1111/1467-8624.00039

Friedrich, M., Mölle, M., Friederici, A. D., & Born, J. (2018). The reciprocal relation between sleep and memory in infancy: Memory-dependent adjustment of sleep spindles and spindle-dependent improvement of memories. *Developmental Science*, e12743. https://doi.org/10.1111/desc.12743

Friedrich, M., Mölle, M., Friederici, A. D., & Born, J. (2019). The reciprocal relation between sleep and memory in infancy: Memory-dependent adjustment of sleep spindles and spindle-dependent improvement of memories. *Developmental Science*, *22*(2), e12743. https://doi.org/10.1111/desc.12743

Friedrich, M., Wilhelm, I., Born, J., & Friederici, A. D. (2015). Generalization of word meanings during infant sleep. *Nature Communications*, *6*, 6004. https://doi.org/10.1038/ncomms7004

Friedrich, M., Wilhelm, I., Mölle, M., Born, J., & Friederici, A. D. (2017). The Sleeping Infant Brain Anticipates Development. *Current Biology*, *27*(15), 2374-2380.e3. https://doi.org/10.1016/j.cub.2017.06.070

Friston, K. J., Williams, S., Howard, R., Frackowiak, R. S. J., & Turner, R. (1996). Movement-related effects in fMRI time-series. *Magnetic Resonance in Medicine*, *35*(3), 346–355. https://doi.org/10.1002/mrm.1910350312

Galland, B. C., Taylor, B. J., Elder, D. E., & Herbison, P. (2012). Normal sleep patterns in infants and children: A systematic review of observational studies. *Sleep Medicine Reviews*, *16*(3), 213–222. https://doi.org/10.1016/J.SMRV.2011.06.001

Gao, W., Alcauter, S., Elton, A., Hernandez-Castillo, C. R., Smith, J. K., Ramirez, J., & Lin, W. (2015). Functional network development during the first year: Relative sequence and socioeconomic correlations. *Cerebral Cortex*, *25*(9), 2919–2928. https://doi.org/10.1093/cercor/bhu088

Gao, W., Alcauter, S., Smith, J. K., Gilmore, J. H., & Lin, W. (2015). Development of human brain cortical network architecture during infancy. *Brain Structure and Function*, *220*(2), 1173–1186. https://doi.org/10.1007/s00429-014-0710-3

Gao, W., Lin, W., Grewen, K., & Gilmore, J. H. (2017). Functional connectivity of the infant human brain: Plastic and modifiable. In *Neuroscientist* (Vol. 23, Issue 2, pp.

169–184). SAGE Publications Inc. https://doi.org/10.1177/1073858416635986
Gartstein, M. A., & Rothbart, M. K. (2003). Studying infant temperament via the Revised Infant Behavior Questionnaire. *Infant Behavior and Development*, *26*(1), 64–86. https://doi.org/10.1016/S0163-6383(02)00169-8
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. In *Developmental Cognitive Neuroscience* (Vol. 1, Issue 1, pp. 22–46). Elsevier. https://doi.org/10.1016/j.dcn.2010.07.004
Geva, R., Yaron, H., & Kuint, J. (2016). Neonatal sleep predicts attention orienting and distractibility. *Journal of Attention Disorders*, *20*(2), 138–150.
Gibson, R., Elder, D., & Gander, P. (2012). Actigraphic sleep and developmental progress of one-year-old infants. *Sleep and Biological Rhythms*, *10*(2), 77–83.
Gilley, P. M., Uhler, K., Watson, K., & Yoshinaga-itano, C. (2017). Spectral-temporal EEG dynamics of speech discrimination processing in infants during sleep. *BMC Neurosci*, *18*. https://doi.org/10.1186/s12868-017-0353-4
Girardeau, G., & Zugaro, M. (2011). Hippocampal ripples and memory consolidation. In *Current Opinion in Neurobiology* (Vol. 21, Issue 3, pp. 452–459). Elsevier Current Trends. https://doi.org/10.1016/j.conb.2011.02.005
Gliga, T., Elsabbagh, M., Andravizou, A., & Johnson, M. (2009). Faces Attract Infants' Attention in Complex Displays. *Infancy*, *14*(5), 550–562. https://doi.org/10.1080/15250000903144199
Gobin, C. M., Banks, J. B., Fins, A. I., & Tartar, J. L. (2015). Poor sleep quality is associated with a negative cognitive bias and decreased sustained attention. *Journal of Sleep Research*, *24*(5), 535–542. https://doi.org/10.1111/jsr.12302
Goldberg, W. A., Lucas-Thompson, R. G., Germo, G. R., Keller, M. A., Davis, E. P., & Sandman, C. A. (2013). Eye of the beholder? Maternal mental health and the quality of infant sleep. *Social Science and Medicine*, *79*(1), 101–108. https://doi.org/10.1016/j.socscimed.2012.07.006
Gómez, R. L., Bootzin, R. R., & Nadel, L. (2006). Naps Promote Abstraction in Language-Learning Infants. *Psychological Science*, *17*(8), 670–674. https://doi.org/10.1111/j.1467-9280.2006.01764.x
Goodlin-Jones, B. L., Burnham, M. M., Gaylor, E. E., & Anders, T. F. (2001). Night waking, sleep-wake organization, and self-soothing in the first year of life. *Journal of Developmental and Behavioral Pediatrics : JDBP*, *22*(4), 226–233. http://www.ncbi.nlm.nih.gov/pubmed/11530895
Gorgoni, M., D'Atri, A., Scarpelli, S., Reda, F., & De Gennaro, L. (2019). Sleep electroencephalography and brain maturation: Developmental trajectories and the relation with cognitive functioning. *Sleep Medicine*. https://doi.org/10.1016/j.sleep.2019.06.025
Gottlieb, D. J., Chase, C., Vezina, R. M., Heeren, T. C., Corwin, M. J., Auerbach, S. H., Weese-Mayer, D. E., & Lesko, S. M. (2004). Sleep-disordered breathing symptoms are associated with poorer cognitive function in 5-year-old children. *Journal of Pediatrics*, *145*(4), 458–464. https://doi.org/10.1016/j.jpeds.2004.05.039
Gozdas, E., Parikh, N. A., Merhar, S. L., Tkach, J. A., He, L., & Holland, S. K. (2018). Altered functional network connectivity in preterm infants: antecedents of cognitive and motor impairments? *Brain Structure and Function*, *223*(8), 3665–3680. https://doi.org/10.1007/s00429-018-1707-0
Gredebäck, G., Johnson, S., & von Hofsten, C. (2009). Eye Tracking in Infancy Research. *Developmental Neuropsychology*, *35*(1), 1–19. https://doi.org/10.1080/87565640903325758
Gregory, A. M., Van der Ende, J., Willis, T. A., & Verhulst, F. C. (2008). Parent-Reported Sleep Problems During Development and Self-reported Anxiety/Depression,

Attention Problems, and Aggressive Behavior Later in Life. *Archives of Pediatrics & Adolescent Medicine*, *162*(4), 330–335. https://doi.org/10.1001/archpedi.162.4.330

Grigg-Damberger, M., Gozal, D., Marcus, C. L., Quan, S. F., Rosen, C. L., Chervin, R. D., Wise, M., Picchietti, D. L., Sheldon, S. H., & Iber, C. (2007). The visual scoring of sleep and arousal in infants and children. *J Clin Sleep Med*, *3*(2), 201–240.

Grigg-Damberger, M. M. (2017). Ontogeny of Sleep and Its Functions in Infancy, Childhood, and Adolescence. In *Sleep Disorders in Children* (pp. 3–29). Springer International Publishing. https://doi.org/10.1007/978-3-319-28640-2_1

Grosmark, A. D., Mizuseki, K., Pastalkova, E., Diba, K., & Buzsáki, G. (2012). REM Sleep Reorganizes Hippocampal Excitability. *Neuron*, *75*(6), 1001–1007. https://doi.org/10.1016/j.neuron.2012.08.015

Gruber, R., & Wise, M. S. (2016). Sleep Spindle Characteristics in Children with Neurodevelopmental Disorders and Their Relation to Cognition. *Neural Plast*, *2016*, 1–27. https://doi.org/10.1155/2016/4724792

Gruber, R., Wise, M. S., Frenette, S., Knäauper, B., Boom, A., Fontil, L., & Carrier, J. (2013). The association between sleep spindles and IQ in healthy school-age children. *International Journal of Psychophysiology*, *89*(2), 229–240. https://doi.org/10.1016/j.ijpsycho.2013.03.018

Gui, A., Mason, L., Gliga, T., Hendry, A., Begum Ali, J., Pasco, G., Shephard, E., Curtis, C., Charman, T., Johnson, M. H., Meaburn, E., & Jones, E. J. H. (2020). Look duration at the face as a developmental endophenotype: Elucidating pathways to autism and ADHD. *Development and Psychopathology*, *32*(4), 1303–1322. https://doi.org/10.1017/S0954579420000930

Guilleminault, C. (2005). *Handbook of Clinical Neurophysiology*.

Güven, A., Altınkaynak, M., Dolu, N., İzzetoğlu, M., Pektaş, F., Özmen, S., Demirci, E., & Batbat, T. (2020). Combining functional near-infrared spectroscopy and EEG measurements for the diagnosis of attention-deficit hyperactivity disorder. *Neural Computing and Applications*, *32*(12), 8367–8380. https://doi.org/10.1007/s00521-019-04294-7

Halit, H., Csibra, G., Volein, A., & Johnson, M. H. (2004). Face-sensitive cortical processing in early infancy. *Journal of Child Psychology and Psychiatry*, *45*(7), 1228–1234. https://doi.org/10.1111/j.1469-7610.2004.00321.x

Hall, W. A., Liva, S., Moynihan, M., & Saunders, R. (2015). A comparison of actigraphy and sleep diaries for infants' sleep behavior. *Frontiers in Psychiatry*, *6*, 19. https://doi.org/10.3389/fpsyt.2015.00019

Halpern, L. F., Anders, T. F., Garcia Coll, C., & Hua, J. (1994). Infant temperament: Is there a relation to sleep-wake states and maternal nighttime behavior? *Infant Behavior and Development*, *17*(3), 255–263. https://doi.org/10.1016/0163-6383(94)90004-3

Henderson, J. M. T., France, K. G., & Blampied, N. M. (2011). The consolidation of infants' nocturnal sleep across the first year of life. *Sleep Medicine Reviews*, *15*(4), 211–220. https://doi.org/10.1016/j.smrv.2010.08.003

Hendry, A., Johnson, M. H., & Holmboe, K. (2019). Early Development of Visual Attention: Change, Stability, and Longitudinal Associations. *Annual Review of Developmental Psychology*, *1*(1), 251–275. https://doi.org/10.1146/annurev-devpsych-121318-085114

Hendry, A., Jones, E. J. H., Bedford, R., Gliga, T., Charman, T., Johnson, M. H., Baron-Cohen, S., Blasi, A., Bolton, P., Cheung, H. M. C., Davies, K., Elsabbagh, M., Fernandes, J., Gammer, I., Green, J., Guiraud, J., Lloyd-Fox, S., Liew, M., Maris, H., … Wass, S. (2018). Developmental change in look durations predicts later effortful control in toddlers at familial risk for ASD. *Journal of Neurodevelopmental*

Disorders, *10*(1), 1–14. https://doi.org/10.1186/s11689-017-9219-4
Hepach, R., & Westermann, G. (2016). Pupillometry in infancy research. Journal of Cognition and Development, 17(3), 359-377.
Hernandez, S. M., & Pollonini, L. (2020). NIRSplot: A Tool for Quality Assessment of fNIRS Scans. *Optics and the Brain*, BM2C-5.
Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O'Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V, Ware, J. C., & Adams Hillard, P. J. (2015). National Sleep Foundation's sleep time duration recommendations: methodology and results summary. *Sleep Health*, *1*(1), 40–43. https://doi.org/10.1016/j.sleh.2014.12.010
Hobson, J. A. (2005). Sleep is of the brain, by the brain and for the brain. In *Nature* (Vol. 437, Issue 7063, pp. 1254–1256). Nature Publishing Group. https://doi.org/10.1038/nature04283
Hobson, J. A., & Pace-Schott, E. F. (2002). The cognitive neuroscience of sleep: neuronal systems, consciousness and learning. *Nature Reviews Neuroscience*. https://doi.org/10.1038/nrn915
Hoedlmoser, K. (2020). Co-evolution of sleep spindles, learning and memory in children. In *Current Opinion in Behavioral Sciences* (Vol. 33, pp. 138–143). Elsevier Ltd. https://doi.org/10.1016/j.cobeha.2020.03.005
Hoedlmoser, K., Heib, D. P. J., Roell, J., Peigneux, P., Sadeh, A., Gruber, G., & Schabus, M. (2014). Slow Sleep Spindle Activity, Declarative Memory, and General Cognitive Abilities in Children. *Sleep*, *37*(9), 1501–1512. https://doi.org/10.5665/sleep.4000
Holmboe, K., Bonneville-Roussy, A., Csibra, G., & Johnson, M. H. (2018). Longitudinal development of attention and inhibitory control during the first year of life. *Developmental Science*, *21*(6), e12690. https://doi.org/10.1111/desc.12690
Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. OUP Oxford.
Hood, B. M., & Atkinson, J. (1993). Disengaging visual attention in the infant and adult. *Infant Behavior and Development*, *16*(4), 405–422. https://doi.org/10.1016/0163-6383(93)80001-O
Horváth, K., Hannon, B., Ujma, P. P., Gombos, F., & Plunkett, K. (2017). Memory in 3-month-old infants benefits from a short nap. *Developmental Science*, e12587. https://doi.org/10.1111/desc.12587
Horváth, K., Hannon, B., Ujma, P. P., Gombos, F., & Plunkett, K. (2018). Memory in 3-month-old infants benefits from a short nap. *Developmental Science*, *21*(3), e12587.
Horváth, K., Myers, K., Foster, R., & Plunkett, K. (2015). Napping facilitates word learning in early lexical development. *Journal of Sleep Research*, *24*(5), 503–509. https://doi.org/10.1111/jsr.12306
Horváth, K., & Plunkett, K. (2016). Frequent daytime naps predict vocabulary growth in early childhood. *Journal of Child Psychology and Psychiatry*, *57*(9), 1008–1017. https://doi.org/10.1111/jcpp.12583
Horváth, K., & Plunkett, K. (2018). Spotlight on daytime napping during early childhood. *Nature and Science of Sleep*, *10*, 97.
Hughes, A., Gallagher, S., & Hannigan, A. (2015). A Cluster Analysis of Reported Sleeping Patterns of 9-Month Old Infants and the Association with Maternal Health: Results from a Population Based Cohort Study. *Maternal and Child Health Journal*, *19*(8), 1881–1889. https://doi.org/10.1007/s10995-015-1701-6
Huhdanpää, H., Morales-Muñoz, I., Aronen, E. T., Pölkki, P., Saarenpää-Heikkilä, O., Paunio, T., Kylliäinen, A., & Paavonen, E. J. (2019). Sleep Difficulties in Infancy

Are Associated with Symptoms of Inattention and Hyperactivity at the Age of 5 Years. *Journal of Developmental & Behavioral Pediatrics*, *40*(6), 432–440. https://doi.org/10.1097/DBP.0000000000000684

Hung, C.-S., Sarasso, S., Ferrarelli, F., Riedner, B., Ghilardi, M. F., Cirelli, C., & Tononi, G. (2013). Local Experience-Dependent Changes in the Wake EEG after Prolonged Wakefulness. *Sleep*, *36*(1), 59–72. https://doi.org/10.5665/sleep.2302

Hupbach, A., Gomez, R. L., Bootzin, R. R., & Nadel, L. (2009). Nap-dependent learning in infants. *Developmental Science*, *12*(6), 1007–1012. https://doi.org/10.1111/j.1467-7687.2009.00837.x

Huppert, T. J., Diamond, S. G., Franceschini, M. A., & Boas, D. A. (2009). HomER: a review of time-series analysis methods for near-infrared spectroscopy of the brain. *Applied Optics*, *48*(10), D280–D298.

Iglowstein, I., Jenni, O. G., Molinari, L., & Largo, R. H. (2003). Sleep duration from infancy to adolescence: reference values and generational trends. *Pediatrics*, *111*(2), 302–307. http://www.ncbi.nlm.nih.gov/pubmed/12563055

Jenni, O. G., Borbély, A. A., & Achermann, P. (2004). Development of the nocturnal sleep electroencephalogram in human infants. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, *286*(3), R528–R538.

Jensen, O., Kaiser, J., & Lachaux, J.-P. (2007). Human gamma-frequency oscillations associated with attention and memory. *Trends in Neurosciences*, *30*(7), 317–324. https://doi.org/10.1016/J.TINS.2007.05.001

Jian, N., & Teti, D. M. (2016). Emotional availability at bedtime, infant temperament, and infant sleep development from one to six months. *Sleep Medicine*, *23*, 49–58. https://doi.org/10.1016/j.sleep.2016.07.001

Jiang, J., Scolaro, A. J., Bailey, K., & Chen, A. (2011). The effect of music-induced mood on attentional networks. *International Journal of Psychology*, *46*(3), 214–222. https://doi.org/10.1080/00207594.2010.541255

Jobsis, F. F. (1977). Noninvasive, infrared monitoring of cerebral and myocardial oxygen sufficiency and circulatory parameters. *Science*, *198*(4323), 1264–1267.

Johnson, M. H., Posner, M. I., & Rothbart, M. K. (1991). Components of visual orienting in early infancy: Contingency learning, anticipatory looking, and disengaging. *Journal of Cognitive Neuroscience*, *3*(4), 335–344. https://doi.org/10.1162/jocn.1991.3.4.335

Johnson, Mark H, & De Haan, M. (2015). *Developmental cognitive neuroscience: An introduction*. Wiley-Blackwell.

Jones, E. J. H., Goodwin, A., Orekhova, E., Charman, T., Dawson, G., Webb, S. J., & Johnson, M. H. (2020). Infant EEG theta modulation predicts childhood intelligence. *Scientific Reports*, *10*(1), 1–10.

Jones, E. J. H., Venema, K., Lowy, R., Earl, R. K., & Webb, S. J. (2015). Developmental changes in infant brain activity during naturalistic social experiences. *Developmental Psychobiology*, *57*(7), 842–853. https://doi.org/10.1002/dev.21336

Jones, E. J. H., Venema, K., Lowy, R., Earl, R. K., & Webb, S. J. (2015). Developmental changes in infant brain activity during naturalistic social experiences. *Developmental Psychobiology*, *57*(7), 842–853. https://doi.org/10.1002/dev.21336

Judge, M. P., Chang, L., & Lammi-Keefe, C. J. (2015). Evidence of Developmental Continuity From Birth to 1 Year. *Advances in Neonatal Care*, *15*(2), 125–133. https://doi.org/10.1097/ANC.0000000000000143

Kahnt, T., Chang, L. J., Park, S. Q., Heinzle, J., & Haynes, J. D. (2012). Connectivity-based parcellation of the human orbitofrontal cortex. *Journal of Neuroscience*, *32*(18), 6240–6250. https://doi.org/10.1523/JNEUROSCI.0257-12.2012

Kaley, F., Reid, V., & Flynn, E. (2012). Investigating the biographic, social and temperamental correlates of young infants' sleeping, crying and feeding routines.

Infant Behavior and Development, *35*(3), 596–605. https://doi.org/10.1016/j.infbeh.2012.03.004

Kamara, D., & Beauchaine, T. P. (2020). A Review of Sleep Disturbances among Infants and Children with Neurodevelopmental Disorders. In *Review Journal of Autism and Developmental Disorders* (Vol. 7, Issue 3, pp. 278–294). Springer. https://doi.org/10.1007/s40489-019-00193-8

Kanda, T., Tsujino, N., Kuramoto, E., Koyama, Y., Susaki, E. A., Chikahisa, S., & Funato, H. (2016). Sleep as a biological problem: an overview of frontiers in sleep research. *The Journal of Physiological Sciences*, *66*(1), 1–13.

Katus, L., Hayes, N. J., Mason, L., Blasi, A., McCann, S., Darboe, M. K., Haan, M. de, Moore, S. E., Lloyd-Fox, S., & Elwell, C. E. (2019). Implementing neuroimaging and eye tracking methods to assess neurocognitive development of young infants in low- and middle-income countries. *Gates Open Research*, *3*. https://doi.org/10.12688/GATESOPENRES.12951.2

Kaufmann, C., Wehrle, R., Wetter, T. C., Holsboer, F., Auer, D. P., Pollmächer, T., & Czisch, M. (2006). Brain activation and hypothalamic functional connectivity during human non-rapid eye movement sleep: An EEG/fMRI study. *Brain*, *129*(3), 655–667. https://doi.org/10.1093/brain/awh686

Keehn, B., Wagner, J. B., Tager-Flusberg, H., & Nelson, C. A. (2013). Functional connectivity in the first year of life in infants at-risk for autism: a preliminary near-infrared spectroscopy study. *Frontiers in Human Neuroscience*, *7*(JUL), 444. https://doi.org/10.3389/fnhum.2013.00444

Klerk, C. C. J. M., Gliga, T., Charman, T., & Johnson, M. H. (2014). Face engagement during infancy predicts later face recognition ability in younger siblings of children with autism. *Developmental Science*, *17*(4), 596–611. https://doi.org/10.1111/desc.12141

Koch, M. A., Norris, D. G., & Hund-Georgiadis, M. (2002). An investigation of functional and anatomical connectivity using magnetic resonance imaging. *NeuroImage*, *16*(1), 241–250. https://doi.org/10.1006/nimg.2001.1052

Kocsis, L., Herman, P., & Eke, A. (2006). The modified Beer–Lambert law revisited. *Physics in Medicine and Biology*, *51*(5), N91–N98. https://doi.org/10.1088/0031-9155/51/5/N02

Konrad, C., Seehagen, S., Schneider, S., & Herbert, J. S. (2016). Naps promote flexible memory retrieval in 12-month-old infants. *Developmental Psychobiology*, *58*(7), 866–874. https://doi.org/10.1002/dev.21431

Krause, A. J., Simon, E. Ben, Mander, B. A., Greer, S. M., Saletin, J. M., Goldstein-Piekarski, A. N., & Walker, M. P. (2017). The sleep-deprived human brain. In *Nature Reviews Neuroscience* (Vol. 18, Issue 7, pp. 404–418). Nature Publishing Group. https://doi.org/10.1038/nrn.2017.55

Kronholm, E., Sallinen, M., Suutama, T., Sulkava, R., Era, P., & Partonen, T. (2009). Self-reported sleep duration and cognitive functioning in the general population. *Journal of Sleep Research*, *18*(4), 436–446. https://doi.org/10.1111/j.1365-2869.2009.00765.x

Krueger, J. M., Frank, M. G., Wisor, J. P., & Roy, S. (2016). Sleep function: Toward elucidating an enigma. *Sleep Medicine Reviews*, *28*, 46–54. https://doi.org/10.1016/j.smrv.2015.08.005

Krueger, J. M., & Tononi, G. (2011). Local use-dependent sleep; synthesis of the new paradigm. *Current Topics in Medicinal Chemistry*, *11*(19), 2490–2492. https://doi.org/10.2174/156802611797470330

Kurdziel, L., Duclos, K., & Spencer, R. M. C. (2013). Sleep spindles in midday naps enhance learning in preschool children. *Proceedings of the National Academy of Sciences*. https://doi.org/10.1073/pnas.1306418110

Kurth, S., Dean, D. C., Achermann, P., O'Muircheartaigh, J., Huber, R., Deoni, S. C. L., & LeBourgeois, M. K. (2016). Increased Sleep Depth in Developing Neural Networks: New Insights from Sleep Restriction in Children. *Frontiers in Human Neuroscience*, *10*(1), 10. https://doi.org/10.3389/fnhum.2016.00456

Kwon, S. H., Scheinost, D., Vohr, B., Lacadie, C., Schneider, K., Dai, F., Sze, G., Constable, R. T., & Ment, L. R. (2016). Functional magnetic resonance connectivity studies in infants born preterm: suggestions of proximate and long-lasting changes in language organization. *Developmental Medicine & Child Neurology*, *58*, 28–34. https://doi.org/10.1111/dmcn.13043

Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence Testing for Psychological Research: A Tutorial. *Advances in Methods and Practices in Psychological Science*, *1*(2), 259–269. https://doi.org/10.1177/2515245918770963

Lam, J. C., Mahone, E. M., Mason, T. B. A., & Scharf, S. M. (2011). The effects of napping on cognitive function in preschoolers. *Journal of Developmental and Behavioral Pediatrics: JDBP*, *32*(2), 90.

Lee, C. W., Blanco, B., Dempsey, L., Chalia, M., Hebden, J. C., Caballero-Gaudes, C., Austin, T., & Cooper, R. J. (2020). Sleep State Modulates Resting-State Functional Connectivity in Neonates. *Frontiers in Neuroscience*, *14*, 347. https://doi.org/10.3389/fnins.2020.00347

Lee, S., Matsumori, K., Nishimura, K., Nishimura, Y., Ikeda, Y., Eto, T., & Higuchi, S. (2018). Melatonin suppression and sleepiness in children exposed to blue-enriched white LED lighting at night. *Physiological Reports*, *6*(24). https://doi.org/10.14814/phy2.13942

Levin, A., & Scher, A. (2016). Sleep Problems in Young Children with Autism Spectrum Disorders: A Study of Parenting Stress, Mothers' Sleep-Related Cognitions, and Bedtime Behaviors. *CNS Neuroscience & Therapeutics*, *22*(11), 921–927. https://doi.org/10.1111/cns.12651

Lewandowski, A. S., Toliver-Sokol, M., & Palermo, T. M. (2011). Evidence-Based Review of Subjective Pediatric Sleep Measures. *Journal of Pediatric Psychology*, *36*(7), 780–793. https://doi.org/10.1093/jpepsy/jsq119

Lim, J., & Dinges, D. F. (2010). A meta-analysis of the impact of short-term sleep deprivation on cognitive variables. *Psychological Bulletin*, *136*(3), 375–389. https://doi.org/10.1037/a0018883

Liu, Z. X., Woltering, S., & Lewis, M. D. (2014). Developmental change in EEG theta activity in the medial prefrontal cortex during response control. *NeuroImage*, *85*, 873–887. https://doi.org/10.1016/j.neuroimage.2013.08.054

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

Lloyd-Fox, Sarah, 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

Loomis, A. L., Harvey, E. N., & Hobart, G. (1935). Potential rhythms of the cerebral cortex during sleep. *Science*.

Lu, J., Sherman, D., Devor, M., & Saper, C. B. (2006). A putative flip-flop switch for control of REM sleep. *Nature*, *441*(7093), 589–594. https://doi.org/10.1038/nature04767

Lukowski, A. F., Liu, X., Peirano, P., Odio, M., & Bauer, P. J. (2015). Disposable diaper use promotes consolidated nighttime sleep and positive mother-infant interactions in Chinese 6-month-olds. *Journal of Family Psychology*.

https://doi.org/10.1037/fam0000072
Lukowski, A. F., & Milojevich, H. M. (2013). Sleeping like a baby: Examining relations between habitual infant sleep, recall memory, and generalization across cues at 10 months. *Infant Behavior and Development*, *36*(3), 369–376. https://doi.org/10.1016/J.INFBEH.2013.02.001
MacDuffie, K. E., Shen, M. D., Dager, S. R., Styner, M. A., Kim, S. H., Paterson, S., Pandey, J., St. John, T., Elison, J. T., Wolff, J. J., Swanson, M. R., Botteron, K. N., Zwaigenbaum, L., Piven, J., & Estes, A. M. (2020). Sleep Onset Problems and Subcortical Development in Infants Later Diagnosed With Autism Spectrum Disorder. *American Journal of Psychiatry*, *177*(6), 518–525. https://doi.org/10.1176/appi.ajp.2019.19060666
MacKinnon, A. L., Tomfohr-Madsen, L., & Tough, S. (2020). Neighborhood Socio-Economic Factors and Associations with Infant Sleep Health. *Behavioral Sleep Medicine*. https://doi.org/10.1080/15402002.2020.1778478
Mangardich, H., & Cribbie, R. A. (2015). Assessing clinical significance using robust normative comparisons. *Psychotherapy Research*, *25*(2), 239–248. https://doi.org/10.1080/10503307.2014.889329
Marcus, C. L., Radcliffe, J., Konstantinopoulou, S., Beck, S. E., Cornaglia, M. A., Traylor, J., DiFeo, N., Karamessinis, L. R., Gallagher, P. R., & Meltzer, L. J. (2012). Effects of positive airway pressure therapy on neurobehavioral outcomes in children with obstructive sleep apnea. *American Journal of Respiratory and Critical Care Medicine*, *185*(9), 998–1003. https://doi.org/10.1164/rccm.201112-2167OC
Marrus, N., Eggebrecht, A. T., Todorov, A., Elison, J. T., Wolff, J. J., Cole, L., Gao, W., Pandey, J., Shen, M. D., Swanson, M. R., Emerson, R. W., Klohr, C. L., Adams, C. M., Estes, A. M., Zwaigenbaum, L., Botteron, K. N., McKinstry, R. C., Constantino, J. N., Evans, A. C., … Pruett, J. R. (2018). Walking, Gross Motor Development, and Brain Functional Connectivity in Infants and Toddlers. *Cerebral Cortex*, *28*(2), 750–763. https://doi.org/10.1093/cercor/bhx313
Marshall, P. J., & Fox, N. A. (2004). A comparison of the electroencephalogram between institutionalized and community children in Romania. *Journal of Cognitive Neuroscience*, *16*(8), 1327–1338. https://doi.org/10.1162/0898929042304723
Martini, J., Petzoldt, J., Knappe, S., Garthus-Niegel, S., Asselmann, E., & Wittchen, H. U. (2017). Infant, maternal, and familial predictors and correlates of regulatory problems in early infancy: The differential role of infant temperament and maternal anxiety and depression. *Early Human Development*, *115*, 23–31. https://doi.org/10.1016/j.earlhumdev.2017.08.005
Matenchuk, B. A., Tamana, S. K., Lou, W. Y. W., Lefebvre, D. L., Sears, M. R., Becker, A. B., Azad, M. B., Moraes, T. J., Turvey, S. E., Subbarao, P., Kozyrskyj, A. L., Mandhane, P. J., Anand, S. S., Befus, A. D., Brauer, M., Brook, J. R., Chen, E., Cyr, M. M., Daley, D., … To, T. (2019). Prenatal depression and birth mode sequentially mediate maternal education's influence on infant sleep duration. *Sleep Medicine*, *59*, 24–32. https://doi.org/10.1016/j.sleep.2019.01.015
Matsuzawa, M., & Shimojo, S. (1997). Infants' fast saccades in the gap paradigm and development of visual attention. *Infant Behavior and Development*, *20*(4), 449–455. https://doi.org/10.1016/S0163-6383(97)90035-7
Matthey, S. (2001). The Sleep and Settle Questionnaire for parents of infants: Psychometric properties. *Journal of Paediatrics and Child Health*, *37*(5), 470–475. https://doi.org/10.1046/j.1440-1754.2001.00703.x
Mazza, S., Pepin, J. L., Naegele, B., Plante, J., Deschaux, C., & Levy, P. (2005). Most obstructive sleep apnoea patients exhibit vigilance and attention deficits on an extended battery of tests. *European Respiratory Journal*, *25*(1), 75–80.
McDonald, L., Wardle, J., Llewellyn, C. H., van Jaarsveld, C. H. M., & Fisher, A. (2014).

