

## REVIEW ARTICLE

# Attrition rate in infant fNIRS research: A meta-analysis

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## Abstract

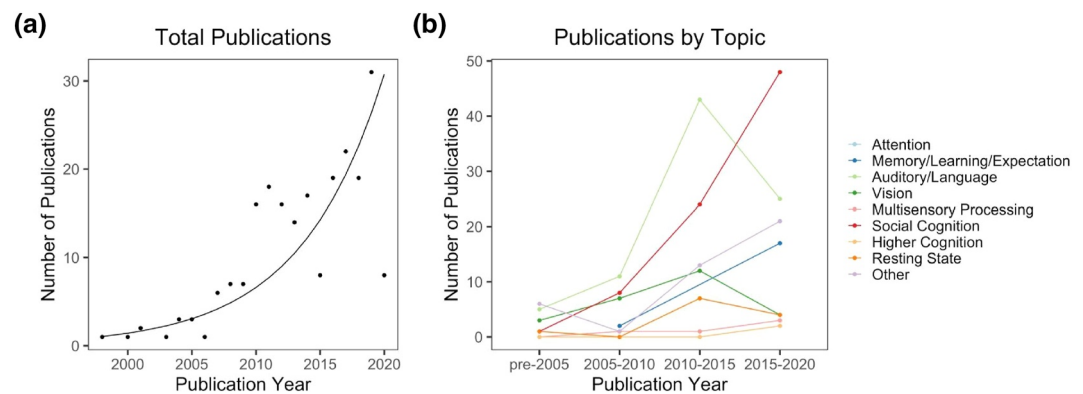
Understanding the trends and predictors of attrition rate, or the proportion of collected data that is excluded from the final analyses, is important for accurate research planning, assessing data integrity, and ensuring generalizability. In this pre-registered meta-analysis, we reviewed 182 publications 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 that reported the specific reasons for subject exclusion, 21.50% of the attrition was infant-driven, while 14.21% was 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 for 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.

# 1 | INTRODUCTION

## 1.1 | Introduction to fNIRS and attrition

The introduction of fNIRS as a neuroimaging technique has transformed the landscape for infant brain research. fNIRS is an increasingly popular tool that uses near-infrared light to non-invasively measure cortical hemodynamic responses (Elwell & Cooper, 2011). fNIRS hardware is commonly in the form of a malleable cloth cap fitted with many source and detector optodes, which are optical sensor devices that measure the hemoglobin concentration. Changes in the intensity of light emitted by a source optode are backscattered to a detector optode, which reveals the oxygenated hemoglobin levels in the small area of the neocortex underneath each pair of source and detector optodes. This small area of the neocortex that fNIRS measures is referred to as channels, and the hemoglobin levels for each channel can be digitized and analyzed. Because fNIRS measures the hemoglobin concentration changes in the brain, the results are comparable to those of fMRI. Given that fMRI is difficult to use for awake infants because fMRI machines are loud, immobile, and often require infants to be separated from their parents in an unfamiliar environment, fNIRS provides a practical alternative that makes a similar measurement. In addition, because fNIRS is usually in the form of a cap worn by the infant, the hardware aspects and the comfort level experienced by infant subjects are similar to those of EEG. Although fNIRS has a poorer spatial resolution than fMRI (but better than EEG) and is only able to record from the neocortex, fNIRS can essentially capture the advantages of both fMRI's localizable hemodynamic data and EEG's comfort and convenience. In addition, a rapid development of analysis techniques (e.g., Behrendt et al., 2018) has helped fNIRS become relatively motion-robust (Lloyd-Fox et al., 2010; Nishiyori, 2016). Thus, fNIRS provides a practical neuroimaging method that is safe, affordable, portable, and helpful to increase infants' task compliance compared to other neuroimaging methods (for reviews, see Aslin & Mehler, 2005; Lloyd-Fox et al., 2010; Gervain et al., 2011).

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). 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 (Figure 1a). Considering these trends by research area, the increase was the most pronounced for research in two



**FIGURE 1** Trends in infant fNIRS research. (a) Since its inception as an infant neuroimaging technique, fNIRS has been used in an increasing number of infant cognitive neuroscience experiments. Each dot represents the total number of publications in a given year. (b) There has been a general increase in the number of publications on all topics, but the increase was most pronounced for research on auditory processing/language and social cognition

categories, auditory processing and language and social cognition, but was observed in all explored topics of research (Figure 1b).

The goal of this meta-analysis is to thoroughly investigate attrition in infant fNIRS studies. Attrition rate is defined as the proportion of participants that are recruited for the study but ultimately excluded from the final analyses. High attrition rate is a prevalent issue in infant research regardless of methodology (e.g., Dehaene-Lambertz et al., 2010; 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. Thus, thoroughly understanding the attrition rate is a key part of scientific integrity. While it is known that the attrition rate is high, there are many questions about attrition rate in infancy studies in general and infant fNIRS studies in particular, such as: What is the field-wide attrition rate? Is the attrition rate in infancy fNIRS similar to infancy behavioral studies (e.g., studies using looking time) or is it higher due to the additional challenges of the fNIRS recordings? How does fNIRS attrition compare to other neuroimaging modalities (e.g., EEG)? Is the attrition rate in fNIRS studies impacted by various experimental factors? What can be done to minimize attrition rate in infant fNIRS studies?

## 1.2 | Possible causes of attrition in infant fNIRS research

### 1.2.1 | Infant-driven attrition

Infants' shorter attention span and likeliness to become fidgety and agitated (e.g., Aylward et al., 2002; Borgaro et al., 2003; Marshall et al., 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 (e.g., 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 et al. (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.

### 1.2.2 | Signal-driven attrition

Cristia et al. (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. While using a larger number of optodes can be beneficial to researchers as it increases the number of cortical locations being sampled, it can also contribute to a higher attrition rate because the fNIRS hardware may be heavier. Heavier hardware can hinder optode-scalp coupling, thereby decreasing data quality and resulting in data exclusion. 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 signal-related factors; for example, infants' hair growth can physically obstruct the optodes and also hinder optode-scalp coupling, thus inducing signal-related issues. This finding differs from those found in the two previously mentioned meta-analyses on attrition (Slaughter & Suddendorf, 2007; Stets et al., 2012), which found no effect of age.

