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ACTIVE ENGAGEMENTS DURING INFANCY SUPPORT COGNITIVE, PERCEPTUAL, AND NEURAL DEVELOPMENT

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ACTIVE ENGAGEMENTS DURING INFANCY SUPPORT COGNITIVE, PERCEPTUAL,
AND NEURAL DEVELOPMENT

Volume I

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Abstract

Young infants are often described as “sponges” that absorb their environment. There is an implicit assumption that infants are passive recipients of experience rather than active directors. In four complementary chapters, we challenge this popular notion of a passive infant and argue that infants can direct their own experiences via several active mechanisms and that this influences their own cognitive, perceptual, and neural development. In Chapter 1, we review prior infant research in the field and defined attention, prediction, and learning as three examples of active mechanisms that may importantly affect infants’ development. In Chapter 2, we report novel fNIRS data showing that infants’ engagement of active mechanisms—specifically, attention and prediction—is supported by an underdeveloped frontoparietal lobes and can bring about neural changes. In Chapter 3, we present novel eye-tracking data showing a bidirectional relationship between two important active mechanisms: Selective attention and learning. We argue that the reciprocal relationship between two active mechanisms may form a crucial link that catalyzes cognitive and perceptual development. In Chapter 4, we present a meta-analysis on infant research methodology to aid clean and reproducible research on how infants’ active engagement influences their developmental trajectories. Together, this thesis lays the foundation for further research on how infants’ active engagement shapes the trajectories of cognitive, perceptual, and neural development in the long-term.

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Introduction

Popular media often describes young infants as “sponges” that absorb what is in their environment. The main point of this analogy is that young infants learn quickly and easily, but it also suggests that infants do not play an active role in what they experience. In other words, it is implicitly accepted that infants are passive recipients of experience rather than active pursuers. This view is particularly strong in our culture with regards to young infants up to about 6 months old, who have not yet developed the motor ability to transport themselves (Goldfield, 1989) or verbalize their wants (Murray & Goldbart, 2009). The apparent lack of independent motor agency is what makes the “sponge” characterization so persuasive when we think of young infants. After all, 6-month-old infants can barely sit up (Rochat & Goubet, 1995); how could they possibly choose which experiences to learn from?

It is then no surprise that prior research on young infants focused primarily on the environment they were exposed to, and investigated how their experiences affect various domains of development. For example, the impact of economic, cultural, and parenting characteristics on infant development has been extensively explored for decades (e.g., Hopkins & Westra, 1988; Super, 1976). Research on the impact of infants’ exposures on their development has continued to flourish, with recent research investigating the impact of various exposures on infants’ cognitive, social, and language development (e.g., Slomian et al. 2019; Ramírez-Esparza, García-Sierra, and Kuhl 2017; Weisleder & Fernald, 2013). Again, the baseline assumption in many of these infancy studies is that infants are placed in environments where they are given some set of experiences, and these experiences affect their development without the infant’s input. This assumption contrasts with how people think about older children, who are thought to agentively shape their environment (e.g., Gopnik, 2012).

We aim to challenge this notion of a passive infant. We provide several results that demonstrate that infants actively choose what they experience and that those choices affect their development. The thesis provides an in-depth overview of how the infants actively explore their environment and the impact this active engagement has on their development. We show that infants can use various active mechanisms to pursue specific things, rather than absorbing experiences without any agency. In our recent review, we defined an active mechanism as “a mechanism that, when engaged, results in short-term differential processing of sensory [information] in the service of information-gathering and/or modifies internal representations of the environment to enable more efficient processing of sensory [information]” (Baek, Jaffe-Dax, & Emberson, 2020). Attention, prediction, and learning are just some examples of active mechanisms that young infants can utilize without requiring sophisticated motor movements that they have not yet mastered (as seen in Tummeltshammer & Amso, 2018). Using these mechanisms, infants can actively engage with their environment to acquire efficient representations of the environment that surrounds them.

The efficient representations, in turn, shape infant development. In this way, active mechanisms play a pivotal role in catalyzing the avalanche of cognitive, perceptual, and neural changes in the early developmental stages. These developments are responsible for transforming the rudimentary abilities that newborns possess to the full spectrum of abstract thoughts and complicated skills that an adult mind can engineer. In this thesis, we therefore describe some of these incredible active mechanisms that young infants utilize and explore the fascinating topic of how these mechanisms may shape our cognition, perception, and the neural systems that make us human.

In Chapter 1, we present an in-depth, comprehensive overview of the field and our understanding of the active engagements that young infants employ. We define attention, prediction, and learning as three important examples of active engagements that infants regularly use and review the relevant literature. We examine previous research on infants' use of active engagements to alter their experiences and explain how infants' use of these active engagements directly and indirectly shape the development of their cognition, perception, and relevant brain regions. This chapter serves to synthesize and summarize the considerable amount of evidence showing infants' active engagements and the resulting impact, even though the researchers may not have explicitly considered the active nature of the infants' behaviors.

In Chapter 2, we report neural data collected from 6-month-old infants while infants were engaging the active engagements of prediction and attention. We used functional near-infrared spectroscopy (fNIRS), an infant-friendly neuroimaging tool, to collect this data. Neuroscientific approach can be particularly valuable for young infants who are not yet capable of more easily observable traditional motor engagements, such as grabbing, crawling, or speaking. We present neural evidence that infants' seemingly underdeveloped brain networks can support and underlie predictive and attentional processes and argue that the development of complex brain networks follow, rather than precede, the functional engagement of the relevant brain areas during active engagements. Thus, we show that infants engage in predictive and attentional processes, and that this active engagement leads to brain development.

In Chapter 3, we report eye-tracking data collected from 12-month-old infants while infants were engaging the active engagements of attention and learning. We present evidence that infants actively engage via learning and selective attention, and that these two engagements influence each

other in a reciprocal manner. This reciprocal relationship enables further learning, which forms the basis of and has long-lasting implications on cognitive and perceptual developments.

Finally, given the life-long consequences of early development and the impact of infant-led experiences on early development, it is imperative that we support and enable research on active engagement in infancy. One such method that can be applied to study this topic, as we also have in Chapter 2, is fNIRS. Despite being a relatively new research methodology, fNIRS is experiencing a rapidly increasing popularity as a neuroimaging tool (Azhari et al., 2020) and its usefulness in infancy research is indisputable (for review, see Boas, Elwell, Ferrari, & Taga, 2014). It would thus be beneficial to the field to develop a reproducible methodology to aid in clean and transparent science using fNIRS. To this end, in Chapter 4, we present our analysis on the methods that can be used with fNIRS to ensure generalizability and reproducibility, and we offer concrete, executable recommendations to assist future researchers in investigating the impact of active engagements in infancy.

In summary, we review previous research, present new empirical studies with various methodological approaches, and provide methodological recommendations to assist future research to advance the field. My research presented in this thesis can move our field toward a multi-dimensional understanding of active engagements in infancy and their impact on development. It is our hope that our re-examination of the notion of a passive infant can break down our preconceived beliefs about infants and facilitate the enhancement of development outcomes, for the benefit of typically and atypically developing children worldwide.

Chapter 1. How an infant's active response to structured experience supports perceptual-cognitive development*

1.1 Abstract

Previous research on perceptual and cognitive development has predominantly focused on infants' passive response to experience. For example, if infants are exposed to acoustic patterns in the background while they are engaged in another activity, what are they able to learn? However, recent work in this area has revealed that even very young infants are also capable of active perceptual and cognitive responses to experience. Specifically, recent neuroimaging work showed that infants' perceptual systems predict upcoming sensory events and that learning to predict new events rapidly modulates the responses of their perceptual systems. In addition, there is new evidence that young infants have access to endogenous attention and their prediction and attention are rapidly and robustly modified through learning about patterns in the environment. In this chapter, we present a synthesis of the existing research on the impact of infants' active responses to experience and argue that this active engagement importantly supports infants' perceptual-cognitive development. To this end, we first define what an engagement of active engagement is and examine how learning, selective attention, and prediction can be considered active engagements. Then, we argue that these active engagements become engaged in response to

*This work has been adapted from a previous publication by the same author.

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higher-order environmental structures, such as temporal, spatial, and relational patterns, and review both behavioral and neural evidence of infants' active responses to these structures or patterns. Finally, we discuss how this active engagement in infancy may give rise to the emergence of specialized perceptual-cognitive systems and highlight directions for future research.

1.2 Introduction

A common metaphor compares infants to “sponges” that absorb information. This description conveys a sense of *passiveness* and appears to suggest that infants are recipients who reflexively absorb or reflect the environment that they experience. Indeed, a key part of infant and early childhood development entails infants’ adaptation to their environment. Given that infants have highly immature motor abilities, including language production, it is perhaps not surprising that their responses were traditionally considered to be passive. However, we question the notion that infants’ adaptation to the environment arises from the passive unidirectional receiving of input. One reason is that adult responses to the environment can be active in the absence of overt motor responses. Thus, at minimum, we must evaluate whether these active engagements are available to human infants or emerge over development. While we do not doubt that some aspects of early development are passive, we review recent work to argue that infants also actively engage with their environment. We then argue that this active engagement directly influences the types of environmental inputs that infants process and are affected by.

In this chapter, we emphasize infant’s active response to experience with environmental patterns. Environmental patterns are a key type of sensory input arising from the structures in the environment. We further review evidence that experience with environmental patterns can result in an infant’s active engagement. It is important to note that environmental patterns are not the only type of input with which infants actively engage; other types of input (e.g., social contexts) can also elicit active engagement. However, we focus specifically on the infant response to environmental patterns in this chapter to lay the foundation for research on the infants’ active engagement with the environment.

Examples of environmental patterns include temporal structures, which refer to statistical regularities within a sequence in auditory, tactile, visual, and other modalities; spatial structures, which refer to statistical regularities in the placement and arrangement of elements in the spatial organization; and relational structures, which refer to the statistical regularities in the relationship between two or more inputs. Research has found that even young infants are responsive to temporal (Basirat, Dehaene, & Dehaene-Lambertz, 2014), spatial (K. Tummeltshammer & Amso, 2018), and relational patterns (Werchan, Collins, Frank, & Amso, 2016). In order to interact with and comprehend a noisy environment, infants likely need to extract these types of regularities. It has been long known that the detection of these patterns, which can be as simple as a highly-repeated stimulus (e.g., checkerboards shown repeatedly in Cohen, 1972a), results in the rapid and robust modification of attention allocation (Rose, Gottfried, Melloy-Carminar, & Bridger, 1982). This modification of attention already provides some evidence that infants are, in some way, actively engaging with environmental patterns. In this chapter, we expand on this body of evidence and examine how experience with temporal, spatial, and relational patterns result in the active engagement of attention, prediction, and learning engagements starting in infancy.

In summary, this chapter focuses on infants' responses to the different types of environmental patterns to lay out the evidence that infants are actively engaging with their environmental input and that this active engagement significantly shapes infants' internal systems and representations. We argue that this cyclical relationship between input and active response in infancy is a key component in the developmental trajectory that gradually leads to the specialization of perceptual-cognitive systems.

1.3 Active engagement: Definitions

This chapter presents convergent evidence that infants actively engage with the environmental patterns that they receive from their environment. The idea that *learning from the environment is active* is not a new one. For example, in 1975, Eleanor Gibson argued that perceptual learning is active: “We use our receptor systems—our hands, eyes and ears—to explore, to search for useful information [in our sensory input]” (E. J. Gibson & Levin, 1975). Here, Gibson is arguing for a definition of “active” that is motor-based. In the next section, we will review evidence from eye movements that infants are active in this way and argue that this is evidence for the active engagement of attention. However, we expand the definition to include other types of active engagement that do not involve a motor component including learning and prediction. Our overall definition of an active engagement is an engagement that, when engaged, results in short-term differential processing of sensory input in the service of information-gathering and/or modifies internal representations of the environment to enable more efficient processing of sensory input. Using this overarching definition of an active engagement, we now consider how attention, learning and prediction can be considered active engagements.

1.3.1 Attention

We present attention as our first example of an active engagement. In previous literature, attention has been largely categorized into two interrelated but distinct concepts of endogenous and exogenous attention. With exogenous attention, attention is automatically directed to a certain stimulus due to the bottom-up characteristics of the stimulus (e.g., visual salience). With endogenous attention, attention is directed to a certain stimulus due to the internal or top-down

effects of factors such as previous experiences. Endogenous attention enables infants to be active directors of their attention, rather than passive recipients of externally-guided attentional processes.

We specifically highlight selective attention as an endogenous attention engagement of active engagement. Selective attention refers to attending to a certain stimulus (or part of a stimulus) in the presence of multiple options presented simultaneously. Importantly, what an infant voluntarily and selectively attends has a powerful effect on the sensory input that the infant experiences, and evidence strongly shows that infants use selective attention to gather information. In other words, infants can intentionally direct attention and alter the environment to obtain different information about the environment. This ability makes infants the active agents in determining their sensory experiences.

Infants' selective attention can be observed through a number of behaviors. Two of the most readily observed methods that infants use to allocate attention are eye movements and multimodal exploration. As infants develop the ability to control their eye movements, they become increasingly able to determine what they see by directing their eye gaze (for review, see Amso & Scerif, 2015). The control over their visual input enables infants to govern the information they receive and process. From around 4 or 5 months of age (E. Gibson, 1988), infants also begin to systematically reach for and explore specific items of interest. With this development, infants can voluntarily and selectively choose the information they receive by exploring a particular object. At first glance, this complex motor behavior may appear to be drastically different from allocating attention via small eye movements we discussed earlier. However, consider that both eye gaze shifts and multimodal exploration of a specific object are caused by an infant's active directing of their attention to a specific stimulus or aspect of a stimulus over other distracting stimuli. From this perspective, both eye movements and more overt motor explorations enable infants to gather

information about the selected stimulus, and thus both can be considered active engagements. We will discuss research that has looked to eye gaze and grasp-based multimodal exploration to test infant attention in more detail in a later section.

The reason that we discuss attention as an important form of active engagement is that the information that infants selectively obtain has a profound impact as the infant detects, explores, and understands the world (Cohen, 1972). For example, research showed that visually attended stimuli affected infant word learning more than unattended stimuli (Yu & Smith, 2011). This view is also convergent with previous findings that infants' attentional processes affect other important functions such as perception and memory (for review, see Amso & Scerif, 2015). In this regard, attention is a powerful engagement that not only enables active and intentional selection of information, but also greatly influences other functions essential for perceptual and cognitive development. We will discuss the impact of attentional processes on the specialization of perceptual-cognitive systems later in this chapter.

1.3.2 Learning

Learning is the process in which internal representations of the environment are modified following experience. Importantly, the creation of these internal representations comprises an active process because 1) internal representations can result in differential processing of future sensory input, and 2) internal representations can serve to more efficiently process this input. For example, when engaging in statistical learning, an infant learns that some stimuli occur together and uses that information to form a unit, chunk, or combined representation of those stimuli. In later sections, we will review evidence that the formation of these new representations results in better cognitive processing.

Moreover, there is a variety of evidence that learning does not simply arise from a low-level or passive response to environmental patterns. First, under some circumstances, learning can create representations that are not merely copies of environmental patterns. These cases suggest that there is some kind of a higher-level or constructive process that uses experience to produce these representations. Indeed, recent neuroimaging studies have also found that exposure to environmental stimuli result in the engagement of higher-level cortices such as the frontal cortex even in very young infants (Sakatani, Chen, Lichty, Zuo, & Wang, 1999; Taga, Asakawa, Hirasawa, & Konishi, 2004). The engagement of these higher-level cortices, similarly, suggests that there is an active component to learning where representations are constructed rather than passively received from sensory input.

In addition, learning depends on factors that affect other active engagements. Since learning and engagement of other active engagements are both contingent on the same factors and are mostly measured using similar tools and under similar circumstances, we argue that, in its essence, learning is an active process. Here, we focus on the links between predictability and learning (see more on prediction as an active engagement below). For example, learning requires more than a mere exposure to a stream of sensory information: The information to be learned should be relatively predictable (i.e., not random), but not too predictable or too easy to learn. Operationalizing this idea, infants' preference is drawn towards moderately-predictable streams of events, rather than towards fully-predictable or fully-unpredictable streams of events (Kidd, Piantadosi, & Aslin, 2012). This sensitivity of preference towards moderate predictability streams is readily available from birth (Bulf, Johnson, & Valenza, 2011) and dynamically changes with age during infancy (Johnson et al., 2009). Predictability also reflects the difficulty in processing the stream of information. In this framing, the effect of moderate predictability is tightly related to

a child's engagement with the stimuli, and the engagement is likely strongly linked to endogenous attention as we discussed earlier. Tasks that are moderately difficult preferentially engage attention compared to trivially easy or highly difficult tasks (Hunter & Ames, 1988). Thus, conditions that produce good learning outcomes are conditions that are particularly beneficial for the two other active engagements covered in this chapter, predictability and attention. Since learning outcomes are linked to other active engagement, we argue that that learning itself is an active process.

1.3.3 Prediction

Prediction-based processes (prediction and prediction error) are a key feature of cognition and development. For example, in a game of peek-a-boo, an infant will experience seeing hands followed by a face in a repeating pattern. After a few repetitions of experiencing this pattern, they likely begin to predict seeing the face upon seeing the hands. However, if the adult waits a particularly long interval before revealing their face, the infant likely experiences a prediction error. Prediction is the process or ability by which previous experience affects the internal likelihood of upcoming events and produces corresponding changes in processing these events based on their likelihood. Prediction error is the difference between the predicted event and the actual event that was experienced. Prediction error also has impacts on processing as well as in updating the internal likelihood of upcoming events. Computationally, prediction and prediction error facilitate engagement between cognition and the environment; prediction uses internal representations of the likelihood of different events (i.e., cognition) directly alter processing of sensory input (i.e., the environment). Relatedly, prediction is an important link between what has been learned and the processing of future sensory input.

Prediction occurs through numerous related sub-processes, many of which can be considered active. The first sub-process is forming a prediction about an upcoming sensory input; the second sub-process is processing sensory input relative to the prediction and possibly producing a prediction error; and the third sub-process is updating the internal models or representations of the environment based on the prediction error. Each sub-process of predictive processes can be considered active according to our definition, as the formation of a prediction changes the processing of upcoming information by processing it relative to an internal state and prediction results in updating internal representations of the environment. For example, after visual stimuli were consistently preceded with auditory cues, the presentation of an auditory cue elicits prediction about this specific upcoming visual presentation. When this visual stimulus is omitted, a prediction error is calculated and the following prediction is updated (Jaffe-Dax et al., 2020).

Recent theories of prediction suggest that the entire brain may be involved in this type of active processing. The focus on prediction and prediction error in learning and updating internal representations was first formalized in the Rescorla-Wagner reinforcement learning model (Rescorla & Wagner, 1972). A more recent expansion on the theoretically-purported role of prediction in neural processing and behavior is the theory of predictive coding (Friston, 2005; Rao & Ballard, 1999). Predictive coding posits that top-down or feedback neural signals in the cortex communicate prediction, and bottom-up neural signals communicate prediction error. According to this view, it is more efficient for sensory processes to convey prediction error rather than continuous flow of sensory input. Coding for prediction error, a comparison between prediction and sensory input facilitates the extraction of meaningful information from the environment starting from the earliest sensory cortices. In later sections, we will review evidence that the infant brain is also engaging in this type of predictive processing similar to what would be posited by the

predictive coding theory. In this way, the entire cortex and perceptual system would be engaged in prediction and, thus, active processing.

Overall, prediction is an engagement of active engagement with the environment because it involves modifying internal representations following experience and changing sensory processes relative to internal states in order to gather information or process future sensory input relative to past experiences.

1.3.4 Interrelationships among these three engagements

As mentioned earlier, the three engagements of active engagement we discuss—attention, learning, and prediction—are closely interrelated concepts that greatly affect one another. For example, the level of infants’ attention to a given stimulus is affected by what they learn and predict (Doherty, Rao, Mesulam, & Nobre, 2005), and infants attend to events that violate their expectations (e.g., Baillargeon, 1987). What infants learn is affected by what they attend to (Johnson, Slemmer, & Amso, 2004; Pereira, Smith, & Yu, 2014), and learning affects what infants predict (Romberg & Saffran, 2013). As stated in a previous section on learning, infants’ attention is drawn towards moderately-predictable events rather than towards fully-predictable or entirely-unpredictable events (Kidd et al., 2012) and toward moderately difficult tasks than trivially easy or notoriously difficult tasks (Hunter & Ames, 1988). Thus, research readily shows that these three engagements relate to each other.

Relatedly, it should be noted that the distinctness of these three engagements is not always clear. It is difficult to differentiate the three engagements in empirical designs because researchers often manipulate one to investigate another engagement. For example, Kidd and colleagues (2012) manipulated the predictability of events to measure attention, while Hunter and Ames (1988)

manipulated the learnability of a task to investigate attention allocation. In these cases, it is difficult to distinguish the individual effect of each active engagement. In addition, whether prediction can be separated from attention at all is a hotly debated topic in itself, as some researchers argue that predictions are a type of top-down attention while some argue that they are distinct constructs (for a review, see Clark, 2013). Similarly, whether learning can be separated from prediction is also unclear; there is somewhat of a chicken-or-egg problem, as it is difficult to conceive of predictions arising without some kind of learning, and it is also possible that predictions are an essential component of learning. However, despite the difficulty with determining the boundaries and independence of these engagements, we maintain the main focus of the current chapter: Infants actively engage with the environmental patterns and this active engagement supports their perceptual-cognitive development.

1.4 Evidence of Active Engagement with Environmental Patterns

So far, we have both laid out a definition of active engagement and made the argument that attention, learning, and prediction are engagements of active engagement. Now, we present existing behavioral and neural evidence that infants engage these active engagements in response to environmental patterns.