Predictors of shorter sleep in early childhood. *Sleep Medicine*, *15*(5), 536–540. https://doi.org/10.1016/j.sleep.2014.01.005

Mcdowall, P. S., Galland, B. C., Campbell, A. J., & Elder, D. E. (2017). *Parent knowledge of children's sleep: A systematic review*. https://doi.org/10.1016/j.smrv.2016.01.002

McGraw, K. O., & Wong, S. P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological Methods*, *1*(1), 30–46. https://doi.org/10.1037/1082-989X.1.1.30

McLay, L., Roche, L., France, K. G., Blampied, N. M., Lang, R., France, M., & Busch, C. (2019). Systematic review of the effectiveness of behaviorally-based interventions for sleep problems in people with rare genetic neurodevelopmental disorders. In *Sleep Medicine Reviews* (Vol. 46, pp. 54–63). W.B. Saunders Ltd. https://doi.org/10.1016/j.smrv.2019.04.004

Meddis, R. (1975). On the function of sleep. *Animal Behaviour*, *23*, 676–691.

Meißner, M., Pfeiffer, J., Pfeiffer, T., & Oppewal, H. (2019). Combining virtual reality and mobile eye tracking to provide a naturalistic experimental environment for shopper research. *Journal of Business Research*, *100*, 445–458. https://doi.org/10.1016/J.JBUSRES.2017.09.028

Meltzer, L. J., & Mindell, J. A. (2006). Sleep and Sleep Disorders in Children and Adolescents. *Psychiatric Clinics of North America*, *29*(4), 1059–1076. https://doi.org/10.1016/j.psc.2006.08.004

Meltzer, L. J., & Mindell, J. A. (2007). Relationship between child sleep disturbances and maternal sleep, mood, and parenting stress: A pilot study. *Journal of Family Psychology*, *21*(1), 67–73. https://doi.org/10.1037/0893-3200.21.1.67

Meltzer, L. J., Montgomery-Downs, H. E., Insana, S. P., & Walsh, C. M. (2012). Use of actigraphy for assessment in pediatric sleep research. *Sleep Medicine Reviews*, *16*(5), 463–475. https://doi.org/10.1016/j.smrv.2011.10.002

Meyer, M., Endedijk, H. M., Van Ede, F., & Hunnius, S. (2019). Theta oscillations in 4-year-olds are sensitive to task engagement and task demands. *Scientific Reports*, *9*(1), 1–11.

Michel, C., Stets, M., Parise, E., Reid, V. M., Striano, T., & Hoehl, S. (2015). Theta-and alpha-band EEG activity in response to eye gaze cues in early infancy. *Neuroimage*, *118*, 576–583.

Mikkelsen, K. B., Ebajemito, J. K., Bonmati-Carrion, M. A., Santhi, N., Revell, V. L., Atzori, G., della Monica, C., Debener, S., Dijk, D., & Sterr, A. (2019). Machine-learning-derived sleep–wake staging from around-the-ear electroencephalogram outperforms manual scoring and actigraphy. *Journal of Sleep Research*, *28*(2), e12786.

Mikkelsen, K. B., Villadsen, D. B., Otto, M., & Kidmose, P. (2017). Automatic sleep staging using ear-EEG. *Biomedical Engineering Online*, *16*(1), 111.

Mindell, J. A., Du Mond, C. E., Sadeh, A., Telofski, L. S., Kulkarni, N., & Gunn, E. (2011). Efficacy of an Internet-Based Intervention for Infant and Toddler Sleep Disturbances. *Sleep*, *34*(4), 451-458B. https://doi.org/10.1093/sleep/34.4.451

Mindell, J. A., & Lee, C. (2015). Sleep, mood, and development in infants. *Infant Behavior and Development*, *41*. https://doi.org/10.1016/j.infbeh.2015.08.004

Mindell, J. A., Owens, J. A., & Carskadon, M. A. (1999). Developmental Features of Sleep. *Child and Adolescent Psychiatric Clinics of North America*, *8*(4), 695–725. https://doi.org/10.1016/S1056-4993(18)30149-4

Mindell, J. A., Sadeh, A., Wiegand, B., How, T. H., & Goh, D. Y. T. (2010). *Cross-cultural differences in infant and toddler sleep*. https://doi.org/10.1016/j.sleep.2009.04.012

Mindell, J. A., Telofski, L. S., Wiegand, B., & Kurtz, E. S. (2009). A nightly bedtime routine: impact on sleep in young children and maternal mood. *Sleep*, *32*(5), 599–606.

Mirmiran, M., Maas, Y. G. H., & Ariagno, R. L. (2003). Development of fetal and neonatal sleep and circadian rhythms. In *Sleep Medicine Reviews* (Vol. 7, Issue 4, pp. 321–334). W.B. Saunders Ltd. https://doi.org/10.1053/smrv.2002.0243

Mitra, A., Snyder, A. Z., Tagliazucchi, E., Laufs, H., Elison, J., Emerson, R. W., Shen, M. D., Wolff, J. J., Botteron, K. N., Dager, S., Estes, A. M., Evans, A., Gerig, G., Hazlett, H. C., Paterson, S. J., Schultz, R. T., Styner, M. A., Zwaigenbaum, L., Schlaggar, B. L., … Raichle, M. (2017). Resting-state fMRI in sleeping infants more closely resembles adult sleep than adult wakefulness. *PLOS ONE*, *12*(11), e0188122. https://doi.org/10.1371/journal.pone.0188122

Miyata, S., Noda, A., Iwamoto, K., Kawano, N., Okuda, M., & Ozaki, N. (2013). Poor sleep quality impairs cognitive performance in older adults. *Journal of Sleep Research*, *22*(5), 535–541. https://doi.org/10.1111/jsr.12054

Moelle, M., & Born, J. (2011). Slow oscillations orchestrating fast oscillations and memory consolidation. In *Progress in brain research* (Vol. 193, pp. 93–110). Elsevier.

Mohns, E. J., & Blumberg, M. S. (2010). Neocortical activation of the hippocampus during sleep in infant rats. *Journal of Neuroscience*, *30*(9), 3438–3449. https://doi.org/10.1523/JNEUROSCI.4832-09.2010

Möhring, W., Urfer-Maurer, N., Brand, S., Holsboer-Trachsler, E., Weber, P., Grob, A., & Lemola, S. (2019). The association between sleep and dual-task performance in preterm and full-term children: an exploratory study. *Sleep Medicine*, *55*, 100–108. https://doi.org/10.1016/j.sleep.2018.11.024

Montagna, P., Gambetti, P., Cortelli, P., & Lugaresi, E. (2003). Familial and sporadic fatal insomnia. In *Lancet Neurology* (Vol. 2, Issue 3, pp. 167–176). Lancet Publishing Group. https://doi.org/10.1016/S1474-4422(03)00323-5

Montgomery-Downs, H. E., & Gozal, D. (2006). Snore-associated sleep fragmentation in infancy: Mental development effects and contribution of secondhand cigarette smoke exposure. *Pediatrics*, *117*(3), e496-502. https://doi.org/10.1542/peds.2005-1785

Montgomery-Downs, H., & Thoman, E. B. (1998). Biological and behavioral correlates of quiet sleep respiration rates in infants. *Physiology & Behavior*, *64*(5), 637–643.

Morales-Muñoz, I., Nolvi, S., Virta, M., Karlsson, H., Paavonen, E. J., & Karlsson, L. (2020). The longitudinal associations between temperament and sleep during the first year of life. *Infant Behavior and Development*, *61*, 101485.

Morin, C. M., LeBlanc, M., Bélanger, L., Ivers, H., Mérette, C., & Savard, J. (2011). Prevalence of insomnia and its treatment in Canada. *Canadian Journal of Psychiatry. Revue Canadienne de Psychiatrie*, *56*(9), 540–548. https://doi.org/10.1177/070674371105600905

Moruzzi, G., & Magoun, H. W. (1949). Brain stem reticular formation and activation of the EEG. *Electroencephalography and Clinical Neurophysiology*, *1*(1–4), 455–473.

Mullen, E. M. (1995). *Mullen scales of early learning*. AGS Circle Pines, MN.

Müller, S., Hemmi, M. H., Wilhelm, F. H., Barr, R. G., & Schneider, S. (2011). Parental report of infant sleep behavior by electronic versus paper-and-pencil diaries, and their relationship to actigraphic sleep measurement. *Journal of Sleep Research*. https://doi.org/10.1111/j.1365-2869.2011.00926.x

Nakagawa, A., & Sukigara, M. (2019). Early development of attentional disengagement and phasic alertness. *Infant Behavior and Development*, *55*, 38–45. https://doi.org/10.1016/j.infbeh.2019.02.004

Nakahara, K., Michikawa, T., Morokuma, S., Ogawa, M., Kato, K., Sanefuji, M., Shibata, E., Tsuji, M., Shimono, M., Kawamoto, T., Ohga, S., Kusuhara, K., Kamijima, M., Yamazaki, S., Ohya, Y., Kishi, R., Yaegashi, N., Hashimoto, K., Mori, C., … Katoh, T. (2020). Association of maternal sleep before and during pregnancy with preterm

birth and early infant sleep and temperament. *Scientific Reports*, *10*(1), 1–14. https://doi.org/10.1038/s41598-020-67852-3

Näsi, T., Virtanen, J., Noponen, T., Toppila, J., Salmi, T., & Ilmoniemi, R. J. (2011). Spontaneous Hemodynamic Oscillations during Human Sleep and Sleep Stage Transitions Characterized with Near-Infrared Spectroscopy. *PLoS ONE*, *6*(10), e25415. https://doi.org/10.1371/journal.pone.0025415

Netsi, E., Santos, I. S., Stein, A., Barros, F. C., Barros, A. J. D., & Matijasevich, A. (2017). A different rhythm of life: sleep patterns in the first 4 years of life and associated sociodemographic characteristics in a large Brazilian birth cohort. *Sleep Medicine*, *37*, 77–87. https://doi.org/10.1016/j.sleep.2017.06.001

Nguyen, T., Babawale, O., Kim, T., Jo, H. J., Liu, H., & Kim, J. G. (2018). Exploring brain functional connectivity in rest and sleep states: a fNIRS study. *Scientific Reports*, *8*(1), 1–10. https://doi.org/10.1038/s41598-018-33439-2

Novosad, C., Freudigman, K., & Thoman, E. B. (1999). Sleep Patterns in Newborns and Temperament at Eight Months: A Preliminary Study. *Journal of Developmental & Behavioral Pediatrics*, *20*(2). https://journals.lww.com/jrnldbp/Fulltext/1999/04000/Sleep_Patterns_in_Newborns_and_Temperament_at.5.aspx

Nyhus, E., & Curran, T. (2010). Functional role of gamma and theta oscillations in episodic memory. In *Neuroscience and Biobehavioral Reviews* (Vol. 34, Issue 7, pp. 1023–1035). Pergamon. https://doi.org/10.1016/j.neubiorev.2009.12.014

O'Callaghan, F. V., Al Mamun, A., O'Callaghan, M., Clavarino, A., Williams, G. M., Bor, W., Heussler, H., & Najman, J. M. (2010). The link between sleep problems in infancy and early childhood and attention problems at 5 and 14years: Evidence from a birth cohort study. *Early Human Development*, *86*(7), 419–424. https://doi.org/10.1016/j.earlhumdev.2010.05.020

Ohayon, M. M., & Vecchierini, M. F. (2005). Normative Sleep Data, Cognitive Function and Daily Living Activities in Older Adults in the Community. *Sleep*, *28*(8), 981–989. https://doi.org/10.1093/sleep/28.8.981

Orekhova, E. V., Stroganova, T. A., Posikera, I. N., & Elam, M. (2006). EEG theta rhythm in infants and preschool children. *Clinical Neurophysiology*, *117*(5), 1047–1062. https://doi.org/10.1016/j.clinph.2005.12.027

Orekhova, E.V., Elsabbagh, M., Jones, E. J., Dawson, G., Charman, T., Baron-Cohen, S., Bedford, R., Bolton, P., Fernandes, J., Ganea, N., Garwood, H., Gliga, T., Hudry, K., Murias, M., Ribeiro, H., Tucker, L., Volein, A., & Webb, S. J. (2014). EEG hyper-connectivity in high-risk infants is associated with later autism. *Journal of Neurodevelopmental Disorders*, *6*(1), 40. https://doi.org/10.1186/1866-1955-6-40

Orekhova, E.V., Stroganova, T. A., & Posikera, I. N. (1999). Theta synchronization during sustained anticipatory attention in infants over the second half of the first year of life. *International Journal of Psychophysiology*, *32*(2), 151–172. https://doi.org/10.1016/S0167-8760(99)00011-2

Ouyang, M., Dubois, J., Yu, Q., Mukherjee, P., & Huang, H. (2019). Delineation of early brain development from fetuses to infants with diffusion MRI and beyond. In *NeuroImage* (Vol. 185, pp. 836–850). Academic Press Inc. https://doi.org/10.1016/j.neuroimage.2018.04.017

Owens, J. A., Spirito, A., & McGuinn, M. (2000). The Children's Sleep Habits Questionnaire (CSHQ): psychometric properties of a survey instrument for school-aged children. *Sleep-New York-*, *23*(8), 1043–1052.

Papageorgiou, K. A., Smith, T. J., Wu, R., Johnson, M. H., Kirkham, N. Z., & Ronald, A. (2014). Individual differences in infant fixation duration relate to attention and behavioral control in childhood. *Psychological Science*, *25*(7), 1371–1379.

Patra, K., Greene, M. M., Patel, A. L., & Meier, P. (2016). Maternal Education Level

Predicts Cognitive, Language, and Motor Outcome in Preterm Infants in the Second Year of Life. *American Journal of Perinatology*, *33*(8), 738–744. https://doi.org/10.1055/s-0036-1572532

Paul, F., Schredl, M., & Alpers, G. W. (2015). Nightmares affect the experience of sleep quality but not sleep architecture: an ambulatory polysomnographic study. *Borderline Personality Disorder and Emotion Dysregulation*, *2*(1), 3. https://doi.org/10.1186/s40479-014-0023-4

Peters, S. E. (2017). *Dense array EEG measures of infant sleep: microstructure and topography as biomarkers of cognitive development*. Rutgers University-Graduate School-Newark.

Philbrook, L. E., & Teti, D. M. (2016). Bidirectional associations between bedtime parenting and infant sleep: Parenting quality, parenting practices, and their interaction. *Journal of Family Psychology*, *30*(4), 431–441. https://doi.org/10.1037/fam0000198

Pinti, P., Aichelburg, C., Gilbert, S., Hamilton, A., Hirsch, J., Burgess, P., & Tachtsidis, I. (2018). A Review on the Use of Wearable Functional Near-Infrared Spectroscopy in Naturalistic Environments. *Japanese Psychological Research*, *60*(4), 347–373. https://doi.org/10.1111/jpr.12206

Pinti, P., Aichelburg, C., Lind, F., Power, S., Swingler, E., Merla, A., Hamilton, A., Gilbert, S., Burgess, P., & Tachtsidis, I. (2015). Using Fiberless, Wearable fNIRS to Monitor Brain Activity in Real-world Cognitive Tasks. *Journal of Visualized Experiments*, *106*, e53336. https://doi.org/10.3791/53336

Pinti, P., Scholkmann, F., Hamilton, A., Burgess, P., & Tachtsidis, I. (2018). Current Status and Issues Regarding Pre-processing of fNIRS Neuroimaging Data: An Investigation of Diverse Signal Filtering Methods Within a General Linear Model Framework. *Frontiers in Human Neuroscience*, *12*, 505. https://doi.org/10.3389/fnhum.2018.00505

Pisch, M., Wiesemann, F., & Karmiloff-Smith, A. (2018). Infant Wake after Sleep onset serves as a marker for different trajectories in cognitive development. *Journal of Child Psychology and Psychiatry*, *Accepted*.

Piteo, A. M., Kennedy, J. D., Roberts, R. M., Martin, A. J., Nettelbeck, T., Kohler, M. J., & Lushington, K. (2011). Snoring and cognitive development in infancy. *Sleep Medicine*, *12*(10), 981–987.

Piteo, A. M., Lushington, K., Roberts, R. M., Van den Heuvel, C. J., Nettelbeck, T., Kohler, M. J., Martin, A. J., & Kennedy, J. D. (2011). Prevalence of snoring and associated factors in infancy. *Sleep Medicine*, *12*(8), 787–792.

Pollonini, L., Bortfeld, H., & Oghalai, J. S. (2016). PHOEBE: a method for real time mapping of optodes-scalp coupling in functional near-infrared spectroscopy. *Biomed. Opt. Express*, *7*(12), 5104–5119. https://doi.org/10.1364/BOE.7.005104

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, *13*(1), 25–42.

Powell, G., Wass, S. V, Erichsen, J. T., & Leekam, S. R. (2016). First evidence of the feasibility of gaze-contingent attention training for school children with autism. *Autism*, *20*(8), 927–937. https://doi.org/10.1177/1362361315617880

Price, A. M. H., Brown, J. E., Bittman, M., Wake, M., Quach, J., & Hiscock, H. (2014). Children's sleep patterns from 0 to 9 years: Australian population longitudinal study. *Archives of Disease in Childhood*, *99*(2), 119–125. https://doi.org/10.1136/archdischild-2013-304150

Putnam, S. P., Helbig, A. L., Gartstein, M. A., Rothbart, M. K., & Leerkes, E. (2014). Development and assessment of short and very short forms of the Infant Behavior Questionnaire–Revised. *Journal of Personality Assessment*, *96*(4), 445–458.

Putnam, S. P., Rothbart, M. K., & Gartstein, M. A. (2008). Homotypic and heterotypic

continuity of fine-grained temperament during infancy, toddlerhood, and early childhood. *Infant and Child Development*, *17*(4), 387–405. https://doi.org/10.1002/icd.582

Quaresima, V., Lepanto, R., & Ferrari, M. (2003). The use of near infrared spectroscopy in sports medicine. *Journal of Sports Medicine and Physical Fitness*, *43*(1), 1.

Rasch, B., & Born, J. (2013). About sleep's role in memory. *Physiological Reviews*, *93*(2), 681–766. https://doi.org/10.1152/physrev.00032.2012

Rawson, H. E., Bloomer, K., & Kendall, A. (1994). Stress, anxiety, depression, and physical illness in college students. *Journal of Genetic Psychology*, *155*(3), 321–330. https://doi.org/10.1080/00221325.1994.9914782

Rechtschaffen, A. (1968). A manual for standardized terminology, techniques and scoring system for sleep stages in human subjects. *Brain Information Service*.

Reddy, R., El Youssef, J., Winters-Stone, K., Branigan, D., Leitschuh, J., Castle, J., & Jacobs, P. G. (2018). The effect of exercise on sleep in adults with type 1 diabetes. *Diabetes, Obesity and Metabolism*, *20*(2), 443–447.

Reynolds, G. D., & Romano, A. C. (2016). The development of attention systems and working memory in infancy. In *Frontiers in Systems Neuroscience* (Vol. 10, Issue MAR, p. 15). Frontiers Research Foundation. https://doi.org/10.3389/fnsys.2016.00015

Richards, J. E. (2010). The development of attention to simple and complex visual stimuli in infants: Behavioral and psychophysiological measures. In *Developmental Review* (Vol. 30, Issue 2, pp. 203–219). Academic Press. https://doi.org/10.1016/j.dr.2010.03.005

Rie, S., Steensel, R. C. M., Gelderen, A. J. S., & Severiens, S. (2020). Level of abstraction in parent–child interactions: the role of activity type and socioeconomic status. *Journal of Research in Reading*, *43*(1), 140–159. https://doi.org/10.1111/1467-9817.12294

Rigato, S., Stets, M., Bonneville-Roussy, A., & Holmboe, K. (2020). Impact of maternal depressive symptoms on the development of infant temperament: Cascading effects during the first year of life. *Social Development*, *29*(4), 1115–1133. https://doi.org/10.1111/sode.12448

Rigney, G., Ali, N. S., Corkum, P. V., Brown, C. A., Constantin, E., Godbout, R., Hanlon-Dearman, A., Ipsiroglu, O., Reid, G. J., Shea, S., Smith, I. M., Van der Loos, H. F. M., & Weiss, S. K. (2018). A systematic review to explore the feasibility of a behavioural sleep intervention for insomnia in children with neurodevelopmental disorders: A transdiagnostic approach. In *Sleep Medicine Reviews* (Vol. 41, pp. 244–254). W.B. Saunders Ltd. https://doi.org/10.1016/j.smrv.2018.03.008

Rivkees, S. A. (2003). Developing Circadian Rhythmicity in Infants. *PEDIATRICS*, *112*(2), 373–381. https://doi.org/10.1542/peds.112.2.373

Roche-Labarbe, N., Wallois, F., Ponchel, E., Kongolo, G., & Grebe, R. (2007). Coupled oxygenation oscillation measured by NIRS and intermittent cerebral activation on EEG in premature infants. *NeuroImage*, *36*(3), 718–727. https://doi.org/10.1016/j.neuroimage.2007.04.002

Roenneberg, T., Kuehnle, T., Juda, M., Kantermann, T., Allebrandt, K., Gordijn, M., & Merrow, M. (2007). Epidemiology of the human circadian clock. In *Sleep Medicine Reviews* (Vol. 11, Issue 6, pp. 429–438). https://doi.org/10.1016/j.smrv.2007.07.005

Roffwarg, H. P., Muzio, J. N., & Dement, W. C. (1966). Ontogenetic development of the human sleep-dream cycle. *Science*, *152*(3722), 604–619. https://doi.org/10.1126/science.152.3722.604

Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. Advances in Methods and Practices in

Psychological Science, 1(1), 27-42.
Rose, S. A., Feldman, J. F., & Jankowski, J. J. (2012). Implications of infant cognition for executive functions at age 11. *Psychological Science*, *23*(11), 1345–1355. https://doi.org/10.1177/0956797612444902
Ross-Sheehy, S., Schneegans, S., & Spencer, J. P. (2015). The Infant Orienting With Attention Task: Assessing the Neural Basis of Spatial Attention in Infancy. *Infancy*, *20*(5), 467–506. https://doi.org/10.1111/infa.12087
Rothbart, M. K. (1981). Measurement of temperament in infancy. *Child Development*, 569–578.
Rovee-Collier, C. K., Sullivan, M. W., Enright, M., Lucas, D., & Fagen, J. W. (1980). Reactivation of infant memory. *Science (New York, N.Y.)*, *208*(4448), 1159–1161. https://doi.org/10.1126/science.7375924
Saby, J. N., & Marshall, P. J. (2012). The utility of EEG band power analysis in the study of infancy and early childhood. *Developmental Neuropsychology*, *37*(3), 253–273. https://doi.org/10.1080/87565641.2011.614663
Sadeh, A., Mindell, J., Luedtke, K., & Wiegand, B. (2009). Sleep and sleep ecology in the first 3 years: a web-based study. *Journal of Sleep Research*, *18*(1), 60–73. https://doi.org/10.1111/j.1365-2869.2008.00699.x
Sadeh, A. (1994). Assessment of intervention for infant night waking: parental reports and activity-based home monitoring. *Journal of Consulting and Clinical Psychology*, *62*(1), 63–68. http://www.ncbi.nlm.nih.gov/pubmed/8034831
Sadeh, A, Alster, J., Urbach, D., & Lavie, P. (1989). Actigraphically based automatic bedtime sleep-wake scoring: validity and clinical applications. *Journal of Ambulatory Monitoring*, *2*(3), 209–216.
Sadeh, A. (2004). *A Brief Screening Questionnaire for Infant Sleep Problems: Validation and Findings for an Internet Sample*. http://www.pediatrics.org/cgi/content/full/113/6/e570
Sadeh, A. (2011). The role and validity of actigraphy in sleep medicine: an update. *Sleep Medicine Reviews*, *15*(4), 259–267. https://doi.org/10.1016/j.smrv.2010.10.001
Sadeh, A. (2015). III. SLEEP ASSESSMENT METHODS. *Monographs of the Society for Research in Child Development*, *80*(1), 33–48. https://doi.org/10.1111/mono.12143
Sadeh, A., De Marcas, G., Guri, Y., Berger, A., Tikotzky, L., & Bar-Haim, Y. (2015). Infant Sleep Predicts Attention Regulation and Behavior Problems at 3–4 Years of Age. *Developmental Neuropsychology*, *40*(3), 122–137. https://doi.org/10.1080/87565641.2014.973498
Sadeh, A., Hauri, P. J., Kripke, D. F., & Lavie, P. (1995). The Role of Actigraphy in the Evaluation of Sleep Disorders. *Sleep*, *18*(4), 288–302. https://doi.org/10.1093/sleep/18.4.288
Sadeh, Avi, Juda-Hanael, M., Livne-Karp, E., Kahn, M., Tikotzky, L., Anders, T. F., Calkins, S., & Sivan, Y. (2016). Low parental tolerance for infant crying: an underlying factor in infant sleep problems? *Journal of Sleep Research*, *25*(5), 501–507. https://doi.org/10.1111/jsr.12401
Sadeh, A., Lavie, P., Scher, A., Tirosh, E., & Epstein, R. (1991). Actigraphic home-monitoring sleep-disturbed and control infants and young children: a new method for pediatric assessment of sleep-wake patterns. *Pediatrics*, *87*(4), 494–499.
Sadeh, A., Sharkey, M., & Carskadon, M. A. (1994). Activity-Based Sleep-Wake Identification: An Empirical Test of Methodological Issues. *Sleep*, *17*(3), 201–207. https://doi.org/10.1093/sleep/17.3.201
Sadeh, A., Tikotzky, L., & Scher, A. (2010). Parenting and infant sleep. In *Sleep Medicine Reviews*. https://doi.org/10.1016/j.smrv.2009.05.003

Sänger, J., Bechtold, L., Schoofs, D., Blaszkewicz, M., & Wascher, E. (2014). The influence of acute stress on attention mechanisms and its electrophysiological correlates. *Frontiers in Behavioral Neuroscience*, *8*(OCT), 353. https://doi.org/10.3389/fnbeh.2014.00353

Saper, C. B. (2013). The neurobiology of sleep. *CONTINUUM: Lifelong Learning in Neurology*, *19*(1), 19–31.

Saper, C. B., & Fuller, P. M. (2017). Wake–sleep circuitry: an overview. In *Current Opinion in Neurobiology* (Vol. 44, pp. 186–192). Elsevier Ltd. https://doi.org/10.1016/j.conb.2017.03.021

Scerif, G. (2010). Attention trajectories, mechanisms and outcomes: at the interface between developing cognition and environment. *Developmental Science*, *13*(6), 805–812. https://doi.org/10.1111/j.1467-7687.2010.01013.x

Schabus, M., Dang-Vu, T. T., Albouy, G., Balteau, E., Boly, M., Carrier, J., Darsaud, A., Degueldre, C., Desseilles, M., Gais, S., Phillips, C., Rauchs, G., Schnakers, C., Sterpenich, V., Vandewalle, G., Luxen, A., & Maquet, P. (2007). Hemodynamic cerebral correlates of sleep spindles during human non-rapid eye movement sleep. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(32), 13164–13169. https://doi.org/10.1073/pnas.0703084104

Schabus, M., Hödlmoser, K., Gruber, G., Sauter, C., Anderer, P., Klö, G., Parapatics, S., Saletu, B., Klimesch, W., & Zeitlhofer, J. (2006). Sleep spindle-related activity in the human EEG and its relation to general cognitive and learning abilities. *European Journal of Neuroscience*, *23*(7), 1738–1746. https://doi.org/10.1111/j.1460-9568.2006.04694.x

Scher, A. (2005). Infant sleep at 10 months of age as a window to cognitive development. *Early Human Development*. https://doi.org/10.1016/j.earlhumdev.2004.07.005

Scher, A., & Asher, R. (2004). Is attachment security related to sleep-wake regulation? Mother's reports and objective sleep recordings. *Infant Behavior and Development*, *27*(3), 288–302. https://doi.org/10.1016/j.infbeh.2003.12.002

Scher, A., Tse, L., Hayes, V. E., & Tardif, M. (2008). Sleep difficulties in infants at risk for developmental delays: A longitudinal study. *Journal of Pediatric Psychology*. https://doi.org/10.1093/jpepsy/jsn013

Scher, M. S., Steppe, D. A., & Banks, D. L. (1996). Prediction of lower developmental performances of healthy neonates by neonatal EEG-sleep measures. *Pediatric Neurology*, *14*(2), 137–144.

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage*, *85*, 6–27. https://doi.org/10.1016/j.neuroimage.2013.05.004

Scholle, S., Zwacka, G., & Scholle, H. C. (2007). Sleep spindle evolution from infancy to adolescence. *Clinical Neurophysiology*, *118*(7), 1525–1531. https://doi.org/10.1016/j.clinph.2007.03.007

Schonhaut, L., Armijo, I., Schönstedt, M., Alvarez, J., & Cordero, M. (2013). Validity of the ages and stages questionnaires in term and preterm infants. *Pediatrics*, *131*(5), e1468–e1474.