### 1.3 | Current meta-analysis

The current meta-analysis adds to the current literature in three main ways. First, we provide the most up-to-date and comprehensive analyses of all experimental infant fNIRS publications from 1998 to 2020. In this more complete sample of studies, we investigated an expanded number of potential predictors of attrition compared to previous meta-analysis and reviews. We examined whether major findings from Cristia et al. (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. Second, we conducted analyses with a specific focus on attrition rates. Though a previous study briefly reported some results on the attrition in fNIRS research in a greater meta-analysis (Cristia et al., 2013), we have expanded our analyses to determine the impact of two branches of factors across a wide age range of infancy (0–2 years). 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 in future research. Finally, we share an in-depth look into the different potential causes of the attrition rate in infant fNIRS and how we may avoid them as much as possible.

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 on 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 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.

## 2 | MATERIAL AND METHODS

### 2.1 | Open-science and ethics

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>. The data for this paper is derived from previously published papers, and, thus, there are no experimental procedures involving human subjects and ethical protocols. All studies reviewed were conducted according to guidelines laid down in the Declaration of Helsinki, with written informed consent obtained from a parent or guardian for each child before any assessment or data collection.

## 2.2 | 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 first defined our inclusion criteria, or a list of criteria a publication needs to meet for us to include it in our analysis. Our inclusion criteria were as follows:

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 identified a validation set of 10 papers (Appendix A) that met all of the inclusion criteria, and used these papers to validate the search query in each of the following databases: Scopus, APA PsycINFO, and PubMed. A database search was considered valid if the search query returned those reference papers located in the database within the search results. If a paper was known to be present in the database and was not retrieved by the search query, the query was re-worked. This validation process ensures the search query has an appropriate level of sensitivity to return the maximum number of relevant papers. From this validation process, 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, documented, and can be found in their entirety in Appendix B. A total of 3812 records were identified via database searching and three records were obtained by requesting for data in ongoing research. 1698 duplicates were removed. Thus, a total of 2117 records were screened for inclusion. From the 2117 records, authors screened the titles and abstracts to determine whether each record meets all inclusion criteria that we defined earlier in this section. We excluded 1901 hits using the inclusion 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 2. In these 182 publications, there were 272 experiments with distinct infant subject samples. Thus, on average, there were approximately 1.42 (range: 1–4) experiments per publication.

### 2.3 | Attrition rates

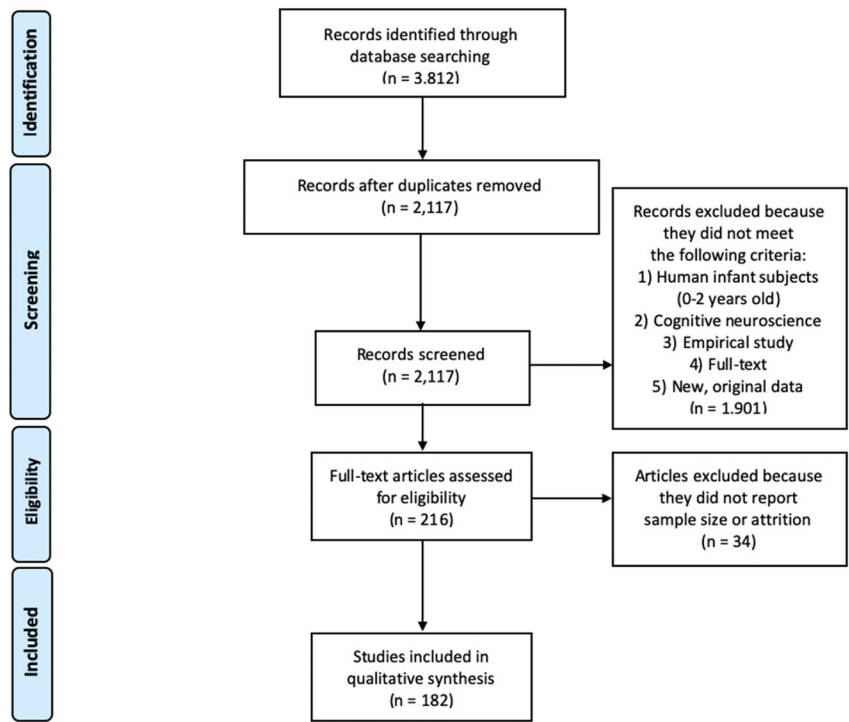
We defined three types of attrition rates as follows to account for different types of data exclusion that could arise in a research setting. We used these definitions to calculate the attrition in each of the 272 experiments.

*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.

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



**FIGURE 2** Study selection process. The study selection process is outlined here using the PRIMA Flow Diagram

*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.

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

## 2.4 | Parameters

### 2.4.1 | 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 (Edwards et al., 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.

### 2.4.2 | 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. Note that the systems being surveyed in this meta-analysis are predominantly before the advent and wide-spread use of light-weight or wearable systems. 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; a study was defined as a 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.



### 2.4.3 | 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.

## 2.5 | 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 4896 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 4418 of the 4896 variables, showing an inter-rater reliability of 90.23%. In case of a disagreement between the two independent coders, a third researcher will cast a tie-breaking vote.

## 2.6 | 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 the 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. We also performed follow-up investigations on the interaction effects from seemingly correlated variables such as hospitalization status x age and study design x type of stimuli.

After identifying the variables that had significant impacts on the attrition rate from the independent models, we performed follow-up analyses to investigate their combined impact in a single combined model. In addition, we further calculated the effect that each variable has by comparing our complete model with simpler models that included only subsets of the variables.