1.4.1 Attention

The engagement of selective attention allows infants to change their sensory input and shape the temporal, spatial and relational information they acquire from the environment. As described earlier in this chapter, we define selective attention as a form of active engagement, because attending to a certain stimulus out of multiple options determines the sensory input that

the infant receives, and this change in sensory input is a result of the information-gathering of the infant. In this section, we describe previous research showing that infants' active engagement via selective attention begins early and grows substantially throughout infancy.

Different motor abilities can assist with attention-guiding processes throughout the stages of development. By 3 months of age, infants are capable of attention-guided oculomotor control (Amso & Johnson, 2006) and their primary visual cortex is mature enough to support this function (Johnson, 1990). Oculomotor-controlled attentional allocation allows infants to selectively attend to input based on factors such as knowledge acquired from statistical regularities in the stimuli (by 6 months of age: Tummeltshammer & Amso, 2018), informational complexity (Kidd et al., 2012), and predictability (Kinney & Kagan, 1976), as well as short-term (Hurley & Oakes, 2018) and long-term (Kirkham, Slemmer, Richardson, & Johnson, 2007; K. Tummeltshammer & Amso, 2018; Wentworth, Haith, & Hood, 2002) exposure to environmental patterns and novel experiences. It was also found that a brief training can improve selective attention in 11-month-old infants, such that infants exhibit trending changes in spontaneous looking during free play after training (Wass, Porayska-Pomsta, & Johnson, 2011). Combined, research suggests that infants modify their sensory input by actively manipulating oculomotor control in the service of information-gathering.

By 5 or 6 months of age, the ability to selectively attend becomes substantially strengthened as infants acquire the ability to systematically reach for and grab objects with their hands, which enables the multimodal exploration of objects (Needham, Barrett, & Peterman, 2002). Infants can use these motor abilities to explore specific objects out of multiple options. In this way, this ability functions similarly to selective attention as measured using eye movements. For example, Stahl and Feigenson (2015) exposed 11-month-old infants to expectation-violating and expectation-

consistent objects and found that infants preferentially attended to expectation-violating toys using their grasp, as a younger infant would attend to the same toys with their eye gaze. In addition, infants multimodally-manipulated the expectation-violating objects in a way that was specific to the types of violations they witnessed (e.g., dropping the toy that previously appeared to defy the principle of object support). Thus, infants selectively explored these objects based on their recent experience. The grasp-based combination of visual, manual, and oral exploration facilitate a richer collection of multi-modal information (Rochat, 1989) about a specific object and has long-term effects on the infants' object exploration (Wiesen, Watkins, & Needham, 2016). These studies show that infants continue to develop more complex methods of selective attention-allocation as they age, and become increasingly sophisticated at actively directing their information-gathering processes.

Investigations of the neural systems supporting the development of endogenous or selective attention provides convergent neuroimaging evidence for the early availability and rapid growth of selective attention in infancy. The areas of particular interest here are the frontal and parietal lobes, which have been implicated in selective and endogenous attention in adults (Sabine; Kastner & Ungerleider, 2000). Although both frontal and parietal lobes exist at birth, they structurally and functionally change drastically in early infancy (for review, see Amso & Scerif, 2015; Colombo & Cheatham, 2006). The frontoparietal pathway undergoes rapid structural maturation and myelination in early infancy (Deoni et al., 2011) and functional connectivity is present by as early as 39 to 42 weeks after birth (Fransson, Åden, Blennow, & Lagercrantz, 2011), with long-range functional connectivity networks developing in the first two years of life (Gao, Lin, Grewen, & Gilmore, 2017). These findings show that the brain areas and connections necessary for endogenous attention both exist and continue to exponentially grow during infancy. This neural

evidence converges with the behavioral evidence for selective attention in early infancy and rapid development and growth.

Together, neural and behavioral research reveal that infants employ various motor abilities and neural engagements to actively engage with their sensory input by selectively allocating attention. In this way, selective attention forms an integral part of the bidirectional and active relationship between the infant and their environment.

1.4.2 Learning

Learning is the process in which experience modifies the internal representations of sensory input. This process of creating or modifying representations can be considered active because a) learning creates representations that are not mere reflections of sensory input; b) these representations facilitate future perceptual and cognitive processing; and c) it engages higher-level cortices like the frontal lobe.

The representations that are created as a result of learning are not simply reflections of the environment, but ways to organize and understand sensory input, which in turn facilitate perceptual and cognitive processing. For instance, in statistical learning, exposure to a consistent stream of individual stimuli results in learning of representations that span beyond the individual stimuli. To illustrate with a simple example, if infants experience *A* is followed by *B* which is followed by *C*, they may form a single, higher-order *ABC* representation. These higher-order representations are often referred to as chunks or new units composed of smaller units (Saffran, Aslin, & Newport, 1996; Saffran & Kirkham, 2018). Importantly, these chunks are not reflections of the statistics of sensory input but are constructed higher-order representations. For example, even though the statistics are uniform between each of the individual stimuli of the chunk, infants only recognize

the complete chunk (i.e., do not recognize subcomponents of the chunk), suggesting that infants have formed a new representation based on the statistics (Orbán, Fiser, Aslin, & Lengyel, 2008; Slone & Johnson, 2018). Moreover, forming these chunks has been found to facilitate subsequent processing. For example, Graf-Estes and colleagues found that forming chunks from a stream of syllables facilitated infants' subsequent association of these speech sounds as labels for objects (Estes, Evans, Alibali, & Saffran, 2007). Thus, the representations that are formed as a result of learning create higher-order representations that are not mere reflections of the environment and in turn, these representations facilitate future processing of sensory input.

Recent neuroimaging studies have found that learning engages higher-level cortices, which suggests active engagement. Higher-level cortices are regions of the brain that are more likely to engage in active construction of new representations. Let us briefly return to the example of creating a representation of *ABC* following experience with *A* followed by *B* followed by *C*. In order for this higher-order representation to be created, regions of the brain have to hold information about these three discrete events (*A*, *B*, *C*) in memory. Given that these events are distinct in their initial representations, they need to be bound together or linked in some way to create a single *ABC* representation. Lower-level cortices (e.g., perceptual cortices) are not believed to be capable of these types of computations. As lower-level cortices are highly sensitive to the current sensory input, they are not able to process items that are no longer present. Thus, they would not have simultaneous access to *A*, *B*, and *C*. Given these limitations of lower-level cortices, higher-level cortices like the frontal lobe are thought to be necessary for these computations, and thus are crucial for the creation of higher-order representations. For these reasons, the engagement of higher-level cortices during suggests that the brain is engaging in active processing.

There have been a myriad of studies showing that the frontal lobe is involved in learning and novelty detection starting from very early in infancy. A recent EEG study investigating sequences in 3-month-old infants revealed that the frontal lobe is involved in learning sequences of stimuli (Basirat et al., 2014). More specifically, Basirat and colleagues found that in early infancy the left frontal lobe attenuates its response to a deviant stimulus when it is in a learned sequence. This finding dovetails with other work demonstrating that the infant frontal lobe is involved in processing of familiarity and novelty (Nakano, Homae, Watanabe, & Taga, 2008), rule learning (Gervain, Macagno, Cogoi, Peña, & Mehler, 2008; Werchan et al., 2016), and audiovisual associations (Kersey & Emberson, 2017) starting early in life. There are also broader proposals that the infant frontal lobe is available to contribute to infant cognition and learning at early infancy (Dehaene-Lambertz & Spelke, 2015; Grossmann, Lloyd-Fox, & Johnson, 2013). Overall, there is convergent evidence that learning in infancy engages the frontal lobe, suggesting that infant learning is an active process of cognitively constructing representations rather than passively processing them. While it is likely that other higher-level cortices are also involved in infant learning, we focus on the frontal lobe because of the large number of studies reporting its involvement and the ease of recording with this region of the brain in both EEG and fNIRS.

Taken together, these findings show that infant learning is an active process. Starting from the first few months of age, infants engage higher-level cortices like the frontal lobe during learning and related processes, infant learning results in the construction of higher-order representations, and these higher-order representations facilitate future perceptual and cognitive processing.

1.4.3 Prediction

Prediction is a process in which internally-calculated probabilities of sensory input modify the internal representations and the subsequent perceptual processing of sensory input (e.g., predicted vs. less-predicted). Prediction is active because the perceiver applies their estimated prediction on the environment to their sensory input and modifies the way it is perceived in a way that uncovers information about the environment that is relevant to the infant's experience. Here, we present evidence that the infant brain is highly predictive and may follow similar principles to the theory of predictive coding.

Based on the framework of predictive coding (Friston, 2005; Rao & Ballard, 1999), many regions of the cortex, from higher-level cortices to sensory cortices, are involved in prediction. As explained above, predictive coding framework posits that the cortex communicates top-down prediction and bottom-up prediction error. One expected observation from this framework is that sensory cortices exhibit neural responses for predicted events compared to less predicted events (e.g., Summerfield & Lange, 2014; Summerfield, Trittschuh, Monti, Mesulam, & Egner, 2008).

While there are relatively extensive findings that the adult brain is predictive, recent research in infants has suggested this adult ability does not rely on extensive experience and maturation of the cortex. By contrast, this ability to form predictions is readily available in early infancy. In young infants, the impact of predictability was first demonstrated using neuroimaging and recording sensory responses when unexpected omissions of stimuli (cued from different sensory modalities) continued to result in sensory cortex responses (Emberson, Richards, & Aslin, 2015). Relatedly, when sensory input from a particular modality is correctly predicted (cued again from a different sensory modality), infants modulate their sensory processing compared to incorrectly predicted stimulus (Kouider et al., 2015). Xiao and Emberson (2019) similarly found

that infants can show increases in their face perception abilities when they are able to predict upcoming faces. Recent work has suggested that predictability may also reflect the processing of repeated stimuli (Emberson, Boldin, Robertson, Cannon, & Aslin, 2019) following the results from Summerfield et al. (2008). Thus, there is emerging evidence that the infant brain is highly predictive and that prediction affects the processing of sensory input and the activity of perceptual systems starting in infancy.

In addition, there is much evidence that prediction results in updating representations. First, infants and toddlers experiencing a prediction error resulted in allocating more time to learn about those objects. In an example we mentioned earlier, when infants observed ordinary events (e.g., a ball hitting a wall) vs. highly unlikely events (e.g., a ball passing through a wall), infants learned more about the object that violated their expectations and behaved against their prediction (Stahl & Feigenson, 2015). Second, a series of studies by Kayhan and colleagues established that infants and toddlers update their internal models of stimuli based on prediction errors (Kayhan, Heil, et al., 2019; Kayhan, Hunnius, O'Reilly, & Bekkering, 2019; Kayhan, Meyer, O'Reilly, Hunnius, & Bekkering, 2019). Finally, the processes supporting prediction errors may represent a continuous ability that guides development from infancy to adulthood: Using pupillometry – a method that can measure infants and adults comparably – we found that the learning trajectory of cross-modal association was similar in 6-month-old infants and adults (F. Zhang, Jaffe-Dax, Wilson, & Emberson, 2019).

Taken together, these findings elucidate the early availability of prediction, a process which actively affects their perceptual processing of these stimuli and their formations of future representations.

1.5 Active engagement shapes perceptual and cognitive development starting in infancy

In the previous sections, we have defined active engagements, identified three examples of active engagements (attention, learning and prediction) that are available early in development, and provided evidence that these active engagements are readily engaged when infants experience environmental patterns. The evidence we have already cited indicates that these active engagements can affect perception and cognition in a number of ways: 1) Attending to different aspects of the environment changes the sensory input and affects learning; 2) Learning can result in the creation of internal representations that have downstream consequences for perceptual and cognitive processing; and 3) Predictive processes modulate neural responses to sensory input, and this neural modulation can have downstream consequences for learning and memory. Thus, young infants have active responses to their experiences, and these active engagements have consequences on perception and cognition.

While findings that infants actively respond to their experiences imply that active engagements can shape the development of perception and cognition, evidence is not sufficient to make a definitive link. In particular, the bulk of these studies focus on the short-term outcomes of active engagements, with the effects tested seconds or minutes after attention, learning, or prediction is engaged. This short-term focus is readily attributable to the methodological difficulties of investigating the consequences of laboratory tasks days after an experimental manipulation in young infants. However, it is necessary to build upon the short-term findings and also ask whether these active engagements result in meaningful medium and long-term changes in infant perception and cognition and, moreover, to link these engagements to broader developmental trajectories.

In this section, we review several studies that provide initial evidence to this end and argue that these active engagements are highly likely to have influences on longer-term developmental trajectories. We present evidence that active engagements shape the development of face perception and are involved in language development. All three of the active engagements considered (attention, learning and prediction) have been linked to development in these domains.

Recent work has linked the engagement of selective attention with the development of face perception in infancy. Markant, Oakes, and Amso (2016) found that attentional engagements are differentially applied to own vs. other-race faces, and results in the differential face perception in these groups that has typically been considered to arise from differences in perceptual representations alone. Following up on these findings, Markant and Scott (2018) published a theoretical position piece linking attentional engagements and the emergence of perceptual specialization for familiar/own-race faces. Overall, this line of work suggests that differences in the active engagement of attention ultimately results in both reflexively applied differences in attention to different types of faces and the emergence of perceptual representations for faces.

Other lines of research have used individual differences to make links between the engagement of active engagements and broader developmental trajectories. Kannass and Oakes (2008) found a relationship between measures of endogenous attention at 9 months of age and measures of language development years later (vocabulary size at 31 months). Reuter, Emberson, Romberg, and Lew-Williams (2018) found that differences in prediction from 12-24 months also relate to language development (vocabulary size measured concurrently). Lany, Shoaib, Thompson, and Estes (2018) found that differences in statistical learning abilities related to real-time language processing at 15 months. These studies of individual differences provide evidence for the broader developmental consequences of an infant's abilities to engage these active

engagements. However, there are some important methodological limitations to the existing literature. For example, the test-retest validity of the measures of these active engagements have not been established (see papers by Siegelman, Frost, Christiansen and colleagues concerning the measuring of individual differences in statistical learning; e.g., Siegelman, Bogaerts, Christiansen, & Frost, 2017 for adults and Arnon, 2019 for children). Test-retest validity is important for measuring stable, reliable individual differences in these engagements. Moreover, the specificity of these findings is unclear. Since “positive” aspects of development often develop together, it is unclear whether these correlations simply reflect generally better development in some individuals whether it reflects more direct links between these active engagements and development. While approaching the investigation of the long-term consequences of these active engagements using an individual differences approach has yielded early positive results and is methodologically tractable, this approach has substantial limitations that need to be addressed in future work.

Finally, one of the most compelling lines of evidence that active engagements are involved in long-term changes in perceptual and cognitive development comes from the work by Lisa Scott and colleagues, who used training studies to examine the impact of verbal labeling on perceptual narrowing. In their seminal work, Scott & Monesson (2009) provided infants with one of three types of exposures to non-human primate faces while controlling for the bottom-up exposure to the faces. Infants were exposed to the faces without labels, faces with general labels (i.e., “monkey”), or faces with specific labels (i.e., “Boris”). Researchers found that infants showed significant alteration of their developmental trajectory in perceptual narrowing only in the specific label condition. Scott (2011) also extended this finding to another category of stimuli (strollers) and similarly found that the specific label affected perceptual narrowing. A follow-up investigated the impact of this training several years later and found that infants who had received specific label

training in their first postnatal year showed differential neural responses to faces when they were 5 years old (Hadley, Rost, Fava, & Scott, 2014). Following this compelling series of studies, we suggest that long-term training studies are important avenues for future investigation of the long-term consequences of active engagements.

However, the studies that use long-term training also have limitations that need to be addressed in future work. Considering the studies by Scott and colleagues, the exact active engagements involved in Scott and Monesson's (2009) intervention are not known. While these findings suggest that it is not only the mere sensory input of these faces, but also the context in which this input, that matters for an infant's perceptual development, it does not reveal what engagements are engaged through this contextual manipulation. An additional caveat is that Scott and Monesson (2009) did not directly quantify the sensory input that infants received. They relied on parental report, which may be limited, and there could be differences in the sensory input that infants received.

In sum, this section reviewed the current, albeit limited, evidence that the engagement of active engagements has consequences for the long-term development of perception and cognition. The findings in this section are scattered and some have notable limitations, but these findings provide an important foundation for linking the short-term effects of these active engagements to longer-term developmental trajectories. Given the recent focus on these active engagements, we propose that a key future direction for the field is to start to make stronger links between these short-term effects and longer-term developmental consequences of these engagements.

1.6 Outstanding Questions

The goal of this chapter is to push the boundaries of the field's thinking *vis-a-vis* active engagements and their role in early development. There has been a growing interest in these engagements, and how they are engaged in response to different types of experience (e.g., environmental patterns, which was the focus on this chapter). While the term “active” has been increasingly used in relation to these engagements, this chapter provides a definition of an active engagement and makes a direct argument for why these engagements are active. Building on seminal demonstrations that these active engagements are available to infants, important avenues of future work involve uncovering the interrelationship between these active engagements, investigating the experiential conditions in which these engagements are engaged, and, particularly for learning and prediction, considering the developmental emergence of these active engagements or whether they are available in an invariant form from birth. Relatedly, do these engagements operate similarly across domains (i.e., are domain-general) or do they exhibit specialization for specific stimuli? It has been argued that there is specialization of attention (e.g., Markant & Scott, 2018) for different types of faces) but this work needed to be extended to consider other domains and types of active engagements as well.

In addition, we argue that it is essential for the field to continue investigating how the active engagements, engaged in the moment, ultimately contribute to broader developmental trajectories. Answering this question will involve tackling a number of difficult outstanding questions, including uncovering the means by which short-term effects relate to long-term effects. To highlight an example where it is important, but difficult, to understand the relationship between short-term effects of active engagements and broader developmental changes, we turn to auditory development. Sussman and colleagues have argued that the engagement of selective attention to stimuli may be linked to developmental changes in auditory processing. Passive responses of the

auditory system to odd-ball stimuli show a developmental trajectory in which there is increased sensitivity of the auditory system to different auditory features (e.g., frequency and intensity). It was previously thought that these passive responses reflect the fixed capacity of the auditory system. Indeed, odd-ball responses are usually measured under passive conditions (e.g., with a stream of auditory stimuli presented in the background with the participant engaged with another stimulus like a video). However, when children are encouraged to actively engage with an odd-ball task, they show sensitivity to these auditory features that cannot be seen using passive paradigms (Sussman & Steinschneider, 2011). Thus, active engagement appears to push the boundaries of the capacities of the system at a given age. While this is a compelling finding and strongly suggests that there is a link between active engagement at a particular age or point in development with the emergence of developmental capacities later, this isn't directly demonstrated. Moreover, it is unclear *how* these active engagements translate into changes in perceptual capacities.

1.7 Summary and Conclusions

Although traditionally considered passive “sponges” that absorb information, we argue that infants play a more active role in using their experience to support their neural and cognitive development. In this chapter, we presented an overview of existing research and argued that infants are actively engaging in their experiences even without overt motor responses. To do so, we first defined an active engagement as an engagement that results in short-term differential processing of sensory input in the service of information-gathering and/or modifying internal representations of the environment to enable more efficient processing of sensory input. Using this definition, we have argued that attention, learning, and prediction are significant examples of active engagements.

Specifically, all of these engagements give an infant the ability to gather information and modify internal representations to support better processing of their sensory input. We then presented behavioral and neural evidence that infants engage these active engagements in response to higher-order environmental structures, including spatial, temporal, and relational patterns. Despite the obvious short-term effects of these active engagements, however, the long-term consequences of active engagement are not yet clear. We reviewed some research that begins to answer how active engagement may shape broader trajectories of perceptual and cognitive development. In future work, it will be necessary to shed light on the developmental changes in the engagement of active engagements, the roles of these active engagements on the long-term developmental trajectories, and their impact in atypically developing populations. This field of research can help us gain an understanding about how the bidirectional relationship between infants' active engagement and the environmental patterns that we have discussed in this chapter ultimately affect the developmental trajectory that results the specialization of perceptual-cognitive systems.

Chapter 2. Temporal predictability modulates cortical activity and functional connectivity in the frontoparietal network in 6-month-old infants[†]

2.1 Abstract

Despite the abundance of behavioral evidence showing the interaction between attention and prediction in infants, the neural underpinnings of this interaction are not yet well-understood. The endogenous attentional function in adults have been largely localized to the frontoparietal network. However, resting state and neuroanatomical investigations have found that this frontoparietal network exhibits a protracted developmental trajectory and involves weak and unmyelinated long-range connections early in infancy. Can this developmentally nascent network still be modulated by predictions? Here, we conducted the first investigation of infant frontoparietal network engagement as a function of the predictability of visual events. Using functional near-infrared spectroscopy (fNIRS), the hemodynamic response in the frontal, parietal, and occipital lobes was analyzed as infants watched videos of temporally predictable or unpredictable sequences. We replicated previous findings of cortical signal attenuation in the frontal and sensory cortices in response to predictable sequences and extended these findings to the parietal lobe. We also estimated background functional connectivity (i.e., by regressing out task-evoked responses) to reveal that frontoparietal functional connectivity was significantly

[†] This work has been adapted from a previous publication by the same author.

Baek, S., Jaffe-Dax, S., Bejjanki, V. & Emberson, L. L. (2022). Temporal predictability modulates cortical activity and functional connectivity in the frontoparietal network in 6-month-old infants. *Journal of Cognitive Neuroscience*. doi: https://doi.org/10.1162/jocn_a_01828

greater during predictable sequences compared to unpredictable sequences, suggesting that this frontoparietal network may underlie how the infant brain communicates predictions. Taken together, our results illustrate that temporal predictability modulates the activation and connectivity of the frontoparietal network early in infancy, supporting the notion that this network may be functionally available early in life despite its protracted developmental trajectory.