Scullin, M. K., Fairley, J., Decker, M. J., & Bliwise, D. L. (2017). The Effects of an Afternoon Nap on Episodic Memory in Young and Older Adults. *Sleep*, *40*(5). https://doi.org/10.1093/sleep/zsx035

Seehagen, S., Konrad, C., Herbert, J. S., & Schneider, S. (2015). Timely sleep facilitates declarative memory consolidation in infants. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(5), 1625–1629. https://doi.org/10.1073/pnas.1414000112

Seifer, R., Sameroff, A., Dickstein, S., Schiller, M., & Hayden, L. C. (2004). Your own children are special: Clues to the sources of reporting bias in temperament assessments. *Infant Behavior and Development*, *27*(3), 323–341. https://doi.org/10.1016/j.infbeh.2003.12.005

Shimko, A. N. (2019). Sleep in infancy: A concept analysis. *Journal of Pediatric Nursing*, *47*, 100–105. https://doi.org/10.1016/J.PEDN.2019.05.001

Shin, J., Von Lühmann, A., Kim, D. W., Mehnert, J., Hwang, H. J., & Müller, K. R. (2018). Data descriptor: Simultaneous acquisition of EEG and NIRS during cognitive tasks for an open access dataset. *Scientific Data*, *5*(1), 1–16. https://doi.org/10.1038/sdata.2018.3

Short, M. A., Blunden, S., Rigney, G., Matricciani, L., Coussens, S., Reynolds, C. M., & Galland, B. (2018). Cognition and objectively measured sleep duration in children: a systematic review and meta-analysis. *Sleep Health*, *4*(3), 292–300.

Simor, P., Horváth, K., Gombos, F., Takács, K. P., & Bódizs, R. (2012). Disturbed dreaming and sleep quality: altered sleep architecture in subjects with frequent nightmares. *European Archives of Psychiatry and Clinical Neuroscience*, *262*(8), 687–696. https://doi.org/10.1007/s00406-012-0318-7

Sinai, D., & Tikotzky, L. (2012). Infant sleep, parental sleep and parenting stress in families of mothers on maternity leave and in families of working mothers. *Infant Behavior and Development*, *35*(2), 179–186. https://doi.org/10.1016/j.infbeh.2012.01.006

Sio, U. N., Monaghan, P., & Ormerod, T. (2013). Sleep on it, but only if it is difficult: effects of sleep on problem solving. *Memory & Cognition*, *41*(2), 159–166.

So, K., Buckley, P., Adamson, T. M., & Horne, R. S. C. (2005). Actigraphy Correctly Predicts Sleep Behavior in Infants Who Are Younger than Six Months, When Compared with Polysomnography. *Pediatric Research*, *58*(4), 761–765. https://doi.org/10.1203/01.PDR.0000180568.97221.56

So, K., Michael Adamson, T., & Horne, R. S. C. (2007). The use of actigraphy for assessment of the development of sleep/wake patterns in infants during the first 12 months of life. *Journal of Sleep Research*, *16*(2), 181–187.

Sorondo, B. M., & Reeb-Sutherland, B. C. (2015). Associations between infant temperament, maternal stress, and infants' sleep across the first year of life. *Infant Behavior and Development*, *39*, 131–135. https://doi.org/10.1016/j.infbeh.2015.02.010

Spielberger, C. D. (2010). State-Trait Anxiety Inventory. In *The Corsini Encyclopedia of Psychology* (pp. 1–1). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470479216.corpsy0943

Sporns, O. (2010). *Networks of the Brain*. MIT press.

Spruyt, K., Aitken, R. J., So, K., Charlton, M., Adamson, T. M., & Horne, R. S. C. (2008). Relationship between sleep/wake patterns, temperament and overall development in term infants over the first year of life. *Early Human Development*. https://doi.org/10.1016/j.earlhumdev.2007.07.002

Squires, J., Bricker, D., & Potter, L. (1997). Revision of a parent-completed developmental screening tool: Ages and Stages Questionnaires. *Journal of Pediatric Psychology*, *22*(3), 313–328.

Stevens, C., & Bavelier, D. (2012). The role of selective attention on academic foundations: A cognitive neuroscience perspective. *Developmental Cognitive Neuroscience*, *2*(SUPPL. 1), S30–S48. https://doi.org/10.1016/j.dcn.2011.11.001

Strijkstra, A. M., Beersma, D. G. M., Drayer, B., Halbesma, N., & Daan, S. (2003). Subjective sleepiness correlates negatively with global alpha (8-12 Hz) and positively with central frontal theta (4-8 Hz) frequencies in the human resting awake electroencephalogram. *Neuroscience Letters*, *340*(1), 17–20.

https://doi.org/10.1016/S0304-3940(03)00033-8
Stroganova, T. A., & Orekhova, E. V. (2007). EEG and infant states. *Infant EEG and Event-Related Potentials*, *251*, 280.
Sun, W., Li, S. X., Jiang, Y., Xu, X., Spruyt, K., Zhu, Q., Tseng, C., & Jiang, F. (2018). A community-based study of sleep and cognitive development in infants and toddlers. *Journal of Clinical Sleep Medicine*, *14*(6), 977–984.
Sun, W., Wang, G., Jiang, Y., Song, Y., Dong, S., Lin, Q., Deng, Y., Zhu, Q., & Jiang, F. (2016). Six-month-old infant long sleepers prefer a human face. *Sleep Medicine*, *27–28*. https://doi.org/10.1016/j.sleep.2016.08.018
Szymanski, J. S. (1918). Versuche über Aktivität und Ruhe bei Säuglingen. *Pflügers Archiv European Journal of Physiology*, *172*(1), 424–429.
Tachtsidis, I., & Scholkmann, F. (2016). False positives and false negatives in functional near-infrared spectroscopy: issues, challenges, and the way forward. *Neurophotonics*, *3*(3), 31405.
Tagliazucchi, E., & Laufs, H. (2014). Decoding Wakefulness Levels from Typical fMRI Resting-State Data Reveals Reliable Drifts between Wakefulness and Sleep. *Neuron*, *82*(3), 695–708. https://doi.org/10.1016/j.neuron.2014.03.020
Tamis-LeMonda, C. S., Briggs, R. D., McClowry, S. G., & Snow, D. L. (2009). Maternal control and sensitivity, child gender, and maternal education in relation to children's behavioral outcomes in African American families. *Journal of Applied Developmental Psychology*, *30*(3), 321–331. https://doi.org/10.1016/j.appdev.2008.12.018
Tarullo, A. R., Balsam, P. D., & Fifer, W. P. (2011). Sleep and infant learning. *Infant and Child Development*, *20*(1), 35–46. https://doi.org/10.1002/icd.685
Tarullo, A. R., Isler, J. R., Condon, C., Violaris, K., Balsam, P. D., & Fifer, W. P. (2016). Neonatal eyelid conditioning during sleep. *Developmental Psychobiology*, *58*(7), 875–882. https://doi.org/10.1002/dev.21424
Taylor, D. J., Lichstein, K. L., Durrence, H. H., Reidel, B. W., & Bush, A. J. (2005). Epidemiology of insomnia, depression, and anxiety. *Sleep*, *28*(11), 1457–1464.
Team, Rs. (2016). *RStudio: Integrated Development for R. RStudio, Inc., Boston, Massachusetts, USA*.
Terrill, P. I., Wilson, S. J., Suresh, S., Cooper, D. M., & Dakin, C. (2010). Attractor Structure Discriminates Sleep States: Recurrence Plot Analysis Applied to Infant Breathing Patterns. *IEEE Transactions on Biomedical Engineering*, *57*(5), 1108–1116. https://doi.org/10.1109/TBME.2009.2038362
Teti, D. M., Kim, B. R., Mayer, G., & Countermine, M. (2010). Maternal Emotional Availability at Bedtime Predicts Infant Sleep Quality. *Journal of Family Psychology*, *24*(3), 307–315. https://doi.org/10.1037/a0019306
Tham, E., Schneider, N., & Broekman, B. (2017). Infant sleep and its relation with cognition and growth: a narrative review. *Nature and Science of Sleep*, *Volume 9*, 135–149. https://doi.org/10.2147/NSS.S125992
Thunström, M. (2007). Severe sleep problems in infancy associated with subsequent development of attention-deficit/hyperactivity disorder at 5.5 years of age. *Acta Paediatrica*, *91*(5), 584–592. https://doi.org/10.1111/j.1651-2227.2002.tb03281.x
Tikotzky, L., & Volkovich, E. (2019). Infant nocturnal wakefulness: a longitudinal study comparing three sleep assessment methods. *Sleep*, *42*(1). https://doi.org/10.1093/sleep/zsy191
Tononi, G., & Cirelli, C. (2003). Sleep and synaptic homeostasis: A hypothesis. *Brain Research Bulletin*, *62*(2), 143–150. https://doi.org/10.1016/j.brainresbull.2003.09.004
Tononi, G., & Cirelli, C. (2014). Sleep and the Price of Plasticity: From Synaptic and Cellular Homeostasis to Memory Consolidation and Integration. In *Neuron* (Vol.

81, Issue 1). https://doi.org/10.1016/j.neuron.2013.12.025
Tsai, S.-Y., Burr, R. L., & Thomas, K. A. (2009). Effect of external motion on correspondence between infant actigraphy and maternal diary. *Infant Behavior and Development*, *32*(3), 340–343. https://doi.org/10.1016/J.INFBEH.2009.02.002
Tüshaus, L., Omlin, X., Tuura, R. O., Federspiel, A., Luechinger, R., Staempfli, P., Koenig, T., & Achermann, P. (2017). In human non-REM sleep, more slow-wave activity leads to less blood flow in the prefrontal cortex. *Scientific Reports*, *7*(1), 14993. https://doi.org/10.1038/s41598-017-12890-7
Van Dongen, H. P. A., & Dinges, D. F. (2005). Sleep, circadian rhythms, and psychomotor vigilance. In *Clinics in Sports Medicine* (Vol. 24, Issue 2, pp. 237–249). W.B. Saunders. https://doi.org/10.1016/j.csm.2004.12.007
van Wieringen, K., & Cribbie, R. A. (2014). Evaluating clinical significance: Incorporating robust statistics with normative comparison tests. *British Journal of Mathematical and Statistical Psychology*, *67*(2), 213–230.
Verweij, I. M., Romeijn, N., Smit, D. J. A., Piantoni, G., Van Someren, E. J. W., & van der Werf, Y. D. (2014). Sleep deprivation leads to a loss of functional connectivity in frontal brain regions. *BMC Neuroscience*, *15*(1), 88. https://doi.org/10.1186/1471-2202-15-88
Villringer, A., Planck, J., Hock, C., Schleinkofer, L., & Dirnagl, U. (1993). Near infrared spectroscopy (NIRS): A new tool to study hemodynamic changes during activation of brain function in human adults. *Neuroscience Letters*, *154*(1–2), 101–104. https://doi.org/10.1016/0304-3940(93)90181-J
Volkovich, E., Ben-Zion, H., Karny, D., Meiri, G., & Tikotzky, L. (2015). Sleep patterns of co-sleeping and solitary sleeping infants and mothers: a longitudinal study. *Sleep Medicine*, *16*(11), 1305–1312. https://doi.org/10.1016/J.SLEEP.2015.08.016
Vyazovskiy, V. V., Cirelli, C., & Tononi, G. (2011). Electrophysiological correlates of sleep homeostasis in freely behaving rats. In *Progress in Brain Research* (Vol. 193, pp. 17–38). Elsevier B.V. https://doi.org/10.1016/B978-0-444-53839-0.00002-8
Vyazovskiy, V. V., Riedner, B. A., Cirelli, C., & Tononi, G. (2007). Sleep homeostasis and cortical synchronization: II. A local field potential study of sleep slow waves in the rat. *Sleep*, *30*(12), 1631–1642. https://doi.org/10.1093/sleep/30.12.1631
Vyazovskiy, V. V, Olcese, U., Hanlon, E. C., Nir, Y., Cirelli, C., & Tononi, G. (2011). Local sleep in awake rats. *Nature*, *472*(7344), 443–447.
Wade, N., & Tatler, B. W. (2005). *The moving tablet of the eye: The origins of modern eye movement research*. Oxford University Press, USA.
Walker, M. P., & van der Helm, E. (2009). Overnight Therapy? The Role of Sleep in Emotional Brain Processing. *Psychological Bulletin*, *135*(5), 731–748. https://doi.org/10.1037/a0016570
Wallois, F., Mahmoudzadeh, M., Patil, A., & Grebe, R. (2012). Usefulness of simultaneous EEG-NIRS recording in language studies. *Brain and Language*, *121*(2), 110–123. https://doi.org/10.1016/j.bandl.2011.03.010
Wass, S., Porayska-Pomsta, K., & Johnson, M. H. (2011). Training attentional control in infancy. *Current Biology : CB*, *21*(18), 1543–1547. https://doi.org/10.1016/j.cub.2011.08.004
Wass, S. V., Noreika, V., Georgieva, S., Clackson, K., Brightman, L., Nutbrown, R., Covarrubias, L. S., & Leong, V. (2018). Parental neural responsivity to infants' visual attention: How mature brains influence immature brains during social interaction. *PLOS Biology*, *16*(12), e2006328. https://doi.org/10.1371/journal.pbio.2006328
Wass, S. V, Jones, E. J. H., Gliga, T., Smith, T. J., Charman, T., Johnson, M. H., Baron-Cohen, S., Bedford, R., Bolton, P., & Chandler, S. (2015). Shorter spontaneous fixation durations in infants with later emerging autism. *Scientific Reports*, *5*, 8284.

Webb, J. M., & Fu, Y. H. (2021). Recent advances in sleep genetics. In *Current Opinion in Neurobiology* (Vol. 69, pp. 19–24). Elsevier Ltd. https://doi.org/10.1016/j.conb.2020.11.012

Webb, W. B. (1974). Sleep as an adaptive response. *Perceptual and Motor Skills*, *38*(3), 1023–1027. https://doi.org/10.2466/pms.1974.38.3c.1023

Webster, J. B., Kripke, D. F., Messin, S., Mullaney, D. J., & Wyborney, G. (1982). An Activity-Based Sleep Monitor System for Ambulatory Use. *Sleep*, *5*(4), 389–399. https://doi.org/10.1093/sleep/5.4.389

Weinraub, M., Friedman, S. L., Knoke, B., Houts, R., Bender, R. H., Susman, E. J., Bradley, R., & Williams, J. (2012). Patterns of developmental change in infants' nighttime sleep awakenings from 6 through 36 months of age. *Developmental Psychology*, *48*(6), 1511–1528. https://doi.org/10.1037/a0027680

Weiss, A. R., Johnson, N. L., Berger, N. A., & Redline, S. (2010). Validity of activity-based devices to estimate sleep. *Journal of Clinical Sleep Medicine*, *6*(4), 336–342. https://doi.org/10.5664/jcsm.27874

Weissbluth, M. (1981). Sleep duration and infant temperament. *The Journal of Pediatrics*, *99*(5), 817–819. https://doi.org/10.1016/S0022-3476(81)80422-2

Werner, H., Molinari, L., Guyer, C., & Jenni, O. G. (2008). Agreement Rates Between Actigraphy, Diary, and Questionnaire for Children's Sleep Patterns. *Archives of Pediatrics & Adolescent Medicine*, *162*(4), 350. https://doi.org/10.1001/archpedi.162.4.350

White, B. R., Snyder, A. Z., Cohen, A. L., Petersen, S. E., Raichle, M. E., Schlaggar, B. L., & Culver, J. P. (2009). Resting-state functional connectivity in the human brain revealed with diffuse optical tomography. *Neuroimage*, *47*(1), 148–156.

Whitford, T. J., Rennie, C. J., Grieve, S. M., Clark, C. R., Gordon, E., & Williams, L. M. (2007). Brain maturation in adolescence: Concurrent changes in neuroanatomy and neurophysiology. *Human Brain Mapping*, *28*(3), 228–237. https://doi.org/10.1002/hbm.20273

Wilhelm, I., Kurth, S., Ringli, M., Mouthon, A.-L., Buchmann, A., Geiger, A., Jenni, O. G., & Huber, R. (2014). Sleep slow-wave activity reveals developmental changes in experience-dependent plasticity. *Journal of Neuroscience*, *34*(37), 12568–12575.

Williams, K. E., & Sciberras, E. (2016). Sleep and self-regulation from birth to 7 years: A retrospective study of children with and without attention-deficit hyperactivity disorder at 8 to 9 years. *Journal of Developmental and Behavioral Pediatrics*, *37*(5), 385–394. https://doi.org/10.1097/DBP.0000000000000281

Winkelman, T., Naples, A., Rolison, M., McNaughton, K., Day, T., Hasselmo, S., McAllister, T., Ellison, K., Jarzabek, E., & Lewis, B. (2018). Resting EEG Architecture is Atypical in Children with ASD and Sleep Problems. *INSAR*, *9*(12), 15.

Wołyńczyk-Gmaj, D., & Szelenberger, W. (2011). Waking EEG in primary insomnia. *Acta Neurobiol Exp*, *71*, 387–392.

Xie, W., Mallin, B. M., & Richards, J. E. (2018). Development of infant sustained attention and its relation to EEG oscillations: an EEG and cortical source analysis study. *Developmental Science*, *21*(3), e12562. https://doi.org/10.1111/desc.12562

Xie, W., & Richards, J. E. (2017). The relation between infant covert orienting, sustained attention and brain activity. *Brain Topography*, *30*(2), 198–219.

Yavuz-Kodat, E., Reynaud, E., Geoffray, M.-M., Limousin, N., Franco, P., Bourgin, P., & Schroder, C. M. (2019). Validity of Actigraphy Compared to Polysomnography for Sleep Assessment in Children With Autism Spectrum Disorder. *Frontiers in Psychiatry*, *10*, 551. https://doi.org/10.3389/fpsyt.2019.00551

Yu, X., Quante, M., Rueschman, M., Ash, T., Kaplan, E. R., Guo, N., Horan, C. M., Haneuse, S., Davison, K., Taveras, E. M., & Redline, S. (2020). Emergence of

racial/ethnic and socioeconomic differences in objectively measured sleep–wake patterns in early infancy: results of the Rise & SHINE study. *Sleep*. https://doi.org/10.1093/sleep/zsaa193

Zhang, Y., Koerner, T., Miller, S., Grice-Patil, Z., Svec, A., Akbari, D., Tusler, L., & Carney, E. (2011). Neural coding of formant-exaggerated speech in the infant brain. *Developmental Science*, *14*(3), 566–581. https://doi.org/10.1111/j.1467-7687.2010.01004.x

Appendix – Chapter 2

Actigraphy comparison study

12 infants (age: 4 to 16 months) were given both actigraphs and wore actigraph 1 (ActiGraph) on one ankle and actigraph 2 (Actiwatch) on the other ankle and sleep was recorded for up to ten days. It was randomized which ankle the actigraphs were placed on. Parents were given a sleep diary and a log to fill out when the actigraphs were removed. Only night sleep was recorded. Some participants had less than 10 nights of sleep but were still included in the study. In total 111 nights of actigraph sleep were recorded. 13 nights were excluded because data was missing from one actigraph or the other. Sleep parameters examined were Night Sleep Duration and WASO. Correlations were moderate for both Night Sleep Duration (r = .58, p < .001) and WASO (r = .35, p < .001).

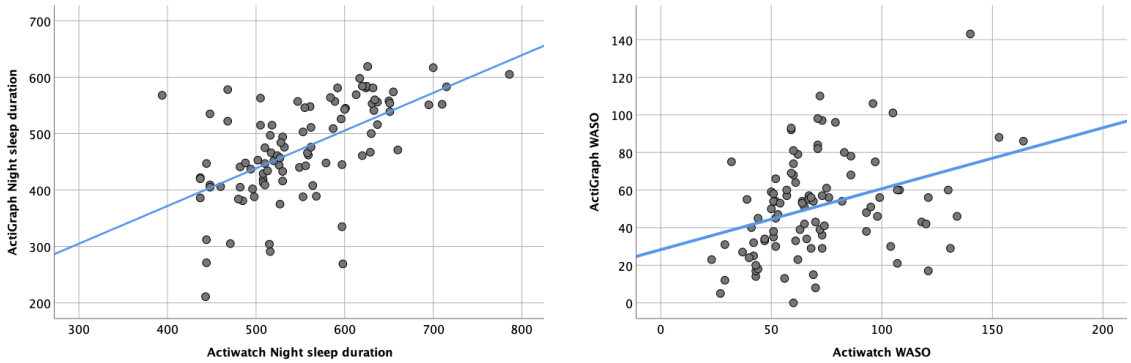


Figure A1. Illustrations of correlations between the two actigraphs.

Bland-Altman plots showed fair agreement across methods though paired samples t-tests were showing that methods were yielding different results for WASO [t(96) = -6.24, p < .001] and Night Sleep Duration [t(96) = -14.41, p < .001].

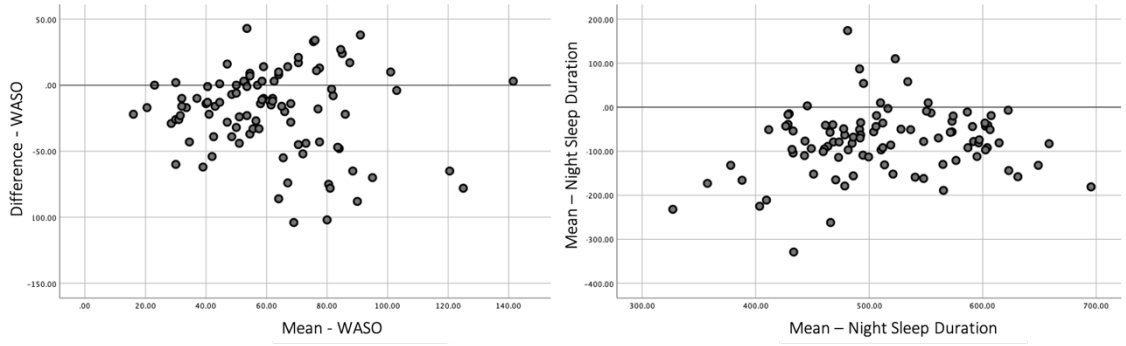


Figure A2. BA plots for Night Sleep Duration and WASO Actigraphy comparison.

Brief Infant Sleep Questionnaire (BISQ) and modified questions

1. Where does your Baby sleep?
    - Infant crib in a separate room
    - Infant crib in parents' room
    - In parents' bed
    - Infant crib in room with sibling
    - Other, Specify: _____
2. In what position does your child sleep most of the time?
   On his/her belly
   On his/her side
   On his/her back
3. How much time does your child spend in sleep during the NIGHT (between 7 in the evening and 7 in the morning)?
   Hours: _____ Minutes: _____
4. How much time does your child spend in sleep during the DAY (between 7 in the morning and 7 in the evening)?
   Hours: _____ Minutes: _____
5. Average number of night wakings per night: _____
6. How much time during the night does your child spend in wakefulness (from 10 in the evening to 6 in the morning)?
   Hours: _____ Minutes: _____
7. How long does it take to put your baby to sleep in the evening?
   Hours: _____ Minutes: _____
8. Do you put your baby into his/her crib asleep or awake into their crib?
   Awake / asleep
9. How does your baby fall asleep?
    - While feeding
    - Being rocked
    - Being held
    - In bed alone
    - In bed near parent
    -
10. When does your baby usually fall asleep for the night:
    Hours: _____ Minutes: _____
11. Do you consider your child's sleep as a problem?
    - A very serious problem
    - A small problem
    - Not a problem at all
12. Do you take your baby to your bed if he/she wakes up?
    - Yes
    - No
13. Do you wait until your baby is asleep or do you leave the room beforehand?
    - Wait until asleep
    - Leave room before
14. Does your baby have a bedtime routine?

    If yes please describe: _____
15. You as parents:

a. Do you enjoy putting your baby to sleep?
    - Yes
    - No
b. Do you like watching your baby sleep?
    - Yes
    - No
c. Do you currently have a sleep deficit that impairs your daily life?
    - Yes
    - No
d. Do you have a permanent sleep deficit?
    - Yes
    - No
e. If you have a permanent sleep deficit: does this permanent sleep deficit impair your relationship with your child?
    - Yes
    - No
f. If you have a permanent sleep deficit: did you have this sleep deficit before your baby was born?
    - Yes
    - No

Anything else you would like to tell us about your baby's sleep? (please write down below)

Sleep Diary Excerpt

Day 1 (Date: _____)

Time at which your baby woke up *today*: _____: _____

Time at which your baby went to sleep *yesterday*: _____: _____

1.Was this a typical night for your baby? (please circle **YES / NO**

If **NO** *please tick all that apply:*

- ☐ More waking up during the night than usual
- ☐ Less waking up during the night than usual
- ☐ My baby went to sleep later than usual
- ☐ A different person put my baby to sleep
- ☐ Primary caregiver (e.g. mom/dad) not present
- ☐ Other (Please describe) _____

2. Did your babies health change ? (please circle)? **YES / NO**

If ***YES,*** *please tick all that apply:*

- ☐ diarreah ☐ stomach problems ☐ vomiting
- ☐ teething ☐ cold ☐ fever
- ☐ ear infection
- ☐ other (Please describe) _____

3. You put your baby down into her/his crib for sleeping when he/she was _____ ?

☐ awake ☐ drowsy ☐ asleep

4. Was there a change in the environment where you put your baby to sleep? **YES / NO**

5. Please list which of the following your baby was exposed to before putting him/her down for sleep (multiple answers possible):

- ☐ lullaby/ music
- ☐ story reading /telling
- ☐ TV/movies
- ☐ playing with toys
- ☐ bath
- ☐ massage/cuddling

6. Do you swaddle your baby for sleep ? **YES / NO**

7. Does your baby use a sucker when being put to sleep? **YES / NO**

8. When did you last feed your baby before putting him/her down for sleep? _____:_____

What did your baby get fed at that time?

☐ Milk ☐ solid food ☐ Both

9a . Was your baby awake at night? **YES / NO**

*If **YES**, please indicate how often:* _____

Night wakening (1) Please write down the time and duration for which your baby was awake at night

Time woken up: _____ : _____ Time falling asleep: _____ : _____

9b. I put my baby to sleep with: __ (Please tick all that apply)

- ☐ change diaper
- ☐ feeding/milk
- ☐ cuddling/carrying around
- ☐ singing/music
- ☐ taking him/her to my bed
- ☐ other (please elaborate): _____

9c. You put your baby down for sleeping again when he/she was _____ ?

☐ awake ☐ drowsy ☐ asleep

Night wakening (2) Please write down the time and duration for which your baby was awake at night

Time woken up: _____ : _____ Time falling asleep: _____ : _____

9d. I put my baby to sleep with: __ (Please tick all that apply)

- ☐ change diaper
- ☐ feeding/milk
- ☐ cuddling/carrying around
- ☐ singing/music
- ☐ taking him/her to my bed
- ☐ other (please elaborate): _____

9e. You put your baby down for sleeping again when he/she was _____ ?

☐ awake ☐ drowsy ☐ asleep

Night wakening (3) Please write down the time and duration for which your baby was awake at night

Time woken up: _____ : _____ Time falling asleep: _____ : _____

9f. I put my baby to sleep with: __ (Please tick all that apply)

- ☐ change diaper
- ☐ feeding/milk
- ☐ cuddling/carrying around
- ☐ singing/music
- ☐ taking him/her to my bed
- ☐ other (please elaborate): _____

9g. You put your baby down for sleeping again when he/she was _____ ?
☐ awake ☐ drowsy ☐ asleep

10. Did your baby sleep during the day? **YES / NO**

Day sleep (1) Please write down the (approximate) time and duration your baby slept for during the day.

Time falling asleep: _____ : _____ Time waking up: _____ : _____

Place where your baby fell asleep (1):
☐Bed ☐ Stroller ☐ car/transport
☐Arm/lap ☐nursery/day care
☐other (please describe): _____

Day sleep (2) Please write down the (approximate) time and duration your baby slept for during the day.

Time falling asleep: _____ : _____ Time waking up: _____ : _____

Place where your baby fell asleep (2):
☐Bed ☐ Stroller ☐ car/transport
☐Arm/lap ☐nursery/day care
☐other (please describe): _____

Day sleep (3) Please write down the (approximate) time and duration your baby slept for during the day.