## 3 | RESULTS

### 3.1 | 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  $23.88 \pm 14.47$  infants. 220 out of 272 experiments reported enough information to calculate the total attrition rate (TAR). On average, 34.23% of subjects were excluded. 178 out of 220 experiments reported reasons for their attrition; 42 studies that did not report the reason for attrition or combined both infant and signal-driven reasons were used for TAR calculations only. 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; Figure 3). Studies that reported IAR or SAR were not significantly different from those that did not in terms of the TAR [ $t(200) = 0.939, p = 0.349$ ]. 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.

3.2 | Comparison with attrition rates reported with other research methodologies

We conducted additional analyses to determine whether there were differences between the attrition rates in infant fNIRS and in other methodologies. To do so, we performed a one-sample  $t$ -test to compare our distribution of TAR and IAR in infant fNIRS research against the distribution of rates reported for infant EEG research (Stets et al., 2012) and infant behavioral research (Slaughter & Suddendorf, 2007). 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 et al. (2012) did not break down their attrition rates into subtypes (e.g., IAR, SAR)

TABLE 1 Overview of the Attrition rates

Type of attrition	Mean attrition rate % $M$ (SD)
Total attrition rate (TAR)	34.23 ( $\pm 17.60$ )
Infant-driven attrition rate (IAR)	21.50 ( $\pm 14.42$ )
Signal-driven attrition rate (SAR)	20.24 ( $\pm 14.22$ )

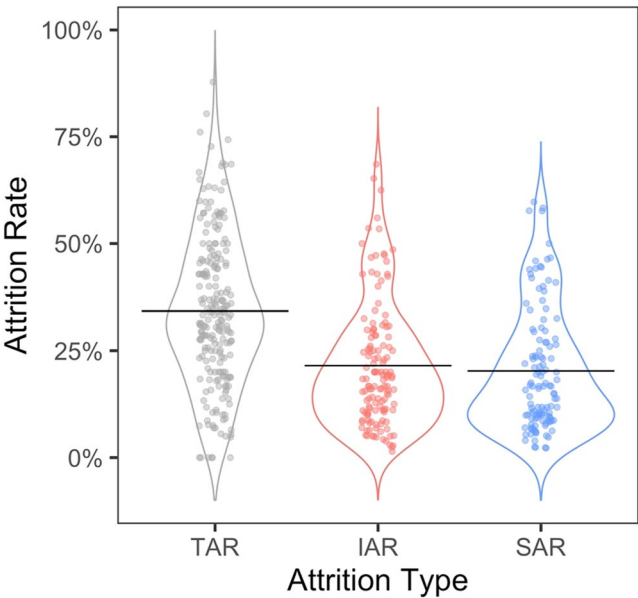


FIGURE 3 Distribution of attrition types in infant fNIRS research. The distributions of attrition rates reported by all infant fNIRS research to date are depicted for the three types of attrition we analyzed in this report (TAR, IAR, and SAR)

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 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 literature.

### 3.2.1 | Change in attrition rate over time

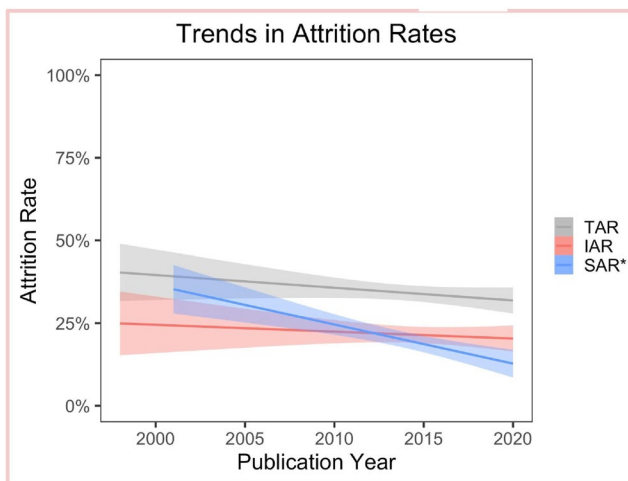
Given the incredible expansion of the field, we examined changes in the attrition rates as a function of publication year using simple linear regression. We found no significant change in TAR over the years ( $\beta = -0.39, t = -1.45, p = 0.148, R^2 = 0.01$ ). However, as hypothesized, there was a significant decrease in SAR over time ( $\beta = -1.19, t = -4.28, p < 0.001, R^2 = 0.13$ ), with IAR remaining stable ( $\beta = -0.21, t = -0.73, p = 0.469, R^2 = 0.00$ ; Figure 4).

We also examined whether the 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 [ $t(115) = 0.06, p = 0.950$ ].