2.2 Introduction

Prediction is an important cognitive engagement that facilitates early learning. Many behavioral studies have demonstrated that young infants can engage in predictions (Emberson et al., 2015; Stahl & Feigenson, 2015; Van Giffen & Haith, 1984), and that these predictions affect attention in infancy (Amso & Johnson, 2006; Baillargeon, 1987; Doherty et al., 2005; Kidd et al., 2012; Kirkham et al., 2007; K. S. Tummeltshammer, Mareschal, & Kirkham, 2014; Wentworth et al., 2002). A likely neural substrate of prediction is the frontoparietal network, which is a large-scale network that is composed of the dorsolateral prefrontal cortex and posterior parietal cortex (Yeo et al., 2011). In adults, the frontoparietal network has been repeatedly implicated during predictive processing (Corbetta, Kincade, Ollinger, McAvoy, & Shulman, 2000; Sabine Kastner, Pinsk, De Weerd, Desimone, & Ungerleider, 1999; Koban, Jepma, López-Solà, & Wager, 2019; Leong, Radulescu, Daniel, DeWoskin, & Niv, 2017); for example, anticipatory shifts of attention to visual targets were found to be mediated by the frontoparietal network. Prior evidence thus suggests that predictive processes modulate attentional processes in both adults and infants, and that they engage the frontoparietal network in adults.

However, the neural basis of prediction in infancy remains unclear, as the frontoparietal network has been found to be immature in young infants. Several studies have reported limited and delayed development of white matter that supports long-range connections in the frontoparietal network (Deoni et al., 2011; Kulikova et al., 2015; Lebel & Deoni, 2018; O’Muircheartaigh et al., 2014). Some studies have also reported underdeveloped resting state connectivity in infants’ frontoparietal network and other long-range networks (Bulgarelli et al., 2020; Damaraju et al., 2014; Fransson et al., 2011). Yet, it is still possible that this immature frontoparietal network could be functionally available and modulated by predictability in young

infants. Converging evidence from several studies has highlighted the importance of the frontal lobe during predictive processing in infancy (Boldin, Geiger, & Emberson, 2018; Emberson et al., 2019; Jaffe-Dax et al., 2019; Kersey & Emberson, 2017). However, no prior study has investigated the engagement of the parietal lobe in these predictive tasks, or functional connectivity across the frontoparietal network during prediction in infancy. Here, we investigate frontoparietal network engagement during predictive processing in infancy using functional near-infrared spectroscopy (fNIRS).

In addition, we also examined the occipital lobe during predictive processing. Previous work in adults found that predictable repetition and deviation of stimuli both attenuated neural responses in the sensory cortices (Summerfield & De Lange, 2014; Sussman & Steinschneider, 2011), suggesting that the attenuation of occipital lobe activity are induced by predictability rather than simple repetition. In this study, we therefore examined the frontoparietal network as well as the occipital lobe to examine the effect of predictive processing and the potential interactions among the frontoparietal network and the sensory cortices.

fNIRS is a particularly suitable neuroimaging method for this investigation because of its utility for infant research (Azhari et al., 2020), especially given its robust resistance to motion artifacts (Brigadoi et al., 2014; Nishiyori, 2016; Wilcox & Biondi, 2015). fNIRS can easily record lobe-level data that can be standardized through spatial registration methods (Tsuzuki & Dan, 2014), and localized anatomically (Ferradal, Eggebrecht, Hassanpour, Snyder, & Culver, 2014) with good reliability (Plichta et al., 2006; H. Zhang et al., 2011). Indeed, it has already been used successfully to localize specific anatomical regions (e.g., Emberson, Crosswhite, Richards, & Aslin, 2017). Because fNIRS allows measurements from the surface of the cortex, we measured connectivity between frontal and parietal lobes as a proxy for the frontoparietal network. This

approach of using lobular measurements from fNIRS as proxy to study network-level functional connectivity have been adopted in previous research (Bulgarelli et al., 2019; Durantin, Dehais, & Delorme, 2015; Liang, Chen, Shewokis, & Getchell, 2016; Rosenbaum et al., 2017; Sasai et al., 2012).

Using fNIRS, we compared the cortical activity in, and functional connectivity between, the frontal, parietal, and occipital lobes as infants watched a Predictable Sequence (PS) or Unpredictable Sequence (UPS) of items (experimental design developed by Jaffe-Dax, Bejjanki, & Emberson, under review). Previous research has shown that predictability attenuates neural responses in adults (e.g., Summerfield et al., 2008; Sussman and Steinschneider, 2011) and in the frontal lobes of infants (Basirat et al., 2014; Kouider et al., 2015). These findings are consistent with the predictive coding framework (Friston K, 2005; Rao & Ballard, 1999), which posits that predictable sequences would be associated with reduced prediction error and thus attenuated neural responses. Building on this prior work, we hypothesized an attenuation of cortical activation in the frontal, parietal, and occipital lobes in response to the PS compared to the UPS. Evidence in support of this hypothesis would confirm the predictability-driven attenuation of activity in the infant frontal cortex using fNIRS and extend the findings to the infant parietal lobe, an area that has been heavily implicated in predictive processes in adults.

We were also interested in examining the interactions among the frontal, parietal and occipital lobes that might underlie the predictability-driven attenuation of activity in the infant brain. Previous research in adults has found greater frontoparietal connectivity during prediction periods compared to neutral periods (Bollinger, Rubens, Zanto, & Gazzaley, 2010). Thus, we hypothesized greater frontoparietal functional connectivity in response to the PS compared to the UPS. Such a finding would provide crucial evidence that the frontoparietal network is engaged

during predictive processes in infancy, and suggests that feedback between the frontal and parietal lobes underlies the attenuation effect of predictability.

2.3 Methods

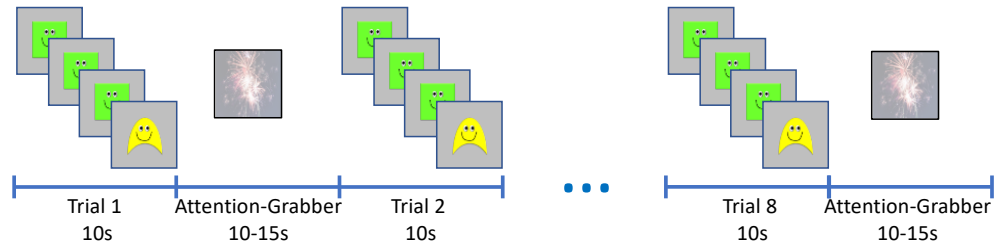
2.3.1 *Experimental design*

Data from 34 infants between the ages of 5 and 7 months (mean $\pm$ SD = 5.71 $\pm$ 0.52 months old; 19 male; 15 female) were used in our analyses. Considering a paired t-test (e.g., comparison of univariate activity between conditions), 34 is a sample size sufficient to detect an effect size of 0.5 (medium effect) with power of 80% at $p = 0.05$ (Dhand & Khatkar, 2014). Our sample size is also double the median sample size among infant fNIRS studies (Cristia et al., 2013). In total, we recruited 44 infants for this study; however, three infants were excluded because they did not want to wear the fNIRS cap; two were excluded because their head was too small for a good fit of the fNIRS cap; three were excluded because they were fussy and did not want to start the task; and two were excluded due to technical error and file corruption. Therefore, data from 34 out of 44 infants were analyzed, resulting in the total attrition rate of 22.72%, compared to the average of 54% among infant studies with more than 20 optodes (Cristia et al., 2013). This experiment was approved by Princeton University's Institutional Review Board. Each infant's caregiver was given a description of the study, and they provided informed consent before starting the experiment. Infants and their caregivers received \$10, a t-shirt, and a children's book as a compensation for their participation.

The visual stimuli developed by Jaffe-Dax, Bejjanki, and Emberson (under review) were used for this study. In each trial, four smiling shapes (green square, yellow crescent, pink star, or blue cloud) sequentially crossed the screen upward, downward, leftward, or rightward, while a

sound of old windows startup, rattle, train, or chimes played for 10 seconds (Movie 1). For each subject, each shape was always paired with one movement and one sound throughout the task, and subjects were pseudo-randomly assigned to particular shape-movement-sound pairings. In other words, the same shape was always associated with the same direction and sound for one infant, and this association was changed between infants. A video of dimmed fireworks accompanied by a nursery song was shown for 10 to 15 seconds between each trial as an attention-grabbing period (Emberson et al., 2015). Within-subject design was used, such that each infant experienced both Predictable Sequence (PS) and Unpredictable Sequence (UPS) conditions. Each condition was comprised of eight consecutive trials in a block design. In PS, the order of the shapes within each trial was consistently AAAB so that the order was predictable in each trial (Fig. 1a). This AAAB was chosen as the format for our predictable trial for all trials because prior research has demonstrated that infants as young as 3 months old are able to represent regularities of this particular sequence and detect violations (Basirat et al., 2014). In UPS, the order of the shapes within each trial was pseudo-randomly chosen between AABA, ABAA, and BAAA so that the order was unpredictable in each trial (Fig. 1b). The order of conditions was counter-balanced between infants. Infants sat on their caregiver's laps while they watched the stimuli on a screen that was placed about 60 cm away. Shapes moved across the screen for about 20 degrees of visual angle, and sounds were played through centrally positioned speakers at a comfortable volume.

1a. Predictable Sequence (PS)



1b. Unpredictable Sequence (UPS)

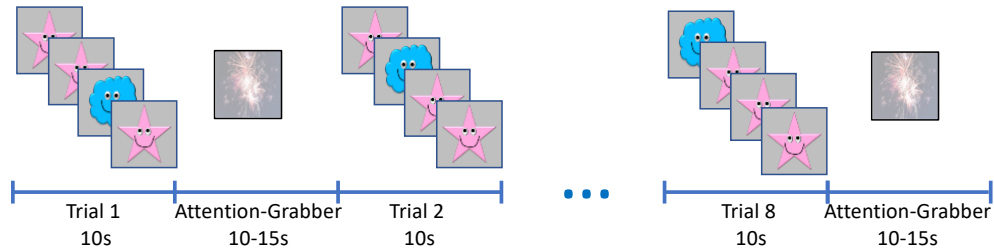


Figure 1. Experimental design

PS was comprised of 8 consecutive trials which displayed the same order of shapes (AAAB). UPS was comprised of 8 consecutive trials which displayed varying orders of shapes (AABA, ABAA, or BAAA). 10-15 second clips of fireworks were shown between each trial.

The fNIRS cap was placed on each infant's head. There were 24 source optodes and 24 detector optodes placed in the frontal, parietal, and occipital regions of the cap. The same cap and placement was used for all infants, although the location of the optodes varied depending on the placement of the cap and the snugness of the fit of the cap. We recorded infants' cortical activity from 80 fNIRS channels at ~ 13.33 Hz (inter-sample interval of 75 ms) at three wavelengths (790, 805 and 830 nm) using custom-made infant fibers connected to Shimadzu LABNIRS. Channel separation on the scalp was 25 mm. For each subject, the position of the fNIRS cap on the infant's head was estimated using a novel motion-resistant, video-based localization technique (Jaffe-Dax, Bermano, Erel, & Emberson, 2020). For this technique, we used a GoPro to capture a video of all views of each infant's head with the fNIRS cap. We then reconstructed a 3D model of each infant's head with the fNIRS cap from this video using structure from motion (SfM), a popular computer vision technique for 3D reconstruction. We extracted the coordinates of relevant fiducials (e.g., Nz, Cz, Iz, AL, AR and cap edges) from this 3D model and the positions of all channels were interpolated and projected to MNI space (Tak, Uga, Flandin, Dan, & Penny, 2016). Based on the coordinates of each channel, we assigned each channel to lobes based on the coordinates listed in the Talairach Daemon (TD) database (Lancaster et al., 2000). Channels in the frontal, parietal, and occipital lobes were used in our analyses. Homologous lobes were aggregated together, and signals were averaged across all channels within each lobe for each subject. In each subject, we recorded between 28 to 37 channels in the frontal lobe (mean $\pm$ SD = 33 ± 3 channels), 25 to 36 channels in the parietal lobe (mean $\pm$ SD = 34 ± 2 channels), and 8 to 16 channels in the occipital lobe (mean $\pm$ SD = 11 ± 3 channels), depending on the subject-specific placement of the fNIRS cap. The distribution of the channels across subjects are shown below (Fig. 2).

2.

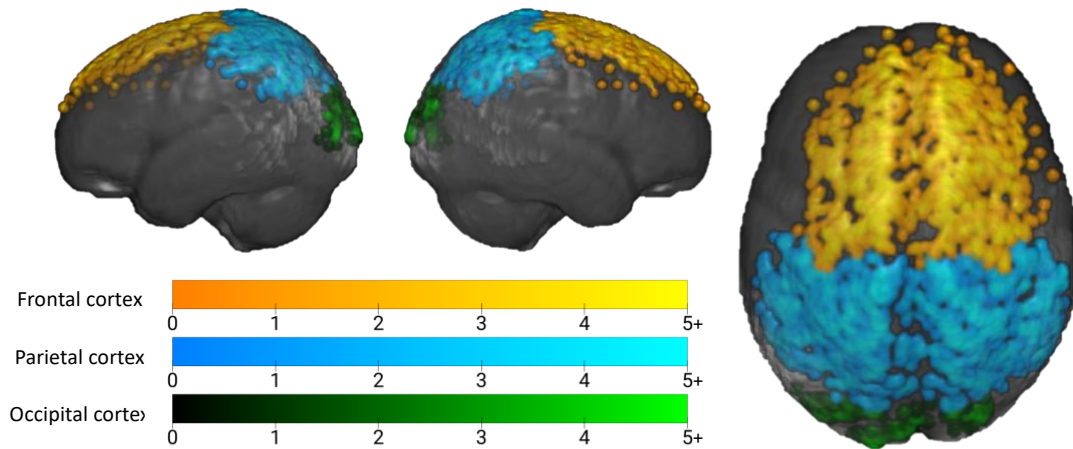


Figure 2. Localization of channels across subjects.

The channels were localized to the frontal cortex (dark yellow to light yellow) parietal cortex (dark blue to light blue), and occipital cortex (dark green to light green). The gradation of colors represents the number of subjects with a channel in a given area. As is standard for fNIRS measurements, the range of head sizes and variation in cap placement (e.g., due to differences in head size and shape) both contribute to the scatter in channel placement. Here, we show the distribution of the channels that were used to aggregate lobe-level data for our analyses. For visualization purposes, all channels with data from 5 or more subjects are represented in the brightest color to show the general range of the recording sites and as a marker that there are differences in the density of sampling between each subject. The maximum overlap for any single channel position is $n=12$.

2.3.2 Statistical Analysis

The Homer2 toolbox for Matlab (Huppert, Diamond, Franceschini, & Boas, 2009b) was used to preprocess the raw data using the parameters recommended by Brigadoi and colleagues (2014). First, raw intensity data were converted to optical density using and filtered using the HOMER2 toolbox. Motion artifacts were detected using the following parameters: tMotion = 0.5, tMask = 1, STDEVthresh = 25, and AMPthresh = 1. Epochs containing detected artifacts were removed from the data and spline interpolated using $p = 0.99$. Data was then band-pass filtered between 0.01 and 0.5 Hz. Then, this filtered optical density was transformed to oxygenated hemoglobin (HbO₂) concentrations using a modified Beer-Lambert equation with partial path factor (ppf) of 6 for all wavelengths. Any channel containing concentration changes beyond $\pm 5 \times 10^{-5}$ μM were considered spurious and were omitted from further analysis.

We chose to use the finite impulse responses (FIR) as a basis function to approximate the hemodynamic response, particularly given that we do not have definitive knowledge about the shape of the hemodynamic response in infant subjects. We defined our impulse response window as 20 seconds to account for 10 seconds of stimulus and 10 seconds of inter-trial baseline period. At one FIR regressor per second, we used 20 FIR regressors to model the neural response, and the weighted sum of those impulses were used to estimate the shape of the hemodynamic response. We used this estimate of hemodynamic response as the measure of task-evoked cortical activity in our following analyses. This technique is widely used in the field to model task-evoked hemodynamic response (see Huppert et al., 2009 and Santosa et al., 2018 for more details on using an FIR model to analyze fNIRS data).

We removed the first trial of both conditions before performing our statistical analyses to offset the effect of initial acclimation period, as it was possible that the novelty of the task itself and its sounds, shapes, and sounds may affect the infants' frontoparietal network engagement. Acclimating to simple novel tasks have been found to evoke frontoparietal engagement in adults (Cole, Braver, & Meiran, 2017). To calculate the differences between conditions in the task-based activations in the frontoparietal network, we aggregated the frontal, parietal, and occipital lobes' cortical activity measured during PS and UPS across all subjects. Lobe-level analysis was appropriate for our level of specificity, given that our hypotheses were about the lobe-level frontoparietal engagement during our task. The mean level of cortical activity was calculated from the 5-second time window from 0 to 5 seconds before the trial onset to obtain the baseline for each lobe. Then, to obtain the activation for each lobe, the mean level of cortical activity was calculated from a window of 5 seconds between 10 and 15 seconds after trial onset. This 5-second time window was selected *a priori* based on a previous finding of predictability-dependent differential activity in the frontal and sensory cortices within this time range (Jaffe-Dax, Bejjanki, & Emberson, under review). We performed within subjects two-tailed t-tests on baseline levels between PS versus UPS across all subjects to test that there were no spurious differences between the conditions in any of the lobes. Then, we performed one-tailed t-tests on activation levels to test the hypothesis that the activity in response to PS is more attenuated compared to the activity in response to UPS. All p-values were corrected for multiple comparisons using the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995).

To assess task-based functional connectivity between the frontal, parietal, and occipital lobes, we used the "background connectivity" approach (Al-Aidroos, Said, & Turk-Browne, 2012; Norman-Haignere, McCarthy, Chun, & Turk-Browne, 2012). In the presence of external

stimulation, hemodynamic responses in different neural areas are correlated not only due to the connectivity between them, but also due to the synchronized task-evoked responses. If the task-evoked responses are not appropriately controlled for, the functional connectivity analysis can yield over-inflated correlation estimates (Cole et al., 2019). The background connectivity approach to inferring functional connectivity models and linearly regresses stimulus-evoked responses out of the data, before measuring correlations in the residual spontaneous fluctuations. Specifically, we modeled task-evoked activations by fitting a generalized linear model (GLM) using the FIR approach described above. The residuals from this model were used to measure background activity. After confirming that the residuals were normally distributed and therefore were suitable for Pearson correlation, we calculated the Pearson correlations over the residuals to infer the functional connectivity between the frontal, parietal and occipital lobes. Similar techniques have been used for fMRI data (Al-Aidroos et al., 2012 and Norman-Haignere et al., 2012), although, unlike with fMRI data, we did not regress out nuisance and global variables due to the lack of coverage of non-responsive regions like brain stems and ventricles in an fNIRS recording. The correlation coefficients (Pearson's r) of each subject were Fisher transformed to z -values to aggregate across all subjects. We tested whether the background connectivity in the frontoparietal network was different in response to PS versus UPS using a two-tailed t -test. We also calculated the same measure between the frontal and occipital lobes and between the parietal and occipital lobes for comparison. Then, the z -values were Fisher transformed back to Pearson's r values.

2.4 Results

2.4.1 Predictability attenuates cortical activity

To test our first hypothesis that the frontal, parietal, and occipital lobe activities would be significantly lower during PS compared to UPS, cortical activity (measured by aggregated HbO₂ levels) in each lobe was averaged across all subjects for each condition, and compared between the conditions (Fig. 3).

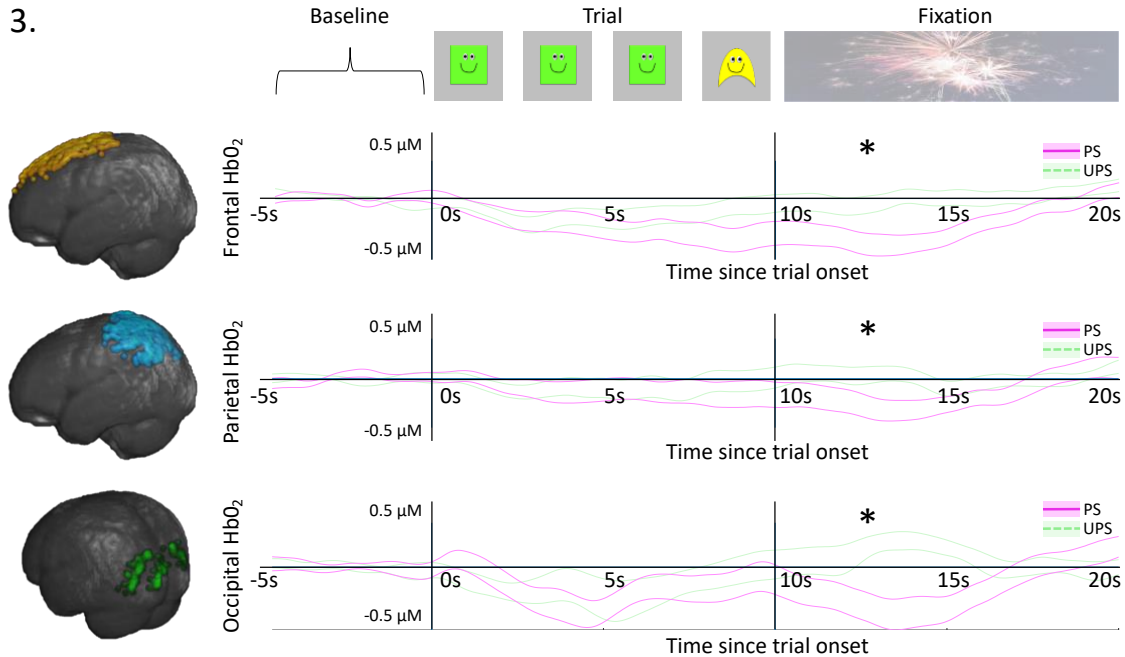


Figure 3. Concentration changes of oxyhemoglobin as a function of time

Cortical activity in the frontal (top), parietal (middle), and occipital lobes (bottom). In each graph, the mean (solid/dashed line) and standard error (shaded region) of activity in response to the Predictable Sequence (PS) condition is depicted in pink, while the mean and standard error of activity in response to the Unpredictable Sequence (UPS) condition is depicted in green. The gray box represents the time window of 10 to 15 second after stimulus onset, which was a priori determined to be used for statistical testing based on previous finding of significant predictability-dependent differences in the frontal and sensory regions (Jaffe-Dax, Bejjanki, & Emberson, under review). The star located at the top of the gray box denotes that the cortical response to PS was significantly attenuated ($p < 0.05$) compared to the response to UPS in this time window.