Time falling asleep: _____ : _____ Time waking up: _____ : _____

Place where your baby fell asleep (3):
☐Bed ☐ Stroller ☐ car/transport
☐Arm/lap ☐nursery/day care
☐other (please describe): _____

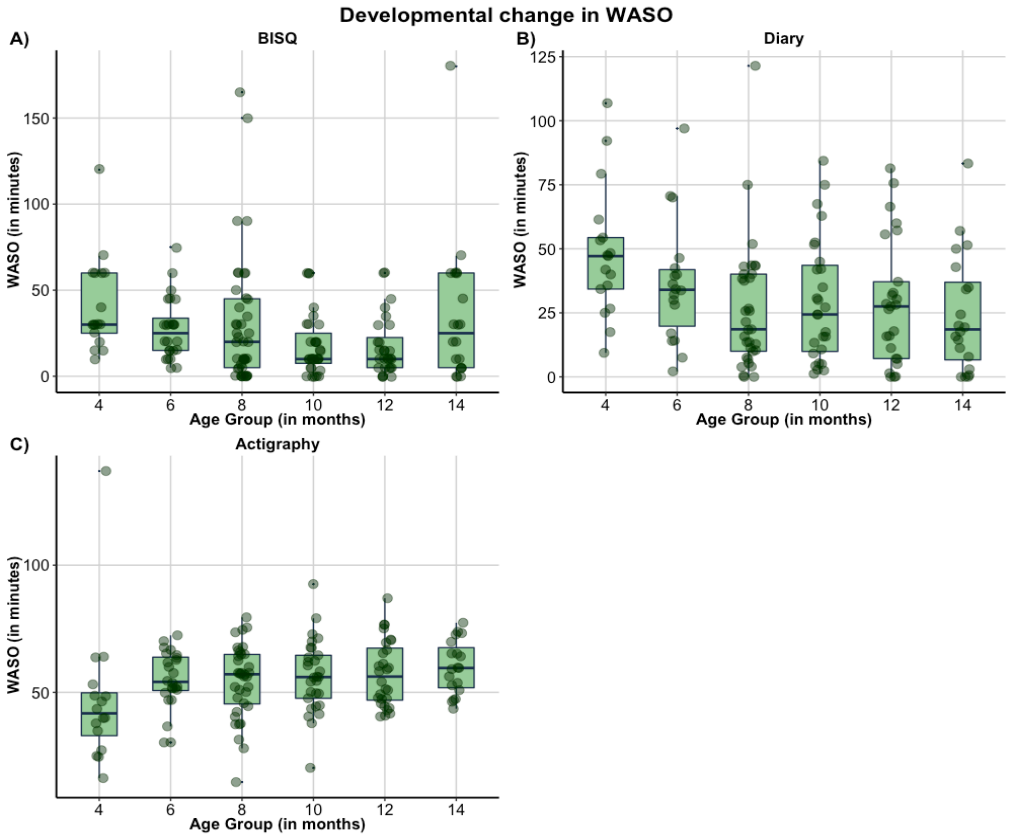
11. Did you notice your baby dreaming or something that might be interpreted as such? *(e.g. She/he was crying in his/her sleep, he/she was smiling in her sleep,...)* **YES / NO**

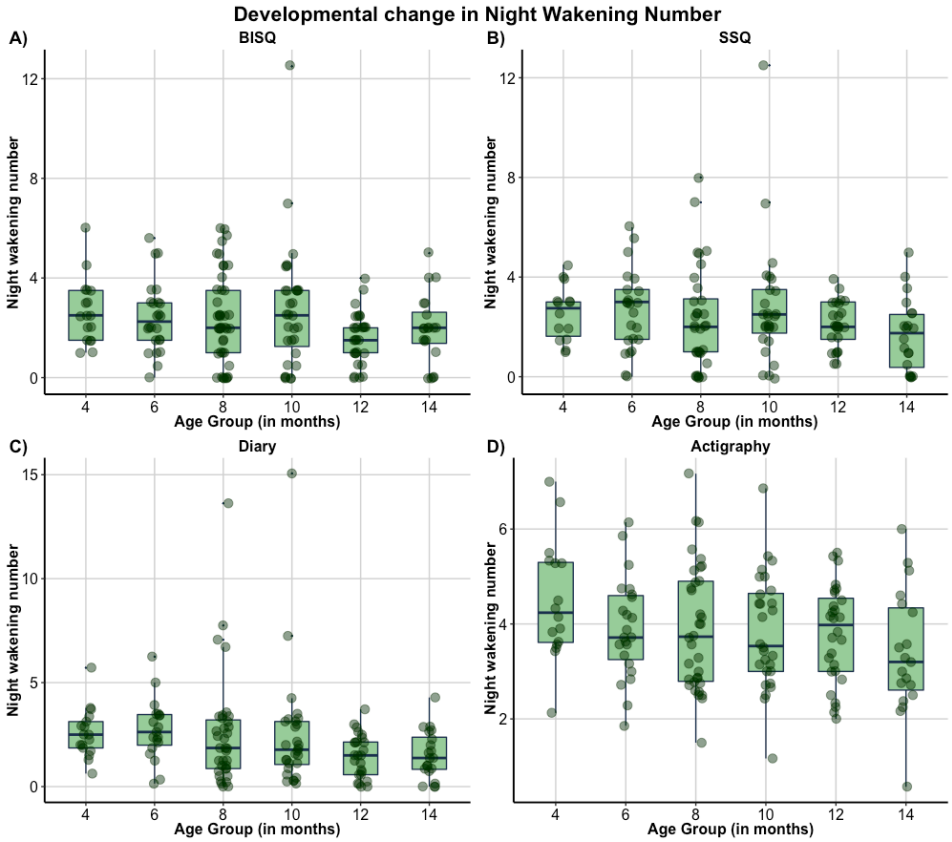
12. on a scale of *very relaxed* to *very tense:* how did you feel today?

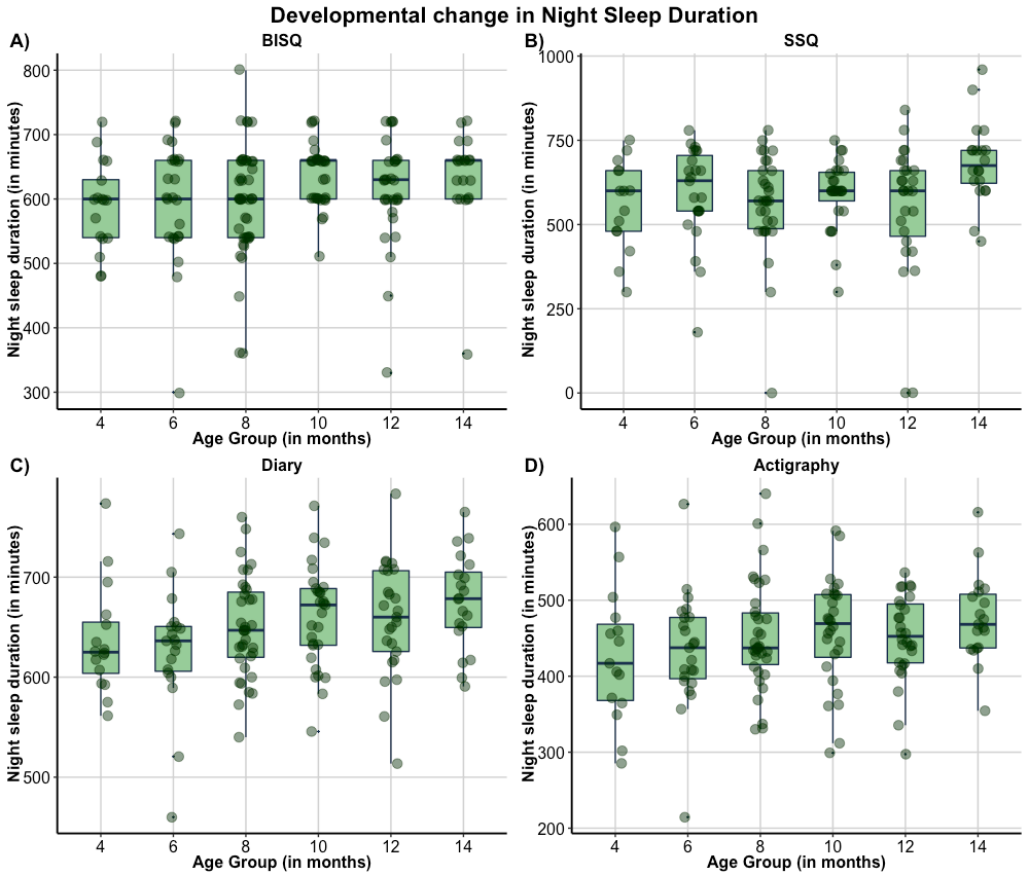
1	2	3	4	5
Very relaxed		neither relaxed nor tense		very tense

Appendix – Chapter 3

Illustrations of Developmental changes in Main Sleep Parameters for BISQ, Diary, and Actigraphy




Developmental change in Night Wakening Number
A)
BISQ
B)
SSQ
C)
Diary
D)
Actigraphy
Night wakening number
Age Group (in months)


Developmental change in Night Sleep Duration
A)
BISQ
B)
SSQ
C)
Diary
D)
Actigraphy
Night sleep duration (in minutes)
Age Group (in months)

Descriptive Statistics Sleep Parameters

	4 months		6 months		8 months		10 months		12 months		14 months		All age groups	
	M ±SD	**N**	**M ±SD**	**N**	**M ±SD**	**N**	**M ±SD**	**N**	**M ±SD**	**N**	**M ±SD**	**N**	**M ±SD**	**N**
BISQ														
Night Sleep Duration	589.41 ± 69.51	17	596.92 ± 92.72	24	597.74 ± 88.57	42	637.26 ± 47.89	31	611.72 ± 83.71	29	634.50 ± 74.94	20	611.26 ± 79.38	163
Day Sleep Duration	240.00 ± 100.40	16	198.63 ± 89.88	24	171.55 ± 72.94	42	146 ± 61.57	31	142.59 ± 59.92	29	130.25 ± 68.08	20	167.27 ± 79.78	162
Total Sleep Duration	818.82 ± 112.63	17	795.54 ± 123.36	24	769.29 ± 90.63	42	783.87 ± 61.11	31	754.31 ± 91.84	29	764.75 ± 76.75	20	777.87 ± 93.28	163
Night Wakening Number	2.65 ± 1.31	17	2.42 ± 1.41	24	2.45 ± 1.81	42	2.74 ± 2.51	31	1.60 ± 1.04	29	1.95 ± 1.39	20	2.31 ± 1.74	163
WASO	41.47 ± 27.54	17	27.50 ± 18.06	24	30.59 ± 37.99	41	18.00 ± 17.60	31	17.32 ± 17.08	28	35.00 ± 41.68	20	27.09 ± 29.73	161
SOL	35.00 ± 23.18	17	38.88 ± 29.56	24	30.67 ± 26.73	42	20.81 ± 9.28	31	24.59 ± 25.39	29	23.00 ± 9.52	20	28.43 ± 23.14	163
SSQ														
Night Sleep Duration	558.00 ± 132.62	15	590.43 ± 142.88	23	562.83 ± 152.86	30	591.48 ± 100.26	27	547.85 ± 198.68	27	684.00 ± 119.84	20	586.46 ± 150.51	142
Day Sleep Duration	225.00 ±73.27	15	198.17 ± 87.15	23	161.77 ± 70.38	31	174.07 ± 123.78	27	171.30 ± 96.42	27	152.25 ± 121.50	20	177.05 ± 98.47	143
Total Sleep Duration	783.00 ± 150.02	15	788.61 ± 134.41	23	716.33 ± 171.91	30	765.56 ± 87.79	27	719.15 ± 206.33	27	836.25 ± 179.93	20	761.87 ± 162.81	142
Nap Number	3.29 ± 1.48	14	2.80 ± 0.75	22	2.41 ± 0.85	32	1.94 ± 0.49	27	1.81 ± 0.57	24	1.40 ± 0.55	20	2.22 ± 0.95	139
Night Wakening Number	2.57 ± 1.12	14	2.63 ± 1.62	23	2.33 ± 2.07	32	2.78 ± 2.48	27	2.08 ± 0.93	25	1.69 ± 1.45	20	2.35 ± 1.78	141
Actigraphy														
Night Longest	200.33 ± 89.67	16	218.71 ± 83.37	24	225.84 ± 96.99	36	216.26 ± 88.78	29	217.06 ± 66.03	28	238.60 ± 87.26	19	220.18 ± 85.35	152

Sleep Period														
Night Longest Sleep Period Variability	83.04 ± 48.35	16	88.86 ± 51.33	24	90.29 ± 66.92	36	93.74 ± 69.48	29	81.63 ± 36.53	28	92.98 ± 54.66	19	88.70 ± 56.41	152
Night Sleep Ratio	0.78± 0.06	15	0.78 ± 0.08	21	0.78 ± 0.07	33	0.80 ± 0.06	27	0.82 ± 0.07	27	0.81 ± 0.05	19	0.80 ± 0.07	142
Day Sleep Duration	119.73 ± 22.26	15	123.64 ± 40.97	21	124.36 ± 41.05	33	112.25 ± 37.14	27	106.32 ± 44.64	27	108.22 ± 26.13	19	115.87 ± 37.87	142
Day Sleep Duration Variability	51.65 ± 20.91	16	75.24 ± 63.80	22	60.40 ± 51.88	35	71.20 ± 80.99	28	63.65 ± 58.12	27	52.33 ± 27.27	19	63.28 ± 56.83	147
Night Sleep Duration	426.26 ± 87.10	15	433.97 ± 75.97	23	452.36 ± 70.86	34	458.42 ± 71.69	28	451.74 ± 56.37	28	475.99 ± 57.42	19	450.91 ± 69.84	147
Night Sleep Duration Variability	86.94 ± 59.72	16	85.15 ± 71.93	24	68.30 ± 59.69	36	82.92 ± 58.89	29	61.20 ± 31.79	28	71.81 ± 32.39	19	74.84 ± 54.85	152
WASO	46.92 ± 27.54	16	55.00 ± 11.44	24	54.38 ± 14.36	36	56.52 ± 14.31	29	57.32 ± 12.99	28	59.89 ± 10.48	19	55.33 ± 15.35	152
Night Wakening Number	4.50 ± 1.26	16	3.90 ± 1.06	23	3.91 ± 1.33	34	3.84 ± 1.20	28	3.79 ± 1.03	28	3.39 ± 1.31	19	3.87 ± 1.21	148
WASO variability	30.91± 55.45	16	17.45 ± 5.02	24	20.31 ± 7.05	36	23.24 ± 7.11	29	17.58 ± 6.85	28	20.59 ± 7.98	19	21.06± 19.02	152
Total Sleep Duration	547.04 ± 90.50	15	562.32 ± 78.24	21	581.72 ± 82.92	33	574.3 ±7 87.95	27	558.71 ± 64.92	27	585.05 ± 61.74	19	569.86 ±78.02	142
Day longest sleep period	64.77 ± 14.64	16	96.95 ± 121.04	24	103.66 ± 120.79	36	96.53 ± 101.23	28	86.81 ± 45.49	28	82.03 ± 17.22	19	91.31± 89.79	151
Day longest sleep period variability	29.43± 15.64	16	54.51 ± 62.58	22	46.74 ± 56.84	35	51.61 ± 84.05	28	50.52 ± 62.14	27	36.08 ± 16.75	19	46.26 ± 58.59	147

Diary														
Night Sleep Ratio	0.78 ± 0.05	16	0.81 ± 0.04	19	0.83 ± 0.05	34	0.84 ± 0.04	29	0.85 ± 0.04	24	0.87 ± 0.03	20	0.83 ± 0.05	142
Night Longest Sleep Period	290.89 ± 83.89	16	344.07 ± 128.67	17	410.32 ± 149.10	31	387.24 ± 150.23	26	422.82 ± 160.18	22	444.75 ± 156.43	19	389.65 ± 148.52	131
Night Longest Sleep Period Variability	80.55 ± 34.16	16	67.30 ± 38.28	17	94.08 ± 63.31	31	81.08 ± 40.33	25	92.59 ± 47.66	22	94.87 ± 62.23	19	86.28 ± 50.51	130
Day longest sleep period	95.72 ± 27.72	16	91.52 ± 24.65	18	85.92 ± 26.39	34	89.09 ± 28.07	28	93.46 ± 27.19	24	90.72 ± 20.51	19	90.37 ± 25.84	139
Day longest sleep period variability	40.45 ± 26.23	16	30.17 ± 13.04	18	31.43 ± 14.55	33	30.53 ± 17.21	28	24.04 ± 8.91	24	35.90 ± 11.56	19	31.46 ± 16.04	138
Nap number	2.86 ± 0.64	16	2.43 ± 0.53	18	2.16 ± 0.41	34	1.86 ± 0.46	28	1.67 ± 0.47	24	1.26 ± 0.36	19	2.01 ± 0.66	139
Nap number variability	0.56 ± 0.29	16	0.45 ± 0.27	18	0.48 ± 0.21	34	0.50 ± 0.16	28	0.39 ± 0.24	24	0.37 ± 0.22	19	0.46 ± 0.23	139
Night Wakening Number	2.57 ± 1.18	17	2.73 ± 1.47	19	2.52 ± 2.71	35	2.47 ± 2.91	28	1.49 ± 1.05	25	1.52 ± 1.16	20	2.23 ± 2.09	144
WASO	48.28 ± 25.60	17	36.40 ± 23.83	18	26.32 ± 24.86	33	29.54 ± 23.96	27	28.83 ± 24.56	25	24.41 ± 22.92	20	31.08 ± 24.97	140
WASO variability	24.80 ± 20.21	16	22.47 ± 17.28	17	17.11 ± 15.65	32	16.97 ± 13.24	26	22.27 ± 22.12	24	16.88 ± 16.79	19	19.57 ± 17.44	134
Night Sleep Duration Variability	58.04 ± 18.00	16	51.27 ± 19.46	18	43.63 ± 19.15	32	46.26 ± 35.15	26	37.85 ± 24.68	22	44.49 ± 20.06	17	46.1 ± 24.38	131

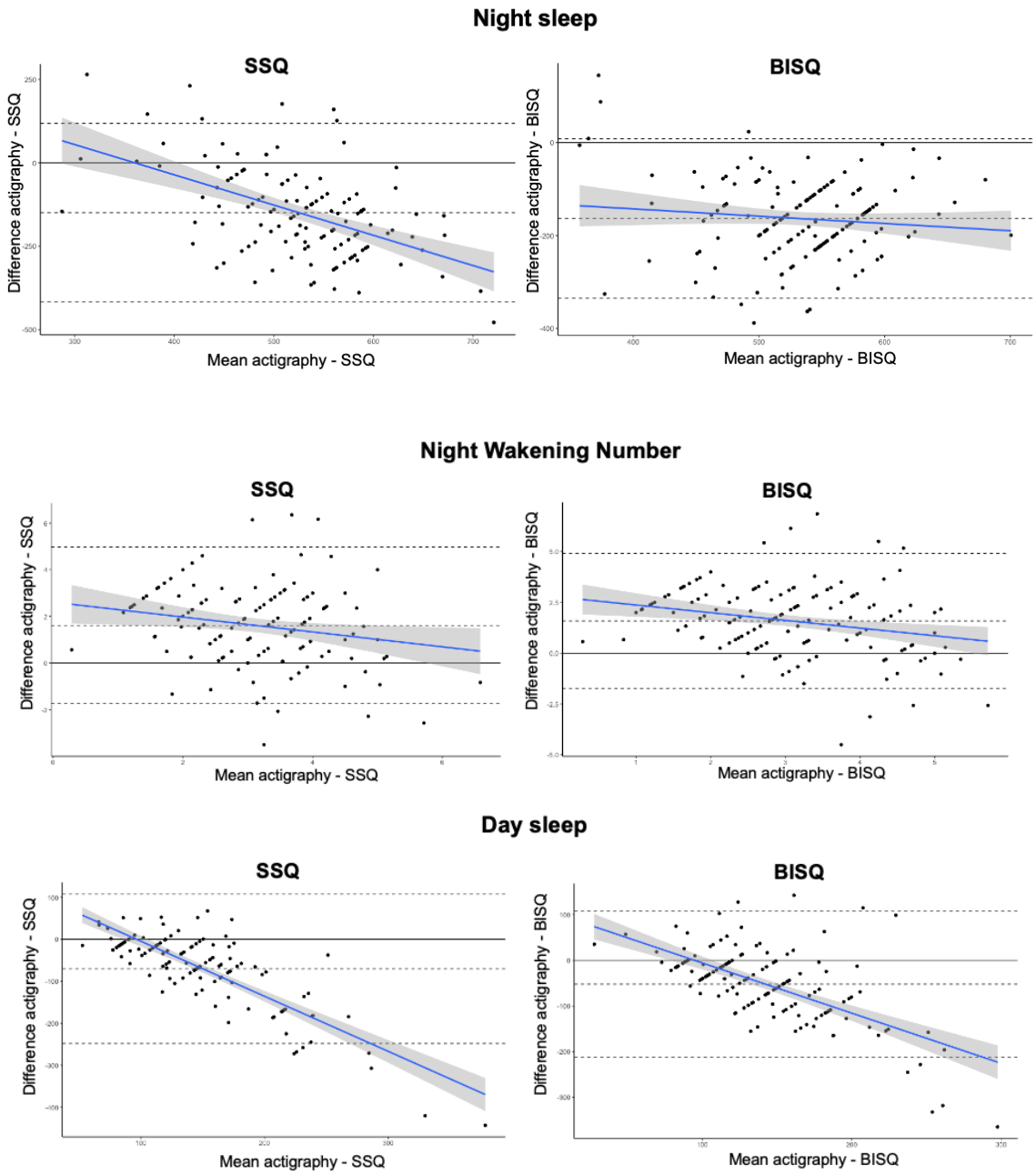
Day Sleep Duration Variability	52.80 ± 22.87	16	43.17 ± 22.61	18	41.84 ± 17.06	33	42.94 ± 19.35	28	32.23 ± 8.60	24	37.00 ± 13.70	19	41.17 ± 18.25	138.
Day Sleep Duration	181.16 ± 50.79	17	151.30 ± 42.49	19	136.15 ± 42.44	34	124.50 ± 33.58	29	118.55 ± 28.97	24	101.96 ± 22.93	20	133.42 ± 43.33	143
Night Sleep Duration	636.37 ± 54.38	16	626.67 ± 61.21	19	649.81 ± 50.67	35	660.56 ± 50.83	29	657.70 ± 57.16	25	675.52 ± 47.66	20	652.37 ± 54.41	144
Total Sleep Duration	814.68 ± 73.96	16	777.97 ± 86.05	19	787.43 ± 50.83	34	785.05 ± 53.00	29	775.67 ± 58.61	24	777.48 ± 50.73	20	785.36 ± 61.05	142

Correlations of main sleep parameters for sleep questionnaires, sleep diary and actigraphy

		Night D	**WASO D**	**NW D**	**Day AG**	**Night AG**	**WASO AG**	**NW AG**	**Day SSQ**	**Night SSQ**	**NW SSQ**	**Night BISQ**	**Day BISQ**	**WASO BISQ**	**NW BISQ**
Day D	Correlation	-.232	.169	-.014	.427	-.357	-.238	.196	.227	-.115	-.094	-.237	.535	.084	-.024
	p-value	*.006*	*.046*	*.871*	*.000*	*.000*	*.006*	*.024*	*.010*	*.202*	*.293*	*.005*	*.000*	*.323*	*.777*
Night D	Correlation		-.007	.028	-.139	.403	.221	-.053	-.076	.247	-.007	.419	-.166	-.100	.046
	p-value		*.934*	*.740*	*.118*	*.000*	*.011*	*.543*	*.395*	*.005*	*.936*	*.000*	*.049*	*.238*	*.582*
WASO D	Correlation			.415	-.026	.013	-.040	.031	.113	-.147	.405	-.015	.102	.437	.457
	p-value			*.000*	*.770*	*.887*	*.657*	*.729*	*.212*	*.105*	*.000*	*.858*	*.236*	*.000*	*.000*
NW D	Correlation				-.189	-.094	.168	.307	-.110	.002	.798	.034	-.026	.235	.778
	p-value				*.033*	*.286*	*.053*	*.000*	*.220*	*.986*	*.000*	*.689*	*.762*	*.005*	*.000*
Day AG	Correlation					-.129	-.169	-.087	.343	-.110	-.194	-.194	.177	-.074	-.073
	p-value					*.125*	*.044*	*.301*	*.000*	*.224*	*.032*	*.021*	*.035*	*.385*	*.387*
Night AG	Correlation						.224	-.601	-.142	.134	-.012	.298	-.211	.027	-.027
	p-value						*.006*	*.000*	*.109*	*.131*	*.897*	*.000*	*.011*	*.748*	*.743*
WASO AG	Correlation							-.018	-.185	.107	.135	.270	-.207	.042	.137
	p-value							*.827*	*.033*	*.219*	*.122*	*.001*	*.011*	*.611*	*.094*
NW AG	Correlation								.059	.000	.237	.019	.099	-.077	.264
	p-value								*.502*	*.998*	*.007*	*.819*	*.233*	*.354*	*.001*
Day SSQ	Correlation									-.206	-.056	-.241	.358	-.018	-.048
	p-value									*.014*	*.511*	*.004*	*.000*	*.835*	*.572*
Night SSQ	Correlation										-.043	.327	.049	-.040	.034
	p-value										*.616*	*.000*	*.568*	*.642*	*.686*
NW SSQ	Correlation											-.007	-.122	.345	.883
	p-value											*.935*	*.151*	*.000*	*.000*
Night BISQ	Correlation												-.345	-.226	.073
	p-value												*.000*	*.004*	*.351*
Day BISQ	Correlation													.067	-.067
	p-value													*.397*	*.396*
WASO BISQ	Correlation														.331
	p-value														*.000*

Notes. Day = Day Sleep Duration, Night = Night Sleep Duration, NW = Night Wakening Number, WASO = Wake after sleep onset, D = diary, AG = actigraphy, BISQ = Brief Infant Sleep Questionnaires, SSQ = Sleep and Settle Questionnaire

Bland-Altman plots for actigraphy vs sleep questionnaires for main sleep parameters



Results of the Equivalence testing for actigraphy vs diary and actigraphy vs BISQ

Actigraphy vs diary

			NHST			**TOST**		
	Raw Equiva-lence bounds	**df**	**t**	**p**	**95 % CI**	**t**	**p**	**90 % CI**
Day Sleep Duration	± 21.85	141	-4.79	<.001	[-24.80; -11.48]	1.17	.12	[-23.85; -11.48]
Night Sleep Duration	± 34.54	131	-33.51	<.001	[-213.39; -189.61]	-27.77	1.00	[-211.46; -191.54]
WASO	± 14.91	139	9.26	<.001	[19.27; 29.23]	3.71	1.00	[20.08; 28.42]
Night Wakening Number	± 1.04	143	9.51	<.001	[1.30; 1.98]	3.51	1.00	[1.36; 1.93]

Actigraphy vs BISQ

			NHST			**TOST**		
	Raw Equi-valence bounds	df	t	p	95 % CI	t	p	90 % CI
Day Sleep duration	± 26.12	140	-3.99	<.001	[-26.25; -8.86]	1.95	.03*	[-24.84; -10.27]
Night Sleep Duration	± 44.36	145	-21.84	<.001	[172.52; 148.21]	-15.80	1.00	[-174.87; -145.85]
WASO	±16.28	148	10.586	<.001	[22.97; 33.51]	4.483	1.00	[23.82; 32.66]
Night Wakening Number	± 0.92	146	10.29	<.001	[1.26; 1.86]	4.29	1.00	[1.31 ;1.81]

Notes. CI = confidence interval; df = degrees of freedom, NHST = Null Hypothesis testing, TOST = test of significanave
TOST

Appendix – Chapter 4

Pearson correlation coefficients (r) for IBQ-R subscales

	Surgency	**Negativity**	**Regulation**
Surgency	1	.114	.384**
Negativity		1	-.268**
Regulation			1

Note. significant at p = .001, adjusted for multiple comparison

Pearson correlation coefficients (r) for Ages & Stages subscales

ASQ-subscale	**Communication**	**Gross motor**	**Fine motor**	**Problem-solving**	**Social**
Communication	1	.228**	.340**	.388**	.347**
Gross motor		1	.130	.106	.307**
Fine motor			1	.439**	.363**
Problem-solving				1	.415**
Social					1

Note. significant at p = .001, adjusted for multiple comparison

Data quality for each questionnaire measure (for pooled N)

	ASQ	**IBQ-R**	**Maternal Stress / Anxiety**	**SES/ Demographics**	**Sleep Ritual Number**	**EPDS**
Data complete	96.4 %	91.6 %	87.5 %	58.6 %	96.9 %	94.6 %
Missing data	3.6 %	8.4 %	12.5 %	42.4 %	3.1 %	5.4 %

Notes. ASQ = Ages and Stages Questionnaire, IBQ-R = Infant Behaviour Questionnaire, EPDS = Edinburgh Postnatal Depression Scale

Results of LMMs for sleep variables of actigraphy, diary, and BISQ and questionnaire measures

Diary sleep quality and questionnaire measures

	Model	AIC	BIC	-2LL	df
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	894.49	925.24	872.49	11
		Age group: $F(5,86) = 4.90$, $p = .001$**			
		Sleep quality cluster: $F(2,119) = 0.55$, $p = .58$			
	M2	904.80	960.71	864.80	20
	M3	894.76	928.31	870.76	12
ASQ subscale: Gross Motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	964.30	995.10	942.30	11
		Age group: $F(5,77) = 4.46$, $p = .001$**			
		Sleep quality cluster: $F(2,116) = 1.44$, $p = .24$			
	M2	974.78	1030.70	934.78	20
	M3	965.51	999.10	941.51	12
ASQ subscale: Fine Motor	Baseline	1199.91	1227.70	1181.91	9
		Age group: $F(5,100) = 2.59$, $p = .03$*°			
	M1	896.51	927.26	874.51	11
		Age group: $F(5,81) = 3.53$, $p = .006$*			
		Sleep quality cluster: $F(2,117) = 0.02$, $p = .98$			
	M2	910.21	966.13	870.21	20
	M3	897.43	930.97	873.43	12
ASQ subscale: Problem-solving	Baseline	1220.15	1247.88	1202.15	9
		Age group: $F(5,127) = 4.46$, $p = .001$**			
	M1	919.75	950.50	897.75	11
		Age group: $F(5,98) = 3.21$, $p = .01$*			
		Sleep quality cluster: $F(2,114) = 0.19$, $p = .83$			
	M2	928.13	984.05	888.13	20
	M3	921.19	954.74	897.20	12
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, $p < .001$**			
	M1	909.48	940.14	887.48	11
		Age group: $F(5,80) = 2.89$, $p = .02$*			
		Sleep quality cluster: $F(2,117) = 0.674$, $p = .511$			
	M2	914.51	970.26	874.51	20
	M3	910.10	943.55	886.10	12
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	186.25	194.21	180.25	11
	M2	183.29	191.01	177.29	19
		Age group: $F(5,53) = 1.45$, $p = .22$			
		Sleep quality cluster: $F(2,83) = 0.98$, $p = .38$			
		Sleep quality x age group: $F(8,56) = 0.91$, $p = .51$			
	M3	188.29	196.22	182.29	12
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	260.24	268.21	254.24	11
	M2	251.70	259.43	245.70	19
		Age group: $F(5,52) = 1.02$, p $= .42$			
		Sleep quality cluster: $F(2,80) = 4.07$, $p = .021$*			
		Sleep quality x age group: $F(8,50) = 0.90$, $p = .52$			
	M3	261.08	269.02	255.08	12
IBQ-R subscale: Regulation	Baseline	234.97	243.92	228.97	9
		Age group: $F(5,85) = 2.01$, $p = .09$°			
	M1	179.90	187.86	173.90	11