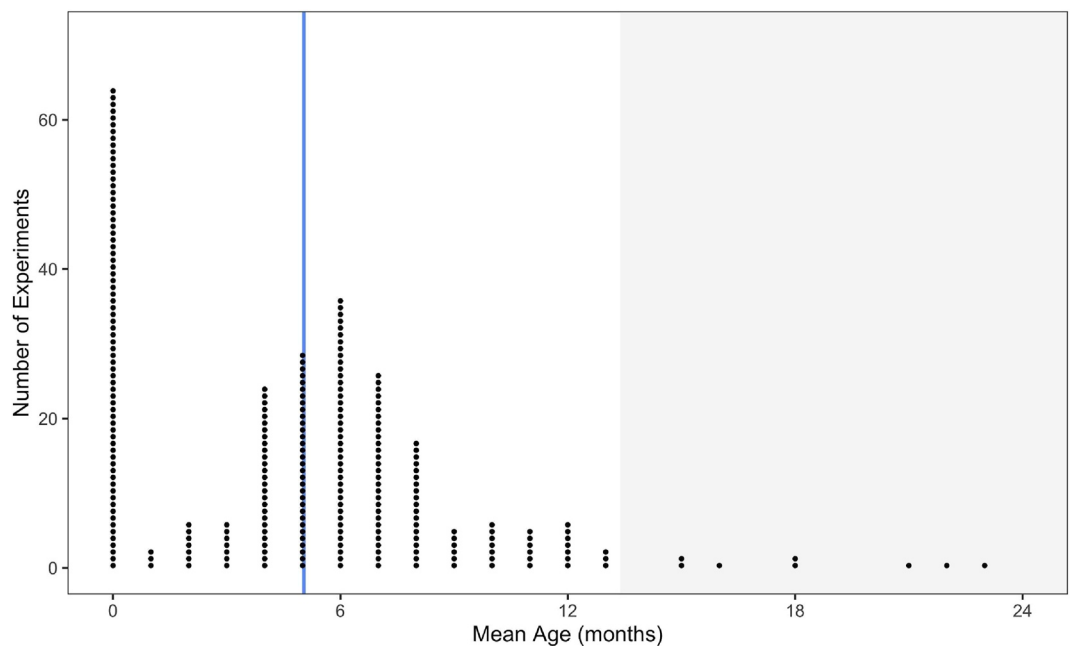
### 3.3 | Subject-related parameters

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

First, we examined the age distribution for all studies (Figure 5). Across 272 experiments, a total of 9114 infants were recruited, with a mean age of  $5.03 \pm 4.19$  months (range: 0.04–23.10). Age was not normally distributed throughout this range, as is found throughout the field of developmen-



**FIGURE 4** Attrition in infant fNIRS research over time. 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)



**FIGURE 5** 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

**TABLE 2** Overview of subject parameters

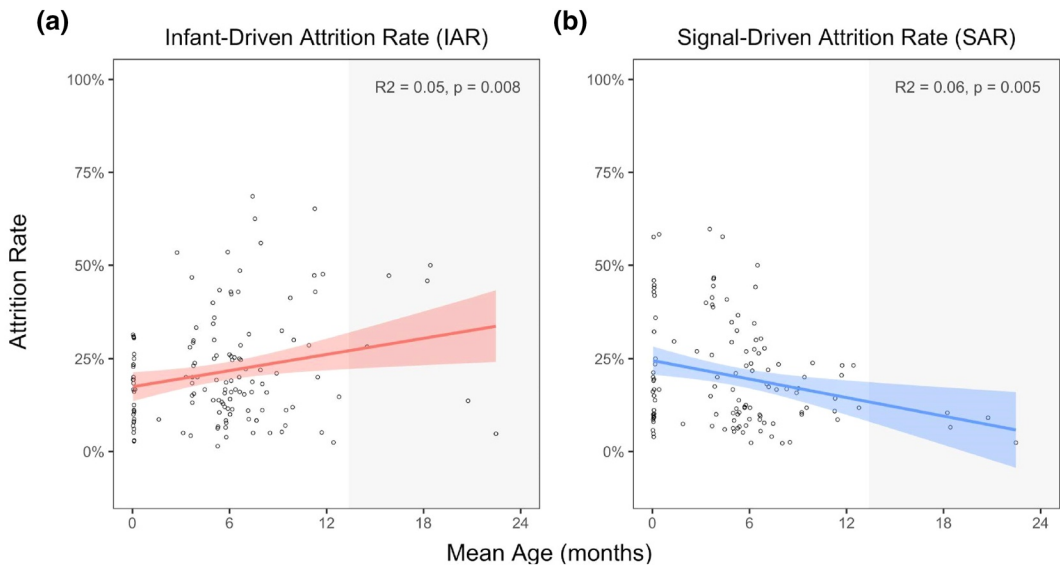
Subject parameters (continuous)	n	M (SD)	Range
Age (months)	272	5.03 (±4.19)	0.04–23.10
Outliers removed	264	4.63 (±3.47)	0.04–13.14
Sex (percentage of female subjects)	245	49.08 (±11.76)	15.38–95.24
Subject parameters (categorical)	n	%	
Hospitalization status	272		
In-Hospital	79	29.04%	
Not in hospital	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.

tal 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 (i.e., after we removed the outliers), as is consistent with best practices regarding transparency in reporting results. However, in our view, we expect the results of the partial sample may be more representative of the true effects, given the sparse number of studies with older infants.

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. The 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 ( $\beta = 0.76$ ,  $t = 2.70$ ,  $p = 0.008$ ,  $R^2 = 0.05$ ; Figure 6a) and weak but significant negative predictor of SAR ( $\beta = -0.83$ ,  $t = -2.86$ ,  $p = 0.005$ ,  $R^2 = 0.06$ ; Figure 6b). 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,



**FIGURE 6** Change in Infant-Driven Attrition Rate (IAR) and Signal-Driven Attrition Rate (SAR) 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

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.

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.

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 versus at-risk infants (e.g., preterm or familial risk for autism spectrum disorder). 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 versus 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% [ $t(218) = -2.09, p = 0.038$ ]. Although it may appear that these results were 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), our examination of the interaction between age and hospitalization status in a linear mixed model revealed no significant interaction effect on the TAR [ $\beta = 0.01, p = 0.624$ ] or IAR [ $\beta = 0.01, p = 0.731$ ]. However, 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 ( $W = 2495.5, p = 0.075$ ).

### 3.4 | Design parameters

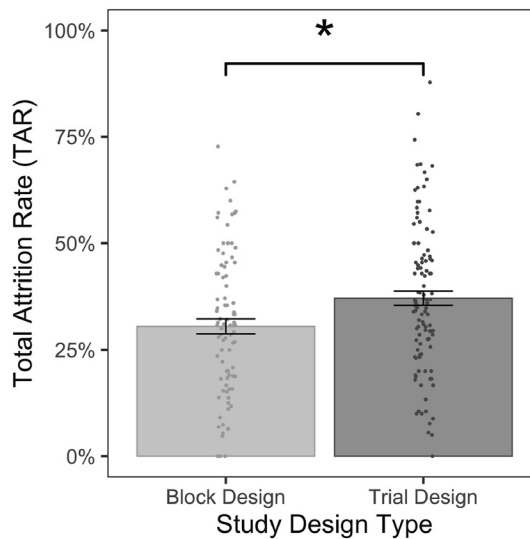
We next examined the impact of the designs of infant fNIRS experiments on the attrition rates (see summary of these variables in Table 3).