In support of our hypothesis, the cortical response to PS was significantly attenuated compared to the cortical response to UPS in the frontal lobe ($t(32) = 3.3846$, adjusted $p = 0.006$), parietal lobe ($t(32) = 2.5057$, adjusted $p = 0.018$), and occipital lobe ($t(31) = 3.2597$, adjusted $p = 0.005$) in the activation period, defined as the 5-second time window 10 seconds after stimulus onset determined based on a previous study by Jaffe-Dax, Bejjanki, and Emberson (under review). These results showed that the differences found 10 seconds after the trial onset were not due to spurious differences in cortical activity unrelated to the task.

The significantly lower cortical activity in the frontal and occipital cortices in response to PS compared to UPS closely replicates the previous findings of attenuated cortical activity in frontal cortex as a result of sequence learning (Jaffe-Dax, Bejjanki, & Emberson, under review). Furthermore, the significantly attenuated parietal lobe activity in PS compared to UPS importantly extends that finding to the parietal lobe. Thus, our univariate outcomes both replicate and extend existing research about the involvement of the frontoparietal and sensory cortices in predictive processes.

2.4.2 Predictability selectively modulates frontoparietal connectivity

To test our second hypothesis that frontoparietal functional connectivity would be significantly greater in response to PS compared to UPS, background functional connectivity between the frontal and parietal lobes was estimated across all subjects, for each condition (Fig. 4). Functional connectivity was also estimated between frontal and occipital lobes and between parietal and occipital lobes for comparison.

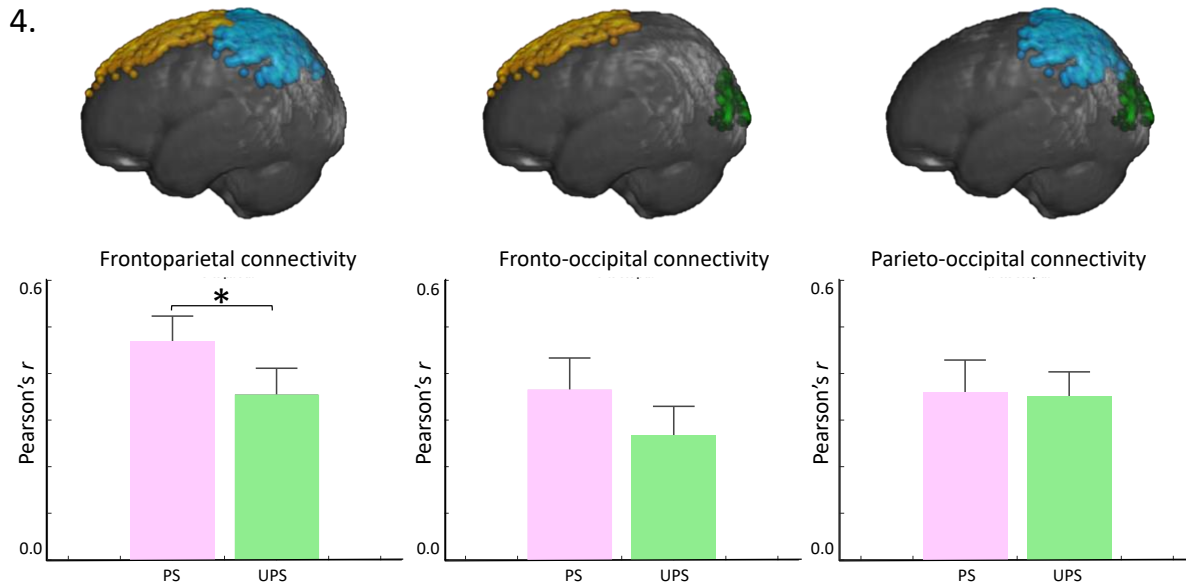


Figure 4. Background connectivity

Correlation between two lobes' cortical activity was used to estimate the interlobular connectivity. Frontoparietal connectivity (left), fronto-occipital connectivity (center), and parieto-occipital connectivity (right) during PS (pink bar) and UPS (green bar) are shown. There was a significant difference in frontoparietal connectivity between PS and UPS ($p < 0.05$), but no significant difference in fronto-occipital or parieto-occipital connectivity between the two conditions.

In support of our hypothesis, frontoparietal background connectivity was significantly different between the two conditions ($r_{PS} = 0.46$; $r_{UPS} = 0.35$; $p = 0.035$). In contrast, the fronto-occipital ($r_{PS} = 0.36$; $r_{UPS} = 0.27$; n.s.) and parieto-occipital background connectivity ($r_{PS} = 0.35$; $r_{UPS} = 0.35$; n.s.) was not significantly different between conditions. The significantly greater background connectivity between the frontal and parietal cortices in PS compared to UPS suggests that the frontoparietal network is modulated by the predictability of stimuli.

2.5 Discussion

Although there is a wealth of behavioral evidence for the interaction between attention and prediction in infants, and abundant neural evidence for the interaction in adults, no study to date has examined prediction in the infant frontoparietal network. Using fNIRS, we recorded from the frontoparietal network and from a sensory cortex (i.e., the occipital lobe) while infants engaged with temporally predictable and unpredictable sequences. As hypothesized, we found markedly attenuated frontal, parietal, and occipital lobe activity in response to predictable sequences compared to unpredictable sequences. We note that it is possible that there were temporal inconsistencies across the unpredictable trials (i.e., AABA, ABAA, and BAAA had different lengths of time until the time of unpredictability), and thus may have elicited different hemodynamic responses; however, our current research design is not optimized to further explore this possibility. The temporal differences in unpredictability could be an exciting avenue of future work using EEG, which can offer a better temporal resolution.

The attenuated frontal, parietal, and occipital lobe activity in response to predictable sequences replicated previous findings of attenuated frontal and occipital lobe responses to predictable temporal sequences (Jaffe-Dax, Bejjanki, & Emberson, under review), and extended

the findings to the parietal lobe. Indeed, despite the theorized importance of the frontal and parietal lobes for mediating predictive processes in infants, no prior study had directly examined the engagement of the parietal lobe. Our findings help to establish that the parietal lobe is functionally available to support an infant's sensitivity to environmental predictability, which infants possess from a very young age (Stahl & Feigenson, 2015; Van Giffen & Haith, 1984). These findings of suppressed activity in response to predictable sequences are consistent with the predictive coding framework (Friston K, 2005; Rao & Ballard, 1999), which suggests that this suppression effect is due to reduced prediction error.

Also as hypothesized, we found different levels of functional connectivity in the frontoparietal network depending on the predictability of the visuo-temporal input. Specifically, we found that increased predictability of events was associated with greater functional connectivity between the frontal and parietal lobes, suggesting that the frontoparietal network is more strongly engaged when there were patterns in the environmental input, compared to when there were no discernible patterns. In contrast, no such differences were observed in the connectivity between either the frontal or the parietal lobe, and the occipital lobe. Thus, our results suggest that the frontoparietal network in infants is modulated by predictability. The increased functional connectivity potentially reflects the feedback processes as suggested by the predictive coding framework (Rao & Ballard, 1999).

Overall, these findings provide compelling evidence that infants as young as 6 months old can engage a rudimentary version of the frontoparietal network despite the relative anatomical immaturity of this network. On the surface, the functional engagement of this network may appear to be in contrast with the previously reported lack of myelination, and the protracted developmental trajectory of resting-state functional connectivity, in this network (Bulgarelli et al., 2020; Deoni et

al., 2011). However, the relationship between anatomical measures of connectivity (white matter and resting-state functional connectivity) and task-based functional engagement is unknown, particularly in the developmental context. Moreover, it has been theorized that brain regions and networks become more selective and specialized with cognitive experiences (i.e., functional engagement) across development (M. H. Johnson, 2011). Thus, it is possible that the functional engagement of this network serves as a catalyst for the anatomical development of the sophisticated attention network seen in adults.

There were a few notable avenues of future research from our study. First, future research can use further counterbalanced stimuli to replicate our results. The predictable sequence utilized in our study was AAAB for all subjects; although this practice is in line with previous research on learning temporal sequences (Basirat et al., 2014), future replication of our results using counterbalanced predictable sequences may further strengthen our findings. Second, researchers can design a similar experiment with a greater number of trials. We only excluded the first trial from each condition in our analyses to adjust for the acclimation period because we did not have enough statistical power to exclude more trials or to perform an analysis on the progression of neural responses across the trials, given the small number of trials in our study design. A replication study with greater number of trials can help explore this interesting topic. Fourth, other experimental designs can be used to accommodate other analytical methods, such as the psychophysiological interaction (PPI). Convergence of results based on diverse analytical methods would further strengthen our results. Finally, future research can delve into the reason behind the direction of effect that predictability had on frontoparietal activity versus functional connectivity. Our findings were in line with our hypotheses and prior research, and one possible explanation is that the activity and functional connectivity are being driven by the ventral and dorsal attention

network differently; this possibility can be more fully explored in future fNIRS research with greater channel density in the relevant anatomical regions of the brain.

Our findings meaningfully advance our knowledge in several directions. First, this study provides neural evidence that complements existing behavioral evidence for the interaction between attention and prediction in infants. In particular, we point to a particular neural substrate by which this interaction can occur: the frontoparietal network, the same general network as would be implicated in adults. Second, our results indicate that, despite the evidence from anatomical scans and resting state functional connectivity that there may be limited connectivity in the infant brain, and in higher-level cognitive networks in particular, 6-month-old infants functionally engage their frontoparietal network during predictive tasks. As the first study to examine task-based functional connectivity of the frontoparietal network in infancy, our findings suggest that long-range functional connectivity during cognition may be more functionally capable than previously estimated via resting-state research. This finding has important theoretical implications regarding the interaction of functional and anatomical development in the brain that will need to be tested in future work. Finally, our study shows the engagement of both higher-order associative and lower-level perceptual regions in a predictive context. This pattern of results reveals that the infant brain is capable of sophisticated, large-scale neural coordination despite having relatively immature long-range connectivity. Overall, this study provides neural evidence that significantly advances our knowledge about prediction in infancy.

Chapter 3. Infants' eye movements have a bidirectional relationship with learning

3.1 Abstract

Investigating how infants can use selective attention to facilitate their learning is important for us to understand the role of infants as active agents that drive their own growth. In this novel eye-tracking experiment, we tested 19 infants (9-15 months old) via an online eye-tracking platform as they were exposed to learnable and non-learnable visual spatial patterns. Specifically, we investigated whether infant's selective attention to these spatial patterns was affected by the learnability of these patterns and, in turn, how these changes in visual selective attention would impact their learning outcomes. We found that infants' selective attention to different components of the visual pattern varied by the learnability of the pattern. When there was a learnable pattern, infants looked toward a visual component that provided more information about the pattern at greater than chance level ($t(17) = 2.578, p = 0.020$); when there was not a learnable pattern, infants looked toward an externally salient component at greater than chance level ($t(18) = 2.129, p = 0.047$). We furthermore found that this looking behavior while they were learning was a significant predictor of learning outcomes ($\beta = 4.675, t(63) = 2.573, p = 0.012$; 95% CI: 1.044 to 8.306). Our findings revealed that there was a bidirectional relationship between learning and selective attention, such that learnability drove selective attention and the resulting selective attention then influenced the learning outcome. Our research can aid our understanding of how infants may use their eye movements to actively govern their learning experiences.

3.2 Introduction

Infancy is an incredible window of time during which vast amounts of learning occurs. Infants experience and engage with new stimuli and make modifications to their internal representations. Prior research suggested that learning arises more readily from actively engaging with the environmental patterns rather than passively receiving them (see Chapter 1 for review). However, given that young infants do not yet possess the ability to reach for objects and manipulate them (Needham, Barrett, & Peterman, 2002) and yet are able to learn rapidly, there may be more subtle forms of active engagement at play.

One tool that young infants can utilize despite their lack of complex motor abilities is their eye movements. Young infants can use their eyes to selectively attend to certain stimuli over others. Infants' selective attention may be endogenously or exogenously guided: Infants can attend to externally salient stimuli (e.g., Amso and Johnson, 2006) at as young as two months old and utilize endogenously directed attention at as young as four months old (Amso & Johnson, 2006; Butcher, Kalverboer, & Geuze, 2000).

Selectively-attended information, in turn, affects infants' exploration and understanding of the world (Cohen, 1972) and exerts influence on important cognitive engagements such as perception, memory, and learning (for review, see Amso & Scerif, 2015). For example, it was found that infant word learning was affected more by attended stimuli compared to unattended stimuli (Yu & Smith, 2011). In summary, by directing their selective attention through their eye movements, infants can alter their environment and facilitate their own learning (for review, see Amso & Scerif, 2015).

On the flipside, learning affects selective attention as well. For instance, learnability was found to be an important factor that determines infants' selective attention toward some stimuli.

Moderately predictable patterns draw infants' attention more than fully predictable or fully unpredictable patterns (Kidd, Piantadosi, & Aslin, 2012). While learning was not tested directly by Kidd et al (2012), it is assumed that these moderately-predictable patterns are also good candidates for learning as opposed to the much more random patterns to which infants paid less attention. Similarly, moderately difficult tasks draw infants' attention more than very-difficult or very-easy tasks (Hunter & Ames, 1988).

It can be inferred from infants' preference for moderately learnable input that infants preferentially attend to input that can result in favorable learning outcomes. In support of this idea, it was found that infants as young as 8 months old selectively attend to the visual components that enabled them to learn relationships between the visual cues, even when highly engaging distractors were available (Tummeltshammer, Mareschal, & Kirkham, 2014). Thus, research seems to suggest that learnability affects selective attention, just as selective attention affects learning. Given the bidirectionality of the influence between learning and selective attention, these two active engagements may form a feedback loop of repeatedly initiating each other (Fig. 5). Such a reciprocal relationship between learning and selective attention may explain how infants are able to attend to and learn specific information from their environment so readily.

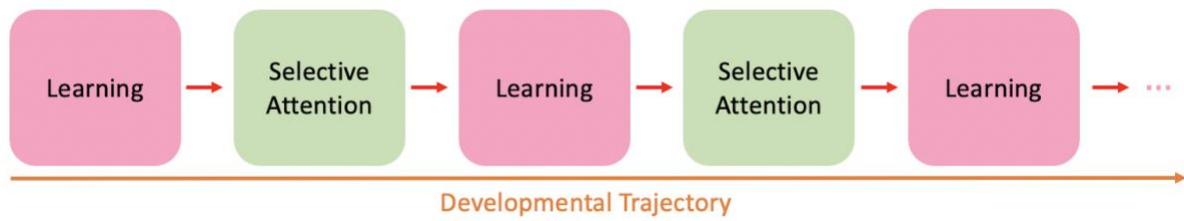


Figure 5. Learning and selective attention reciprocally influence each other

We theorize that learning activates infants' selective attention, which in turn influences their learning outcomes. This learning outcome then influences their selective attention again, forming a feedback cycle. The reciprocal relationship between learning and attention may underlie how infants are able to understand their environment so readily.

In a broad sense, the idea that infant learning guides selective attention has always been presumed in many experimental designs in infancy research. Many methods such as looking time measures, visual Paired comparisons, and head-turn preferences are regular fixtures in our field that use eye gazes to understand what the infant subject learned (for examples of such infant eye-tracking research, see review by Gredebäck, Johnson, & Hofsten, 2009). The implicit assumption that underlies these eye gaze-based studies is that eye gazes are being driven by learning.

This assumption that learning affects infants' selective attention was tested by Fiser and Aslin (2002). In their research, 9-month-old infants were first presented with scenes in which two objects always co-occurred ("Base Pairs") and another object that changed each time ("Noise Element"). The Base Pairs and the Noise Element were spatially separated and did not appear connected. When infants were presented with Base Pairs and a Noise Element after training, they preferentially looked toward the Base Pairs compared to Noise Elements. The result that infants preferred the objects that followed the pattern that they learned showed that infant selective attention is, in fact, affected by learning.

Wu and colleagues (2011) also explored the effect that pattern-learning has on attention, by testing the effect of breaking or following the learned pattern on eye movement. They presented 9-month-old infants with scenes in which two objects always touched each other ("Base Pairs") and another object that changed each time ("Noise Element"). After training, infants were shown one of the objects being split away. If one of the Base Pairs split away, this was contrary to their learning that Base Pairs are stuck together. If the Noise Element split away, this was consistent with what infants learned. Their results showed that infants looked longer if the split contradicted what they learned compared to if the split was consistent with what they learned.

Fiser and Aslin (2002) and Wu and colleagues (2011) interestingly revealed seemingly opposite infant behaviors. On one hand, Fiser and Aslin (2002) found that infants looked more toward co-occurring objects, which followed the pattern that they learned; this result is consistent with familiarity preference. On the other hand, Wu and colleagues (2011) found that infants looked more when the stuck-together objects split apart, which violated the pattern that they learned; this result is consistent with novelty preference or a violation-of-expectation effect. The differences in the directionality of the findings may be due to several factors, including differences in experimental design. Regardless, the common consensus between the two studies was that infants were capable of learning patterns based on statistical regularities and selectively attended based on the patterns.

While prior studies have linked selection attention and learning in multiple ways, these studies stopped short of explicitly investigating the bidirectionality of the relationship between selective attention and learning in infants. Fiser and Aslin (2002) as well as Wu and colleagues (2011) have revealed how learning may affect selective attention, but they did not explore how that selective attention, in turn, may affect learning as well. On the flipside, Yu and Smith (2011) have revealed how selective attention may affect learning, but did not consider how learning might have influenced selective attention. Therefore, in this chapter, we aimed to fill this gap and reveal both how learnability of stimuli may drive selective attention and how selective attention affects learning outcomes during infancy in a loop.

Using an online eye-tracking system, we tested two main hypotheses to explore the bidirectional relationship between selective attention and learnability (Fig. 6). Our first hypothesis was that (H1) Selective attention is affected by learnability while the infant is being trained. Given the conflicting results for familiarity and novelty preference in prior studies (Fiser & Aslin, 2002;

Wu et al., 2011), we remained agnostic about the direction of effect that learning would have on selective attention. Our second hypothesis was that (H2) Learning outcomes are affected by selective attention during training. We aimed to analyze how the selective attention, which were in turn affected by learnability, influenced learning outcomes.



Figure 6. Bidirectional relationship between learning and selective attention in our task

We test our hypothesis that (H1) learning activates infants' selective attention, and that (H2) this selective attention in turn influences the learning outcomes. Our task will evaluate these two simple relationships that form the greater cycle in the infant developmental trajectory shown in Fig. 5.

3.3 Methods

3.3.1 Experimental Design

The target sample size for this study was $n = 30$, but data collection and subject recruitment were substantially delayed due to the impact of COVID-19. We collected data from 19 subjects between the ages of 9 and 15 months (age, 11.55 ± 0.44 months; 6M, 13F). Data was collected remotely via LabVanced, an online experiment platform with an eye-tracking program. Infants' caretakers were contacted via email to participate in a virtual study. If the caretakers consented, they were emailed detailed instructions and a link to our online experiment. In the online experiment, caretakers were prompted to place the infant subject on their lap, have them face the computer about 12 inches away from the screen, and have the webcams pointed to the infant subject's eyes in a well-lit room. Infant subjects participated in this experiment by sitting on their caretaker's lap and watching the stimuli on their computer screen. During the experiment, infant subjects' eye movements were recorded in video and coordinates of where they were looking on the screen. Subjects were compensated with a \$5 Amazon gift card for their time.

In the experiment, infants were presented with 12 blocks, alternating between Pattern Condition and Control Condition. The task was counterbalanced so that half the subjects were given the Pattern Condition first, while the other half of the subjects were given the Control Condition first. Regardless of the condition, each block consisted of 4 trials in the Training Phase and 2 trials in the Testing Phase.

The Training Phase consisted of 4 trials in a randomized order (Fig. 7). In each trial, infants were presented with a 250 pixel x 250 pixel cluster of three boxes (125 pixel x 125 pixel each) and one blank (125 pixel x 125 pixel) stacked in a 2-by-2 formation. Each box contained a different

color and shape. This cluster was presented for 4000ms in each trial. During the Training Phase in the Pattern Condition block, two of the boxes were always presented physically touching each other, such that they appeared stuck together, in every trial (Pair Boxes); one of the boxes changed in each trial (Rogue Box). During the Training Phase in the Control Condition block, two of the boxes appeared in every trial but did not always touch each other so that they did not appear stuck together (Pair Boxes), while one box changed in every trial (Rogue Box).

It is worth noting that the pieces of the Pair Boxes appear in identical frequency in the Pattern Condition blocks as they do in the Control Condition blocks. That is, in Figure 7, blue and green boxes appear 4 times each, in both Pattern and Control Condition blocks. Because the frequency and color are identical between Pattern Condition blocks and Control Condition blocks, any differences in behavior between conditions can be interpreted to arise from the viewer's learning of the patterns of visual combination of the boxes, rather than a simple familiarity with more frequently occurring boxes.