	M2	177.79 *Age group:* $F(5,50) = 2.04$, $p = .09$ *Sleep quality cluster:* $F(2,73) = 1.05$, $p = .35$ *Sleep quality x age group:* $F(8,50) = 1.01$, $p = .44$	185.51	171.79	19
	M3	181.27	189.21	175.27	12
Bed ritual	Baseline	460.56 *Age group:* $F(5,104) = 1.73$, $p = .134$	488.30	442.56	9
	M1	349.60	357.80	343.60	11
	M2	331.24 *Age group:* $F(5,82) = 1.95$, $p = .10$ *Sleep quality cluster:* $F(2,99) = 3.50$, $p = .03$ *Sleep quality x age group:* $F(9,85) = 0.95$, $p = .49$	339.20	325.24	20
	M3	349.21	357.40	243.21	12
Stress	Baseline	302.05 *Age group:* $F(5,67) = 1.65$, $p = .16$	328.72	284.05	9
	M1	239.43 *Age group:* $F(5,45) = 0.86$, $p = .51$ *Sleep quality cluster:* $F(2,65) = 0.63$, $p = .54$	268.73	217.43	11
	M2	247.51	298.12	209.51	19
	M3	240.65	272.61	216.65	12

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy sleep quality and questionnaire measures

		AIC	BIC	-2LL	df
ASQ subscale: communication	Baseline	1213.96 *Age group* $F(5,124) = 5.38$, $p<.001$**	1241.75	1195.96	9
	M1	1036.92 *Age group:* $F(5,76) = 5.86$, $p <.001$** *Sleep quality cluster:* $F(1,135) = 0.01$, $p = .90$	1066.12	1016.92	10
	M2	1039.93	1083.73	1009.93	15
	M3	1038.52	1070.64	1016.52	11
ASQ subscale: Gross motor	Baseline	1278.42 *Age group:* $F(5,93) = 6.84$, $p <.001$**	1306.21	1260.42	9
	M1	1087.55 *Age group:* $F(5,81) = 5.83$, $p <.001$** *Sleep quality cluster:* $F(1,136) = 3.11$, $p = .08$	1116.75	1067.55	10
	M2	1089.48	1133.28	1059.48	15
	M3	1089.40	1121.52	1067.40	11
ASQ subscale: Fine motor	Baseline	1199.91 *Age group:* $F(5,100) = 2.59$, $p = .03$*°	1227.70	1181.91	9
	M1	1019.54 *Age group:* $F(5,79) = 2.21$, $p = .06$ *Sleep quality cluster:* $F(1,128) = 1.40$, $p = .24$	1048.74	999.54	10
	M2	1025.30	1069.10	995.29	15
	M3	1021.40	1053.50	999.38	11
ASQ subscale: Problem-solving	Baseline	1220.15 *Age group:* $F(5,127) = 4.46$, $p = .001$**	1247.88	1202.15	9
	M1	1012.53 *Age group:* $F(5,95) = 4.34$, $p = .001$ *Sleep quality cluster:* $F(1,131) = 0.082$, $p = .775$	1041.73	992.53	10
	M2	1018.02	1061.82	988.02	15
	M3	1014.49	1046.61	992.49	11
ASQ subscale: Social	Baseline	1215.78 *Age group:* $F(5,106) = 5.14$, $p <.001$**	1243.46	1197.78	9
	M1	1052.34 *Age group:* $F(5,100) = 5.02$, $p <.001$** *Sleep quality cluster:* $F(1,137) = 0.00$, $p = .99$	1081.54	1032.34	10

	M2	1060.21	1104.01	1030.21	15
	M3	1052.49	1084.61	1030.49	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	204.83	213.24	198.83	10
	M2	200.98	209.26	194.98	15
		Age group: F(5,68) = 4.24, *p* =. 002*			
		Sleep quality cluster: F(1,110) = 0.59, *p* =.44			
		Sleep quality x age group: F(5,75) = 1.95, *p* =.10			
	M3	206.96	215.25	200.96	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	303.39	311.80	297.39	10
	M2	296.81	305.10	290.81	15
		Age group: F(5,63) = 1.45, *p* = .219			
		Sleep quality cluster: F(1,105) = 1.96, *p* =.17			
		Sleep quality x age group: F(5,74) = 1.67, *p* = .15			
	M3	301.74	310.13	295.74	11
IBQ-R subscale: Regulation	Baseline	234.97	243.92	228.97	9
		Age group: F(5,85) = 2.01, *p* =.09°			
	M1	213.86	222.28	207.86	10
	M2	212.44	220.73	206.44	15
		Age group: F(5,68) = 1.14, *p* =.35			
		Sleep quality cluster: F(1,110) = 0.36, *p* =.55			
		Sleep quality x age group: F(5,76) = 1.34, *p* =.26			
	M3	215.66	224.04	209.66	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	389.95	398.55	383.95	10
	M2	383.91	392.40	377.91	15
		Age group: F(5,82) =2.82, *p* =.415			
		Sleep quality cluster: F(1,119) =2.82, *p* =.10			
		Sleep quality x age group: F(5,103) =0.792, *p* =.56			
	M3	391.07	399.65	385.07	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	270.41	298.37	250.41	10
		Age group: F(5,53) = 5.02, *p* =.16			
		Sleep quality cluster: F(1,84) = 0.14, *p* =.71			
	M2	270.93	312.86	240.92	15
	M3	272.10	302.86	250.10	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ sleep quality and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: F(5,124) =5.38, *p* <.001**			
	M1	1183.69	1217.37	1161.68	11
		Age group: F(5,100) =4.82, *p* =.001**			
		Sleep quality cluster: F(2,151) =0.02, *p* = .98			
	M2	1188.14	1249.39	1148.14	20
	M3	1184.90	1221.65	1160.90	12
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1250.25	1283.94	1228.25	11
		Age group: F(5,96) = 6.47, *p* <.001**			
		Sleep quality cluster: F(2,152) = 0.91, *p* = .41			

	M2	1261.72	1323.00	1221.72	20
	M3	1251.13	1287.88	1227.13	12
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) =2.59, p =.03*°			
	M1	1177.22	1210.91	1155.22	11
		Age group F(5,11 5) =2.32, p = .047			
		Sleep quality cluster: F(2,146) = 0.35, *p* = .71			
	M2	1179.88	1241.13	1139.88	20
	M3	1178.62	1215.37	1154.62	12
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1183.65	1217.27	1161.65	11
		Age group: F(5,11 9) = 5.09, p <.001**			
		Sleep quality cluster: *F*(2,152) = 0.92, *p* = .40			
	M2	1191.65	1252.78	1151.65	20
	M3	115.64	1222.32	1161.64	12
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1192.04	1225.59	1170.04	11
		Age group: F(5,100) = 4.77, *p* =.001**			
		Sleep quality cluster: F(2,151) = 0.131, *p* = .88			
	M2	1199.32	1260.32	1159.32	20
	M3	1192.46	1229.06	1168.46	12
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	263.23	272.03	257.23	11
	M2	253.20	261.80	247.20	20
		Age group: F(5,86) = 5.42, p <.001**			
		Sleep quality cluster: F(2,112) = 4.34, *p* =.015*			
		Sleep quality x age group: F(9,91) = 1.57, *p* =.14			
	M3	265.03	273.81	259.03	12
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	350.32	359.13	344.32	11
	M2	342.92	351.53	336.92	20
		Age group: F(5,69) = 0.92, p =.48			
		Sleep quality cluster: F(2,95) = 0.59, *p* =.56			
		Sleep quality x age group: F(9,73) = 0.611, *p* =.78			
	M3	351.02	259.80	345.02	12
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	227.69	236.50	221.69	11
		Age group: F(5,85) = 2.03, *p* =.08			
		Sleep quality cluster: F(2,114) = 0.59, *p* =.02			
	M2	229.35	238.00	223.35	20
	M3	229.47	238.25	223.47	12
Bed time ritual number	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	448.23	457.26	442.23	11
		Age group: F(5,98) = 1.66, *p* =.15			
		Sleep quality cluster: F(2,136) = 1.91, *p* =.15			
		Sleep quality x age group: F(9,117) = 0.54, *p* = .85			
	M2	436.48	445.33	430.48	20
	M3	449.34	458.35	443.34	12
Stress	Baseline	302.05	328.72	284.05	
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	294.88	327.08	272.88	
		Age group: F(5,62) = 0.66, *p* = .65			
		Sleep quality cluster: F(2,87) = 2.10, *p* = .13			

	M2	299.93	258.47	259.93
	M3	296.51	331.64	272.51

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Sleep Duration and questionnaire measures

		AIC	BIC	-2LL	df
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	1091.45	1121.15	1071.45	10
		Age group: $F(5,113) = 5.14$, $p < .001$**			
		Night Sleep Duration: $F(1,129) = 0.04$, $p = .84$			
	M2	1096.47	1141.02	1066.47	15
	M3	1092.58	1125.24	1070.58	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	1149.91	1179.61	1129.91	10
		Age group: $F(5,88) = 5.17$, $p < .001$**			
		Night Sleep Duration: $F(1,127) = 0.25$, $p = .62$			
	M2	1153.21	1197.75	1123.21	15
	M3	1151.31	1183.98	1129.31	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group: F(5,100) =2.59, p =.03*°			
	M1	1076.67	1106.37	1056.67	10
		Age group: F(5,82) = 1.86, p = .11			
		Night Sleep Duration: $F(1,119) = 0.04$, $p = .84$			
	M2	1084.50	1129.05	1054.50	15
	M3	1077.97	1110.64	1055.97	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1091.65	1121.35	1071.65	10
		Age group: $F(5,103) = 4.64$, p =.001**			
		Night Sleep Duration: $F(1,120) = 0.67$, $p = .42$			
	M2	1096.22	1140.77	1066.22	15
	M3	1093.42	1126.09	1071.42	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, p <.001**			
	M1	1103.22	1132.91	1083.22	10
		Age group: $F(5,100) = 4.77$, p =.001**			
		Night Sleep Duration: $F(2,151) = 0.131$, $p = .88$			
	M2	1099.77	1144.32	1069.77	15
		Age group: F(5,125) = 3.02, p = .02*			
		Night Sleep Duration: $F(1,132) = 0.31$, $p = .58$			
		Age group x Night Sleep Duration: F(5,125) = 2.84, p = .02*			
	M3	1100.17	1147.69	1068.17	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, p =.001**			
	M1	263.23	272.03	257.23	10
		Age group: $F(5,75) = 3.83$, p = .004*			
		Night Sleep Duration: $F(1,121) = 1.22$, $p = .27$			
	M2	270.65	279.11	264.65	15
	M3	272.88	281.32	266.88	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, p =.14			
	M1	334.62	343.20	328.62	10
		Age group: $F(5,70) = 1.83$, p = .12			
		Night Sleep Duration: $F(1,120) = 0.25$, $p = .62$			
	M2	371.31	379.77	365.31	15
	M3	372.01	380.44	366.01	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, p =.134			
	M1	230.22	238.80	224.22	10
		Age group: $F(5,74) = 1.22$, p =.31			

		Night Sleep Duration: $F(1,122) = 0.35$, $p = .55$			
	M2	276.13	284.593	270.13	15
	M3	231.80	240.36	223.47	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	416.31	446.01	396.31	10
		Age group: $F(5,89) = 0.93$, $p = .465$			
		Night Sleep Duration: $F(1,106) = 0.26$, $p = .61$			
	M2	422.00	466.50	392.00	15
	M3	417.64	450.30	395.64	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	274.69	303.13	254.69	10
		Age group: $F(5,55) = 1.68$, $p = .15$			
		Night Sleep Duration: $F(1,103) = 1.39$, $p = .24$			
	M2	274.64	317.30	244.64	15
	M3	276.51	307.80	254.51	9

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Day Sleep Duration and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	1054.73	1084.07	1034.73	10
	M2	1046.90	1090.92	1016.90	15
		Age group: $F(5,129) = 3.14$, $p = .01$*			
		Day Sleep Duration: $F(1,138) = 2.53$, $p = .11$			
		Age group x Day Sleep Duration: $F(5,132) = 3.83$, $p = .003$*			
	M3	1047.71	1094.66	1015.71	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	1111.74	1141.08	1091.74	10
		Age group: $F(5,106.5) = 4.93$, $p < .001$**			
		Day Sleep Duration: $F(1,138) = 1.32$, $p = .25$			
	M2	1120.05	1164.06	1090.05	15
	M3	1113.30	1145.58	1091.30	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group $F(5,100) = 2.59$, $p = .03$*°			
	M1	1036.16	1065.50	1016.16	10
		Age group $F(5,91) = 1.70$, $p = .14$			
		Day Sleep Duration: $F(1,133) = 6.16$, $p = .01$*			
	M2	1036.02	1080.03	1006.02	15
	M3	1037.46	1069.74	1015.46	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: $F(5,127) = 4.46$, $p = .001$**			
	M1	1058.23	1987.58	1038.23	10
	M2	1049.57	1093.59	1019.57	15
		Age group: $F(5,119) = 5.88$, $p < .001$**			
		Day Sleep Duration: $F(1,137) = 2.77$, $p = .10$			
		Age group x Day Sleep Duration: $F(5,128) = 4.03$, $p = .002$*			
	M3	1051.10	1098.06	1019.10	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, $p < .001$**			
	M1	1063.80	1093.14	1042.80	10
		Age group: $F(5,95) = 5.05$, $p < .001$**			
		Day Sleep Duration: $F(1,137) = 4.24$, $p = .04$			
	M2	1064.45	1108.47	1108.47	15
	M3	1063.36	1095.64	1041.36	11
IBQ-R subscale:	Baseline	273.05	282.00	267.05	
		Age group: $F(5,89) = 4.45$, $p = .001$**			

Surgency	M1	215.26	223.72	209.26	10
		Age group: F(5,71) = 3.70, *p* <.005*			
		Day Sleep Duration: F(1,119) = 0.74, *p* = .39			
	M2	257.91	266.25	251.91	15
	M3	117.22	225.56	211.22	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	320.30	328.76	314.30	10
	M2	352.06	360.40	346.06	15
	M3	319.74	328.18	313.74	11
		Age group: F(5,65) = 1.63, *p* =.17			
		Day Sleep Duration: F(1,116) = 0.08, *p* = .78			
		Gender: F(1,57) = 1.83, *p* = .18			
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	221.63	230.09	215.63	10
		Age group: F(5,69) = 1.64, *p* =.16			
		Day Sleep Duration: F(1,111) = 3.19, *p* =.08			
	M2	264.67	273.01	258.67	15
	M3	222.56	231.00	216.56	11
Bed time ritual number	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	403.44	432.79	383.44	10
		Age group: F(5,83) = 0.99, *p* =.43			
		Day Sleep Duration: F(1,131) = 1.27, *p* =.26			
	M2	406.61	450.63	376.61	15
	M3	404.85	437.18	382.85	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	270.18	298.30	250.18	10
	M2	266.95	209.13	236.95	15
		Age group: F(5,69) = 2.77, *p* = .03*			
		Day Sleep Duration: F(1,93) = 6.93, *p* = .01*			
		Age group x Day Sleep Duration: F(5,70) = 3.27, *p* = .01*			
	M3	271.89	302.83	249.89	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy WASO and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: F(5,124) =5.38, *p* <.001**			
	M1	1123.11	1153.15	1103.11	10
		Age group: F(5,85) = 5.78, *p* <.001**			
		WASO: F(1,141) = 1.72, *p* = .19			
	M2	1128.87	1173.93	1098.87	15
	M3	1124.38	1157.42	1102.38	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1184.06	1214.10	1164.06	10
	M2	1181.64	1226.70	1151.64	15
		Age group: F(5,112) = 3.87, *p* =.003**			
		WASO: F(1,139) = 0.04, *p* = .84			
		Age group x WASO: F(5,107) = 2.76, *p* <.02*			
	M3	1185.35	1218.40	1163.35	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) = 2.59, p =.03*°			
	M1	1109.41	1139.45	1089.41	10
		Age group F(5,73) = 1.67, p = .15			
		WASO: F(1,145) = 0.01, *p* = .93			
	M2	1117.26	1162.32	1087.26	15
	M3	1110.96	1144.00	1088.96	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: F(5,127) = 4.46, p =.001**			

	M1	1129.81	1159.78	1109.81	10
		Age group: $F(5,116) = 4.27$, p =.001**			
		WASO: $F(1,147) = 0.97$, $p = .33$			
	M2	1137.39	1182.34	1107.39	15
	M3	1131.46	1164.43	1109.46	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, p <.001**			
	M1	1130.75	1160.72	1110.75	10
		Age group: $F(5,96) = 4.51$, p =.001**			
		WASO: $F(1,139) = 2.41$, $p = .12$			
	M2	1135.08	1180.04	1105.08	15
	M3	1109.11	1164.08	1109.11	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, p =.001**			
	M1	259.77	268.46	253.77	10
		Age group: $F(5,89) = 3.41$, p =.007*			
		WASO: $F(1,119) = 3.67$, p =.06			
	M2	287.40	295.98	281.40	15
	M3	261.92	270.59	255.92	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, p =.14			
	M1	344.20	352.89	338.20	10
		Age group: $F(5,74) = 1.64$, p =.16			
		WASO: $F(1,98) = 0.13$, p =.72			
	M2	376.06	384.64	370.06	15
	M3	344.30	353.00	338.30	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, p =.134			
	M1	232.88	241.57	226.88	10
		Age group: $F(5,78) = 1.25$, p =.29			
		Sleep quality cluster: $F(1,99) = 0.37$, $p = .55$			
	M2	268.67	277.25	262.67	15
	M3	234.45	243.12	228.45	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, p =.134			
	M1	428.35	458.39	408.35	10
		Age group: $F(5,94) = 1.06$, p =.39			
		WASO: $F(1,145) = 0.64$, p =.43			
	M2	433.19	478.24	403.19	15
	M3	430.00	463.01	408.00	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, p =.16			
	M1	280.40	309.23	260.40	10
		Age group: $F(5,56) = 1.61$, $p = .17$			
		WASO: $F(1,79) = 2.26$, $p = .08$			
	M2	286.01	329.25	256.01	15
	M3	282.23	313.94	260.23	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Wakening Number and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, p <.001**			
	M1	1097.84	1127.61	1077.84	10
		Age group: $F(5,90) = 4.97$, p <.001**			
		Night Wakening Number: $F(1,121) = 0.36$, $p = .55$			
	M2	1104.48	1149.13	1074.48	15
	M3	1099.00	1131.72	1076.98	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, p <.001**			

	M1	1154.39	1184.16	1134.39	10
		Age group: F(5,86) = 5.46, *p* <.001**			
		Night Wakening Number: F(1,132) = 2.63, *p* = .11			
	M2	1157.04	1201.69	1127.04	15
	M3	1155.77	1188.52	1133.77	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) =2.59, p =.03*°			
	M1	1082.69	1112.46	1062.69	10
		Age group F(5,78) =1.71, p = .14			
		Night Wakening Number: F(1,115) = 0.64, *p* = .43			
	M2	1083.73	1128.38	1053.73	15
	M3	1084.01	1116.75	1062.01	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: F(5,127) =4.46, p =.001**			
	M1	1109.78	1139.55	1089.78	10
		Age group: F(5,107) = 3.77, p = .004*			
		Night Wakening Number: *F*(1,122) = 0.09, *p* = .77			
	M2	1113.62	1158.27	1083.62	15
	M3	1111.43	1144.18	1089.43	10
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1109.32	1139.09	1089.32	10
		Age group: F(5,97) = 4.43, *p* =.001**			
		Night Wakening Number: F(1,128) = 0.94, *p* = .33			
	M2	1116.65	1161.30	1086.65	15
	M3	1109.30	1142.046	1087.30	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	222.44	231.04	216.44	10
		Age group: F(5,75) = 3.86, p = .004*			
		Night Wakening Number: F(1,128) = 0.13, *p* =.72			
	M2	226.52	235.01	220.52	15
	M3	224.60	233.18	218.60	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	326.68	335.28	320.68	11
		Age group: F(5,72) = 2.19, p =.06			
		Night Wakening Number: F(1,128) = 1.08, *p* =.30			
	M2	327.50	335.98	321.50	20
	M3	326.55	335.13	320.55	12
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	220.17	228.78	214.17	11
		Age group: F(5,74) = 1.37, *p* =.25			
		Night Wakening Number: F(1,129) = 2.47, *p* =.12			
	M2	225.49	234.00	219.49	15
	M3	221.86	230.44	215.86	11
Bed time ritual number	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	419.30	449.06	399.29	10
	M2	419.08	463.73	389.08	15
		Age group: F(5,111) = 2.00, *p* =.08			
		Night Wakening Number: F(1,113) = 0.28, *p* =.60			
		Night Wakening Number x age group: F(5,114) = 2.20, *p* = .06			
	M3	420.78	453.52	398.78	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	276.73	305.25	256.73	10
		Age group: F(5,55) = 1.65, *p* = .16			
		Night Wakening Number: F(1,93) = 0.10, *p* = .75			
	M2	278.95	321.73	248.95	15
	M3	278.52	309.89	256.52	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Sleep Duration and questionnaire measures

		AIC	BIC	-2LL	df
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: F(5,124) = 5.38, *p* <.001**			
	M1	1052.92	1082.41	1032.92	10
		Age group: F(5,87) = 5.68, *p* <.001**			
		Night Sleep Duration: F(1,104) =0.00, *p* = .98			
	M2	1056.59	1100.83	1026.59	15
	M3	1053.90	1086.34	1031.90	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1117.59	1147.07	1097.59	10
		Age group: F(5,93) = 5.24, *p* <.001**			
		Night Sleep Duration: F(1,132) = 1.37, *p* = .24			
	M2	1124.35	1168.58	1094.35	15
	M3	1118.80	1151.23	1096.80	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) =2.59, p =.03*°			
	M1	1041.85	1071.34	1021.85	10
		Age group F(5,105) = 2.45, p = .04*			
		Sleep quality cluster: F(1,115) = 0.10, *p* = .75			
	M2	1044.70	1088.93	1014.70	15
	M3	1041.66	1074.10	1019.66	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1063.78	1093.27	1043.78	10
		Age group: F(5,110) = 3.41, p =.007*			
		Night Sleep Duration: *F*(1,113) = 0.46, *p* = .50			
	M2	1069.52	1113.75	1039.52	15
	M3	1065.62	1098.05	1043.62	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1057.06	1086.48	1037.06	10
		Age group: F(5,84) = 3.98, *p* = .003*			
		Night Sleep Duration: F(1,129) = 0.02, *p* = .89			
	M2	1058.93	1103.06	1028.93	15
	M3	1057.13	1089.49	1035.13	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	216.43	224.91	210.43	10
		Age group: F(5,69) = 3.86, *p* = .004*			
		Night Sleep Duration: F(1,121) = 1.40, *p* = .24			
	M2	266.25	274.61	260.25	15
	M3	218.53	227.00	212.53	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	316.73	325.21	310.73	10
	M2	356.00	364.35	350.00	15
	M3	315.89	324.36	309.89	11
		Age group: F(5,68) = 1.07, *p* = .39			
		Night Sleep Duration: F(1,121) = 1.98, *p* = .16			
		Gender: F(1,59) = 2.02, *p* = .16			
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	215.62	224.10	209.62	10
		Age group: F(5,71) = 2.78, *p* =.02*			
		Night Sleep Duration: F(1,121) = 0.04, *p* =.84			
	M2	264.21	272.52	258.21	15
	M3	217.32	225.78	211.32	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	398.23	427.72	378.23	11
		Age group: F(5,88) = 1.11, *p* =.361			
		Night Sleep Duration: F(1,96) = 7.09, *p* =.009*			
	M2	400.24	444.47	370.24	15

	M3	399.70	432.13	377.70	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	257.23	285.35	237.23	10
		Age group: $F(5,54) = 1.17$, $p = .34$			
		Night Sleep Duration: $F(1,96) = 0.63$, $p = .43$			
	M2	259.07	301.25	229.07	15
	M3	258.41	289.35	236.41	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Day Sleep Duration and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	1046.37	1075.79	1026.37	10
		Age group: $F(5,88) = 5.15$, $p < .001$**			
		Day Sleep Duration: $F(1,130) = 0.00$, $p = .98$			
	M2	1050.18	1094.31	1020.18	15
	M3	1047.42	1079.78	1025.42	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	1106.76	1136.17	1086.76	10
	M2	1102.80	1146.93	1072.80	15
		Age group: $F(5,89) = 3.27$, $p = .009$*			
		Day Sleep Duration: $F(1,131) = 0.61$, $p = .44$			
		Age group x Day Sleep Duration: $F(5,96) = 3.38$, $p = .007$*			
	M3	1102.80	1149.87	1070.80	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group $F(5,100) = 2.59$, $p = .03$*°			
	M1	1034.65	1064.07	1014.65	10
	M2	1033.78	1077.90	1003.78	15
		Age group: $F(5,102) = 1.93$, $p = .10$			
		Day Sleep Duration: $F(1,140) = 6.12$, $p = .02$*			
		Age group x Day Sleep Duration: $F(5,113) = 2.29$, $p = .05$*			
	M3	1034.15	1066.51	1012.15	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: $I(5,127) = 4.46$, $p = .001$**			
	M1	1056.52	1085.93	1036.52	10
	M2	1054.68	1098.80	1024.68	15
		Age group: $F(5,117) = 1.26$, $p = .29$			
		Day Sleep Duration: $F(1,138) = 3.53$, $p = .06$			
		Age group x Day Sleep Duration: $F(5,123) = 2.54$, $p = .03$*			
	M3	1056.58	1103.65	1024.58	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, $p < .001$**			
	M1	1048.86	1078.21	1028.86	10
		Age group: $F(5,83) = 4.38$, $p = .001$**			
		Day Sleep Duration: $F(1,137) = 1.14$, $p = .29$			
	M2	1054.18	1098.20	1024.18	15
	M3	1048.69	1081.00	1026.69	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	213.27	221.70	207.26	10
		Age group: $F(5,63) = 3.25$, $p = .01$*			
		Day Sleep Duration: $F(1,112) = 1.26$, $p = .27$			
	M2	257.00	265.30	251.00	15
	M3	215.40	223.81	209.40	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	310.53	318.96	304.53	10
		Age group: $F(5,68) = 0.94$, $p = .01$*			
		Day Sleep Duration: $F(1,119) = 1.46$, $p = .23$			

	M2	350.18	358.49	344.18	15
	M3	310.15	318.68	304.15	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	207.55	216.00	201.5	11
		Age group: F(5,85) = 2.03, *p* =.03*			
		Day Sleep Duration: F(1,114) = 3.865, *p* =.052			
	M2	253.15	261.46	247.15	15
	M3	209.24	217.66	203.24	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	406.28	435.77	386.28	10
	M2	405.34	449.57	375.34	15
		Age group: F(5,93) = 2.21, *p* =.06			
		Day Sleep Duration: F(1,138) = 0.43, *p* =.51			
		Day Sleep Duration x age group: F(5,103) = 2.62, *p* = .029*			
	M3	405.61	452.80	373.61	16
Stress	Baseline	302.05	328.72	284.05	9
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	255.55	283.59	235.55	10
		Age group: F(5,56) = 0.90, *p* = .49			
		Day Sleep Duration: F(1,91) = 0.00, *p* = .99			
	M2	260.85	302.91	230.85	15
	M3	256.80	287.65	234.80	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary WASO and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: F(5,124) =5.38, *p* <.001**			
	M1	1025.30	1054.50	1005.30	10
		Age group: F(5,89) = 6.08, *p* <.001**			
		WASO: F(1,130) = 1.92, *p* = .17			
	M2	1027.39	1071.18	997.39	15
	M3	1026.35	1058.47	1004.35	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1088.37	1117.57	1068.37	10
		Age group: F(5,92) = 4.68, *p* = .001**			
		WASO: F(1,129) = 0.03, *p* = .86			
	M2	1095.04	1138.84	1065.04	15
	M3	1089.18	1121.30	1067.18	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) =2.59, p =.03*°			
	M1	1009.83	1039.03	989.83	10
		Age group F(5,92) = 2.26, p = .06			
		WASO: F(1,125) = 2.89, *p* = .09			
	M2	1010.58	1054.38	980.58	15
	M3	1009.46	1041.58	987.46	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1029.42	1058.62	1009.42	10
		Age group: F(5,106) = 3.82, p = .003*			
		WASO: *F*(1,128) = 0.07, *p* = .79			
	M2	1032.62	1076.42	1002.62	15
	M3	1031.18	1063.30	1009.18	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1025.44	1054.57	1005.44	10
		Age group: F(5,100) = 4.77, *p* =.001**			
		WASO: F(2,151) = 0.131, *p* = .88			
	M2	1024.48	1068.17	994.48	15
	M3	1024.45	1071.05	992.45	11

		Age group: $F(5,96) = 4.25$, $p = .002$* *WASO:* $F(1,134) = 1.17$, $p = .28$ *WASO x age group:* $F(5,102) = 2.45$, $p = .039$* *Gender:* $F(1,56) = 2.07$, $p = .16$			
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	213.11	221.47	207.11	10
		Age group: $F(5,61) = 4.33$, $p = .002$* *WASO:* $F(1,111) = 0.28$, $p = .60$			
	M2	245.80	254.03	239.80	15
	M3	215.13	223.47	209.13	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	299.64	308.00	293.64	10
		Age group: $F(5,65) = 2.24$, $p = .06$ *WASO:* $F(1,107) = 2.80$, $p = .10$			
	M2	336.14	344.37	330.14	15
	M3	230.00	308.28	293.94	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	208.16	216.52	202.16	10
		Age group: $F(5,68) = 2.20$, $p = .07$ *WASO:* $F(1,106) = 0.29$, $p = .594$			
	M2	249.48	257.72	243.48	15
	M3	209.87	218.21	203.87	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	400.97	430.24	380.97	10
		Age group: $F(5,79) = 1.10$, $p = .37$ *WASO:* $F(1,122) = 0.00$, $p = .96$			
	M2	402.87	446.78	372.87	15
	M3	402.37	434.57	380.37	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	253.68	281.55	233.68	10
		Age group: $F(5,53) = 1.01$, $p = .42$ *WASO:* $F(1,84) = 0.31$, $p = .58$			
	M2	258.00	299.75	227.94	15
	M3	254.66	285.32	232.66	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Wakening Number and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	1052.00	1081.48	1032.00	10
		Age group: $F(5,88) = 5.59$, $p < .001$** *Night Wakening Number:* $F(1,120) = 0.94$, $p = .33$			
	M2	1059.55	1103.79	1029.55	15
	M3	1053.00	1085.41	1031.00	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	1116.74	1146.23	1096.74	10
		Age group: $F(5,98) = 5.67$, $p < .001$** *Night Wakening Number:* $F(1,129) = 2.52$, $p = .12$			
	M2	1120.66	1164.89	1090.66	15
	M3	1117.74	1150.17	1095.74	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group $F(5,100) = 2.59$, $p = .03$*°			
	M1	1043.13	1072.62	1023.13	10
	M2	1041.70	1085.94	1011.70	15
	M3	1040.35	1087.53	1008.35	11