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 s (range: 0.1–7200 s,  $n = 251$ ). 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% [ $t(195) = -2.71, p = 0.007$ ; Figure 7]. 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

TABLE 3 Overview of design parameters

Design parameters (continuous)	n	M (SD)	Range
fNIRS configuration (# of channels)	248	26.10 ( $\pm 20.58$ )	2–94
Number of trials/blocks	190	17.22 ( $\pm 16.52$ )	1–92
Length of trials/blocks (seconds)	254	76.64 ( $\pm 471.45$ )	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%	



**FIGURE 7** 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

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 versus 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 s, meaning that outliers would have heavily influenced any observed effects and excluding these outliers would have left little to no variation to examine.

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 toward 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 versus 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 versus 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). To tease apart these two possible inter-related factors (study design and stimulus type), we examined the interaction between the type of stimulus and the experimental design in a linear mixed model. Our findings revealed that there was a significantly positive interaction effect between the trial design and the audiovisual stimuli on both the TAR [ $\beta = 0.22, p = 0.001$ ] or IAR [ $\beta = 0.14, p = 0.037$ ]. In other words, audiovisual stimuli significantly raised the attrition rate when the experiment used a trial design rather than a block design. 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 ( $W = 985, p = 0.328$ ).

### 3.5 | Single model for attrition rate to calculate projected attrition rate

After we found that the participant age, number of channels, task design, and type of stimulus were the four variables that had the largest impact on the attrition rate, we performed a linear model analysis to estimate the relative weight of these variables on the TAR. We coded participant age and the number of channels as continuous variables and task design and type of stimulus as categorical variables. We found that, in this combined model, the participant age was not a significant predictor of TAR ( $\beta = 0.000, p = 0.994$ ) but the number of channels was a weak but significant predictor of TAR ( $\beta = 0.003, p = 0.001$ ). Trial design non-significantly increased the TAR compared to block design ( $\beta_{\text{trial}} = 0.036, p = 0.237$ ). For the type of stimulus, audiovisual stimuli ( $\beta_{\text{audiovisual}} = 0.038, p = 0.306$ ) and visual stimuli ( $\beta_{\text{visual}} = 0.036, p = 0.376$ ) both non-significantly increased the TAR compared to audio-only stimuli. In other words, only the number of channels accounted for unique variance. The relative importance of the number of channels was further confirmed with residual sum of squares (RSS) analyses. We found that the RSS was only significant when the number of channels was excluded from the model (RSS = 4.89,  $p = 0.001$ ) and not when participant age (RSS = 4.58,  $p = 0.994$ ), task design (RSS = 4.62,  $p = 0.237$ ), or type of stimuli (RSS = 4.61,  $p = 0.565$ ) were excluded from the model. Using the abovementioned beta-values, researchers can estimate the total attrition rate they can expect based on participant age, number of channels, task design, and type of stimuli.

## 4 | 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, the database of all of this information is publicly available at (<https://github.com/soribaek/Attrition-Rate-in-Infant-fNIRS-Research>) and we have included a single model with all significant or important parameters in our analysis so researchers can calculate their projected attrition rate based on their experimental parameters.

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: After all, both non-invasively collect data via a lightweight and relatively noiseless device that infants can wear on their head while sitting on their parent's lap. 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 only 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 et al., 2010; Virtanen et al., 2011) and the development of advanced toolboxes (Fantini, 2014; Hassanpour et al., 2014; Huppert et al., 2009; 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 the age of participants predicted overall greater attrition. However, when considering sub-types of attrition, the picture is more complex. On one hand, age was a positive predictor of IAR (i.e., older infants are more likely to be fussy). On the other hand, age was a negative predictor of SAR. As infants' behaviors, mobility, and understanding of their surroundings change drastically in the first 2 years of life, the reasons for exclusion also appear to change with age. Our results indicate that younger infants were more likely to be excluded due to signal-related reasons, perhaps because standard fNIRS caps do not fit as snugly on their small heads or because they are less comfortable with the additional weight of the fNIRS hardware. In contrast, older infants were more likely to be excluded due to reasons related to their behavior, such as being more fussy. 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 and 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 relating age to attrition 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).

As suggested by one anonymous reviewer, it is important to consider what best engages the participant to increase compliance and to balance getting sufficient data for inclusion in the study with not making the task too long or boring for them to complete. The findings from our study suggest that this balance may be more important as infants get older. 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). These null findings are in contrast to prior research, which found that clinical characteristics greatly influenced how likely adult subjects were to cooperate in an experimental study (Andreescu et al., 2008; Chang et al., 2009; Issakidis & Andrews, 2004). It is important to note that a limitation of our meta-analysis is the inability to distinguish between different clinically relevant groups due to the small number of these studies. Grouping all clinically relevant populations together may be obfuscating patterns linking particular clinical groups with attrition rates. However, this discrepancy may also point to a difference in the predictors of attrition between infant and adult subject populations.

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; Watanabe et al., 2008). However, these findings should be considered in context. The vast majority of the research included in this study is from the use of systems designed before the advent of light-weight or wearable fNIRS systems. It is likely that the wide-spread use of these systems could affect either the overall attrition rate and/or the relationship between the number of optodes and attrition. Future research will be needed to determine whether this is the case.

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 et al., 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 s) is not equivalent to participating in a long study. Second, these findings point to 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 that 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 et al., 2008; Stets et al., 2012) and thus have been employed to increase subject retention (e.g., Nikkel & Karrer, 1994; Snyder et al., 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 et al. (2013), which 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 regard 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 paper 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.

## 5 | CONCLUSION

### 5.1 | Guidelines to report the attrition rates in infant fNIRS research

1. Report the total number of subjects recruited prior to any data exclusion.
2. Report the infant-driven attrition rate (IAR), calculated as the percentage of excluded subjects due to infant behaviors.
3. 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).
4. When possible, operationalize the criteria by which infants are excluded due to their signal (e.g., how long does an infant have to look away in order to be excluded for fussiness; use SD of the fNIRS signal to reflect excessive artifacts).
5. Report the percentage of subjects who were excluded due to technical difficulties (e.g., file corruption, program crash), experimenter error, or other reasons.
6. Report the total attrition rate (TAR), calculated as the percentage of all subjects who were excluded from the final analyses.
7. 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 it.