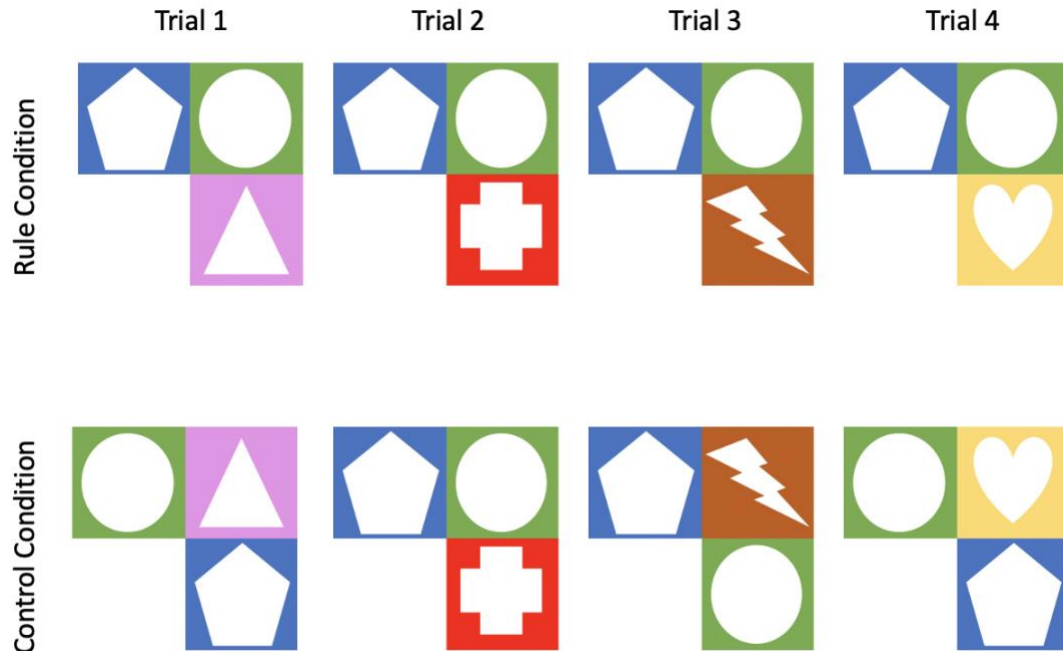


Figure 7. Training Phase

Each block was either a Pattern Condition (top row) or a Control Condition (bottom row). Each block consisted of 4 trials in the Training Phase. In each trial, subjects were presented with a cluster of 3 boxes and 1 blank space. 2 of the 3 boxes were Pair Boxes (i.e., blue and green boxes) and 1 box was the Rogue Box (i.e., pink, red, brown, and yellow boxes). In the Pattern Condition blocks (top row), the Pair Boxes stayed attached to each other, while the Rogue Box changed. In the Control Condition blocks (bottom row), the Pair Boxes were not always attached to each other. The Pair Boxes appeared in the same frequency across conditions.

The Testing Phase consisted of one Consistent Trial and one Inconsistent Trial in random order (Fig. 8). In the Testing Phase, a cluster of three colorful boxes appeared in the center of the screen for 500ms, before one of the boxes moved away from the other boxes for 500ms and stayed in the corner of the screen for 3000ms. The Rogue Box split away in the Consistent trial, while one of the Pair Boxes split away in the Inconsistent trial. A fixation cross was shown in the center of the screen for 500ms between the two Test Trials.

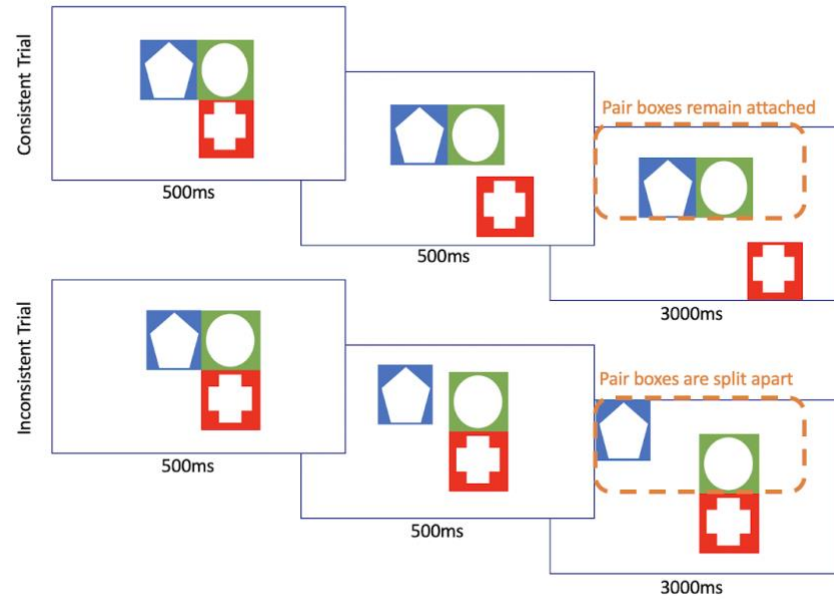


Figure 8. Testing Phase

Immediately after 4 trials in the Training Phase, subjects were presented with 2 trials in the Testing Phase. There was one Consistent Trial and one Inconsistent Trial. In the Consistent Test trial, the Pair Boxes remained stuck and Rogue Box split away. In the Inconsistent Test trial, the Pair Boxes were separated while Rogue Box stayed still.

3.3.2 Analysis

In each trial, a series of Cartesian [x,y] coordinates representing the infant's eye gaze were obtained. These coordinates were automatically generated through LabVanced's webcam-based eye-tracking algorithm. The coordinates were converted to depict where the infant was looking in an 800 pixel x 450 pixel screen, where [400,225] corresponded the center of the screen and [800,450] corresponded to the top-right corner of the screen. An undergraduate researcher manually reviewed all video footage and coded the infant subjects' eye movements as top left, top right, bottom left, or bottom right of the screen, and confirmed that the generated coordinates corresponded to the manual coding. Each coordinate was given a timestamp (ms). The amount of time that elapsed between each coordinate varied within and between subjects, as it depended on factors such as the refresh rate of the subject's webcam, the speed of their computer, and the strength of their internet connection. To preprocess this unevenly acquired data, we performed data binning and computed the average coordinates in 100ms bins. We calculated the looking time by computing the number of bins in which the eye gaze coordinate fell in the boundaries of the stimuli of interest. Time that each subject spent looking outside the 800 pixel x 450 pixel computer screen were not counted for our analyses. If a subject had fewer than two blocks with usable eye tracking coordinates within the 800 pixel x 450 pixel computer screen, their data were not used for our analyses.

For the Training Phase, we excluded the first trial in each block because the pattern cannot be learned on the first trial regardless of condition and thus there would be no differences in looking patterns between conditions in the first trial. We considered the looking behaviors during the first 2000ms of each trial in the Training Phase to replicate Wu and colleagues' methods (2011). We calculated the number of 100ms-bins where the average coordinates were located within the

250 pixel x 250 pixel cluster consisting of three boxes and empty space to obtain a measure of total length time in which the subject looked toward any stimuli in each trial. Any trial in which the subject looked inside the cluster for less than 400ms was excluded from analyses. From this total length of time that infants looked inside the cluster, the proportion of time they spent on the Rogue or Pair Boxes were used for analyses.

Wu and colleagues (2011) similarly considered all 2000ms during the Testing Phase to analyze their looking behavior, as well. We did not collect data while the split was taking place for the first 1000ms due to technical constraints and the overpowering effect of the movement on selective attention in infants at this age. We instead collected data during the first 1000ms of static image after the boxes had already split (see Fig. 4), which corresponded to the time window from 1000ms to 2000ms after the initial onset of stimuli. We calculated the total time that infants looked at any of the three boxes to measure learning outcomes in the following analyses.

We tested the first hypothesis (H1) that learnability affects infants' selective attention during Training. First, we compared the mean total look (ms) toward the cluster between Pattern versus Control Condition blocks with a two-tailed t-test. Second, we performed two-tailed t-tests to compare the proportion of gaze toward a Pair Box to chance level in each condition and to compare the proportion of gaze toward a Rogue Box to chance level in each condition. Finally, we compared the proportion of gaze toward a Pair Box and the proportion of gaze toward a Rogue Box in each condition with two-tailed t-tests.

We also tested the second hypothesis (H2) that selective attention affects learning by investigating whether learning outcomes, measured during the test phase, varied depending on each subject's looking behavior during training. First, we tested whether there were differences in the infants' overall look to the Consistent versus Inconsistent trials in the Pattern Condition using

a two-tailed t-test. Second, we performed linear mixed-effects modeling to calculate the impact of selective attention during training on learning outcomes after controlling for subject effects in the Pattern Condition. Then, we used the same model in the Control Condition to see whether there were learnability-based differences.

3.4 Results

We collected data from a total of 19 subjects. Among 19 subjects who participated in this study, one subject completed fewer than two blocks in the Pattern Condition. Therefore, data from the other 18 subjects were used for the Pattern Condition and data from all 19 subjects were used for the Control Condition in our analyses. Given our small sample size, we note that the following results are preliminary and presented with caution for the purpose of this dissertation.

3.4.1 *Learnability affects selective attention*

To test how learnability of the pattern affects infants' eye gaze, we compared the mean total look (ms) toward the cluster (containing both the Rogue and the Pair) between Pattern versus Control Condition blocks with a t-test. The mean length of time that infants looked toward the cluster in the Pattern Condition blocks was $M \pm SE = 914 \pm 140$ ms, while the mean length of time that infants looked toward the cluster in the Control Condition blocks was $M \pm SE = 893 \pm 109$ ms. There was no significant difference in the looking time between the two conditions ($t(18) = 0.171$, $p = 0.866$). Thus, we found that the overall looking time to the stimuli does not differ across conditions.

However, there were substantial condition-dependent differences when we compared the proportions of mean look toward different components of the stimuli rather than the total looking time. We compared the proportion of looks toward the Rogue versus Pair Boxes within each

condition. As noted previously, the cluster of stimuli was 250 pixel x 250 pixel. Given that there are 4 equal-size boxes or blank space in a cluster, the proportion of looks toward any single box by chance would be 25% of the total look to the cluster. We found that the mean proportion of looks toward a Pair Box in the Pattern Condition ($M \pm SE = 29.78 \pm 1.85\%$) was significantly greater than 25% chance ($t(17) = 2.578, p = 0.020$). The mean proportion of looks toward a Rogue Box in the Pattern Condition ($M \pm SE = 23.80 \pm 2.90\%$) was not different from chance level ($t(17) = 0.414, p = 0.684$). In comparison, in the Control Condition, the mean proportion of looks toward a Pair Box ($M \pm SE = 28.06 \pm 1.91\%$) was not significantly different from 25% chance ($t(18) = 1.600, p = 0.127$). Instead, the likelihood of looks toward a Rogue Box ($M \pm SE = 31.57 \pm 3.08\%$) was statistically greater from 25% chance in the Control Condition ($t(18) = 2.129, p = 0.047$). We did not find statistical differences in a direct comparison between the looks toward Rogue vs. Pair Box in either the Pattern Conditions ($t(17) = 1.310, p = 0.208$) or the Control Condition ($t(18) = -0.719, p = 0.481$). Despite this, our earlier findings still showed that infants look toward the Pair Boxes when there are patterns (i.e., Pattern Condition) and toward the Rogue Box when there are no patterns (i.e., Control Condition), suggesting that learnability guides infants' selective attention.

3.4.1 Selective attention affects learning

Our second set of analysis tested how selective attention during learning affected learning outcomes. First, we tested whether there were reliable differences in looking across test trial types in the two conditions. This difference would be reflective of having learned the pattern during training. A two-tailed t-test revealed no differences in the subjects' total looking time during Consistent versus Inconsistent trials in the Control Condition ($t(18) = -0.531, p = 0.602$) as expected. In contrast, there were statistically significant differences in the subjects' total looking time during Consistent versus Inconsistent trials in the Pattern Condition ($t(18) = 2.306, p = 0.033$).

Thus, we found that there were significant differences in looking during the Testing Phase across trial type in only the Pattern Condition.

We investigated the patterns of looking during training to predict looking preferences during the Testing Phase. All subjects did not contribute data equally across all trials. To better control for differences in the amount of data that infants contributed as well as individual differences in looking pattern, we then used a linear mixed-effects model, where the Pair-preference during Training Phase was the predictor variable, subjects were the random variable, and the learning outcome during Testing Phase was the outcome variable. We ran the models separately for the Pattern and Control Conditions given the small sample size and ease of interpretability. For the learning outcome, we calculated how much longer infants looked toward inconsistent versus consistent splits. To do so, we subtracted the total looking time toward the screen during Inconsistent Test Trials from the total looking time during Consistent Test Trials.

Across 18 subjects, there were 65 clusters with data in the Training Phase and the Testing Phase in the Pattern Condition to conduct this analysis. There were significant subject-level effects ($\beta = -2.757$, $t(63) = -2.425$, $p = 0.018$; 95% CI: -5.030 to -0.485), and infants' Pair-preference during Training Phase was a significant positive predictor of how much longer infants looked toward consistent splits than they did toward the inconsistent splits ($\beta = 4.675$, $t(63) = 2.573$, $p = 0.012$; 95% CI: 1.044 to 8.306).

The results differed when we performed the same linear mixed-effects model in the Control Condition. Across 19 subjects, there were 78 clusters with enough data during the Training Phase and the Testing Phase in the Control Condition to conduct this analysis. There were no significant effects of either subjects ($\beta = 1.229$, $t(76) = 1.066$, $p = 0.290$; 95% CI: -1.067 to 3.526) or looking behavior during Training Phase ($\beta = -1.787$, $t(76) = -0.940$, $p = 0.350$; 95% CI: -5.574 to 2.000)

on the behavior during the Testing Phase. Thus, we find that the patterns of looking during Training predicted overall looking patterns at Test in the Pattern Condition and no such relationships in the Control condition.

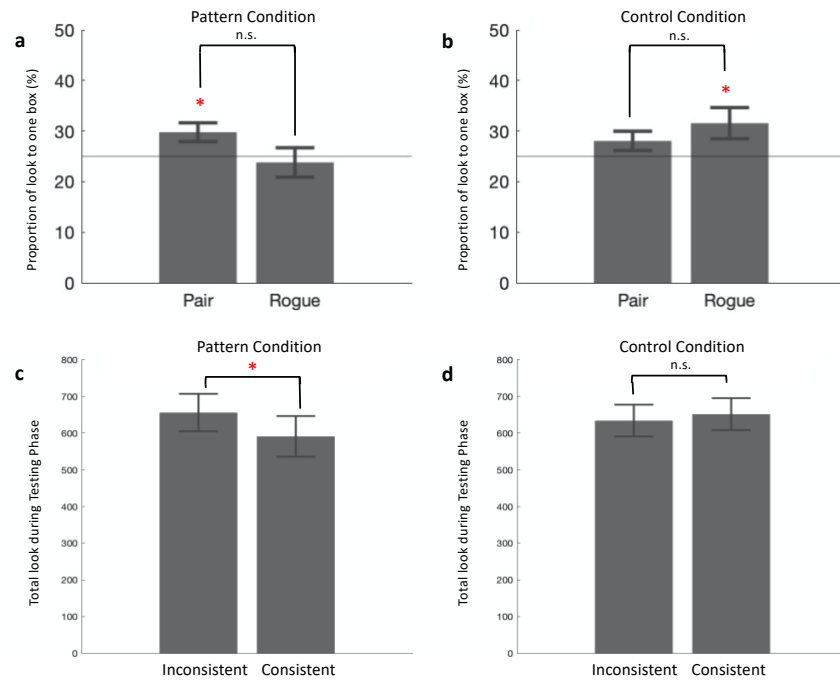


Figure 9. Selective attention is affected by learning

There were differences in the selective look toward a Pair Box or a Rogue Box depending on whether the condition was the Pattern Condition (a) and Control Condition (b). There were also differences in the look toward stimuli depending on whether the pattern was consistent with what was learned (left) or inconsistent with what was learned (right) in the Pattern Condition (c) but not in the Control Condition (d). A star (*) denotes a significant difference with p-value < 0.05.

3.5 Discussion

In this chapter, we aimed to understand the cyclical relationship between learning and selective attention. To do so, we specifically tested how (H1) learnability affects selective attention and (H2) this resulting selective attention affects learning outcomes. Consistent with hypothesis H1, our results revealed that the learnability of a pattern affected infants' selective attention. In the Pattern Condition, it was possible to learn that two boxes were attached to each other. In this setting, infants were much more likely than chance to selectively attend to the Pair Boxes in the Training Phase. Infants' behavior during the Pattern Condition was consistent with the familiarity preference framework, as the infants preferred to look toward more repetitive, familiar boxes that appear in all 4 trials of each block. In other words, it was found that infants guided their attention toward the components that can provide more information about the visual pattern, suggesting that the eye movements are endogenously driven. In the Control Condition, where it was not learnable that two boxes were attached, infants instead selectively attended to the Rogue Boxes. Infants' behavior during the Control Condition is more closely aligned with the novelty preference framework, as the infants preferred to look toward less frequent, novel boxes that newly appeared in each trial. That is, infants' selective attention in the Control Condition may have been more exogenously driven in the absence of a different visual pattern to learn.

Notably, the frequencies of presentation for the Pair Boxes and the Rogue Box were the same in the Pattern Condition and the Control Condition. In other words, the relative frequency and therefore the novelty/familiarity of each shape were controlled for in our experimental paradigm. We found clear differences in infants' looking behavior depending on the conditions, which cannot be explained by simple familiarity or novelty preferences alone. Our results

therefore showed that infants' selective attention shifted across conditions which differed in learnability, supporting our first hypothesis. Our results are in line with prior research which found that infants' attention was moderated by learnability (Hunter & Ames, 1988; Kidd, Piantadosi, & Aslin, 2012). Our findings further showcased the nuanced complexity of the preferences toward novelty versus familiarity in infancy and suggest that these preferences may be endogenously or exogenously guided depending on the environment.

For our second hypothesis H2, we tested how selective attention affected learning outcomes. We first tested whether infants' attention differed depending on whether an event was consistent or inconsistent with the pattern they learned. The first analysis to this end was to determine if we find group-level evidence of learning through overall looking patterns at test. As hypothesized, our group-level results showed that infants' total looks differed significantly based on whether the event was consistent or inconsistent with what they learned in only the Pattern Condition, where it was possible to learn that the two boxes were attached. We replicated Wu and colleagues' (2011) finding that infants looked longer toward an event which refuted what they learned previously compared to an event which was consistent with what they learned previously.

Finally, we performed a detailed modeling of the selective attention during Training and Testing Phases for both conditions. Also in support of our second hypothesis H2, we found a statistically significant, positive relationship in the Pattern Condition, meaning that infants' selective attention during learning significantly predicted how they reacted to an event was consistent versus inconsistent with the pattern. In contrast, selective attention during the Training Phase did not predict the learning outcomes in the Testing Phase.

The theoretical importance of this difference between the conditions is substantial. In the Pattern Condition, infants were likely exerting an endogenous control of attention during training where the more frequent (i.e., less novel) shapes were preferentially attended; in our analysis, we previously found that infants were much more likely than chance to look toward the Pair Boxes in the Pattern Condition during training. This behavior during the Training Phase in turn predicted the learning outcomes, suggesting that this endogenously-driven selective attention is reflective of internal goals and the learning process. In contrast, in the Control Condition, infants' selective attention was likely exogenously guided toward the less frequent (i.e., more novel) shapes; in our analysis, we previously found that infants were much more likely than chance to look toward the always-changing Rogue Box in the Control Condition during training. This behavior during the Training Phase did not predict the learning outcomes, suggesting that this exogenously directed, novelty-seeking selective attention was not reflective of the learning process.

Overall, this experiment provided evidence that learning and selective attention guide each other in a reciprocal manner. These findings represent a small subset of the broader reciprocal chain between learning and selective attention that facilitate infant learning (see Fig. 1). Furthermore, our results suggested that endogenous, rather than exogenous, selective attention may be reflective of the internal goals and the learning process and affect learning outcomes.

However, there were some limitations to this study. One limitation was that we were not able to obtain data from a larger sample size due to the difficulties in recruitment during the COVID pandemic. Despite the small number of subjects, our study was able to reveal the impact that learnability of the environment had on infants' external and internal attention, as well as the

impact that internally driven selective attention had on their own learning outcomes. However, future replication of our results with a larger sample size will strengthen our findings.

Another potential limitation of this study was that we conducted this study online. Because the at-home nature of this experiment could have introduced some inaccuracies or between-subject variability compared to an in-lab experiment, we incorporated three methods to combat the potential issues. First, we provided detailed instructions in both email and in the experiment itself about how to set up the computer, lighting, and webcam to minimize the differences. Second, we checked the video recordings from each subject and only included data if the subject was following the instructions that we provided. Third, we manually checked the video recording of the subjects' eyes from every trial and checked that the eye gaze coordinates were reasonably accurate to the naked eye. Fourth, we preprocessed our data so that all subjects had the same recording characteristics, such as the repetition time between each eye gaze coordinate. Finally, we explicitly accounted for subject-level differences as a random effect in our modeling analyses. Through these methods, we were able to mitigate the potential negative impacts of an online remote study as much as possible.

There are several interesting avenues of further research from our study. First, combining online eye-tracking and fNIRS can be particularly useful in the discovery of the relationship between selective attention and learning outcomes. Online eye-tracking and fNIRS can be a convenient and practical combination, because online eye-tracking would not interfere with fNIRS signals, and because it adds no further weight or constraints to the infant compared to the fNIRS cap. Exploring the impact of learnability on those neural structures that underlie selective attention and how these neural activities can influence learning outcomes can shed light on the relationship between the infant brain and cognitive-perceptual development. Specifically, future research can

test the activation and functional connectivity in the ventral attention network and dorsal attention network, as they are theorized to subserve exogenous and endogenous attention, respectively. Activation of different attention networks depending on the condition and the correlation between the neural activity and the learning outcomes would greatly strengthen our findings across research modalities.

Second, future research can examine the changes in the infants' selective attention while they learn. Although we were not able to perform this time-based analysis in our dataset because of our small sample size, this finding can potentially reveal important information about how infants may move their eyes as they progress through learning a pattern, and how these minute changes might affect learning outcomes. Results showing differences in eye movements between the conditions can reveal the interplay between the endogenous and exogenous attentional patterns and how their interaction may affect learning outcomes as well.