		Age group: $F(5,106) = 1.43$, $p = .22$ *Night Wakening Number:* $F(1,132) = 0.01$, $p = .95$ *Age group x Night Wakening Number:* $F(5,119) = 2.58$, $p = .03$ *Gender:* $F(1,57) = 3.44$, $p = .07$			
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1062.04	1091.52	1042.04	10
		Age group: $F(5,110) = 3.62$, p =.004* *Night Wakening Number*: $F(1,117) = 0.04$, $p = .84$			
	M2	1064.13	1108.36	1034.13	15
	M3	1063.90	1096.33	1041.89	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, p <.001**			
	M1	1058.18	1087.60	1038.18	10
		Age group: $F(5,82) = 4.04$, $p = .003$ *Night Wakening Number:* $F(1,125) = 0.06$, $p = .81$			
	M2	1066.07	1110.20	1036.07	15
	M3	1158.10	1090.44	1036.09	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	208.52	217.00	202.52	10
		Age group: $F(5,61) = 4.60$, p =.001** *Night Wakening Number:* $F(1,123) = 4.34$, $p = .13$			
	M2	218.21	226.55	212.21	15
	M3	210.61	219.05	204.61	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	300.63	309.09	294.63	10
		Age group: $F(5,68) = 2.66$, p =.03* *Night Wakening Number:* $F(1,119) = 13.86$, p <.001**			
	M2	303.00	311.33	297.00	15
	M3	300.41	308.85	294.41	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	206.81	215.27	200.81	10
		Age group: $F(5,71) = 2.74$, $p = .08$ *Night Wakening Number:* $F(1,122) = 0.62$, $p = .43$			
	M2	213.09	221.42	207.09	15
	M3	208.49	216.93	202.49	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	408.68	438.17	388.68	10
		Age group: $F(5,79) = 1.14$, $p = .35$ *Night Wakening Number:* $F(1,106) = 0.29$, $p = .59$			
	M2	411.14	455.37	381.14	15
	M3	410.21	442.65	388.21	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	259.69	287.89	239.69	19
		Age group: $F(5,56) = 1.01$, $p = .42$ *Night Wakening Number:* $F(1,88) = 0.09$, $p = .76$			
	M2	267.89	310.19	237.89	15
	M3	261.00	292.00	238.97	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Sleep Duration and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, p <.001**			
	M1	1203.27	1234.08	1183.27	10
		Age group: $F(5,84) = 5.26$, p <.001** *Night Sleep Duration:* $F(1,158) = 2.68$, $p = .10$			
	M2	1208.66	1254.88	1178.66	15

	M3	1204.44	1238.38	1182.44	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1269.84	1300.65	1249.84	10
		Age group: F(5,92) = 6.93, *p* <.001**			
		Night Sleep Duration: F(1,161) = 3.51, *p* = .06			
	M2	1273.70	1319.92	1243.70	15
	M3	1270.45	1304.34	1248.45	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group: F(5,100) =2.59, p =.03*°			
	M1	1195.71	1226.53	1175.71	10
		Age group: F(5,101) = 2.41, p = .04			
		Night Sleep Duration: F(1,158) = 0.03, *p* = .87			
	M2	1201.05	1247.27	1171.05	15
	M3	1197.05	1230.95	1175.05	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: I(5,127) =4.46, p =.001**			
	M1	1214.91	1245.66	1194.91	10
		Age group: F(5,125) = 4.35, p =.001**			
		Night Sleep Duration: *F*(1,159) = 0.11, *p* = .75			
	M2	1220.87	1267.00	1190.87	15
	M3	1216.86	1250.69	1194.86	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1209.50	1240.20	1189.50	10
		Age group: F(5,101) = 5.10, *p* <.001**			
		Night Sleep Duration: F(1,159) = 0.04, *p* = .84			
	M2	1210.65	1256.68	1180.65	15
	M3	1210.00	1243.68	1187.92	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	284.17	293.06	278.17	10
		Age group: F(5,89) = 4.22, *p* =.002*			
		Night Sleep Duration: F(1,141) = 0.60, *p* = .44			
	M2	330.85	339.63	324.85	15
	M3	386.10	295.00	280.10	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	364.96	373.85	358.96	10
		Age group: F(5,82) = 1.82, *p* =.12			
		Night Sleep Duration: F(1,131) = 0.08, *p* = .78			
	M2	416.02	424.80	410.02	15
	M3	365.78	374.65	359.78	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	244.69	253.58	238.69	10
		Age group: F(5,84) = 2.05, *p* =.08			
		Night Sleep Duration: F(1,130) = 3.02, *p* =.09			
	M2	296.86	305.64	290.86	15
	M3	246.22	255.08	240.21	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	461.78	492.60	441.78	10
		Age group: F(5,104) = 1.76, *p* =.127			
		Night Sleep Duration: F(1,156) = 0.78, *p* =.38			
	M2	471.00	517.22	441.00	15
	M3	463.64	497.54	441.64	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: F(5,67) = 1.65, *p* =.16			
	M1	300.23	329.72	280.23	10
		Age group: F(5,62) = 1.39, *p* = .24			
		Night Sleep Duration: F(1,103) = 0.00, *p* = .98			
	M2	305.14	349.37	275.14	15
	M3	280.06	334.50	280.06	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Day Sleep Duration and questionnaire measures

		AIC	BIC	-2LL	df
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: F(5,124) =5.38, *p* <.001**			
	M1	1198.82	1229.58	1178.82	10
		Age group: F(5,88) = 5.31, *p* <.001**			
		Day Sleep Duration: F(1,160) = 0.51, *p* = .48			
	M2	1204.81	1250.94	1174.81	15
	M3	1200.11	1233.93	1178.11	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: F(5,93) = 6.84, *p* <.001**			
	M1	1266.38	1297.13	1246.38	11
		Age group: F(5,94) = 6.62, *p* <.001**			
		Day Sleep Duration: F(1,156) = 0.17, *p* = .68			
	M2	1270.77	1316.90	1240.77	20
	M3	1267.26	1301.08	1245.26	12
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group F(5,100) =2.59, p =.03*°			
	M1	1188.48	1219.23	1168.48	10
	M2	1185.93	1232.05	1155.93	15
		Age group: F(5,113) = 1.33, p = .25			
		Day Sleep Duration: F(1,140) = 1.42, *p* = .24			
		Age group x Day Sleep Duration: F(5,125) = 2.70, p = .02*			
	M3	1189.75	1223.58	1167.75	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: F(5,127) = 4.46, *p* =.001**			
	M1	1197.31	1228.00	1177.31	10
	M2	1193.83	1239.86	1163.83	15
		Age group: F(5,126) = 0.94, p = .46			
		Day Sleep Duration: F(1,153) = 1.38, *p* = .24			
		Age group x Day Sleep Duration: F(5,138) = 2.92, p = .02*			
	M3	1195.80	1244.90	1163.80	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: F(5,106) = 5.14, p <.001**			
	M1	1201.47	1232.10	1181.47	10
		Age group: F(5,101) = 4.80, *p* =.001**			
		Day Sleep Duration: F(2,153) = 1.76, *p* = .19			
	M2	1204.41	1250.35	1174.41	15
	M3	1201.88	1235.57	1179.88	12
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	
		Age group: F(5,89) =4.45, *p* =.001**			
	M1	280.45	289.32	274.45	10
		Age group: F(5,90) = 5.23, *p* <.001**			
		Day Sleep Duration: F(1,135) = 3.16, *p* = .08			
	M2	324.53	333.30	318.54	15
	M3	282.47	291.32	276.47	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: F(5,82) = 1.73, *p* =.14			
	M1	350.32	359.13	344.32	11
		Age group: F(5,78) = 1.79, *p* =.12			
		Day Sleep Duration: F(1,119) = 0.00, *p* = .99			
	M2	411.64	420.40	405.64	15
	M3	364.64	373.48	358.64	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: F(5,104) = 1.73, *p* =.134			
	M1	243.52	252.39	237.52	10
		Age group: F(5,87) = 1.82, *p* =.12			
		Day Sleep Duration: F(1,125) = 3.86, *p* =.052			
	M2	296.69	305.45	290.69	15

	M3	244.75	253.60	238.75	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	457.14	487.90	437.14	10
		Age group: $F(5,107) = 1.99$, $p = .09$			
		Day Sleep Duration: $F(1,156) = 1.33$, $p = .250$			
	M2	463.76	509.88	433.76	15
	M3	459.01	492.84	437.01	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	299.34	328.76	279.34	10
		Age group: $F(5,62) = 1.24$, $p = .30$			
		Day Sleep Duration: $F(1,100) = 0.07$, $p = .79$			
	M2	304.14	348.27	274.14	15
	M3	301.14	333.50	279.14	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ WASO and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: Communication	Baseline	1213.96	1241.75	1195.96	9
		Age group: $F(5,124) = 5.38$, $p < .001$**			
	M1	1187.89	1218.58	1167.89	10
		Age group: $F(5,101) = 4.98$ $p = .001$**			
		WASO: $F(1,150) = 0.10$, $p = .75$			
	M2	1194.58	1240.61	1164.58	15
	M3	1189.16	1222.92	1167.16	11
ASQ subscale: Gross motor	Baseline	1278.42	1306.21	1260.42	9
		Age group: $F(5,93) = 6.84$, $p < .001$**			
	M1	1255.98	1286.66	1235.98	10
		Age group: $F(5,91) = 7.11$, $p < .001$**			
		WASO: $F(1,153) = 0.66$, $p = .42$			
	M2	1264.72	1310.50	1234.46	15
	M3	1256.92	1290.68	1234.91	11
ASQ subscale: Fine motor	Baseline	1199.91	1227.70	1181.91	9
		Age group: $F(5,100) = 2.59$, $p = .03$*°			
	M1	1183.11	1213.80	1163.11	10
		Age group: $F(5,110) = 2.14$, $p = .07$			
		WASO: $F(1,132) = 0.00$, $p = .97$			
	M2	1184.00	1230.03	1154.00	15
	M3	1184.43	1218.19	1162.43	11
ASQ subscale: Problem-solving	Baseline	1220.15	1247.884	1202.15	9
		Age group: $I(5,127) = 4.46$, $p = .001$**			
	M1	1199.17	1229.80	1179.17	10
		Age group: $F(5,125) = 3.41$, $p = .006$*			
		WASO: $F(1,152) = 1.97$, $p = .16$			
	M2	1206.72	1252.65	1176.72	15
	M3	1201.02	1234.71	1179.02	11
ASQ subscale: Social	Baseline	1215.78	1243.46	1197.78	9
		Age group: $F(5,106) = 5.14$, $p < .001$**			
	M1	1196.58	1227.14	1176.58	10
		Age group: $F(5,98) = 4.57$, $p = .001$**			
		WASO: $F(1,154) = 0.06$, $p = .80$			
	M2	1201.62	1247.46	1171.62	15
	M3	1196.95	1230.57	1174.95	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	280.33	289.18	274.33	10
		Age group: $F(5,89) = 4.35$, $p = .001$**			
		WASO: $F(1,136) = 0.15$ $p = .69$			
	M2	319.21	327.94	313.21	15
	M3	282.32	291.15	276.32	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	354.04	362.88	348.04	10

		Age group: $F(5,81) = 1.86$, $p = .11$ *WASO:* $F(1,122) = 5.55$, $p = .02$*			
	M2	387.04	395.78	381.04	15
	M3	351.02	259.80	345.02	11
IBQ-R subscale: Regulation	Baseline	460.56 *Age group:* $F(5,104) = 1.73$, $p = .134$	488.30	442.56	9
	M1	241.25 *Age group:* $F(5,83) = 1.71$, $p = .14$ *WASO:* $F(1,127) = 0.24$, $p = .62$	250.09	235.25	10
	M2	284.21	292.95	278.21	15
	M3	242.75	251.57	236.75	11
Bed time ritual number	Baseline	460.56 *Age group:* $F(5,104) = 1.73$, $p = .134$	488.30	442.56	9
	M1	455.52	486.20	435.52	10
	M2	452.30 *Age group:* $F(5,117) = 1.01$, $p = .42$ *WASO:* $F(2,136) = 1.89$, $p = .17$ *WASO x age group:* $F(5,125) = 2.85$, $p = .02$	498.34	422.30	15
	M3	454.30	503.40	422.30	11
Stress	Baseline	302.05 *Age group:* $F(5,67) = 1.65$, $p = .16$	328.72	284.05	9
	M1	294.07 *Age group:* $F(5,61) = 0.95$, $p = .45$ *WASO:* $F(1,138) = 3.93$, $p = .05$*	323.41	274.07	10
	M2	300.95	344.97	270.95	15
	M3	295.73	328.01	273.73	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Wakening Number and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
ASQ subscale: Communication	Baseline	1213.96 *Age group:* $F(5,124) = 5.38$, $p < .001$**	1241.75	1195.96	9
	M1	1205.60 *Age group:* $F(5,90) = 5.83$, $p < .001$** *Night Wakening Number:* $F(1,140) = 0.29$, $p = .59$	1236.41	1185.60	10
	M2	1210.68	1256.90	1180.68	15
	M3	1206.83	1240.73	1184.83	11
ASQ subscale: Gross motor	Baseline	1278.42 *Age group:* $F(5,93) = 6.84$, $p < .001$**	1306.21	1260.42	9
	M1	1272.07 *Age group:* $F(5,95) = 6.89$, $p < .001$** *Night Wakening Number:* $F(1,149) = 1.20$, $p = .28$	1302.88	1252.07	10
	M2	1277.83	1324.05	1247.83	15
	M3	1273.09	1307.00	1251.09	11
ASQ subscale: Fine motor	Baseline	1199.91 *Age group:* $F(5,100) = 2.59$, $p = .03$*°	1227.70	1181.91	9
	M1	1195.45 *Age group:* $F(5,102) = 2.42$, $p = .04$* *Night Wakening Number:* $F(1,131) = 0.29$, $p = .60$	1226.26	1175.45	10
	M2	1197.41	1243.63	1167.41	15
	M3	1196.67	1230.57	1174.67	11
ASQ subscale: Problem-solving	Baseline	1220.15 *Age group:* $F(5,127) = 4.46$, $p = .001$**	1247.884	1202.15	9
	M1	1214.52 *Age group:* $F(5,127) = 4.25$, $p = .001$** *Night Wakening Number*: $F(1,132) = 0.50$, $p = .48$	1245.27	1194.52	10
	M2	1217.07	1263.20	1187.07	15
	M3	1216.44	1250.26	1194.44	11
ASQ subscale: Social	Baseline	1215.78 *Age group:* $F(5,106) = 5.14$, $p < .001$**	1243.46	1197.78	9
	M1	1209.50 *Age group:* $F(5,101) = 5.21$, $p < .001$** *Night Wakening Number:* $F(1,141) = 0.05$, $p = .82$	1240.28	1189.50	10
	M2	1213.24	1259.27	1183.24	15

	M3	1209.98	1243.74	1187.98	11
IBQ-R subscale: Surgency	Baseline	273.05	282.00	267.05	9
		Age group: $F(5,89) = 4.45$, $p = .001$**			
	M1	276.58	285.47	270.58	10
		Age group: $F(5,90) = 4.36$, $p = .001$**			
		Night Wakening Number: $F(1,138) = 0.30$, $p = .58$			
	M2	287.17	295.95	281.17	15
	M3	278.57	287.44	272.57	11
IBQ-R subscale: Negativity	Baseline	355.88	364.83	349.88	9
		Age group: $F(5,82) = 1.73$, $p = .14$			
	M1	352.29	361.17	346.29	11
		Age group: $F(5,82) = 4.36$, $p = .05$*			
		Night Wakening Number: $F(1,142) = 5.65$, $p = .02$*			
	M2	353.12	361.90	347.12	15
	M3	354.20	362.96	348.20	11
IBQ-R subscale: Regulation	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	238.88	246.76	231.88	10
		Age group: $F(5,81) = 2.03$, $p = .05$*			
		Sleep quality cluster: $F(1,142) = 1.98$, $p = .16$			
	M2	247.27	256.05	241.27	15
	M3	239.11	247.98	233.11	11
Bed time ritual number	Baseline	460.56	488.30	442.56	9
		Age group: $F(5,104) = 1.73$, $p = .134$			
	M1	462.56	493.37	442.56	10
		Age group: $F(5,103) = 1.73$, $p = .13$			
		Night Wakening Number: $F(1,123) = 0.00$, $p = .98$			
	M2	467.92	514.14	437.92	15
	M3	464.47	498.37	442.47	11
Stress	Baseline	302.05	328.72	284.05	9
		Age group: $F(5,67) = 1.65$, $p = .16$			
	M1	298.46	327.95	278.46	10
		Age group: $F(5,60) = 1.50$, $p = .20$			
		Night Wakening Number: $F(1,120) = 1.92$, $p = .17$			
	M2	300.56	344.79	270.56	15
	M3	300.25	332.68	278.25	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Appendix – Chapter 5

Data Quality Eye-tracking measures (for pooled N)

	% Data valid	% Missing data
Gap-overlap task		
Baseline mean SRT	68.1 %	31.9 %
Gap mean SRT	68.1 %	31.9 %
Overlap mean SRT	68.1 %	31.9 %
Disengagement	68.1 %	31.9 %
Facilitation	68.1 %	31.9 %
Baseline SRT variability	68.1 %	31.9 %
Face pop-out task		
1st face look proportion	92.2 %	7.8 %
Face peak look	71.1 %	28.9 %
Total face look proportion	88.6 %	11.4 %
Novelty habituation paradigm		
Look duration interesting	88.6 %	11.4 %
Look duration boring	90.4 %	9.4 %

Notes. SRT = Saccadic reaction time

Results of LMMs for sleep variables of actigraphy, diary, and BISQ and eye-tracking measures

Actigraphy sleep quality and eye-tracking measures

		AIC	BIC	-2LL	df
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1092.42	1118.17	1092.42	10
		Age group: $F(5,36) = 8.65$, $p < .001$**			
		Night Sleep Duration: $F(1,86) = 0.24$, $p = .62$			
	M2	1098.69	1137.31	1068.69	15
	M3	1093.28	1121.61	1071.28	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1054.97	1080.72	1035.00	10
		Age group: $F(5,55) = 5.21$, $p = .001$**			
		Night Sleep Duration: $F(1,92) = 0.10$, $p = .77$			
	M2	1059.11	1097.73	1029.11	15
	M3	1056.73	1085.05	1034.73	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001			
	M1	1142.85	1168.60	1122.85	10
	M2	1142.30	1180.91	1112.29	15
		Age group: F(5,80) = 4.81, p = .001**			
		Sleep quality: $F(1,97) = 0.01$, $p = .91$			
		Age group x sleep quality: $F(5,87) = 2.25$, $p = .06$			
	M3	1143.42	1171.75	1121.43	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, p =.34			
	M1	1060.22	1085.97	1040.22	10
		Age group: $F(5,50) = 1.84$, p =.121			
		Sleep quality: $F(1,95) = 4.60$, $p = .04$*			
	M2	1063.40	1102.02	1033.40	15
	M3	1061.67	1090.00	1039.67	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, p = .22			
	M1	1041.18	1066.93	1021.18	10
	M2	1046.26	1084.88	1016.26	15
	M3	1040.42	1068.74	1018.42	11
		Age group: $F(5,50) = 1.50$, p =.21			
		Sleep quality: $F(1,94) = 0.34$, $p = .56$			
		Gender $F(1,50) = 2.85$, $p = .10$			
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1126.77	1152.51	1106.77	10
	M2	1126.48	1165.10	1096.48	15
		Age group: $F(5,75) = 67.02$, p = .16			
		Night Sleep Duration: $F(1,95) = 0.13$, $p = .72$			
		Age group x sleep quality: $F(5,79)$ 2.42, p = .043*			
	M3	1126.44	1165.63	1092.44	16
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-24.02	16.02	-52.02	14
		Age group: $F(5,30) = 6.39$, $p < .001$**			
		Sleep quality: $F(1,108) = 0.06$, $p = .81$			
	M2	-20.33	34.00	-58.33	19
	M3	-24.25	18.65	-54.25	15
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	252.18	278.03	232.18	10
		Age group: $F(5,75) = 3.84$, $p = .004$*			
		Sleep quality: $F(1,98) = 0.03$, $p = .86$			
	M2	257.63	293.82	229.63	14
	M3	253.91	282.34	231.91	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-80.21	-51.92	-100.21	10

		Age group: $F(5,99) = 5.66$, $p = <.001$** *Sleep quality:* $F(1,119) = 0.17$, $p = .68$			
	M2	-71.24	-28.82	-101.24	15
	M3	-78.41	-47.30	-100.41	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	736.03	764.15	716.03	10
		Age group: $F(5,100) = 0.17$, $p = .97$ *Sleep quality:* $F(1,116) = 0.01$, $p = .93$			
	M2	740.77	782.95	710.77	15
	M3	737.00	767.92	714.99	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	657.83	686.19	636.93	10
		Age group: $F(5,67) = 3.40$, $p = .009$* *Sleep quality:* $F(1,116) = 0.89$, $p = .35$			
	M2	661.45	704.00	631.45	15
	M3	658.12	689.32	636.12	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary sleep quality and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p = <.001$**			
	M1	885.95	912.01	863.95	11
		Age group: $F(5,52) = 6.31$, $p = <.001$** *Sleep quality:* $F(2,129) = 1.25$, $p = .29$			
	M2	893.05	938.07	855.05	19
	M3	887.05	915.48	863.05	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p = <.001$**			
	M1	837.59	863.66	815.59	11
		Age group: $F(5,54) = 6.35$, $p = <.001$** *Sleep quality:* $F(1, 79) = 5.02$, $p = .009$*			
	M2	845.26	890.28	807.26	19
	M3	839.10	867.53	815.10	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p = <.001$			
	M1	924.27	950.34	902.27	11
	M2	921.82	966.84	883.82	19
		Age group: $F(5,71) = 9.50$, $p = <.001$** *Sleep quality:* $F(2,78) = 2.20$, $p = .12$ *Age group x sleep quality:* $F(8,68) = 2.65$, $p = .01$*			
	M3	922.72	970.131	882.74	20
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	871.01	897.07	849.01	11
		Age group: $F(5,63) = 1.37$, $p = .25$ *Sleep quality:* $F(2,72) = 1.88$, $p = .16$			
	M2	877.08	922.10	839.08	19
	M3	872.73	901.17	848.73	12
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	846.08	872.15	824.08	11
		Age group: $F(5,30) = 1.50$, $p = .22$ *Sleep quality:* $F(2,56) = 1.32$, $p = .28$			
	M2	853.53	898.55	815.53	19
	M3	846.44	874.87	822.44	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	899.91	925.97	877.91	11
	M2	893.12	938.14	855.12	19
	M3	892.72	940.11	852.72	20
		Age group: $F(5,63) = 2.83$, $p = .02$* *Sleep quality:* $F(2,78) = 0.23$, $p = .80$			

		Age group x sleep quality: F(8,59) = 4.01, p = .001** *Gender:* F(1,46) = 2.46, p = .12			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: F(5,112) = 4.82, *p* =.001**			
	M1	-5.83	24.27	-27.83	11
		Age group: F(5,88) = 5.20, p < .001** *Sleep quality: F*(2,101) = 0.68, *p* = .51			
	M2	0.10	54.83	-39.90	20
	M3	-3.85	29.00	-27.85	12
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: F(5,74) = 2.83, *p* =.004*			
	M1	208.83	235.83	186.83	11
		Age group: F(5,86) = 4.31, *p* =.002* *Sleep quality: F*(1,86) = 1.38, *p* =.28			
	M2	214.55	258.72	178.55	18
	M3	210.60	240.05	186.60	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: F(5,97) = 5.567, *p* <.001**			
	M1	-72.24	-42.64	-94.24	11
		Age group: F(5,69) = 5.35, *p* < .001** *Sleep quality: F*(2,76) = 1.07, *p* = .35			
	M2	-61.08	-7.25	-101.08	20
	M3	-71.32	-39.02	-95.32	12
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	647.15	676.65	625.15	11
	M2	657.61	711.25	617.61	20
	M3	645.32	677.51	621.33	12
		Age group: F(5,69) = 0.38, *p* = .86 *Sleep Quality: F*(2,102) = 2.07, *p* = .13 *Gender: F*(1,42) = 3.94, *p* = .05*			
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	587.26	617.07	565.26	11
	M2	598.48	652.67	558.48	20
	M3	585.31	617.83	561.31	12
		Age group: F(5,63) = 0.65, *p* = .66 *Sleep Quality: F*(2,105) = 1.30, *p* = .23 *Gender: F*(1,36) = 4.10, *p* = .05*			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ sleep quality and questionnaire measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: F(5,38) = 8.54, *p* <.001**			
	M1	1229.48	1259.10	1207.48	11
		Age group: F(5,74) = 4.40, *p* =.001** *Sleep quality: F*(2,106) = 1.65, *p* = .20			
	M2	1234.43	1288.26	1194.43	20
	M3	1230.91	1263.20	1206.91	12
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: F(5,57) = 5.25, *p* <.001**			
	M1	1179.05	1208.65	1157.05	11
		Age group: F(5,70) = 5.10, *p* <.001** *Sleep quality: F*(1,93) = 0.753, *p* = .47			
	M2	1198.61	1243.44	1149.61	20
	M3	1180.69	1212.98	1156.69	12
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001**			
	M1	1286.06	1315.67	1264.06	11
		Age group: F(5,82) = 4.95, p = .001** *Sleep quality: F*(1,119) = 0.04, *p* = .84			
	M2	1294.59	1348.41	1254.59	20
	M3	1286.00	1318.21	1261.91	12

Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: F(5,87) = 1.15, p =.34			
	M1	1092.06	1221.67	1170.06	11
		Age group: F(5,81) = 1.12, p = .35			
		Sleep quality: *F*(2,99) = 0.54, *p* = .58			
	M2	1198.59	1252.42	1158.59	20
	M3	1092.54	1224.84	1168.54	12
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: F(5,65) = 1.43, p = .22			
	M1	1158.63	1188.24	1136.63	11
		Age group: F(5,59) = 0.87, *p* =.51			
		Sleep quality: F(2,75) = 8.98, *p* = <.001**			
	M2	1167.84	1221.67	1127.84	20
	M3	1158.98	1191.27	1134.98	12
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: F(5,82) = 1.23, *p* =.304			
	M1	1269.26	1298.87	1247.26	11
	M2	1278.69	1332.52	1238.69	20
	M3	1267.16	1299.45	1243.16	12
		Age group: F(5,75) = 1.20, *p* =.32			
		Sleep quality: F(2,105) = 0.10, *p* = .90			
		Gender: F(1,56) = 4.27, *p* = .04*			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: F(5,112) = 4.82, *p* =.001**			
	M1	-21.16	11.81	-43.16	11
		Age group: F(5,120) = 5.54, p <.001			
		Sleep quality: F(1,145) = 0.71, *p* = .49			
	M2	-7.87	52.08	-47.87	20
	M3	-19.31	16.65	-43.31	12
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: F(5,74) = 2.83, *p* =.004*			
	M1	287.05	317.34	265.05	11
	M2	270.46	322.77	232.46	19
		Age group: F(5,107) = 4.81, *p* =.001**			
		Sleep quality: F(2,114) = 2.05 5, *p* =.13			
		Age group x sleep quality: F(8,112) = 4.99, *p* < .001**			
	M3	288.85	321.89	264.85	12
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: F(5,97) = 5.567, *p* <.001**			
	M1	-96.57	-63.98	-118.57	11
		Age group: F(5,110) = 6.01, *p* <.001**			
		Sleep quality: F(1,132) = 0.57, *p* = .57			
	M2	-90.50	-31.24	-130.50	20
	M3	-95.30	-59.75	-119.30	12
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	841.42	873.94	819.42	11
		Age group: F(5,106) = 0.49, *p* = .78			
		Sleep Quality: F(2,136) = 0.17, *p* = .84			
	M2	853.56	912.67	813.56	20
	M3	842.31	877.78	818.31	12
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	755.72	788.46	733.72	11
		Age group: F(5,99) = 2.06, *p* =.08			
		Sleep Quality: F(1,135) = 1.38, *p* = .26			
	M2	755.77	815.31	715.77	20
	M3	756.00	818.48	713.97	12

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Wakening Number and eye-tracking measures