### 5.2 | Guidelines to minimize the attrition rate in infant fNIRS research

1. Develop fNIRS caps that are fitted to infants' head sizes
2. Limit the number of channels in the fNIRS cap to only those that are necessary
3. Increase comfort for the infant subjects
4. Use block designs rather than trial designs whenever possible
5. Use stimuli rather than no stimuli
6. 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).

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## REFERENCES

- Andresescu, C., Chang, C. C., Mulsant, B. H., & Ganguli, M. (2008). Twelve-year depressive symptom trajectories and their predictors in a community sample of older adults. *International Psychogeriatrics*, 20(02), 221–236. <https://doi.org/10.1017/s1041610207006667>
- Aslin, R. N., & Mehler, J. (2005). Near-infrared spectroscopy for functional studies of brain activity in human infants: Promise, prospects, and challenges. *Journal of Biomedical Optics*, 10(1), 11009. <https://doi.org/10.1117/1.1854672>
- Aylward, G. P., Brager, P., & Harper, D. C. (2002). Relations between visual and auditory continuous performance tests in a clinical population: A descriptive study. *Developmental Neuropsychology*, 21(3), 285–303. [https://doi.org/10.1207/s15326942dn2103\\_5](https://doi.org/10.1207/s15326942dn2103_5)
- Azhari, A., Truzzi, A., Neoh, M. J. Y., Balagtas, J. P. M., Tan, H. H., Goh, P. P., Ang, X. A., Setoh, P., Rigo, P., Bornstein, M. H., & Esposito, G. (2020). A decade of infant neuroimaging research: What have we learned and where are we going? *Infant Behavior and Development*, 58, 101389. <https://doi.org/10.1016/j.infbeh.2019.101389>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Behrendt, H. F., Firk, C., Nelson, C. A., & Perdue, K. L. (2018). Motion correction for infant functional near-infrared spectroscopy with an application to live interaction data. *Neurophotonics*, 5(01), 1. <https://doi.org/10.1117/1.NPh.5.1.015004>
- Borgaro, S., Pogge, D. L., DeLuca, V. A., Bilginer, L., Stokes, J., & Harvey, P. D. (2003). Convergence of different versions of the continuous performance test: Clinical and scientific implications. *Journal of Clinical and Experimental Neuropsychology*, 25(2), 283–292. <https://doi.org/10.1076/jcen.25.2.283.13646>
- Brannon, E. M., Libertus, M. E., Meck, W. H., & Woldorff, M. G. (2008). Electrophysiological measures of time processing in infant and adult brains: Weber's law holds. *Journal of Cognitive Neuroscience*, 20(2), 193–203. <https://doi.org/10.1162/jocn.2008.20016>
- Chang, C. C., Yang, H. C., Tang, G., & Ganguli, M. (2009). Minimizing attrition bias: A longitudinal study of depressive symptoms in an elderly cohort. *International Psychogeriatrics*, 21(05), 869–878. <https://doi.org/10.1017/s104161020900876x>
- Cope, M., Delpy, D. T., Reynolds, E. O. R., Wray, S., Wyatt, J., & Van der Zee, P. (1988). Methods of quantitating cerebral near infrared spectroscopy data. In M. Mochizuki, C. R. Honig, T. Koyama, T. K. Goldstick, & D. F. Bruley (Eds.), *Oxygen transport to tissue X* (pp. 183–189). Springer US).
- Cristia, A., Dupoux, E., Hakuno, Y., Lloyd-Fox, S., Schuetze, M., Kivits, J., Bergvelt, T., van Gelder, M., Filippin, L., Charron, S., & Minagawa-Kawai, Y. (2013). An online database of infant functional near infrared spectroscopy studies: A community-augmented systematic review. *PLoS One*, 8(3), e58906. <https://doi.org/10.1371/journal.pone.0058906>
- Cui, X., Bray, S., & Reiss, A. L. (2010). Functional near infrared spectroscopy (fNIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. *NeuroImage*, 49(4), 3039–3046. <https://doi.org/10.1016/j.neuroimage.2009.11.050>
- Dehaene-Lambertz, G., Montavont, A., Jobert, A., Alliol, L., Dubois, J., Hertz-Pannier, L., & Dehaene, S. (2010). Language or music, mother or Mozart? Structural and environmental influences on infants' language networks. *Brain and Language*, 114(2), 53–65. <https://doi.org/10.1016/j.bandl.2009.09.003>
- Edwards, L. A., Wagner, J. B., Tager-Flusberg, H., & Nelson, C. A. (2017). Differences in neural correlates of speech perception in 3 Month olds at high and low risk for autism spectrum disorder. *Journal of Autism and Developmental Disorders*, 47(10), 3125–3138. <https://doi.org/10.1007/s10803-017-3222-1>
- Elwell, C. E., & Cooper, C. E. (2011). Making light work: Illuminating the future of biomedical optics. *Philosophical transactions. Series A, Mathematical, physical, and engineering sciences*, 369(1955), 4358–4379. <https://doi.org/10.1098/rsta.2011.0303>
- Fantini, S. (2014). Dynamic model for the tissue concentration and oxygen saturation of he-moglobin in relation to blood volume, flow velocity, and oxygen consumption: Implications for functional neuroimaging and coherent hemodynamics spectroscopy (CHS). *NeuroImage*, 85, 202–221. <https://doi.org/10.1016/j.neuroimage.2013.03.065>
- Flick, S. N. (1988). Managing attrition in clinical research. *Clinical Psychology Review*, 8(5), 499–515. [https://doi.org/10.1016/072-7358\(88\)90076-1](https://doi.org/10.1016/072-7358(88)90076-1)
- Gervain, J., Mehler, J., Werker, J. F., Nelson, C. a., Csibra, G., Lloyd-Fox, S., Shukla, M., & Aslin, R. N. (2011). Near-infrared spectroscopy: A report from the McDonnell infant methodology consortium. *Dev Cogn Neurosci*, 1, 22–46. Pmid:22436417. <https://doi.org/10.1016/j.dcn.2010.07.004>