In summary, our study advanced the field by revealing important insights about the bidirectionality of the relationship between learning and selective attention in infancy. Specifically, our results furthered the understanding of how young infants' selective attention may be guided by learning, and how endogenous selective attention can facilitate learning in return. As shown in Figure 5, this infant-directed loop between learning and attention can catalyze a cascade that ultimately affects infants' greater development. These findings are in line with our previous chapters, where we argue that infants are not passive recipients of information, but rather an active, governing agent of their own development. This study can serve as a foundation for continued research on active engagements that infants can employ to direct their future cognitive and perceptual development.

Chapter 4. How to Report and Minimize Attrition Rate in Infant fNIRS Research[‡]

4.1 Abstract

Understanding the trends and predictors of attrition rate, or the proportion of collected data that is excluded from the final analyses, is important for accurate research planning, assessing data integrity, and ensuring generalizability. In this pre-registered meta-analysis, we reviewed 182 publications in infant (0-24 months) functional near-infrared spectroscopy (fNIRS) research published from 1998 to April 9, 2020 and investigated the trends and predictors of attrition. The average attrition rate was 34.23% among 272 experiments across all 182 publications. Among a subset of 136 experiments which reported the specific reasons of subject exclusion, 21.50% of the attrition were infant-driven while 14.21% were signal-driven. Subject characteristics (e.g., age) and study design (e.g., fNIRS cap configuration, block/trial design, and stimulus type) predicted the total and subject-driven attrition rates, suggesting that modifying the recruitment pool or the study design can meaningfully reduce the attrition rate in infant fNIRS research. Based on the findings, we established guidelines on reporting the attrition rate for scientific transparency and made recommendations to minimize the attrition rates. This research can facilitate developmental cognitive neuroscientists in their quest toward increasingly rigorous and representative research.

[‡] This work has been adapted from a preprint by the same author.

Baek, S., Marques, S., Casey, K., Testerman, M., McGill, F., & Emberson, L. (2021). Attrition Rate in Infant fNIRS Research: A Meta-Analysis. *BioRxiv*. doi:

<https://www.biorxiv.org/content/10.1101/2021.06.15.448526v1>

4.2 Introduction

4.2.1 Importance of attrition rate in fNIRS research

The introduction of fNIRS as a neuroimaging technique has transformed the landscape for infant brain research. fNIRS is an increasingly popular tool that non-invasively measures cortical hemodynamic responses (Elwell & Cooper, 2011). fNIRS is safe, affordable, portable, and increases infants' task compliance compared to other neuroimaging techniques (Aslin & Mehler, 2005; Gervain et al., 2011; Lloyd-Fox, Blasi, & Elwell, 2010). A rapid development of analyses techniques (Behrendt, Firk, Nelson 3rd, & Perdue, 2018) has helped fNIRS become relatively motion-robust (Nishiyori, Bisconti, Meehan, & Ulrich, 2016). Likely because of these advantages, a recent meta-analysis of infant neuroimaging showed that fNIRS studies were rapidly increasing in number even compared to other neuroimaging modalities (Azhari et al., 2020).

One major limitation of infant fNIRS research, however, is the attrition rate. Thoroughly understanding attrition is essential for the scientific integrity of the field. Attrition rate is defined as the proportion of collected data that was excluded from final analyses. High attrition rate is a prevalent issue in infant research regardless of methodology (e.g., Dehaene-Lambertz et al., 2010; Leroy et al., 2011; Picton & Taylor, 2007) and presents major challenges: A high attrition rate can lead to a smaller representative sample which threatens the external validity and reproducibility of results. High attrition also increases the cost of research. Understanding the attrition rate for fNIRS research and the factors that affect it is crucial to efficiently design scientific research, ensure external validity of results (Flick, 1988), and mitigate factors that increase attrition.

4.2.2 Possible causes of attrition in infant fNIRS research

4.2.2.1 Infant-driven attrition

Infants' shorter attention span and likeliness to become fidgety and agitated (e.g., Aylward, Brager, & Harper, 2002; Borgaro et al., 2003; Marshall, Reeb, & Fox, 2009) may increase the attrition rate in infant research. Researchers attempt to reduce the attrition rate by limiting the number of experimental conditions and the duration of stimuli (e.g., Hoehl & Wahl, 2012) and using multimodal stimuli to make the stimuli more attention-grabbing (Reynolds & Guy, 2012; Richards, 2003).

However, evidence for the effectiveness of focusing on these factors to reduce attrition in infant research is mixed according to two previous meta-analyses. On one hand, Slaughter and Suddendorf (2007) found that the most common reason for attrition in infant behavioral studies (habituation-based looking time studies) is infant fussiness (13.7%, total attrition rate: 22.6%). This meta-analysis found no effect on attrition rate as a result of experimental design or subject age. On the other hand, Stets and colleagues (2012) analyzed attrition rate in infant EEG research and found that the average attrition rate in infant EEG research was 47.3%. Unintuitively, they found that the overall attrition rate was 18.6% lower when auditory-only stimuli were used, instead of visual or audiovisual stimuli. This result is in direct contrast to the assumption in infant research that using multimodal stimuli can decrease attrition (e.g., Reynolds & Guy, 2012; Richards, 2003). These mixed conclusions from meta-analyses and common practice in the field emphasizes the need for systematic research on the factors that affect attrition.

4.2.2.2 *Signal-driven attrition*

Cristia and colleagues (2013) conducted a review of the infant fNIRS literature and noted that fNIRS-specific factors affected the attrition rate. Studies using headsets with more than 20 optodes experienced very high attrition rates (upwards of 50%), although this finding may be driven by the small number of labs that used a large number of sensors in the early days of fNIRS. Also, fNIRS research on newborns and 5-to-8 month old infants experienced lower attrition rates compared to research on 2-to-4 month old infants, but it is not clear whether this finding is a result of infant-specific factors (e.g., fussiness) or fNIRS factors (e.g., hair, strength). This finding differs from those found in the two previously mentioned meta-analyses on attrition (Slaughter & Suddendorf, 2007; Stets et al., 2012) that found no effect of age.

4.2.3 *Current Analysis*

The current meta-analysis updates and extends these meta-analyses and reviews with a specific focus on fNIRS and attrition. We investigated an expanded number of potential predictors of attrition compared to previous meta-analysis and reviews. We examined whether major findings from Cristia and colleagues (2013) replicate (e.g., age related effects) and include 7 more years of data, which represents a high proportion of the total publications in this young field. In addition, we investigated three types of attrition rates that could arise in a research setting: Total Attrition Rate (TAR; proportion of subjects who were excluded for any reason), Infant-Driven Attrition Rate (IAR; proportion of subjects who were excluded for the infant subjects' behavior, such as fussiness), and Signal-Driven Attrition Rate (SAR; proportion of subjects who were excluded due to fNIRS signal-related issues such as poor optical contact). Although there may be other types of attrition rates that are also at play, we focused on these

three types because they were the largest share of the attrition, were commonly disclosed, and were targets for improvement for future research.

We examined attrition rates and their predictors in three sections. First, we explored the overall trends in fNIRS research over the years reviewed. Second, we explored the possible effects of subject-related parameters on attrition rate (e.g., age). Third, we explored the effects of experimental design-related parameters (e.g., stimulus type). Then, we concluded a set of guidelines on how to report attrition rate to ensure transparent scientific results and suggestions how to best minimize the attrition rate to ensure replicable results with minimal data loss. We also have a visualization tool that is open to researchers who want to quantify estimated attrition rates for their studies based on our meta-analysis, find studies with the same experimental parameters and to consider how your experimental choices might influence your attrition rate. Together, this meta-analysis is aimed at increasing the validity and transparency of infancy and fNIRS research.

4.3 Material and Methods

4.3.1 Open Science

Prior to any of the following analyses, the scope, hypotheses, and analyses of this meta-analysis were pre-registered on Open Science Framework (OSF) Registries: <http://osf.io/6a2vq>. The entirety of this dataset can be accessed via <https://github.com/soribaek/Attrition-Rate-in-Infant-fNIRS-Research>. We have also launched an attrition rate calculator to help estimate the attrition rate for an infant fNIRS experiment a priori to aid with research planning.

4.3.2 Literature Search

To ensure a thorough and complete review of the literature, data collection for this meta-analysis used the methodology presented in “Searching for studies: A guide to information retrieval for Campbell Systematic Reviews” for comprehensive, transparent, reproducible, and unbiased data collection (Kugley et al., 2016). We designed the overall search strategy, parameters, language, validated the search, conducted and documented all searches, and deduplicated the search results in consultation with an experienced behavioral sciences librarian.

Database searching and snowballing provided the initial pool of studies to be screened for inclusion. We identified 10 studies that fully met the inclusion criteria to use as a validation set. The validation set was then used to design and validate custom searches in each of the following databases: Scopus, APA PsycINFO, and PubMed. From this set of studies, the following search terms were identified from the title, abstracts, and keywords: fnirs, functional near infrared spectroscopy, nirs, near infrared spectroscopy, baby, babies, infant, infants, toddler. The search terms were connected with OR or AND, truncation devices were used where appropriate, and syntax was adjusted for each database. When available, database limiters were applied to limit the results to language (English) and document type (articles, conference papers, dissertations, and theses). There was no limitation placed on publication date. These data searches were conducted on April 3, 2020.

Searches were conducted and documented. A total of 3,812 records were identified via database searching and three records were obtained by requesting for data in ongoing research. 1,698 duplicates were removed. Thus, a total of 2,117 records were screened for inclusion. From the 2,117 records, authors screened the titles and abstracts to determine whether each record meets the following criteria: 1) human infant subjects, between 0 and 2 years old; 2) cognitive

neuroscience research (i.e., looking at blood oxygenation as a proxy for neural activity), rather than a clinical or medical study (e.g. looking at oxygenation levels unrelated to neural activity); 3) empirical study, rather than reviews or case reports; 4) full-text available, rather than only abstracts; 5) presentation of new data, rather than a re-analysis of a previously published dataset. We excluded 1,901 hits using these criteria to result in a list of 216 publications for analysis.

Finally, after reading the 216 publications, we excluded 34 publications that did not report total or final sample size. Thus, we conducted the final analyses on 182 publications. The study selection process is articulated in Figure 10. In these 182 publications, there were 272 experiments with distinct infant subject samples. Thus, on average, there were approximately 1.42 (range: 1 to 4) experiments per publication.

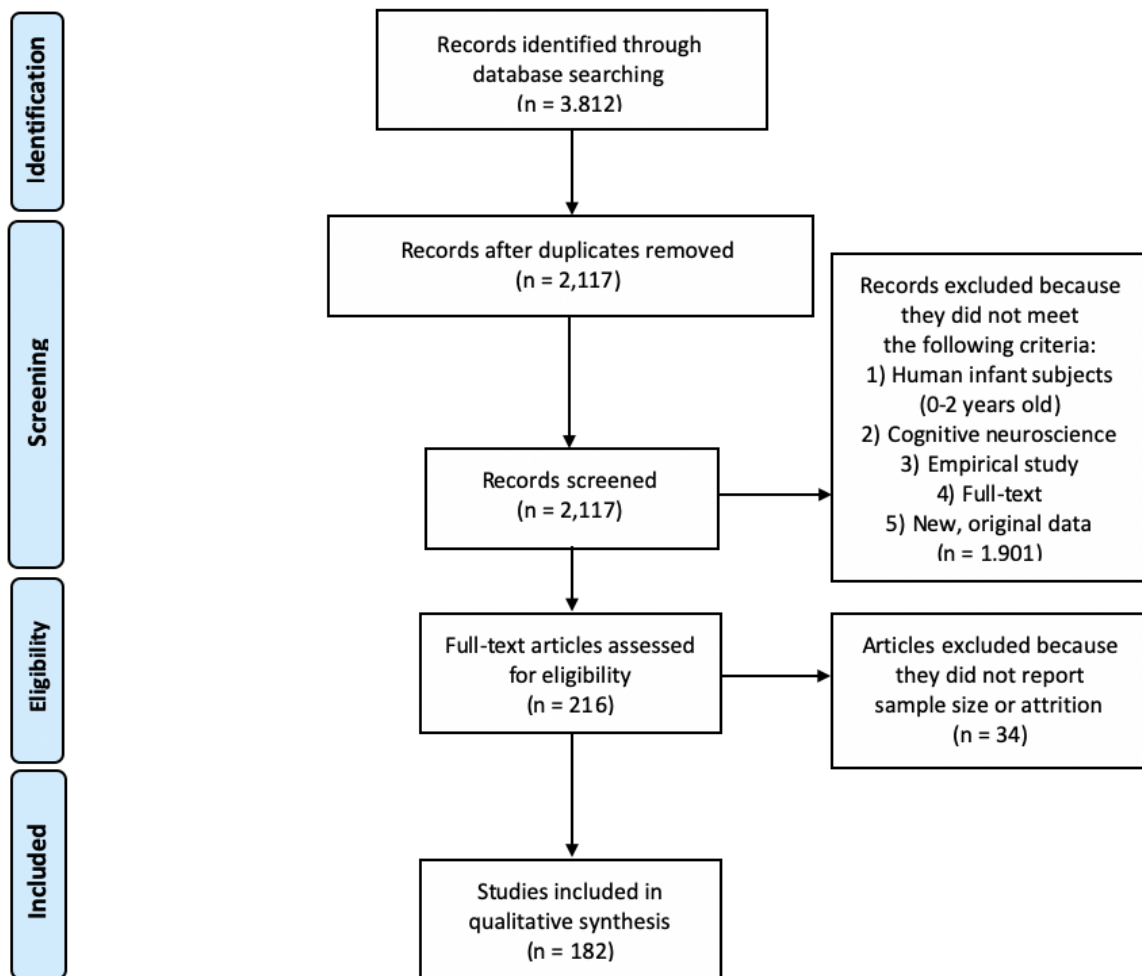


Figure 10. Study selection process

The study selection process is outlined here using the PRIMA Flow Diagram.

4.3.3 Attrition Rates

We defined the three types of attrition rates as follows to account for different types of data exclusion that could arise in a research setting. We used these definitions to calculate the attrition in each of the 272 experiments.

Total Attrition Rate (TAR). Total Attrition Rate (TAR) referred to the total proportion of subjects who were excluded for any reason from the total recruitment pool. This was defined as the ratio of the number of subjects who remained in the final analysis sample over the total number of subjects who were recruited.

$$\text{Total Attrition Rate (TAR)} = \frac{n \text{ excluded for any reason}}{n \text{ total recruited}}$$

Infant-Driven Attrition Rate (IAR). Infant-Driven Attrition Rate (IAR) referred to the proportion of subjects who were excluded for the infant subjects' behavioral reasons, such as the subject resisting the fNIRS cap or being fussy and inattentive during the task.

$$\text{Infant-Driven Attrition Rate (IAR)} = \frac{n \text{ excluded for reasons related to infant behavior}}{n \text{ total recruited}}$$

Signal-Driven Attrition Rate (SAR). Signal-Driven Attrition Rate (SAR) referred to the proportion of subjects who were excluded for signal-related reasons, such as weak signals or strong artifacts.

$$\text{Signal-Driven Attrition Rate (SAR)} = \frac{n \text{ excluded for reasons related to signal quality}}{n \text{ total recruited}}$$

4.3.4 Parameters

4.3.4.1 Subject Parameters

We defined Subject Parameters as characteristics of the infant subjects that may have influenced the attrition rate. We coded five Subject Parameters: Age, sex, hospitalization status, preterm status, and clinical status. Age was defined as the mean age in months of all infant subjects in the experiment. Sex was defined as the percentage of infants that were female among the subjects; although researchers in the field of developmental cognitive neuroscience are working to allow non-binary reporting of sex in future studies, our analyses were performed on publications that report only binary sex and, thus, we summarize sex in this way. Hospitalization status was binarily defined based on whether the study was conducted in the hospital (1) or not (0). Preterm status was defined based on whether the recruited infant subjects of each study were preterm (1) or full-term (0) infants, as determined by each experimenter's criteria. Finally, the clinical status of the infants was coded as typically developing (0), at-risk, such as preterm or familial risk for autism spectrum disorder (1), or atypically developing, such as Down's syndrome (2). All parameters that did not correspond to exactly one of these options were coded as "other" (-1); for example, some studies (e.g., Edwards, Wagner, Tager-Flusberg, & Nelson, 2017; Lloyd-Fox et al., 2013) reported results from all subjects without differentiating among at-risk and low-risk subjects when reporting reasons for attrition, so this variable was coded as -1. There were 8 of these -1 values in the total dataset. They were removed from further analyses for clearer interpretability.

4.3.4.2 *Design Parameters*

We defined Design Parameters as characteristics of each experimental study design that may have influenced the attrition rate. We coded for six Design Parameters: fNIRS cap configuration, study design (i.e., whether blocks or trials were used), number of trials/blocks, length of trials/blocks, presence of stimuli, and type of stimuli. fNIRS configuration was a continuous variable, defined as the number of channels used to collect data in each study. Study design was a binary variable, defined as trial design (0), or block design (1). A study was defined as a block design if multiple trials in the same condition were used consecutively, a tactic often used to maximize signal, and trial design for all others. The number of trials/blocks was a continuous variable, defined as the number of trials and blocks that were separated from other segments by a rest period or a fixation period. The length of trials/blocks was a continuous variable, defined as the duration of each experimental trial/block (i.e., not including baseline or ISI periods). Presence of stimuli was a binary variable, defined based on whether the study was conducted with stimuli (1) or without stimuli (0). Finally, the type of stimuli was a categorical variable, defined as audio (0), visual (1), or audiovisual (2); Here, we only coded for the stimuli specifically designed in the task and did not code for non-task stimuli that may have been present (e.g., attention-grabbers, layout of the lab, etc.). All variables that did not correspond to exactly one of these options were noted and excluded from analyses.

4.3.4.3 *Other Parameters*

We also coded for the final sample size, year of publication, and topic of research. Final sample size was defined as the total number of infants included in each paper's original analyses. The year of publication was defined as the year in which the publication was accepted. For the

topic of research, each experiment was classified as one of the 9 topic categories: Attention, Memory/Learning/Prediction, Auditory/Language, Vision, Multisensory Processing, Social Cognition, Higher Cognition, Resting State, and Other.

4.3.5 Coding

To test our hypotheses outlined in the introduction section, we coded for three types of attrition rates, five Subjects Parameters, six Design Parameters, and three Other Parameters for each experiment. As a result, there were 4,896 possible variables (18 variables x 272 experiments). Not all variables were reported by all experiments. Variables that were neither reported in the experiment nor calculable based on the information given were noted and excluded from analyses.

For each experiment, two researchers independently coded these variables. Two independent coders agreed on 4,418 of the 4,896 variables, showing an inter-rater reliability of 90.23%. In the case of a disagreement between the two independent coders, a third researcher cast a tie-breaking vote.

4.3.6 Statistical Analysis

All analyses were conducted in R via RStudio (version 4.0.3; R Core Team, 2020). To test our hypotheses about the influence of subject- and design-related variables, we examined whether each parameter of interest independently predicted attrition rate by fitting linear mixed-effects models using the lme4 package (version 1.1-23; Bates et al., 2015). Models including the parameter of interest as a single fixed effect and publication year as a random intercept were used to predict TAR, IAR, and SAR. While we intuitively assumed that some parameters would

be more likely to predict certain types of attrition (e.g., age relating to fussiness such that IAR is affected, or fNIRS cap configuration relating to signal quality such that SAR is affected), we report each parameter's influence on all types of attrition to paint a full and transparent picture of its effect on data loss.

4.4 Results

4.4.1 Attrition Rates

We examined the overall trends for sample size and attrition rate. Over the 272 experiments, the average final sample size (after attrition) was 23.88 ± 14.47 infants. 220 out of 272 experiments reported enough information to calculate the total attrition rate (TAR). On average, 34.23% of subjects were excluded. Among the 178 experiments that reported reasons for their attrition, 136 experiments reported infant-driven reasons (IAR), and 121 experiments reported signal-driven reasons (SAR). Among studies that reported IAR, 21.50% of the data were excluded due to IAR on average, while among studies that reported SAR, 20.24% were excluded due to SAR on average (Table 1; Fig. 11). Studies that reported IAR or SAR were not significantly different from those that did not in terms of the TAR [$t(200) = 0.939$, $p = 0.3488$]. Our analysis showed that an increasing number of studies are reporting attrition rates; while only 65% of studies reported attrition information between 1998 and 2005, 85% of studies reported attrition since 2005.