		AIC	BIC	-2LL	df
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1079.56	1105.20	1059.56	10
		Age group: $F(5,45) = 8.01$, $p < .001$**			
		Night Wakening Number: $F(1,70) = 0.93$, $p = .34$			
	M2	1082.03	1120.50	1052.03	15
	M3	1081.45	1109.66	1059.45	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1039.97	1065.62	1019.97	10
		Age group: $F(5,55) = 3.69$, $p = .006$*			
		Night Wakening Number: $F(1, 61) = 0.60$, $p = .44$			
	M2	1046.82	1085.29	1016.82	15
	M3	1041.44	1069.65	1019.44	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p < .001$			
	M1	1119.51	1145.15	1099.51	10
	M2	1113.78	1152.24	1083.78	15
		Age group: $F(5,81) = 3.31$, $p = .009$*			
		Night Wakening Number: $F(1,94) = 0.41$, $p = .51$			
		Age group x Night Wakening Number: $F(5,85) = 3.51$, $p < 0.01$*			
	M3	1114.59	1155.62	1082.59	16
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1049.85	1075.49	1029.85	10
		Age group: $F(5,65) = 1.39$, $p = .24$			
		Night Wakening Number: $F(1,79) = 2.32$, $p = .13$			
	M2	1050.64	1089.11	1020.64	15
	M3	1052.64	1093.67	1020.64	16
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	1027.28	1052.93	1007.28	10
		Age group: $F(5,39) = 1.93$, $p = .11$			
		Night Wakening Number: $F(1,71) = 0.01$, $p = .94$			
	M2	1030.52	1068.98	1000.52	15
	M3	1028.68	1056.89	1006.68	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1094.78	1120.42	1074.78	10
	M2	1092.06	1130.52	1062.06	15
		Age group: $F(5,73) = 1.42$, $p = .23$			
		Night Wakening Number: $F(1,93) = 0.05$, $p = .83$			
		Age group x Night Wakening Number: $F(5,78) = 3.01$, $p = .02$*			
	M3	1092.49	1133.52	1060.49	16
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-14.98	13.93	-34.98	10
		Age group: $F(5,101) = 4.56$, $p = .001$**			
		Night Wakening Number: $F(1,109) = 0.06$, $p = .81$			
	M2	-6.32	37.04	-36.32	15
	M3	-13.00	18.79	-35.00	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	246.71	272.96	226.71	10
		Age group: $F(5,73) = 3.90$, $p = .003$*			
		Night Wakening Number: $F(1,81) = 0.41$, $p = .52$			
	M2	249.66	289.03	219.66	15
	M3	249.60	289.07	220.60	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-91.43	-62.91	-111.43	10
		Age group: $F(5,87) = 6.64$, $p < .001$**			
		Night Wakening Number: $F(1,93) = 0.82$, $p = .37$			
	M2	-85.00	-42.22	-115.00	11
	M3	-90.31	-58.94	-112.31	12

Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	751.36	779.80	731.47	10
	M2	751.75	794.41	721.75	15
	M3	749.97	781.26	727.97	11
		Age group: F(5,93) = 0.43, *p* = .83 *Night Wakening Number: F*(1,105) = 0.93, *p* = .34 *Gender: F*(1,47) = 3.47, *p* = .07			
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	678.45	707.13	658.45	10
	M2	680.39	723.41	650.39	15
	M3	676.26	707.801	654.26	11
		Age group: F(5,87) = 1.86, *p* = .11 *Night Wakening Number: F*(1,95) = 0.29, *p* = .59 *Gender: F*(1,36) = 4.34, *p* = .05*			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary WASO and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: F(5,38) = 8.54, *p* <.001**			
	M1	1057.76	1083.20	1037.76	10
		Age group: F(5,29) = 6.97, *p* <.001** *WASO: F*(1,94) = 0.50, *p* = .48			
	M2	1062.08	1100.23	1032.08	15
	M3	1059.46	1087.43	1037.46	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: F(5,57) = 5.25, *p* <.001**			
	M1	1016.48	1041.92	996.48	10
		Age group: F(5,80) = 3.62, *p* =.005* *WASO: F*(1, 76) = 0.90, *p* = .35			
	M2	1019.81	1057.96	989.81	15
	M3	1017.86	1045.84	995.86	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001			
	M1	1096.25	1121.69	1076.26	11
	M2	1091.34	1129.49	1061.34	15
		Age group: F(5,80) = 1.80, p = .12 *WASO: F*(1,92) = 0.98, *p* = .33 *Age group x WASO:* F(5,80) = 3.42, p = .007*			
	M3	1091.61	1132.31	1059.61	16
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: F(5,87) = 1.15, p =.34			
	M1	1025.09	1050.53	1005.92	10
		Age group: F(5,77) = 1.70, p =.15 *WASO*: *F*(1,79) = 5.94, *p* = .02*			
	M2	1032.07	1070.22	1002.07	15
	M3	1027.05	1055.03	1005.05	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: F(5,65) = 1.43, p = .22			
	M1	1000.09	1025.52	980.09	10
		Age group: F(5,41) = 2.51, *p* =.05* *WASO: F*(1,83) = 0.22, *p* = .64			
	M2	1008.95	1047.10	978.95	15
	M3	1000.83	1028.80	978.83	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: F(5,82) = 1.23, *p* =.304			
	M1	1073.59	1099.02	1053.59	10
	M2	1073.30	1111.44	1043.30	15
		Age group: F(5,76) = 0.78, p = .56 *WASO: F*(1,94) = 3.10, *p* = .08 *Age group x WASO:* F(5,76) = 2.42, p = .04*			
	M3	1073.32	1101.30	1051.32	11

1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-14.17	14.50	-34.17	10
		Age group: $F(5,99) = 4.61$, $p = .001$**			
		WASO: $F(1,110) = 0.16$, $p = .69$			
	M2	-8.55	34.47	-38.455	15
	M3	-12.24	19.31	-34.24	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	238.27	264.32	218.27	10
		Age group: $F(5,79) = 3.68$, $p = .005$*			
		WASO: $F(1,81) = 0.12$, $p = .73$			
	M2	240.00	279.98	210.90	15
	M3	239.75	268.41	217.75	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-90.34	-62.06	-110.34	10
	M2	-91.15	-48.73	-121.15	15
		Age group: $F(5,103) = 4.34$, $p = .001$**			
		WASO: $F(1,106) = 0.65$, $p = .18$			
		Age group x WASO: $F(5,106) = 2.38$, $p = .04$*			
	M3	-89.84	-44.59	-121.84	16
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	731.83	760.04	711.83	10
	M2	730.92	773.23	700.92	15
	M3	729.26	774.38	697.26	16
		Age group: $F(5,110) = 1.51$, $p = .19$			
		WASO: $F(1,93) = 5.32$, $p = .02$			
		WASO x Age group: $F(5,114) = 2.36$, $p = .05$*			
		Gender: $F(1,41) = 3.83$, $p = .06$			
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	663.41	691.85	643.41	10
	M2	669.18	711.84	639.18	15
	M3	661.57	692.86	639.57	11
		Age group: $F(5,78) = 1.67$, $p = .15$			
		WASO: $F(1,95) = 1.77$, $p = .19$			
		Gender: $F(1,30) = 3.97$, $p = .06$			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Sleep Duration and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1090.11	1115.86	1070.11	10
		Age group: $F(5,47) = 7.32$, $p < .001$**			
		Sleep quality: $F(1,92) = 0.16$, $p = .69$			
	M2	1090.56	1129.18	1060.56	15
	M3	1091.92	1120.24	1069.92	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1048.45	1074.20	1028.45	10
	M2	1046.50	1085.12	1016.50	15
		Age group: $F(5,89) = 2.58$, $p = .03$*			
		Night Sleep Duration: $F(1,83) = 1.36$, $p = .25$			
		Age group x Night Sleep Duration: $F(5,91) = 2.62$, $p = .03$*			
	M3	1048.28	1089.48	1016.28	16
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p < .001$			
	M1	1131.05	1156.79	1111.05	10
		Age group: $F(5,78) = 6.40$, $p < .001$**			
		Night Sleep Duration: $F(1,85) = 0.60$, $p = .44$			
	M2	1132.72	1171.34	1102.72	15
	M3	1131.99	1160.32	1109.99	11

Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: F(5,87) = 1.15, p =.34			
	M1	1061.40	1087.14	1041.40	10
		Age group: F(5,77) = 1.26, *p* =.29			
		Night Sleep Duration: *F*(1,57) = 0.65, *p* = .43			
	M2	1065.16	1103.78	1035.16	15
	M3	1063.25	1091.57	1041.25	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: F(5,65) = 1.43, p = .22			
	M1	1037.19	1062.94	1017.19	10
		Age group: F(5,40) = 1.35, *p* =.26			
		Night Sleep Duration: F(1,82) = 1.38, *p* = .24			
	M2	1046.90	1085.52	1016.90	15
	M3	1038.92	1067.24	1016.92	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: F(5,82) = 1.23, *p* =.304			
	M1	1107.50	1133.24	1087.50	10
	M2	1103.24	1141.86	1073.24	15
	M3	1101.73	1142.93	1069.73	16
		Age group: F(5,74) = 3.42, *p* = .008*			
		Night Sleep Duration: F(1,89) = 1.02, *p* = .32			
		Age group x Night Sleep Duration: F(5,74) = 3.48, p = .007**			
		G*ender:* F(1,54) = 3.83, p = .06			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: F(5,112) = 4.82, *p* =.001**			
	M1	-15.52	13.39	-35.52	10
		Age group: F(5,101) = 4.70, p = .001**			
		Night Sleep Duration: F(1,91) = 0.05, *p* = .82			
	M2	-12.72	30.64	-42.72	15
	M3	-13.52	18.27	-35.52	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: F(5,74) = 2.83, *p* =.004*			
	M1	242.58	268.73	222.58	10
		Age group: F(5,87) = 5.45, *p* <.001**			
		Sleep quality: F(1,88) = 0.75, *p* =.39			
	M2	250.89	290.112	220.89	15
	M3	244.53	273.30	222.53	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: F(5,97) = 5.567, *p* <.001**			
	M1	-91.09	-62.57	-111.09	10
		Age group: F(5,88) = 6.19, *p* < .001**			
		Night Sleep Duration: F(1,83) = 0.57, *p* = .45			
	M2	-86.09	-43.31	-116.09	15
	M3	-90.02	-58.65	-112.02	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	752.20	780.64	732.20	10
	M2	758.02	800.68	728.02	15
	M3	751.14	782.42	729.14	11
		Age group: F(5,94) = 0.38, *p* = .86			
		Night Sleep Duration: F(1,92) = 0.03, *p* = .87			
		Gender: F(1,50) = 3.18, *p* = .08			
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	677.11	705.79	657.11	10
	M2	685.17	728.18	655.17	15
	M3	674.18	705.73	652.18	11
		Age group: F(5,91) = 1.46, *p* = .21			
		Night Sleep Duration: F(1,91) = 0.81, *p* = .37			
		Gender: F(1,38) = 5.13, *p* = .03*			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Day Sleep Duration and eye-tracking measures

		AIC	BIC	-2LL	df
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1078.53	1104.18	1058.53	10
		Age group: $F(5,51) = 7.50$, $p < .001$**			
		Day Sleep Duration: $F(1,87) = 1.59$, $p = .21$			
	M2	1079.27	1117.74	1049.27	15
	M3	1080.25	1108.45	1058.25	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1037.62	1063.26	1017.62	10
		Age group: $F(5,71) = 4.93$, $p = .001$**			
		Day Sleep Duration: $F(1, 57) = 3.88$, $p = .05$*			
	M2	1041.34	1079.80	1011.34	15
	M3	1039.41	1067.61	1017.41	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p < .001$			
	M1	1118.01	1143.65	1098.01	10
	M2	1117.65	1156.12	1087.65	15
		Age group: $F(5,81) = 1.07$, $p = .38$			
		Day Sleep Duration: $F(1,96) = 0.02$, $p = .89$			
		Age group x Day Sleep Duration: $F(5,84) = 2.24$, $p = .06$			
	M3	1119.12	1147.33	1097.12	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1049.31	1074.95	1029.31	10
		Age group: $F(5,56) = 1.60$, $p = .17$			
		Day Sleep Duration $F(1,46) = 2.41$, $p = .13$			
	M2	1055.65	1094.11	1025.65	15
	M3	1051.10	1079.31	1029.10	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	1028.74	1054.38	1008.74	10
		Age group: $F(5,36) = 1.32$, $p = .28$			
		Day Sleep Duration: $F(1,90) = 0.03$, $p = .86$			
	M2	1036.62	1075.08	1006.62	15
	M3	1030.39	1058.60	1008.39	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1091.95	1117.59	1071.95	10
		Age group: $F(5,73) = 1.69$, $p = .15$			
		Day Sleep Duration: $F(1,95) = 2.93$, $p = .09$			
	M2	1097.49	1135.96	1067.49	15
	M3	1092.07	1120.28	1070.07	11
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-16.46	12.37	-36.46	10
		Age group: $F(5,104) = 5.21$, $p < .001$**			
		Sleep quality: $F(1,118) = 1.53$, $p = .22$			
	M2	-10.79	32.46	-40.79	15
	M3	-14.49	17.70	-36.49	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	241.88	267.93	221.88	10
		Age group: $F(5,72) = 4.31$, $p = .002$*			
		Sleep quality: $F(1,83) = 0.85$, $p = .36$			
	M2	247.54	286.62	217.54	15
	M3	243.58	272.24	221.58	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-92.06	-63.62	-112.06	10
		Age group: $F(5,69) = 5.35$, $p < .001$**			
		Sleep quality: $F(1,105) = 2.80$, $p = .10$			
	M2	-85.48	-42.82	-115.48	15
	M3	-91.18	-59.89	-113.18	11

Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	746.47	774.83	726.47	10
	M2	751.25	793.80	721.25	15
	M3	744.95	776.15	722.95	11
		Age group: $F(5,96) = 0.49$, $p = .78$			
		Sleep Quality: $F(1,112) = 0.18$, $p = .67$			
		Gender: $F(1,49) = 3.63$, $p = .06$			
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	674.60	703.20	654.60	10
	M2	681.70	724.60	681.70	15
	M3	672.33	703.79	650.33	11
		Age group: $F(5,87) = 1.41$, $p = .23$			
		Sleep Quality: $F(1,113) = 0.30$, $p = .58$			
		Gender: $F(1,37) = 4.42$, $p = .04$*			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Wakening and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p <.001$**			
	M1	1172.26	1198.70	1152.26	10
		Age group: $F(5,37) = 5.39$, $p = .001$**			
		Night Wakening Number: $F(1,92) = 0.22$, $p = .64$			
	M2	1178.44	1218.10	1148.44	15
	M3	1173.13	1202.22	1151.13	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p <.001$**			
	M1	1125.23	1151.67	1105.23	10
		Age group: $F(5,56) = 5.05$, $p = .001$**			
		Night Wakening Number: $F(1,80) = 0.59$, $p = .44$			
	M2	1133.61	1173.28	1103.61	15
	M3	1127.08	1156.17	1105.08	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p <.001$			
	M1	1219.65	1246.09	1199.65	10
		Age group: $F(5,84) = 5.30$, $p < .001$**			
		Night Wakening Number: $F(1,92) = 0.01$, $p = .91$			
	M2	1219.77	1259.44	1189.77	15
	M3	1120.10	1249.19	1198.10	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1133.36	1159.81	1113.36	10
		Age group: $F(5,87) = 2.00$, $p = .09$			
		Night Wakening Number: $F(1,80) = 3.26$, $p = .08$			
	M2	1138.68	1178.35	1108.68	15
	M3	1134.19	1163.28	1112.19	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	1115.68	1142.12	1095.68	10
	M2	1123.65	1163.31	1093.65	15
	M3	1115.25	1144.34	1093.25	11
		Age group: $F(5,74) = 1.26$, $p = .29$			
		Night Wakening Number: $F(1,92) = 0.05$, $p = .83$			
		Gender: $F(1,46) = 2.48$, $p = .12$			
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1203.73	1230.17	1183.73	10
	M2	1195.36	1225.03	1165.36	15
	M3	1192.59	1234.90	1160.59	16
		Age group: $F(5,80) = 4.75$, $p = .001$*			
		Night Wakening Number: $F(1,85) = 2.53$, $p = .12$			
		Age group x Night Wakening Number: $F(5,83) = 4.51$, $p = .001$**			
		Gender: $F(1,51) = 5.04$, $p = .03$*			

1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-22.17	7.03	-42.17	10
		Age group: $F(5,107) = 4.74$, $p = .001$**			
		Night Wakening Number: $F(1,102) = 0.26$, $p = .61$			
	M2	-12.46	31.34	-42.46	15
	M3	-21.96	10.16	-43.96	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	256.60	282.85	236.60	10
	M2	244.02	283.39	214.02	15
		Age group: $F(5,83) = 5.90$, $p < .001$*			
		Night Wakening Number: $F(1,91) = 14.72$, $p < .001$*			
		Age group x Night Wakening Number: $F(5,83) = 5.06$, $p < .001$*			
	M3	245.94	287.94	213.94	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-91.35	-62.60	-111.35	10
		Age group: $F(5,96) = 5.35$, $p < .001$**			
		Night Wakening Number: $F(1,96) = 1.76$, $p = .19$			
	M2	-86.02	-42.89	-116.02	15
	M3	-89.91	-58.29	-111.91	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	782.51	811.34	762.51	10
		Age group: $F(5,109) = 0.30$, $p = .91$			
		Night Wakening Number: $F(1,104) = 0.28$ $p = .60$			
	M2	789.77	833.02	759.77	15
	M3	782.54	814.24	760.53	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	700.17	729.15	680.17	10
	M2	708.83	752.30	678.83	15
	M3	699.75	617.83	677.75	11
		Age group: $F(5,63) = 1.86$, $p = .11$			
		Night Wakening Number: $F(1,90) = 0.28$, $p = .60$			
		Gender: $F(1,36) = 4.10$, $p = .13$			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy WASO and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1183.58	1210.12	1163.58	10
		Age group: $F(5,47) = 5.00$, $p = .001$**			
		WASO: $F(1,94) = 0.45$, $p = .50$			
	M2	1189.77	1229.58	1159.77	15
	M3	1184.24	1213.43	1162.24	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1134.52	1161.06	1114.52	10
		Age group: $F(5,75) = 4.87$, $p = .001$**			
		WASO: $F(1,104) = 3.16$, $p = .08$			
	M2	1138.19	1178.00	1108.19	15
	M3	1136.48	1165.68	1114.48	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p < .001$			
	M1	1128.95	1255.49	1208.95	10
		Age group: $F(5,84) = 5.67$, $p < .001$**			
		WASO: $F(1,103) = 1.58$, $p = .21$			
	M2	1233.37	1273.18	1203.37	15
	M3	1229.48	1258.68	1207.48	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1144.20	1170.72	1124.18	10

		Age group: F(5,92) = 1.14, p =.35 *WASO*: *F*(1,104) = 2.71, *p* = .10			
	M2	1145.42	1185.23	1115.42	15
	M3	1144.40	1173.59	1122.40	11
Facilitation	Baseline	1208.25 *Age group: F*(5,65) = 1.43, p = .22	1232.80	1190.25	9
	M1	1124.33	1150.87	1104.33	10
	M2	1132.22	1172.03	1102.22	15
	M3	1123.87 *Age group: F*(5,56) = 1.46, *p* =.22 *WASO: F*(1,100) = 1.04 *p* = .31 *Gender: F*(1,33 = 2.52 *p* = .12	1153.06	1101.87	11
Disengagement	Baseline	1309.95 *Age group: F*(5,82) = 1.23, *p* =.304	1334.50	1291.95	9
	M1	1213.70	1240.23	1193.70	10
	M2	1215.54	1255.35	1185.54	15
	M3	1212.09 *Age group:* F(5,83) = 1.30, p = .27 *WASO: F*(1,101) = 2.27, *p* = .14 *Gender: F*(1,53) = 3.84, *p* = .055*	1241.28	1190.09	11
1st face look proportion	Baseline	-26.97 *Age group: F*(5,112) = 4.82, *p* =.001**	-1.23	-44.96	9
	M1	-23.08 *Age group: F*(5,119) = 4.17, *p* = .002* *WASO: F*(1,140) = 1.01, *p* = .32	6.34	-43.08	10
	M2	-18.58	25.55	-48.58	15
	M3	-22.21	10.15	-44.21	11
Face peak	Baseline	250.21 *Age group: F*(5,74) = 2.83, *p* =.004*	273.47	232.21	9
	M1	265.63	292.17	245.63	10
	M2	257.52 *Age group:* F(5,95) = 3.14, *p* = .007* *WASO: F*(1,102) = 15, *p* < .001** *Age group x WASO: F*(1,97) = 4.13, *p* = .002*	297.33	227.52	15
	M3	259.52	301.99	227.52	11
Face prop AOI	Baseline	-82.03 *Age group: F*(5,97) = 5.567, *p* <.001**	-56.58	-100.03	9
	M1	-88.18	-59.20	-108.18	10
	M2	-86.03 *Age group: F*(5,120) = 1.03, *p* = .40 *WASO: F*(1,132) = 0.47, *p* = .47 *Age group x WASO: F*(1,114) = 1.66, *p* = .15	-42.56	-116.03	15
	M3	-86.90	-55.02	-108.90	11
Look duration interesting	Baseline	869.01 *Age group: F*(5,114) = 0.23, *p* =.95	895.92	851.01	9
	M1	797.44 *Age group: F*(5,111) = 0.34, *p* = .89 *WASO: F*(1,134) = 0.30, *p* = .59	826.49	777.44	10
	M2	799.63	843.21	769.63	15
	M3	797.84	829.80	775.84	11
Look duration boring	Baseline	780.90 *Age group: F*(5,102) = 2.25, *p* =.055	808.00	762.90	9
	M1	712.16	741.36	692.16	10
	M2	720.56	764.36	690.56	15
	M3	711.87 *Age group: F*(5,91) = 2.03, *p* = .08 *WASO: F*(1,128) = 0.43, *p* = .52 *Gender: F*(1,39) = 2.32, *p* = .14	743.99	689.87	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Sleep Duration and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66 *Age group: F*(5,38) = 8.54, *p* <.001**	1113.83	1072.65	9
	M1	1169.39 *Age group: F*(5,18) = 5.66 *p* =.003*	1195.83	1149.39	10

		Night Sleep Duration: F(1,64) = 3.39, *p* = .07			
	M2	1178.51	1218.17	1148.51	15
	M3	1170.05	1199.13	1148.05	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: F(5,57) = 5.25, *p* <.001**			
	M1	1123.51	1149.95	1103.51	10
		Age group: F(5,62) = 5.42, *p* <.001**			
		Night Sleep Duration: F(1,86) = 2.41, *p* = .12			
	M2	1133.18	1172.85	1103.18	15
	M3	1125.39	1154.48	1103.39	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001			
	M1	1216.03	1242.47	1196.03	10
		Age group: F(5,84) = 6.30, *p* <.001**			
		Night Sleep Duration: F(1,101) = 3.70, *p* = .057			
	M2	1222.74	1262.41	1192.74	15
	M3	1216.53	1245.62	1194.53	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: F(5,87) = 1.15, p =.34			
	M1	1133.25	1159.70	1113.25	10
		Age group: F(5,88) = 1.98, *p* =.09			
		Night Sleep Duration: *F*(1,93) =3.2, *p* = .08			
	M2	1134.39	1174.06	1104.39	15
	M3	1133.82	1162.91	1111.82	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: F(5,65) = 1.43, p = .22			
	M1	1115.00	1141.45	1095.00	10
	M2	1224.14	1163.81	1094.14	15
	M3	1114.48	1143.56	1092.48	11
		Age group: F(5,67) = 1.48, *p* =.21			
		Night Sleep Duration: F(1,95) = 0.86, *p* = .36			
		Gender: F(1,47) = 2.57, *p* =.12			
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: F(5,82) = 1.23, *p* =.304			
	M1	1203.69	1230.14	1183.69	10
	M2	1210.31	1249.97	1180.31	15
	M3	1201.62	1230.71	1179.62	11
		Age group: F(5,76) = 1.36, *p* = .25			
		Night Sleep Duration: F(1,97) = 0.23, *p* = .62			
		Gender: F(1,49) = 4.37, *p* = .04			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: F(5,112) = 4.82, *p* =.001**			
	M1	-26.47	2.66	-46.47	10
		Age group: F(5,116) = 4.89, p < .001**			
		Night Sleep Duration: F(1,114) = 0.24, *p* = .62			
	M2	-20.59	23.10	-50.59	15
	M3	-26.78	5.26	-48.78	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: F(5,74) = 2.83, *p* =.004*			
	M1	256.48	282.73	236.48	10
		Age group: F(5,46) = 4.48, p = .002*			
		Night Sleep Duration: F(1,92) = 0.15, *p* = .69			
	M2	263.05	302.43	233.05	15
	M3	258.10	286.98	236.10	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: F(5,97) = 5.567, *p* <.001**			
	M1	-91.93	-63.18	-111.93	10
		Age group: F(5,69) = 5.35, *p* < .001**			
		Sleep quality: F(2,76) = 1.07, *p* = .35			
	M2	-83.95	-40.82	-113.95	15
		Age group: F(5,123) = 0.58, *p* = .71			
		Night Sleep Duration: F(1,94) = 2.44, *p* = .12			
		Age group x Night Sleep Duration: F(1,122) = 0.42, *p* = .83			
	M3	-90.62	-58.99	-112.62	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	776.81	805.56	756.81	10
		Age group: F(5,105) = 0.35, *p* = .88			

		Night Sleep Duration: $F(1,119) = 1.05$, $p = .31$			
	M2	784.68	827.81	754.68	15
	M3	776.84	808.46	754.83	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	693.34	722.24	673.34	10
	M2	694.43	737.78	664.43	15
	M3	692.85	724.64	670.85	11
		Age group: $F(5,76) = 2.13$, $p = .07$			
		Night Sleep Duration: $F(1,99) = 0.73$, $p = .39$			
		Gender: $F(1,36) = 2.53$, $p = .12$			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Day Sleep Duration and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p <.001$**			
	M1	1122.91	1148.96	1102.91	10
	M2	1122.88	1161.96	1092.88	15
		Age group: $F(5,61) = 2.51$, $p = .04$*			
		Day Sleep Duration: $F(1,88) = 0.57$, $p = .45$			
		Age group x Day Sleep Duration: $F(5,77) = 2.11$, $p = .07$			
	M3	1123.96	1152.62	1101.96	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p <.001$**			
	M1	1084.70	1110.76	1064.70	10
		Age group: $F(5,58) = 5.39$, $p <.001$**			
		Day Sleep Duration: $F(1,95) = 0.14$, $p = .71$			
	M2	1086.73	1125.81	1056.73	15
	M3	1086.57	1115.23	1064.57	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p <.001$			
	M1	1174.36	1200.41	1154.36	10
		Age group: $F(5,82) = 4.78$, $p = .001$**			
		Day Sleep Duration: $F(1,96) = 2.07$, $p = .15$			
	M2	1180.53	1219.61	1150.53	15
	M3	1174.79	1203.43	1152.78	11
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1096.29	1122.34	1076.29	10
		Age group: $F(5,79) = 1.53$, $p = .19$			
		Day Sleep Duration: $F(1,93) = 0.01$, $p = .92$			
	M2	1099.08	1138.16	1069.08	15
	M3	1097.34	1125.99	1075/34	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	1073.38	1099.43	1053.38	10
		Age group: $F(5,68) = 1.39$, $p = .24$			
		Day Sleep Duration: $F(1,95) = 0.12$, $p = .74$			
	M2	1079.30	1118.38	1049.30	15
	M3	1073.21	1101.87	1051.21	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1155.73	1181.78	1135.73	10
	M2	1160.47	1199.55	1130.47	15
	M3	1153.59	1182.25	1131.59	11
		Age group: $F(5,74) = 1.43$, $p = .22$			
		Day Sleep Duration: $F(1,96) = 3.61$, $p = .06$			
		Gender: $F(1,51) = 4.50$, $p = .04$*			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-25.28	3.47	-45.28	10
		Age group: $F(5,113) = 5.20$, $p = .001$**			
		Day Sleep Duration: $F(1,123) = 0.49$, $p = .49$			
	M2	-18.11	25.02	-28.11	15

	M3	-26.47	5.16	-48.47	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	248.13	273.98	228.13	10
		Age group: $F(5,68) = 3.56$, $p = .006$*			
		Day Sleep Duration: $F(1,94) = 2.31$, $p = .13$			
	M2	249.18	287.95	219.18	15
	M3	250.01	240.05	232.01	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-84.69	-56.25	-104.69	10
		Age group: $F(5,103) = 4.87$, $p < .001$**			
		Day Sleep Duration: $F(1,114) = 0.52$, $p = .47$			
	M2	-80.86	-38.20	-110.86	15
	M3	-83.00	-51.72	-105.00	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	752.52	780.88	732.52	10
		Age group: $F(5,103) = 0.29$, $p = .92$			
		Day Sleep Duration: $F(1,117) = 0.13$, $p = .72$			
	M2	758.39	728.39	728.39	15
	M3	752.82	784.02	730.82	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	666.60	695.12	646.60	10
	M2	669.92	712.70	639.92	15
	M3	666.17	697.54	644.17	11
		Age group: $F(5,65) = 3.50$, $p = .008$*			
		Day Sleep Duration: $F(1,114) = 0.96$, $p = .33$			
		Gender: $F(1,41) = 2.45$, $p = .13$			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Wakening and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1251.10	1278.19	1231.10	10
		Age group: $F(5,76) = 4.96$, $p = .001$**			
		Night Wakening Number: $F(1,98) = 0.01$, $p = .91$			
	M2	1261.00	1301.63	1231.00	15
	M3	1052.13	1281.93	1230.13	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1197.42	1224.51	1177.42	10
		Age group: $F(5,91) = 4.81$, $p = .001$**			
		Night Wakening Number: $F(1, 69) = 0.67$, $p = .42$			
	M2	1204.91	1245.55	1174.91	15
	M3	1199.34	1229.15	1177.34	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001			
	M1	1306.24	1333.33	1286.24	10
	M2	1311.73	1352.38	1281.73	15
	M3	1305.68	1335.48	1283.68	11
		Age group: $F(5,85) = 6.33$, $p < .001$**			
		Night Wakening Number: $F(1,87) = 1.49$, $p = .23$			
		Gender: $F(1,58) = 2.65$, $p = .11$			
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, p =.34			
	M1	1213.15	1240.25	1193.15	10
		Age group: $F(5,95) = 1.15$, p =.34			
		Night Wakening Number: $F(1,75) = 0.02$, $p = .89$			
	M2	1220.96	1261.61	1190.96	15
	M3	1191.85	1243.66	1191.85	11§
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, p = .22			