- Hassanpour, M. S., White, B. R., Eggebrecht, A. T., Ferradal, S. L., Snyder, A. Z., & Culver, J. P. (2014). Statistical analysis of high density diffuse optical tomography. *NeuroImage*, 85, 104–116. <https://doi.org/10.1016/j.neuroimage.2013.05.105>
- Hessels, R. S., Andersson, R., Hooge, I. T. C., Nyström, M., & Kemner, C. (2015). Consequences of eye color, positioning, and head movement for eye-tracking data quality in infant research. *Infancy*, 20(6), 601–633. <https://doi.org/10.1111/inf.12093>
- Hoehl, S., & Wahl, S. (2012). Recording infant ERP data for cognitive research. *Developmental Neuropsychology*, 37(3), 187–209. <https://doi.org/10.1080/87565641.2011.627958>
- Hoerger, M. (2010). Participant dropout as a function of survey length in Internet-mediated university studies: Implications for study design and voluntary participation in psychological research. *Cyberpsychology, Behavior, and Social Networking*, 13(6), 697–700. <https://doi.org/10.1089/cyber.2009.0445>
- Hunter, M. A., & Ames, E. W. (1988). A multifactor model of infant preferences for novel and familiar stimuli. *Advances in Infancy Research*, 5, 69–95.
- Huppert, T. J., Diamond, S. G., Franceschini, M. A., & Boas, D. A. (2009). HomER: A review of time-series analysis methods for near-infrared spectroscopy of the brain. *Applied Optics*, 48(10), D280–D298. <https://doi.org/10.1364/ao.48.00d280>. <https://psycnet.apa.org/record/1997-72976-001>
- Issakidis, C., & Andrews, G. (2004). Pretreatment attrition and drop-out in an outpatient clinic for anxiety disorders. *Acta Psychiatrica Scandinavica*, 109(6), 426–433. <https://doi.org/10.1111/j.1600-0047.2004.00264.x>
- Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks effect: Human infants allocate attention to visual sequences that are neither too simple nor too complex. *PLoS One*, 7(5), e36399. <https://doi.org/10.1371/journal.pone.0036399>
- Koh, P. H., Glaser, D. E., Flandin, G., Kiebel, S., Butterworth, B., Maki, A., Delpy, D. T., & Elwell, C. E. (2007). Functional optical signal analysis: A software tool for near-infrared spectroscopy data processing incorporating statistical parametric mapping. *Journal of Biomedical Optics*, 12(6), 064010. <https://doi.org/10.1117/1.2804092>
- Kugley, S., Wade, A., Thomas, J., Mahood, Q., Jørgensen, A. M. K., Hammerstrøm, K., & Sathe, N. (2016). Searching for studies: A guide to information retrieval for Campbell systematic reviews. *Campbell Methods Guides*, 1, 1–73. <https://doi.org/10.4073/cm.2016.1>. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0036399>
- Lloyd-Fox, S., Blasi, A., & Elwell, C. E. (2010). Illuminating the developing brain: The past, present and future of functional near infrared spectroscopy. *Neuroscience & Biobehavioral Reviews*, 34(3), 269–284. <https://doi.org/10.1016/j.neubiorev.2009.07.008>
- Lloyd-Fox, S., Blasi, A., Elwell, C. E., Charman, T., Murphy, D., & Johnson, M. H. (2013). Reduced neural sensitivity to social stimuli in infants at risk for autism. *Proc R Soc B*, 280(1758), 20123026. <https://doi.org/10.1098/rspb.2012.3026>
- Marshall, P. J., Reeb, B. C., & Fox, N. A. (2009). Electrophysiological responses to auditory novelty in temperamentally different 9-month-old infants. *Developmental Science*, 12(4), 568–582. <https://doi.org/10.1111/j.1467-7687.2008.00808.x>
- Nikkel, L., & Karrer, R. (1994). Differential effects of experience on the ERP and behavior of 6-month-old infants: Trends during repeated stimulus presentations. *Developmental Neuropsychology*, 10, 1–11. <https://doi.org/10.1080/87565649409540561>
- Nishiyori, R. (2016). fNIRS: An emergent method to document functional cortical activity during infant movements. *Frontiers in Psychology*, 7, 533. <https://doi.org/10.3389/fpsyg.2016.00533>
- Picton, T. W., & Taylor, M. J. (2007). Electrophysiological evaluation of human brain development. *Developmental Neuropsychology*, 31(3), 249–278. <https://doi.org/10.1080/87565640701228732>
- R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>
- Reynolds, G. D., & Guy, M. W. (2012). Brain–behavior relations in infancy: Integrative approaches to examining infant looking behavior and event-related potentials. *Developmental Neuropsychology*, 37(3), 210–225. <https://doi.org/10.1080/87565641.2011.629703>
- Richards, J. E. (2003). Attention affects the recognition of briefly presented visual stimuli in infants: An ERP study. *Developmental Science*, 6(3), 312–328. <https://doi.org/10.1111/1467-7687.00287>
- Slaughter, V., & Suddendorf, T. (2007). Participant loss due to “fussiness” in infant visual paradigms: A review of the last 20 years. *Infant Behavior and Development*, 30(3), 505–514. <https://doi.org/10.1016/j.infbeh.2006.12.006>