Table 1. Overview of the Attrition Rates

Type of Attrition	Mean Attrition Rate %
	M (SD)
Total Attrition Rate (TAR)	34.23 (± 17.60)
Infant-Driven Attrition Rate (IAR)	21.50 (± 14.42)
Signal-Driven Attrition Rate (SAR)	20.24 (± 14.22)

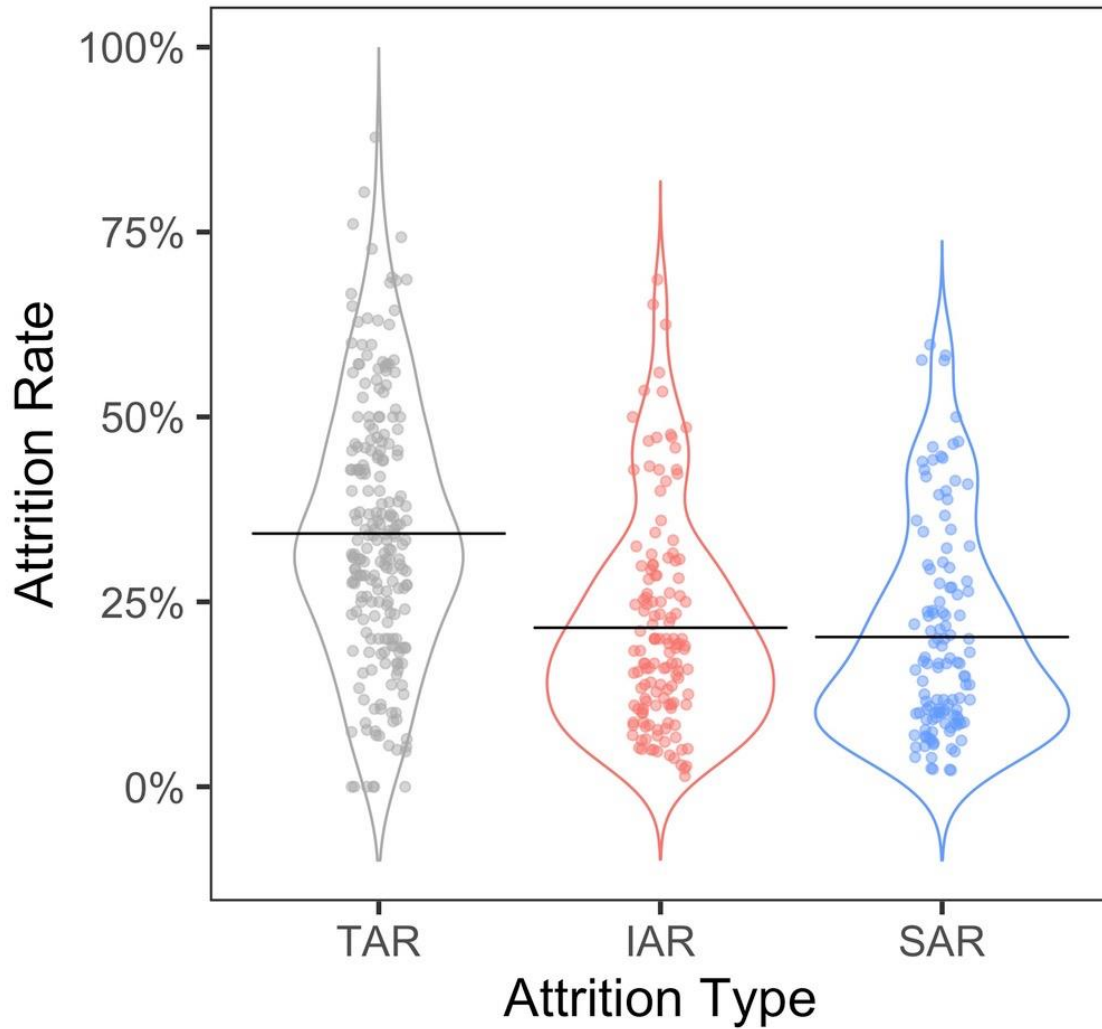


Figure 11. Distribution of attrition types in infant fNIRS research

The distributions of attrition rates reported by all infant fNIRS research to date are depicted for the three types of attrition we analyzed in this report (TAR, IAR, and SAR).

4.4.2 Comparison with other research methodologies

One-sample t-tests were conducted to determine if a difference existed between the attrition rates in infant fNIRS and in other methodologies. We compared our TAR/IAR values and the values reported in previously mentioned meta-analyses. Our TAR value of 34.23% was significantly lower than the Stets and colleagues estimate of attrition for infant EEG: 47.3% [$t(222) = 14.98, p < 0.001$]) suggesting that infant fNIRS studies have less attrition than EEG. Though, Stets and colleagues (2012) did not break down their attrition rates into subtypes (e.g., IAR, SAR) so we are not able to determine which aspect(s) of attrition differ between the modalities. FNIRS attrition rate is significantly higher than the 22.6% attrition rate reported by Slaughter and Suddendorf (2007) for infant looking time studies [$t(222) = 4.89, p < 0.001$]). However, as we conceptualized in our approach, fNIRS research likely has multiple sources of attrition including from signal issues as well as infant compliance. To see whether IAR is similar across these methodologies, we compared the IAR we found in fNIRS research (21.50%) to the overall infant-related attrition rate reported by Slaughter and Suddendorf in 2007 (13.7%). We found that there was no significant difference [$t(198) = 0.51, p = 0.608$]. This similarity suggests that types or sources of attrition might be similar across methods and literatures.

Change in attrition rate over time. The number of infant fNIRS research publications by year has been exponentially increasing since the inception of fNIRS as an infant neuroimaging technique in 1998 (Fig. 12A). Considering these trends by research area, the increase was the most pronounced for research in two categories, auditory processing and language and social cognition, but was observed in all explored topics of research (Fig. 12B). Given the incredible expansion of the field, we examined changes in the attrition rates as a function of publication year using simple linear regression. We found no significant change in TAR over the years ($\beta = -$

0.39, $t = -1.45$, $p = 0.148$, $R^2 = 0.01$). However, as hypothesized, there was a significant decrease in SAR over time ($\beta = -1.19$, $t = -4.28$, $p < 0.001$, $R^2 = 0.13$), with IAR remaining stable ($\beta = -0.21$, $t = -0.73$, $p = 0.469$, $R^2 = 0.00$; Fig. 12C).

We also examined whether final sample size has changed over the history of infant fNIRS studies. The average sample size per experiment significantly increased from $n = 12.91$ in the beginning to $n = 21.90$ in 2010 [$t(112) = 2.55$, $p = 0.030$] and has remained steady from $n = 24.26$ to $n = 24.14$ in the last decade ($[t(115) = 0.06$, $p = 0.950]$).

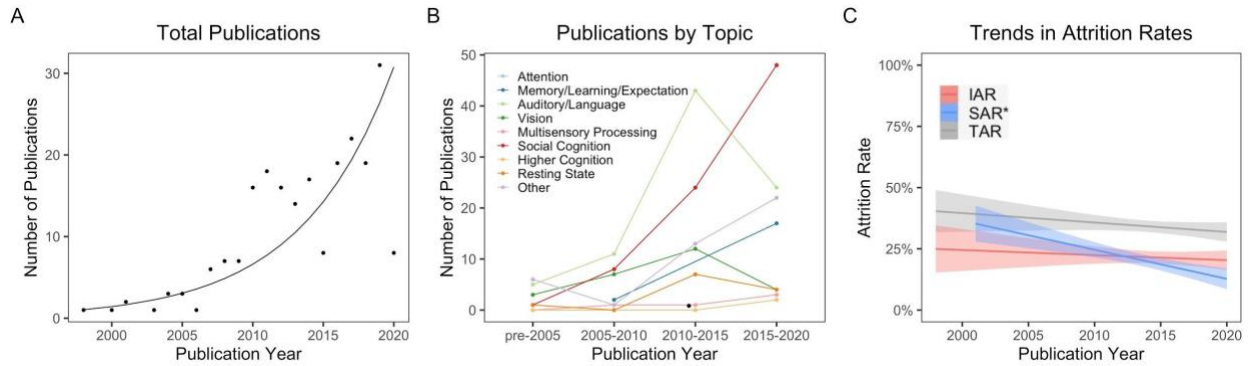


Figure 12. Trends in infant fNIRS research over time

(A) Since its inception as an infant neuroimaging technique, fNIRS has been used in an increasing number of infant cognitive neuroscience experiments. (B) There has been a general increase in the number of publications on all topics, but the increase was the most pronounced for research on auditory processing/language and social cognition. (C) All three types of attrition rates have generally been decreasing over the years, but the only significant decrease was in the attrition rate driven by signal quality (SAR).

4.4.3 Subject-Related Parameters

Table 2 presents a brief summary of the subject-related parameters across all experimental groups (n = 272).

Table 2. Overview of Subject Parameters

Subject Parameters (Continuous)	n	M (SD)	Range
Age (months)	272	5.03 (± 4.19)	0.04 - 23.10
Outliers removed	264	4.63 (± 3.47)	0.04 - 13.14
Sex (percentage of female subjects)	245	49.08 (± 11.76)	15.38 - 95.24
Subject Parameters (Categorical)	n	%	
Hospitalization Status	272		
In-Hospital	79	29.04%	
Not in hospital	193	70.96%	
Preterm Status	266		
Preterm	16	6.02%	
Full-term	250	93.98%	
Clinical Status	266		
Typically developing	230	86.47%	
At-risk (e.g., familial risk, preterm)	34	12.78%	
Atypically developing (e.g., Down's syndrome)	2	0.75%	

Note. In this table, n refers to the number of experimental groups rather than the number of infant subjects. For example, participant age was reported for 272 experimental groups, and the mean age ranged from 0.04 to 23.10 months.

First, we examined the age distribution for all studies (Fig. 13). Across 272 experiments, 9,114 total infants were recruited, with a mean age of 5.03 ± 4.19 months (range: 0.04-23.10). Age is not normally distributed throughout this range as is found throughout the field of developmental cognitive neuroscience (Azhari et al., 2020). Indeed, seven experiments included infants whose average age was greater than 2 standard deviations away from the overall mean. These outliers (mean age >13.41 months) were retained in the analyses reported below, but we note any instance where the findings diverge for the full sample versus partial sample (excluding outliers).

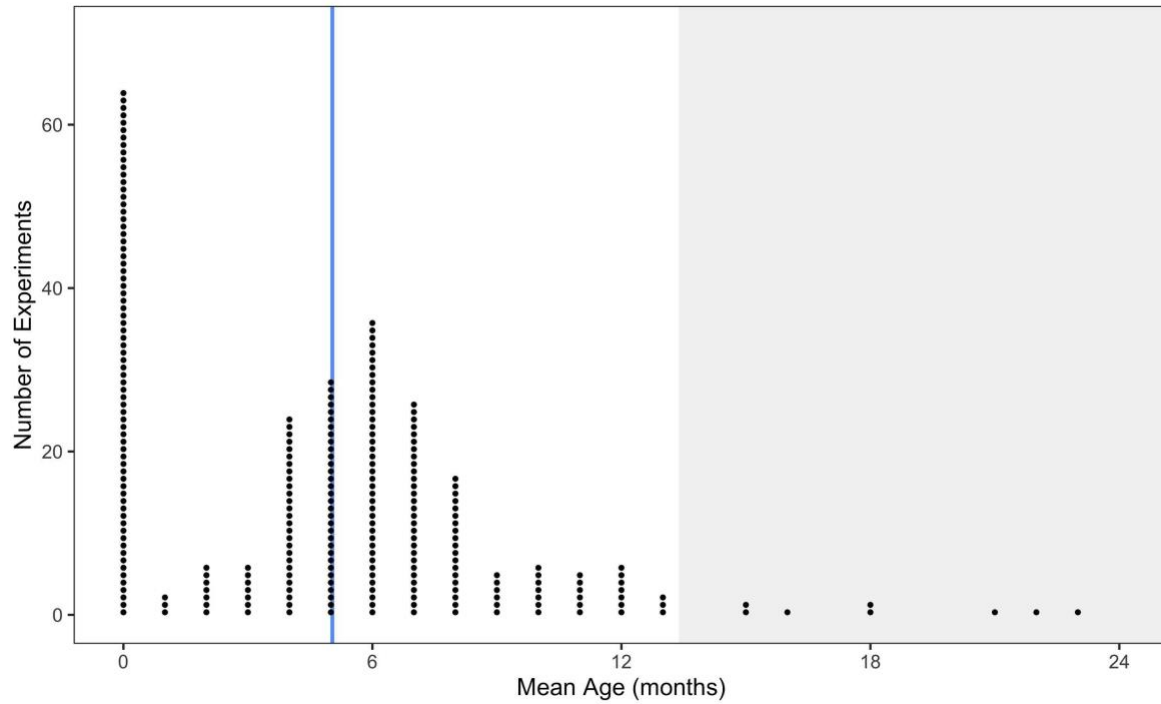


Figure 13. Age distribution for all infant fNIRS experiments

Each point represents a single experiment. The vertical line at 5.03 months reflects the mean age across all experiments. The shaded gray area beginning at 13.41 months denotes the outlier region, defined as $>2SD$ away from the mean age across all experiments.

To test whether participant age influenced attrition rates, we fit a linear mixed-effects model predicting attrition with mean age (in months) as a fixed effect and publication year as a random intercept. Results indicated that age was unrelated to TAR ($\beta = -0.33$, $t = 1.15$, $p = 0.253$, $R^2 < 0.01$), likely due to the conflicting effects of age on IAR and TAR. Age was a weak but significant positive predictor of IAR ($\beta = 0.76$, $t = 2.70$, $p = 0.008$, $R^2 = 0.05$; Fig. 14A) and weak but significant negative predictor of SAR ($\beta = -0.83$, $t = -2.86$, $p = 0.005$, $R^2 = 0.06$; Fig. 14B). These age effects on IAR ($\beta = 0.87$, $t = 2.40$, $p = 0.018$, $R^2 = 0.04$) and SAR ($\beta = -0.77$, $t = -2.04$, $p = 0.044$, $R^2 = 0.04$) held after removing the oldest outliers from the sample. As a robustness check, we also re-ran these analyses after removing newborns from the sample since there are many differences in the types of experimental tasks used for newborns and older infants (e.g., sleeping vs. awake and behaving), and there is a large concentration of the sample at birth. Only the age effect on SAR remained statistically significant and, in fact, increased in magnitude ($\beta = -1.30$, $t = -3.58$, $p < 0.001$, $R^2 = 0.12$). Thus, across all three analyses we found that age significantly predicts SAR in the negative direction, such that increased age of infant participants is associated with decreasing attrition due to signal quality issues. The estimates for the effects of age on SAR ranged from $\beta = -0.33$ to -1.30 .

To further explore the effects of age and consider current findings in relation to past studies, we parsed age into categorical bins to determine whether there exists a non-linear influence of age. We first examined whether there were differences in attrition across four age groups (0-2 months, 3-4 months, 5-8 months, 9 months and older; consistent with Cristia et al. (2013) via a one-way ANOVA. Results revealed a significant effect of age on TAR [$F(3, 216) = 3.33$, $p = 0.021$] and SAR [$F(3, 117) = 6.70$, $p < 0.001$], but not IAR. To better understand these significant effects, we performed follow-up pairwise t-tests. First, replicating the age effect

observed by Cristia et al. (2013), we found that TAR for the 3- to 4-month-old age range was significantly higher than that of the 0- to 2-month group ($p = 0.003$) and the 5- to 8-month group ($p = 0.019$), with only the 0- to 2-month difference remaining significant after Tukey adjustments. For SAR, we similarly found that the 3- to 4-month-old age range experienced higher rates of data loss due to poor signal quality than the 0- to 2-month group ($p = 0.012$), the 5- to 8-month group ($p < 0.001$), and the 9-month and older group ($p < 0.001$), all of which remained significant after Tukey adjustments. Additionally, we found that 0- to 2-month-old age range also experienced higher SAR than the 9-month and older group ($p = 0.016$), though this effect did not hold after correction for multiple comparisons. Together, these findings suggest that studies with younger infants, particularly in the 3- to 4-month age range, may experience higher rates of data loss, particularly due to signal quality issues.

However, this categorization of ages adopted from Cristia et al. (2013) led to uneven group sizes in our sample, with the 3- to 4-month group being the smallest. We therefore re-ran these analyses with updated bin sizes to more systematically sample the 0-to 24-month range (newborns, 1-5, 6-11, 12-17, 18+). With these updated groups, we found no statistically significant categorical differences for any type of attrition via a one-way ANOVA, suggesting that the linear trends reported above could best capture the effects of age.

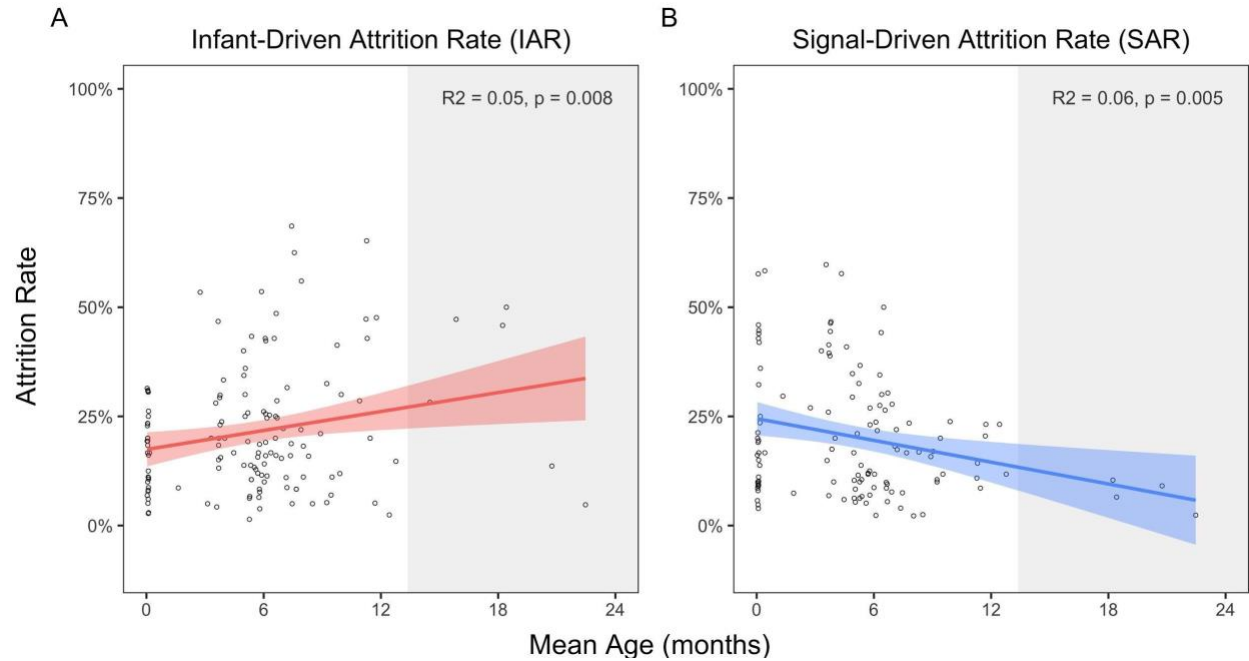


Figure 14. Change in attrition rates as a function of participant age

(A) Attrition rate due to infant behavior increased with age. (B) Attrition rate due to signal quality decreased with age. The shaded gray area beginning at 13.41 months denotes the outlier region, defined as $>2SD$ away from the mean age across all experiments.

To test the hypothesis that subjects' sex affects attrition rate, we calculated the proportion of female subjects from the total sample size for each experiment and tested whether this variable predicted unique variance in attrition rates via mixed-effects regression modeling, with proportion of female subjects as a single fixed effect and publication year as a random intercept. We found that the proportion of female subjects was not a significant predictor for any type of attrition, suggesting that subjects' sex is generally unrelated to attrition.

We next tested whether there were differences in attrition rate based on the clinical characteristics of subjects. We found that clinical status did not predict significant variance in any type of attrition based on a linear mixed-effects model including clinical status as a single fixed effect and publication year as a random intercept, and we also found no categorical differences in TAR [$t(218) = 1.12, p = 0.265$], IAR [$t(130) = -0.13, p = 0.592$], or SAR [$t(115) = 0.99, p = 0.323$] among typically developing infants vs. at-risk infants. Similarly, we found that preterm status was not a significant predictor of any type of attrition based on a linear mixed-effects model including preterm status a single fixed effect and publication year as a random intercept, and there were also no categorical differences in TAR [$t(215) = 0.59, p = 0.557$], IAR [$t(133) = 0.23, p = 0.820$], or SAR [$t(117) = -0.88, p = 0.380$] for preterm vs. full-term infants. Finally, we also examined the effect of hospitalization status and found that it was a significant negative predictor of TAR ($\beta = -6.12, t = -2.14, p = 0.033, R^2 = 0.02$) and IAR ($\beta = -6.97, t = -2.41, p = 0.017, R^2 = 0.04$) but unrelated to SAR. Specifically, studies with in-hospital infants had an average TAR of 29.58%, and in-lab studies had a significantly higher average TAR of 35.53% [$t(218) = -2.09, p = 0.038$]. It is important to note that these results were likely confounded by age differences, with hospitalized infants ($M = 0.43, SD = 1.40$ months) tending to be significantly younger than the typical participants of in-lab studies ($M = 7.02, SD = 3.47$

months). Indeed, when looking at the subset of studies with infants up to 7.67 months (i.e., the maximum age for in-hospital participants), we found no significant differences in TAR according to testing location based on a Wilcoxon test for non-normally distributed groups ($W = 2495.5$, $p = 0.075$).

4.4.4 Design Parameters

We next examined the impact of the designs of infant fNIRS experiments on the attrition rates (see summary of these variables in Table 3).

Table 3. Overview of Design Parameters

Design Parameters (Continuous)	n	M (SD)	Range
fNIRS configuration (# of channels)	248	26.10 (± 20.58)	2 - 94
Number of trials/blocks	190	17.22 (± 16.52)	1 - 92
Length of trials/blocks (seconds)	254	76.64 (± 471.45)	0.1 - 7200
Design Parameters (Categorical)	n	%	
Study design	234		
Block design	105	44.87%	
Trial design	129	55.13%	
Presence of stimuli	271		
With stimuli	256	94.46%	
Without stimuli	15	5.54%	
Type of stimuli	256		
Audio	83	32.42%	
Visual	67	26.17%	
Audiovisual	66	25.78%	

Other	40	15.63%
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First, we examined the effect of the fNIRS cap configuration on attrition. We found that the average number of channels used per experiment increased from 12.56 in 1998 to 23.23 in 2010 [$t(110) = 2.17$, $p = 0.057$] but stayed stagnant in the last decade [$t(113) = 1.75$, $p = 0.117$]. We ran a linear mixed-effects regression analysis predicting attrition as a function of the number of channels, while controlling for both publication year and participant age. Replicating a previous meta-analysis (Cristia et al., 2013), we found that number of channels was a weak positive predictor of attrition ($\beta = 0.24$, $t = 3.73$, $p < 0.001$, $R^2 = 0.06$). Interestingly, this was primarily driven by infant behavior rather than signal quality: IAR increased linearly with the number of channels ($\beta = 0.16$, $t = 2.89$, $p = 0.005$, $R^2 = 0.05$; consistent with Cristia et al. (2013), where the inclusion of more fNIRS optodes was associated with higher attrition rates), while the number of channels did not predict significant variance in SAR ($\beta = 0.10$, $t = 1.53$, $p = 0.129$, $R^2 = 0.02$).