	M1	1190.28	1217.38	1217.38	10
		Age group: $F(5,71) = 1.41$, $p = .22$			
		Night Wakening Number: $F(1,89) = 0.91$, $p = .34$			
	M2	1198.03	1238.67	1168.03	15
	M3	1190.59	1220.39	1168.59	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1289.24	1316.33	1269.24	10
	M2	1293.20	1333.84	1263.20	15
	M3	1285.97	1315.77	1263.97	
		Age group: $F(5,80) = 1.30$, $p = .27$			
		Night Wakening Number: $F(1,93) = 1.97$, $p = .16$			
		Gender: $F(1,57) = 5.59$, $p = .02$*			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-17.67	12.50	-37.67	10
		Age group: $F(5,124) = 4.62$, $p = .001$**			
		Night Wakening Number: $F(1,105) = 0.15$, $p = .70$			
	M2	-9.64	35.62	-39.64	15
	M3	-15.75	17.44	-37.75	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	287.34	314.96	267.34	10
		Age group: $F(5,88) = 4.73$, $p = .001$*			
		Night Wakening Number: $F(1,82) = 0.53$, $p = .47$			
	M2	292.64	334.07	262.64	15
	M3	289.14	319.52	267.14	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			
	M1	-101.53	-71.76	-121.53	10
		Age group: $F(5,104) = 6.55$, $p < .001$**			
		Night Wakening Number: $F(1,110) = 0.71$, $p = .40$			
	M2	-96.15	-51.50	-126.15	15
	M3	-100.58	-67.74	-122.48	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: $F(5,114) = 0.23$, $p = .95$			
	M1	854.95	884.72	834.95	10
		Age group: $F(5,109) = 0.46$, $p = .80$			
		Night Wakening Number: $F(1,101) = 0.29$, $p = .59$			
	M2	858.32	902.97	828.32	15
	M3	855.74	888.48	833.74	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: $F(5,102) = 2.25$, $p = .055$			
	M1	770.18	800.15	750.18	10
	M2	771.82	816.77	741.82	15
	M3	768.76	801.73	746.76	11
		Age group: $F(5,103) = 2.36$, $p = .05$*			
		Night Wakening Number: $F(1,90) = 0.34$, $p = .56$			
		Gender: $F(1,42) = 3.49$, $p = .07$			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ WASO and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1230.47	1257.38	1210.47	10
		Age group: $F(5,77) = 5.25$, $p < .001$**			
		WASO: $F(1,111) = 0.34$, $p = .56$			
	M2	1238.81	1279.18	1208.81	15
	M3	1231.58	1261.19	1209.58	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1178.37	1205.29	1158.37	10
		Age group: $F(5,89) = 4.78$, $p = .001$**			
		WASO: $F(1,101) = 0.14$, $p = .71$			

	M2	1185.27	1225.64	1155.27	15
	M3	1080.16	1209.77	1158.16	11
Overlap – Mean	Baseline	1326.66 *Age group:* F(5,88) = 6.14, p <.001	1351.21	1308.66	9
	M1	1284.37 *Age group:* F(5,83) = 5.62, p <.001** *WASO: F*(1,109) = 0.51, *p* = .48	1311.28	1264.37	10
	M2	1289.69	1330.06	1259.69	15
	M3	1284.51	1314.11	1262.51	11
Baseline Variability	Baseline	1232.19 *Age group: F*(5,87) = 1.15, p =.34	1256.74	1214.19	9
	M1	1190.80 *Age group: F*(5,73) = 1.26, *p* =.29 *WASO*: *F*(1,99) = 0.34, *p* = .56	1217.71	1170.80	10
	M2	1193.27	1233.64	1163.27	15
	M3	1191.25	1220.85	1169.25	11
Facilitation	Baseline	1208.25 *Age group: F*(5,65) = 1.43, p = .22	1232.80	1190.25	9
	M1	1168.86 *Age group: F*(5,60) = 1.56, *p* =.19 *WASO: F*(1,97) = 3.24, *p* = .08	1195.77	1148.86	10
	M2	1176.60	1216.97	1146.60	15
	M3	1168.96	1198.57	1146.96	11
Disengagement	Baseline	1309.95 *Age group: F*(5,82) = 1.23, *p* =.304	1334.50	1291.95	9
	M1	1267.35	1294.26	1247.35	10
	M2	1275.56	1315.93	1245.56	15
	M3	1265.28 *Age group: F*(5,77) = 1.23, *p* = .31 *WASO: F*(1,104) = 0.08, *p* = .78 *Gender: F*(1,55) = 4.21, *p* = .05*	1294.88	1243.28	11
1st face look proportion	Baseline	-26.97 *Age group: F*(5,112) = 4.82, *p* =.001**	-1.23	-44.96	9
	M1	-17.09 *Age group: F*(5,123) = 4.57, p = .001** *WASO: F*(1,137) = 0.01, *p* = .94	12.95	-37.09	10
	M2	-14.01	31.05	-44.01	15
	M3	-15.12	17.12	-37.12	11
Face peak	Baseline	250.21 *Age group: F*(5,74) = 2.83, *p* =.004*	273.47	232.21	9
	M1	285.01 *Age group: F*(5,91) = 4.84, *p* =.001* *Sleep quality: F*(1,111) = 0.20, *p* =.66	312.55	265.01	10
	M2	287.83	329.13	257.83	15
	M3	286.83	317.12	264.83	11
Face prop AOI	Baseline	-82.03 *Age group: F*(5,97) = 5.567, *p* <.001**	-56.58	-100.03	9
	M1	-97.48 *Age group: F*(5,105) = 6.17, *p* < .001** *Sleep quality: F*(1,131) = 0.02, *p* = .90	-67.85	-117.48	10
	M2	-91.73	-47.29	-121.73	15
	M3	-96.19	-63.60	-118.19	11
Look duration interesting	Baseline	869.01 *Age group: F*(5,114) = 0.23, *p* =.95	895.92	851.01	9
	M1	841.94 *Age group: F*(5,110) = 0.68, *p* = .64 *WASO: F*(1,136) = 2.85, *p* = .09	871.57	821.94	10
	M2	849.21	893.66	819.21	15
	M3	842.93	875.53	820.93	11
Look duration boring	Baseline	780.90 *Age group: F*(5,102) = 2.25, *p* =.055	808.00	762.90	9
	M1	758.16	787.99	738.16	10
	M2	763.80	808.56	733.80	15
	M3	756.52 *Age group: F*(5,107) = 2.27, *p* = .053 *WASO: F*(1,128) = 4.03, *p* = .05* *Gender: F*(1,43) = 3.56, *p* = .07	789.52	734.70	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Sleep Duration and eye-tracking measures

		AIC	BIC	-2LL	df
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: $F(5,38) = 8.54$, $p < .001$**			
	M1	1246.38	1273.48	1226.38	10
		Age group: $F(5,56) = 7.18$, $p < .001$**			
		Night Sleep Duration: $F(1,98) = 7.03$, $p = .009$*			
	M2	1251.68	1292.32	1221.68	15
	M3	1247.99	1277.79	1225.99	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: $F(5,57) = 5.25$, $p < .001$**			
	M1	1194.19	1221.28	1174.19	11
		Age group: $F(5,97) = 5.63$, $p < .001$**			
		Night Sleep Duration: $F(1,86) = 4.10$, $p = .05$*			
	M2	1201.03	1241.68	1171.03	19
	M3	1195.65	1225.45	1173.65	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: $F(5,88) = 6.14$, $p < .001$			
	M1	1305.88	1332.98	1285.88	10
	M2	1314.65	1355.29	1284.65	15
	M3	1305.22	1335.02	1283.22	11
		Age group: $F(5,82) = 6.39$, $p < .001$**			
		Night Sleep Duration: $F(1,97) = 2.01$, $p = .16$			
		Gender: $F(1,51) = 2.74$, $p = .10$			
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: $F(5,87) = 1.15$, $p = .34$			
	M1	1209.48	1236.58	1189.48	10
		Age group: $F(5,81) = 1.23$, $p = .30$			
		Night Sleep Duration: $F(1,86) = 3.78$, $p = .055$*			
	M2	1210.68	1251.32	1180.68	15
	M3	1210.76	1240.57	1188.76	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: $F(5,65) = 1.43$, $p = .22$			
	M1	1190.32	1217.41	1170.32	10
		Age group: $F(5,71) = 1.40$, $p = .24$			
		Night Sleep Duration: $F(1,96) = 0.85$, $p = .36$			
	M2	1192.21	1232.85	1162.21	15
	M3	1190.70	1220.51	1168.70	11
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: $F(5,82) = 1.23$, $p = .304$			
	M1	1290.41	1317.51	1270.41	10
	M2	1296.18	1336.81	1266.18	15
	M3	1287.82	1317.62	1265.82	11
		Age group: $F(5,79) = 1.22$, $p = .31$			
		Night Sleep Duration: $F(1,101) = 0.08$, $p = .78$			
		Gender: $F(1,53) = 4.74$, $p = .03$*			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: $F(5,112) = 4.82$, $p = .001$**			
	M1	-18.03	12.14	-38.03	10
		Age group: $F(5,110) = 4.57$, $p = .001$**			
		Night Sleep Duration: $F(1,137) = 0.51$, $p = .48$			
	M2	-14.00	31.26	-44.00	15
	M3	-16.10	17.09	-38.10	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: $F(5,74) = 2.83$, $p = .004$*			
	M1	285.04	312.66	265.04	10
	M2	283.35	324.78	253.35	15
		Age group: $F(5,99) = 2.21$, $p = .06$			
		Night Sleep Duration: $F(1,109) = 2.22$, $p = .14$			
		Age group x Night Sleep Duration: $F(1,100) = 2.52$, $p = .03$*			
	M3	285.16	329.35	253.16	11
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: $F(5,97) = 5.567$, $p < .001$**			

	M1	-101.18	-71.41	-121.18	10
	M2	-106.61	-61.96	-136.61	15
		Age group: F(5,136) = 2.68, *p* = .02*			
		Night Sleep Duration: F(1,142) = 0.32, *p* = .57			
		Age group x Night Sleep Duration: F(1,136) = 3.27, *p* = .008*			
	M3	-105.35	-57.73	-137.35	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	855.22	884.98	835.22	10
		Age group: F(5,110) = 0.45, *p* = .81			
		Night Sleep Duration: F(1,135) = 0.01 *p* = .95			
	M2	864.20	908.85	834.20	15
	M3	855.84	888.58	833.84	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	763.94	793.91	743.94	10
	M2	767.94	812.89	737.94	15
	M3	762.77	795.74	740.77	11
		Age group: F(5,96) = 2.02, *p* = .08			
		Night Sleep Duration: F(1,139) = 6.63, *p* = .01			
		Gender: F(1,46) = 3.26, *p* = .08			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Day Sleep Duration and eye-tracking measures

		AIC	**BIC**	**-2LL**	**df**
Baseline – Mean	Baseline	1090.66	1113.83	1072.65	9
		Age group: F(5,38) = 8.54, *p* <.001**			
	M1	1250.59	1277.68	1230.59	10
		Age group: F(5,52) = 6.31, *p* =.001**			
		Day Sleep Duration: F(1,107) = 0.52, *p* = .47			
	M2	1253.87	1294.51	1223.87	15
	M3	1251.72	1281.53	1229.72	11
Gap – Mean	Baseline	1053.05	1076.22	1035.05	9
		Age group: F(5,57) = 5.25, *p* <.001**			
	M1	1191.12	1218.21	1171.12	10
		Age group: F(5,94) = 6.63, *p* <.001**			
		Day Sleep Duration: F(1,108) = 7.23, *p* = .008*			
	M2	1195.19	1235.83	1165.19	15
	M3	1192.62	1222.42	1170.62	11
Overlap – Mean	Baseline	1326.66	1351.21	1308.66	9
		Age group: F(5,88) = 6.14, p <.001			
	M1	1306.19	1333.29	1286.19	10
	M2	1310.54	1351.18	1280.54	15
	M3	1305.84	1335.64	1283.84	11
		Age group: F(5,86) = 6.21, p <.001**			
		Day Sleep Duration: F(1,111) = 1.33, *p* = .25			
		Gender: F(1,57) = 2.43, *p* = .13			
Baseline Variability	Baseline	1232.19	1256.74	1214.19	9
		Age group: F(5,87) = 1.15, p =.34			
	M1	1212.46	1239.56	1192.46	10
		Age group: F(5,98) = 1.26, p =.29			
		Day Sleep Duration F(1,108) = 0.71, *p* = .40			
	M2	1216.97	1257.61	1186.97	15
	M3	1213.43	1243.23	1191.43	11
Facilitation	Baseline	1208.25	1232.80	1190.25	9
		Age group: F(5,65) = 1.43, p = .22			
	M1	1187.93	1215.03	1167.93	10
	M2	1196.86	1237.51	1166.86	15
	M3	1186.84	1216.65	1164.84	11
		Age group: F(5,86) = 1.15, p =.34			
		Day Sleep Duration: F(1,111) = 4.51, *p* = .04*			
		Gender: F(1,54) = 3.18, *p* = .08			
Disengagement	Baseline	1309.95	1334.50	1291.95	9
		Age group: F(5,82) = 1.23, *p* =.304			
	M1	1290.32	1317.42	1270.32	10

	M2	1298.31	1338.95	1268.31	15
	M3	1287.56	1317.37	1265.56	11
		Age group: F(5,82) = 1.27, p = .29 *Day Sleep Duration: F*(1,104) = 0.34, *p* = .56 *Gender:* F(1,56) = 4.99, p = .03*			
1st face look proportion	Baseline	-26.97	-1.23	-44.96	9
		Age group: F(5,112) = 4.82, *p* =.001**			
	M1	-22.23	7.88	-42.23	10
		Age group: F(5,123) = 4.81, p < .001** *Day Sleep Duration: F*(1,146) = 0.00, *p* = .99			
	M2	-16.70	28.47	-46.70	15
	M3	-20.47	12.65	-42.47	11
Face peak	Baseline	250.21	273.47	232.21	9
		Age group: F(5,74) = 2.83, *p* =.004*			
	M1	277.76	305.38	257.76	10
	M2	277.50	318.93	247.50	15
		Age group: F(5,89) = 5.58, *p* <.001** *Day Sleep Duration: F*(1,112) = 11.77 *p* = .001* *Age group x Day Sleep Duration: F*(1,95) = 2.30, *p* = .051*			
	M3	278.87	309.25	256.87	10
Face prop AOI	Baseline	-82.03	-56.58	-100.03	9
		Age group: F(5,97) = 5.567, *p* <.001**			
	M1	-100.83	-71.06	-120.83	11
		Age group: F(5,114) = 6.38, *p* < .001** *Sleep quality: F*(1,132) = 0.01, *p* = .35			
	M2	-98.02	-53.37	-128.02	15
	M3	-99.57	-66.82	-121.57	11
Look duration interesting	Baseline	869.01	895.92	851.01	9
		Age group: F(5,114) = 0.23, *p* =.95			
	M1	849.17	878.87	829.17	10
		Age group: F(5,113) = 0.48, *p* = .79 *Day Sleep Duration: F*(1,141) = 1.11, *p* = .29			
	M2	856.40	900.95	826.40	15
	M3	849.69	882.36	827.69	11
Look duration boring	Baseline	780.90	808.00	762.90	9
		Age group: F(5,102) = 2.25, *p* =.055			
	M1	764.69	794.59	744.69	10
	M2	773.78	818.63	743.78	15
	M3	762.85	795.74	740.85	11
		Age group: F(5,102) = 2.43, *p* = .04* *Day Sleep Duration: F*(1,133) = 0.00, *p* = .97 *Gender: F*(1,43) = 3.98, *p* = .052			

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Appendix – Chapter 6

Results of LMMs for sleep variables of actigraphy, diary, and BISQ and EEG measures

Actigraphy sleep quality and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	47.52	71.59	27.52	10
	M2	55.61	91.71	15.61	15
	M3	46.86	73.24	24.86	11
		Age group: $F(5,31) = 12.06$, $p < .001$**			
		Sleep quality: $F(1,65) = 0.10$, $p = .76$			
		Age group x sleep quality: $F(1,50) = 2.74$, $p = .10$			
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-51.32	-28.15	-71.32	10
		Age group: $F(5,52) = 0.28$, $p = .92$			
		Sleep quality: $F(1,69) = 3.35$, $p = .07$			
	M2	-43.87	-9.11	-73.87	15
	M3	-49.60	-24.11	-71.60	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary sleep quality and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	23.19	48.98	1.19	10
		Age group: $F(5,18) = 16.51$, $p < .001$**			
		Sleep quality: $F(1,22) = 1.58$, $p = .23$			
	M2	27.02	71.55	-10.98	19
	M3	24.76	52.89	0.76	12
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-40.28	-16.03	-62.28	11
		Age group: $F(5,16) = 1.41$, $p = .27$			
		Night Sleep Duration: $F(1,44) = 0.09$, $p = .91$			
	M2	-27.63	14.26	-65.63	19
	M3	-38.34	-11.88	-62.34	12

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ sleep quality and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	60.52	88.37	38.52	11
		Age group: $F(5,58) = 6.60$, $p < .001$**			
		Sleep quality: $F(1,83) = 0.55$ $p = .58$			
	M2	66.40	117.05	26.40	20
	M3	61.44	91.83	37.44	12
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-50.53	-24.06	-72.53	11
		Age group: $F(5,74) = 0.58$, $p = .71$			
		Night Sleep Duration: $F(1,70) = 0.120$, $p = .82$			
	M2	-41.81	6.32	-81.81	20
	M3	-48.57	-19.69	-72.57	12

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Wakening Number and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, p <.001**			
	M1	41.20	66.09	21.20	10
	M2	40.95	78.28	10.95	15
		Age group: $F(5,51) = 9.62$, $p < .001$**			
		Night Wakening Number: $F(1,82) = 2.65$, $p = .11$			
		Age group x Night Wakening Number: $F(5,21) = 4.24$, $p = .008$*			
	M3	41.42	81.24	9.42	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-57.87	-34.05	-77.87	10
		Age group: $F(5,51) = 0.60$, $p = .70$			
		Night Wakening Number: $F(1,65) = 5.50$, $p = .02$*			
	M2	-43.87	-9.11	-73.87	15
	M3	-49.60	-24.11	-71.60	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy WASO and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, p <.001**			
	M1	44.04	69.04	24.04	10
		Age group: $F(5,29) = 14.39$, p <.001**			
		WASO: $F(1,67) = 0.11$, $p = .74$			
	M2	47.80	85.29	17.80	15
	M3	44.03	71.53	22.03	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-54.72	-30.78	-74.72	10
		Age group: $F(5,58) = 0.60$, $p = .70$			
		WASO: $F(1,78) = 0.23$, $p = .63$			
	M2	-46.44	-10.53	-76.44	15
	M3	-52.85	-26.51	-74.85	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Night Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, p <.001**			
	M1	43.61	68.49	23.61	10
		Age group: $F(5,26) = 19.37$, p <.001**			
		Night Sleep Duration: $F(1,71) = 1.73$, $p = .19$			
	M2	49.10	86.43	19.10	15
	M3	43.85	71.23	21.85	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-53.03	-29.21	-73.03	10
		Age group: $F(5,55) = 0.53$, $p = .76$			
		Night Sleep Duration: $F(1,62) = 0.44$, $p = .51$			
	M2	-45.94	-10.21	-75.94	15
	M3	-51.21	-25.01	-73.21	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Actigraphy Day Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	44.16	68.59	24.16	10
	M2	48.05	84.67	18.05	15
	M3	44.13	71.00	22.13	11
		Age group: $F(5,29) = 11.05$, $p < .001$**			
		Day Sleep Duration: $F(1,73) = 1.67$, $p = .201$			
		Age group x Day Sleep Duration: $F(1,52) = 2.07$, $p = .16$			
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-50.68	-27.24	-70.68	10
		Age group: $F(5,55) = 0.62$, $p = .68$			
		Day Sleep Duration: $F(1,76) = 0.61$, $p = .44$			
	M2	-44.02	-8.86	-74.02	15
	M3	-48.68	-22.89	-70.68	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Wakening Number and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	41.82	66.48	21.82	10
	M2	39.59	76.58	9.59	15
		Age group: $F(5,29) = 9.30$, $p < .001$**			
		Night Wakening Number: $F(1,65) = 6.62$, $p = .01$*			
		Age group x Night Wakening Number: $F(5,27) = 3.25$, $p = .02$*			
	M3	41.02	80.48	9.02	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-48.88	-25.44	-68.88	10
		Age group: $F(5,49) = 0.53$, $p = .75$			
		Night Wakening Number: $F(1,76) = 4.37$, $p = .04$*			
	M2	-43.20	-8.04	-73.20	15
	M3	-46.98	-21.20	-68.98	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary WASO and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	47.56	71.87	27.56	10
		Age group: $F(5,44) = 10.30$, $p < .001$**			
		WASO: $F(1,39) = 0.99$, $p = .33$			
	M2	55.16	91.62	25.16	15
	M3	49.44	76.18	27.44	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-42.10	-19.06	-62.10	10
		Age group: $F(5,51) = 0.36$, $p = .88$			
		WASO: $F(1,47) = 1.18$, $p = .28$			
	M2	-34.59	-0.03	-64.59	15
	M3	-40.10	-14.75	-62.10	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Night Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	47.81	72.35	27.81	10
		Age group: $F(5,55) = 9.07$, $p < .001$**			
		Nigh Sleep Duration: $F(1,71) = 0.00$, $p = .96$			
	M2	54.21	91.22	24.21	15
	M3	49.56	76.56	27.56	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-44.70	-21.39	-64.70	10
		Age group: $F(5,60) = 0.48$, $p = .79$			
		Night Sleep Duration: $F(1,58) = 0.19$, $p = .66$			
	M2	-37.12	-2.16	-67.12	15
	M3	-42.78	-17.14	-64.78	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Diary Day Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	47.91	72.45	27.91	10
		Age group: $F(5,52) = 7.05$, $p < .001$**			
		Day Sleep Duration: $F(1,84) = .25$, $p = .62$			
	M2	55.11	91.93	25.11	15
	M3	49.53	76.53	27.53	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-44.71	-21.41	-64.71	10
		Age group: $F(5,58) = 0.52$, $p = .76$			
		Day Sleep Duration: $F(1,67) = 0.31$, $p = .58$			
	M2	-36.52	-1.56	-66.52	15
	M3	-42.73	-17.09	-64.73	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Wakening Number and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	51.55	76.99	31.55	10
	M2	57.46	95.61	27.46	15
	M3	51.00	78.96	28.98	11
		Age group: $F(5,54) = 10.26$, $p < .001$**			
		Night Wakening Number: $F(1,59) = 10.32$, $p = .002$*			
		Gender $F(1,61) = 2.62$, $p = .11$			
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-55.62	-31.43	-75.62	10
		Age group: $F(5,66) = 0.75$, $p = .59$			
		Night Wakening Number: $F(1,80) = 1.85$, $p = .18$			
	M2	-46.63	-10.35	-76.63	15
	M3	-53.81	-27.20	-75.81	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ WASO and EEG theta power

		AIC	BIC	-2LL	df
Theta power 8	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	58.75	84.08	38.75	10
		Age group: $F(5,54) = 8.24$, $p < .001$**			
		WASO: $F(1,90) = 0.89$ $p = .35$			
	M2	66.47	104.47	36.48	15
	M3	59.53	87.39	37.53	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-56.37	-32.30	-76.37	10
		Age group: $F(5,69) = 1.09$, $p = .38$			
		WASO: $F(1,79) = 4.40$, $p = .04$			
	M2	-50.77	-14.67	-80.77	15
	M3	-44.37	-27.89	-76.37	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Night Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	59.12	84.55	39.12	10
		Age group: $F(5,54) = 8.11$, $p < .001$**			
		Night Sleep Duration: $F(1,89) = 0.16$, $p = .69$			
	M2	60.13	98.28	30.13	15
	M3	59.73	87.71	37.73	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-54.38	-30.19	-74.38	10
		Age group: $F(5,74) = 0.58$, $p = .71$			
		Night Sleep Duration: $F(1,70) = 0.120$, $p = .82$			
	M2	-48.29	-12.01	-78.29	15
	M3	-52.46	-25.85	-74.46	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

BISQ Day Sleep Duration and EEG theta power

		AIC	BIC	-2LL	df
Theta power	Baseline	58.21	81.20	40.21	9
		Age group: $F(5,57) = 7.61$, $p < .001$**			
	M1	59.26	84.69	39.26	10
		Age group: $F(5,53) = 7.60$, $p < .001$**			
		Sleep quality: $F(1,88) = 0.02$, $p = .90$			
	M2	63.78	101.93	33.78	15
	M3	59.84	87.82	37.84	11
Theta power change (video 1)	Baseline	-57.48	-35.60	-75.48	9
		Age group: $F(5,73) = 0.63$, $p < .68$			
	M1	-54.14	-30.00	-74.14	10
		Age group: $F(5,71) = 0.68$, $p = .64$			
		Day Sleep Duration: $F(1,75) = 0.161$, $p = .69$			
	M2	-41.81	6.32	-81.81	15
	M3	-52.22	-25.62	-74.22	11

Notes. *p <.05, **p <.001, °did not survive multiple comparison correction with the Bonferroni method, AIC = Akaike's Information Criterion, BIC = Schwarz's Bayesian Criterion, -2LL = -2 Log Likelihood, df = degrees of freedom.

Appendix – Chapter 7

Poor quality channels identified by QT-NIRS vs. researcher examination

Participant	Poor quality channels NIRS – QT-NIRS	Poor quality channels NIRS – Researcher examination of data
P05 (f)	11, 12, 23, 28, 29,30, 31, 32, 34	12, 13, 14, 23, 29, 30, 31, 32, 33, 34
2002 (f)	6, 7, 8, 9, 10,11, 21, 24, 28, 29, 30, 31, 32, 35, 36, 37, 38	6, 8, 9, 10, 11, 12, 13, 15, 19, 21, 22, 28, 29, 30, 31, 32, 33, 34, 36, 37
2004 (f)	9, 10, 11, 21, 22, 37	4, 6, 8, 10, 11, 21, 22, 23, 29, 31,32, 33, 34, 36, 37
2005 (m)	1, 2, 6, 7, 9, 11, 13, 14, 15, 23, 24, 25, 26, 27, 28, 31, 38	3, 6, 7, 13, 14, 15, 23, 24, 25, 28, 32, 37, 38
2013 (f)	1,4, 6, 7, 8, 9, 10, 11, 23, 24, 25, 26, 27, 28, 32, 33, 35, 36, 38	2, 4, 6, 7, 8, 9, 10,11, 16, 17, 23, 24, 26, 35
2015 (f)	1, 7, 11, 23, 24, 25, 28, 29	1, 6, 7, 8, 9, 11, 14, 23, 25, 28, 33
2019 (m)	1, 2, 3, 6, 7, 11, 12, 23, 24, 25, 26, 27, 28, 38	1, 2, 3, 4, 5, 7, 12, 23, 24, 35, 36, 38, 39
2020 (f)	8, 9, 10,11,12,17,21,22,23,24,25, 26, 27, 28, 35, 36, 37	2, 3, 5, 6, 8, 9, 10, 21, 22, 25, 26, 35, 36, 37
2021 (m)	4, 6, 7, 11, 12, 16, 17, 21, 32,33, 34, 35, 36	6, 11, 12,13, 21, 22, 23, 26, 27, 28, 35, 39
2023 (m)	8, 9, 11, 12, 15, 23, 24, 25, 26 ,27, 28, 39	2, 7, 8, 9, 10, 11, 12, 13, 14, 21, 22, 23, 24, 25, 38
2024 (f)	1, 2, 11, 16, 17, 26, 27, 28, 32, 33	3, 10, 11, 12, 13, 16, 17, 25, 32, 34, 35

Notes. f = female, m = male.

Examples of good (A & C) and poor (B & D) data quality channels using Power Spectrum Density and Raw Intensity plots for HbO_2 and HbR

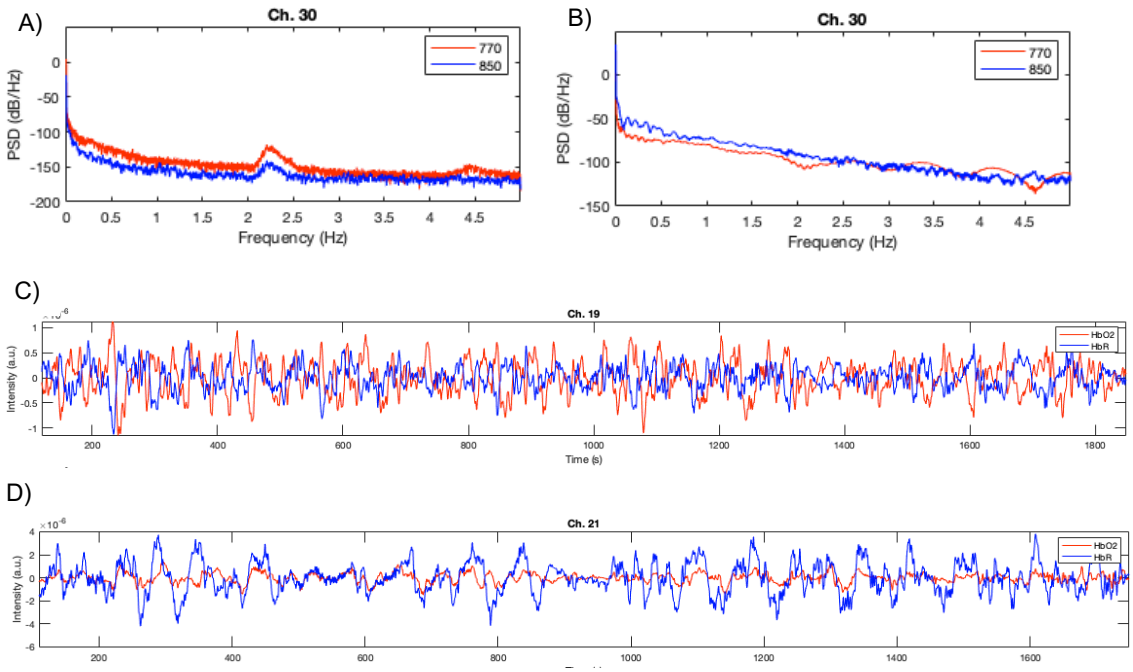


Illustration of different connectivity matrices for HbO_2 of sleep epochs in one participant