Next, we tested the effects of the experimental task design on attrition. The duration of a study segment averaged 76.75 seconds (range: 0.1 to 7200 secs, $n = 251$). We found that study design (block vs. trial) was a positive predictor of TAR ($\beta = 6.59$, $t = 2.71$, $p = 0.007$, $R^2 = 0.04$) and a trending positive predictor of IAR ($\beta = 4.94$, $t = 1.97$, $p = 0.0051$, $R^2 = 0.03$) but not SAR. Specifically, studies using a block design had an average TAR of 30.54%, and trial designs had a significantly higher average TAR of 37.14% [$t(195) = -2.71$, $p = 0.007$; Fig. 15]. In terms of variance accounted for, this is one of the strongest effects observed. Our findings are in contrast to Cristia et al. (2013) which found that presentation of repeated stimuli resulted in higher attrition rates. We demonstrate that block designs, which by definition are repeating stimuli, significantly lowered the overall attrition rate.

Next, we examined the effect of the number of study segments (i.e., total number of blocks or trials) on attrition. We fit a linear mixed-effects model predicting attrition, with the number of study segments included as a single fixed effect and publication year as a random effect. Results indicated that number of study segments was a significant negative predictor of both TAR ($\beta = -0.21$, $t = -2.36$, $p = 0.030$, $R^2 = 0.04$) and IAR ($\beta = -0.18$, $t = -2.26$, $p = 0.026$, $R^2 = 0.05$) but not SAR. The amount of variance explained by this parameter is low, and the effect on IAR did not remain statistically significant after removing the oldest age outliers. Given that we found significant differences in TAR and IAR between studies with block vs. trial designs, we also examined the effect of the number of study segments separately for these groups. We found that the effect on TAR held for trial designs ($\beta = -0.23$, $t = -2.18$, $p = 0.033$, $R^2 = 0.08$) but not block designs, and the effect on IAR was not significant for block or trial designs. Thus, we do not present conclusive evidence that the number of study segments impacts attrition rate.

Given the characteristics of the data, there was not enough variation in this parameter to analyze the effect of study segment duration on attrition. Specifically, the distribution of study segment durations across experiments was highly right-skewed, with only 10 total experiments featuring durations greater than 60 seconds, meaning that outliers would have heavily influenced any observed effects and excluding these outliers would have left little to no variation to examine.

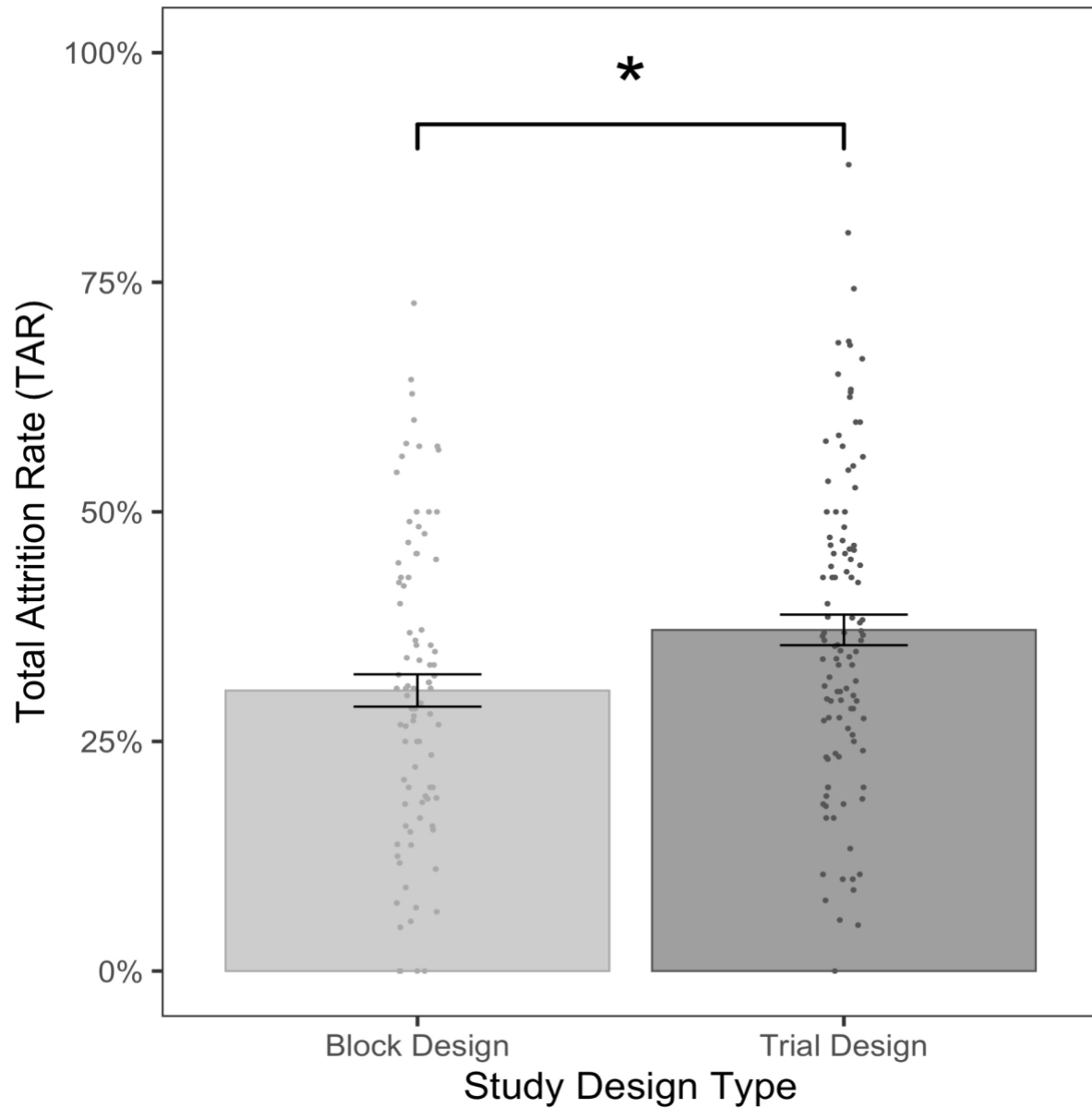


Figure 15. Effect of Study Design Type on Attrition Rate

Studies using a trial design experienced higher attrition rates compared to those using a block design. Points reflect individual TAR means for each experiment, with error bars indicating standard error of the overall mean, * denotes a statistically significant difference.

Finally, we examined the effects of experimental stimuli on attrition rates. We found that the presence of stimuli was not a significant predictor of TAR or SAR but was a significant negative predictor of IAR ($\beta = -21.55$, $t = -3.03$, $p = 0.003$, $R^2 = 0.06$). Specifically, studies including any type of experimental stimulus had an average IAR of 20.87%, and studies not featuring stimuli experienced a higher average IAR of 42.42%. This difference was only trending towards statistical significance based on a Wilcoxon test between non-normally distributed groups ($W = 405$, $p = 0.070$), possibly because of the small sample of studies with no stimulus. However, similar to the trial vs. block designs, this is one of the largest differences in attrition rate, numerically, reported in this meta-analysis.

Then, we compared attrition rates for the three most common types of experimental stimuli (auditory, visual, and audiovisual) using a one-way ANOVA. We found no differences in TAR or SAR according to the type of experimental stimulus but a trending difference in IAR [$F(2, 122) = 2.92$, $p = 0.058$, $\eta^2 = 0.05$]. A follow-up pairwise analysis revealed that studies using audiovisual stimuli experienced marginally greater IAR than studies using only auditory stimuli ($p = 0.017$, adjusted $p = 0.051$; 23.53% vs. 16.67%, respectively). This effect may be at least partially explained by differences in the typical study designs employed for experiments featuring audiovisual vs. only auditory stimuli. Specifically, studies with audiovisual stimuli were more likely to use trial designs, which are associated with higher rates of attrition (68.75% trial designs for audiovisual studies, relative to 24.53% for auditory-only studies). Further research would be needed to tease apart these two possible inter-related factors (study design and stimulus type). There were no significant differences between auditory and visual stimuli ($p = 0.249$; 16.67% vs. 20.40%, respectively) or visual and audiovisual stimuli ($p = 0.304$).

Additionally, we found no differences in IAR regardless of whether visual stimuli were static or dynamic ($W = 985$, $p = 0.328$).

4.5 Discussion

A detailed understanding of attrition is essential for any field. It allows researchers to characterize external validity, to plan sample sizes in pre-registered studies, and to reduce attrition by understanding the relevant experimental factors. In this meta-analysis, we built on past work to present a detailed examination of attrition rates across 272 experiments in all 182 infant fNIRS studies published before April 9, 2020. We had two main goals: One was to present a clear characterization of the state of the field concerning attrition and to provide benchmarks upon which future studies could be compared; the second was to examine what factors influence attrition to provide insight for researchers when designing future studies. To this end, we have launched an attrition rate calculator that will aid researchers in using this meta-analysis to plan future studies, and the database of all of this information is publicly available

(<https://github.com/soribaek/Attrition-Rate-in-Infant-fNIRS-Research>).

Overall, we found that infant fNIRS studies experienced 34.23% attrition. Compared to corresponding adult research (Lloyd-Fox et al., 2010), infant fNIRS research reported greater attrition. Compared to infant EEG (the most comparable methodology, fNIRS research reported significantly lower attrition rate. This difference between fNIRS and EEG is surprising given many similarities between the methodologies. However, the sources of these differences remain unclear given that the meta-analysis of infant EEG research did not consider sub-types of attrition (e.g., SAR). Compared to behavioral infant research, fNIRS research reported greater attrition, but considering the common type of attrition across these methodologies (IAR in fNIRS

research vs. infant non-compliance in behavioral research) revealed no significant difference. This similarity in IAR across these methodologies suggests that certain sources of attrition might be constant across modalities, although the current meta-analyses in EEG and infant eye-tracking are unfortunately not sufficiently detailed to allow these comparisons.

We found a general downward trend in attrition over the years, and that this decrease was attributable to fNIRS signal factors (SAR, as opposed to IAR). This trend likely stems from improvements in signal processing (Cope et al., 1988; Cui, Bray, & Reiss, 2010; Virtanen, Noponen, Kotilahti, Virtanen, & Ilmoniemi, 2011) and the development of advanced toolboxes (Ferradal et al., 2014; Franceschini, Toronov, Filiaci, Gratton, & Fantini, 2000; Huppert, Diamond, Franceschini, & Boas, 2009a; Koh et al., 2007; Tsuzuki & Dan, 2014) and shows promise for continued improvements in the future. Similar findings were observed in a meta-analysis on infant EEG (Stets et al., 2012), where older articles reported higher attrition rates, but this effect could not be attributed to any particular variable because of the limitations of the meta-analysis. In contrast, Cristia et al. (2013) found no change in attrition with years; This difference may be because Cristia et al. (2013) did not separate sources of attrition and our study adds 8 more years of studies which is a substantial proportion of studies in this young field.

We examined subject characteristics that could affect attrition rates. As hypothesized, we found that age of participants predicted overall greater attrition. However, when considering subtypes of attrition, the picture is more complex. Age was a positive predictor of IAR (i.e., older infants are more likely to be fussy), but a negative predictor of SAR. This negative relationship could be due to the fNIRS cap fitting better on older infants with larger heads or older infants being comfortable with the additional weight of the fNIRS hardware. Overall, our investigation

into the relationship between age and attrition rate suggests that there is a compromise between the infant-driven and signal-driven attrition rate.

Our age-related findings are in line with previous work that has implicated subject age as a key predictor of attrition rate in neuroimaging research. Cristia et al. (2013) found that older infants show lower overall attrition rates than younger infants, and Slaughter & Suddendorf (2007) found a negative correlation between attrition caused by reasons other than fussiness and the age of the infants. We replicated both of these findings. These findings indicate that research can be improved by tackling different causes of attrition depending on the target age. For example, scientists conducting research on older infants can focus on helping them be less fussy (e.g., by focusing on factors presented in section 5). Meanwhile, scientists conducting research on younger infants can focus on improving the signal quality of the data (e.g., by focusing on cap fit and related factors).

Inconsistent with our hypotheses, we found that clinical characteristics were not systematically related to attrition rates (consistent with Stets et al., 2012). This null findings is in contrast to prior research which found that clinical characteristics greatly influenced how likely adult subjects were to cooperate in an experimental study (Andreescu, Chang, Mulsant, & Ganguli, 2008; Chang, Yang, Tang, & Ganguli, 2009; Issakidis & Andrews, 2004). This discrepancy shows that there are stark differences in the predictors of attrition between infant and adult subject populations, and further highlight that scientists need to explore age-conscious methods to reduce attrition rates.

Finally, we determined which aspects of infant fNIRS research influences attrition. Replicating a key finding from Cristia et al. (2013), we found that number of fNIRS channels positively predicted infant-driven attrition rate. This relationship is likely because the increased

weight and size of the fNIRS cap (Lloyd-Fox et al., 2010) increases in infant fussiness.

Understanding this relationship is particularly informative since we see a trend of increasing numbers of optodes over time in our field (consistent with Cristia et al., 2013). Although the development of newer fNIRS systems with more channels allows for better coverage of the cortex and the ability to obtain more fine-grained spatial information within regions of interest, it is important to recognize the trade-off between increased signal potential and increased weight or size of the fNIRS cap, which may lead to more participant movement or fussiness (Cristia et al., 2013; Lloyd-Fox et al., 2010; Nakano et al., 2008).

Interestingly, stimulus design had the largest numerical impact on attrition. We found that studies using block designs experienced significantly lower attrition rates than studies using trial designs. This finding suggests that using a block design, when possible, is likely to reduce data loss. This finding may appear to contradict established findings, which tend to implicate longer study segments as a predictor of higher attrition due to infant behavior. For instance, longer studies lead to greater subject dropout across a wide array of data collection techniques (e.g., surveys: Hoerger, 2010; eye-tracking: Hessels, Andersson, Hooge, Nyström, & Kemner, 2015) and long, repetitive experimental blocks may be linked to subject restlessness in fNIRS (Cristia et al., 2013). However, our findings are not in opposition to those results. First, the finding regarding block designs does not refer to the length of the overall experiment but instead the duration of stimulation between periods of rest. Thus, viewing a block of stimuli (mean duration = 71.76 seconds) is not equivalent to participating in a long study. Second, these findings point to a likely to be a non-linear relationship between the length of stimulus presentation and engagement with infants, reflective of both the classic Hunter and Ames model (Hunter & Ames, 1988) and Goldilocks effect (Kidd et al., 2012).

The presence and type of stimuli also substantially influenced attrition rate. Studies which presented stimuli experienced half as much IAR compared to studies which presented no stimuli (21.94% vs. 42.41% attrition). Studies using audiovisual stimuli experienced marginally greater IAR than studies using only auditory stimuli. These results are in line with meta-analytic findings from infant EEG (Stets et al., 2012), which reported that audiovisual stimuli resulted in a 19.9% increase in attrition compared to auditory stimuli. This finding is puzzling, given that audiovisual stimuli are widely believed to be more attention-grabbing than visual-only or audio-only stimuli (e.g., Brannon, Libertus, Meck, & Woldorff, 2008; Stets et al., 2012) and thus have been employed to increase subject retention (e.g., Nikkel & Karrer, 1994; Snyder, Webb, & Nelson, 2002). These counterintuitive results could be reconciled by the fact that studies using only auditory stimuli commonly study sleeping infants, where there is reduced likelihood of data loss due to subject fussiness or movement (Stets et al., 2012). Audio-only studies also commonly use block designs (see previous paragraph) which is also associated with reduced attrition. In addition, it is also possible that there are some differences in the data inclusion criteria depending on the stimuli; for example, the data inclusion criteria for an audiovisual study may require that infants have to watch the audiovisual stimuli, which would be more stringent than the criteria for an audio-only study. Considering these findings highlights that experimental decisions are not made in isolation and often are related to several other factors, all of which might influence attrition rate. More research is needed to ascertain the reason for this counterintuitive result.

This study is presently the first comprehensive meta-analysis on the attrition rates in all infant fNIRS research. The most related study is by Cristia and colleagues' (2013) who included some analyses on the attrition rate in infant fNIRS research as a part of introducing their online database of infant research. However, their study included only the small sample of studies that

were uploaded to the database at the time of publication (76 publications and theses), and their analyses did not focus on attrition rate or outline possible ways to mitigate it. We improved upon these limitations by including all infant fNIRS research published to date identified using a comprehensive search approach. This resulted in a sizable sample of 218 publications. Moreover, we focused our analyses on attrition rate. We also identified various subtypes of attrition and their potential predictors in experimental research. This more comprehensive approach allowed us to gather the trends in research and specifically make conclusions about factors that can moderate the attrition rate.

Despite the potential utility of our findings in future research, our meta-analyses had a number of notable limitations. First, there was variance in the sample size among the studies, which made it more difficult to accurately depict the general trends in the attrition. Although we used the ratio of final sample size versus all recruited subjects for simplicity and consistency, a few studies with small sample sizes may have skewed results. Second, there was a large proportion of studies that did not clearly report their attrition rates. This lack of information obfuscates the true relationship between some of the factors we explored and the attrition rate and reduces the strength of transparency of the field. Among 218 infant fNIRS research publications between 1998 and 2020, 34 (15.5%) did not report sample size; among those that did, only 182 reported enough information for us to calculate the total attrition rate. Furthermore, many experiments did not explain the reason for data exclusion. Thus, only 83% of studies in the field provided even the most basic information needed to calculate attrition rates and many more did not include further information necessary to evaluate key sources and causes of attrition. In Section 5.1, we make six recommendations for infant fNIRS researchers with regards to reporting attrition rates moving forward to enable a more transparent reporting of data selection

criteria. These recommendations could be useful for researchers in related fields (infant fMRI, EEG, looking time or other behavioral methods). Additional guidelines on reporting fNIRS results can be found in Cristia et al. (2013).

Given the growing popularity of fNIRS as a neuroimaging tool to study infant neuroscience, understanding factors that decrease the attrition rate in an infant fNIRS research study is helpful to reduce the attrition rate and increase the quality and quantity of infant fNIRS research. We therefore combine the findings of this chapter and previous research to suggest six recommendations to minimize the attrition rate in future infant fNIRS research.

Understanding attrition rate and its related factors will contribute to greater reproducibility and generalizability of the findings in the field in the future.

4.6 Conclusion

4.6.1 Guidelines to report the attrition rates in infant fNIRS research

- A. Report the total number of subjects recruited prior to any data exclusion.
- B. Report the infant-driven attrition rate (IAR), calculated as the percentage of excluded subjects due to infant behaviors.
- C. Report the subject-driven attrition (SAR), calculated as the percentage of subjects who were excluded due to signal-driven reasons (e.g., poor fit of the fNIRS cap, excessive artifacts).
- D. When possible, operationalize the criteria by which infants are excluded due to their signal (e.g., what number of seconds does an infant have to look away in order to be excluded for fussiness; use SD of the fNIRS signal to reflect excessive artifacts).

- E. Report the percentage of subjects who were excluded due to technical difficulties (e.g., file corruption, program crash), experimenter error, or other reasons.
- F. Report the total attrition rate (TAR), calculated as the percentage of all subjects who were excluded from the final analyses.
- G. Report the demographics of the population included in as much detail as is feasible (sex, race/ethnicity, socio-economic status, language exposure, etc.) as well as the demographics of the population excluded with the same detail (ideally broken down by source of attrition). This step is essential for determining the external validity of your sample and the ways in which attrition is impacting that.

4.6.2 Guidelines to minimize the attrition rate in infant fNIRS research

- A. Develop fNIRS caps that are fitted to infants' head sizes
- B. Limit the number of channels in the fNIRS cap to only those that are necessary
- C. Increase comfort for the infant subjects
- D. Use block designs rather than trials designs, whenever possible
- E. Use stimuli rather than no stimuli
- F. Seek to minimize behavioral issues when working with older infants (e.g., > 5 months); seek to minimize signal-related issues when working with younger infants (e.g., < 5 months).

Summary

Despite the well-established importance of experiences during infancy on development outcomes, there is much to discover about the role that infants themselves may play. We challenged the traditional notion of an infant as a “sponge,” a passive recipient who is unidirectionally given information. We instead argued that infants are active agents who direct their experiences and influence their own developments.

In this thesis, we provided evidence that infants engage in active engagements, such as prediction, attention, and learning, which allow infants to gather information and modify their internal representations. We furthermore discussed the impact of these active engagements on infants’ cognitive, perceptual, and neural development in four chapters. In our first chapter, we started with an in-depth review of research evidence showing the active engagements that infants use. We specifically defined attention, prediction, and learning as three examples of active engagements that importantly affect infants’ developments. Then, in the second chapter, we reported neural data we collected from a novel fNIRS experiments we conducted and discussed how infants’ engagement in these active engagements precede and bring about neural developments. In the third chapter, we presented eye-tracking data showing a reciprocal relationship between two important active engagements of selective attention and learning and discussed how the cyclical loop may play a crucial role in catalyzing cognitive and perceptual developments. Finally, in the fourth chapter, we presented analyses on the infant research methodology to aid clean and reproducible research on the developmental impact of infants’ active engagements.

Combined, the work presented in this thesis further our understanding of infants’ active engagements and how these active engagements shape the trajectories of cognitive, perceptual,

and neural development. Our work lays the foundation for further exploration the roles of the active engagements on long-term changes in the infants' development. This area of research will reveal how the relationship between infants' active engagement and the environmental patterns may ultimately lead to the specialization of perceptual-cognitive systems.

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