- Snyder, K., Webb, S. J., & Nelson, C. A. (2002). Theoretical and methodological implications of variability in infant brain response during a recognition memory paradigm. *Infant Behavior and Development*, 25(4), 466–494. [https://doi.org/10.1016/s0163-6383\(02\)00146-7](https://doi.org/10.1016/s0163-6383(02)00146-7)
- Stets, M., Stahl, D., & Reid, V. M. (2012). A meta-analysis investigating factors underlying attrition rates in infant ERP studies. *Developmental Neuropsychology*, 37(3), 226–252. <https://doi.org/10.1080/87565641.2012.654867>
- Tsuzuki, D., & Dan, I. (2014). Spatial registration for functional near-infrared spectroscopy: from channel position on the scalp to cortical location in individual and group analyses. *NeuroImage*, 85, 92–103. <https://doi.org/10.1016/j.neuroimage.2013.07.025>
- Virtanen, J., Noponen, T., Kotilahti, K., Virtanen, J., & Ilmoniemi, R. J. (2011). Accelerometer-based method for correcting signal baseline changes caused by motion artifacts in medical near-infrared spectroscopy. *Journal of Biomedical Optics*, 16(8), 087005. <https://doi.org/10.1117/1.3606576>
- Watanabe, H., Homae, F., Nakano, T., & Taga, G. (2008). Functional activation in diverse regions of the developing brain of human infants. *NeuroImage*, 43(2), 346–357. <https://doi.org/10.1016/j.neuroimage.2008.07.014>

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## APPENDIX A

### Validation set

Altvater-Mackensen, N., & Grossmann, T. (2016). The role of left inferior frontal cortex during audio-visual speech perception in infants. *NeuroImage*. <https://doi.org/10.1016/j.neuroimage.2016.02.061>

Scopus: YES

Boldin, A. M., Geiger, R., & Emberson, L. L. (2018). The emergence of top-down, sensory prediction during learning in infancy: A comparison of full-term and preterm infants. *Developmental Psychobiology*. <https://doi.org/10.1002/dev.21624>

Scopus: YES

Emberson, L. L., Boldin, A. M., Robertson, C. E., Cannon, G., & Aslin, R. N. (2019). Expectation affects neural repetition suppression in infancy. *Developmental Cognitive Neuroscience*, 37(100,597). <https://doi.org/10.1016/j.dcn.2018.11.001>

Scopus: YES

Emberson, L. L., Cannon, G., Palmeri, H., Richards, J. E., & Aslin, R. N. (2017). Using fNIRS to examine occipital and temporal responses to stimulus repetition in young infants: Evidence of selective frontal cortex involvement. *Developmental Cognitive Neuroscience*. <https://doi.org/10.1016/j.dcn.2016.11.002>

Scopus: YES

Emberson, L. L., Richards, J. E., & Aslin, R. N. (2015). Top-down modulation in the infant brain: Learning-induced expectations rapidly affect the sensory cortex at 6 months. *Proceedings of the National Academy of Sciences of the United States of America*, 112(31), 9585–9590. <https://doi.org/10.1073/pnas.1510343112>

Scopus: YES

Hyde, D. C., Boas, D. A., Blair, C., & Carey, S. (2010). Near-infrared spectroscopy shows right parietal specialization for number in pre-verbal infants. *NeuroImage*. <https://doi.org/10.1016/j.neuroimage.2010.06.030>

Scopus: YES

Lloyd-Fox, S., Blasi, A., Volein, A., Everdell, N., Elwell, C. E., & Johnson, M. H. (2009). Social perception in infancy: A near infrared spectroscopy study. *Child Development*. <https://doi.org/10.1111/j.1467-8624.2009.01312.x>

Scopus: YES

Lloyd-Fox, S., Wu, R., Richards, J. E., Elwell, C. E., & Johnson, M. H. (2015). Cortical activation to action perception is associated with action production abilities in young infants. *Cerebral Cortex*. <https://doi.org/10.1093/cercor/bht207>

Scopus: YES

Miguel, H. O., Lisboa, I. C., Gonçalves, O. F., & Sampaio, A. (2019). Brain mechanisms for processing discriminative and affective touch in 7-month-old infants. *Developmental Cognitive Neuroscience*. <https://doi.org/10.1016/j.dcn.2017.10.008>

Scopus: YES

Werchan, D. M., & Amso, D. (2020). Top-down knowledge rapidly acquired through abstract rule learning biases subsequent visual attention in 9-month-old infants. *Developmental Cognitive Neuroscience*. <https://doi.org/10.1016/j.dcn.2020.100761>

Scopus: In database, not retrieved. No mention of fNIRS/NIRS

## APPENDIX B

### Database search

fnirs or functional near infrared spectroscopy or nirs or near infrared spectroscopy  
baby OR babies OR infant OR infants OR toddler\*

Scopus

1911

PsycINFO

275

PubMed

1626

Total Records

3812

Duplicates Removed

1695

Records for Screening

2117

Databases

Scopus

Date Searched: 04/03/2020

( TITLE-ABS-KEY ( fnirs OR "functional near infrared spectroscopy" OR nirs OR "near infrared spectroscopy" ) AND TITLE-ABS-KEY ( baby OR babies OR infant OR infants OR infancy OR toddler\* ) )

Results: 1911

PsycINFO

Date Searched: 04/03/2020

( fnirs or functional near infrared spectroscopy or nirs or near infrared spectroscopy ) AND ( baby OR babies OR infant OR infants OR infancy OR toddler\* )

Limiters - English; Publication Type: All Journals, Dissertation Abstract

Search modes - Boolean/Phrase

Results: 275

PubMed

Date Searched: 04/03/2020

((("spectroscopy, near-infrared"[MeSH Terms] OR ("spectroscopy"[All Fields] AND "near-infrared"[All Fields]) OR "near-infrared spectroscopy"[All Fields] OR ("near"[All Fields] AND "infrared"[All Fields] AND "spectroscopy"[All Fields]) OR "near infrared spectroscopy"[All Fields]) OR (functional[All Fields] AND ("spectroscopy, near-infrared"[MeSH Terms] OR ("spectroscopy"[All Fields] AND "near-infrared"[All Fields]) OR "near-infrared spectroscopy"[All Fields] OR ("near"[All Fields] AND "infrared"[All Fields] AND "spectroscopy"[All Fields]) OR "near infrared spectroscopy"[All Fields]))) OR fNIRS[All Fields]) OR NIRS[All Fields]) AND ("baby"[All Fields] OR "babies"[All Fields] OR "infant"[All Fields] OR "infants"[All Fields] OR "infancy"[All Fields] OR "toddler\*"[All Fields])

Results: 1626

Limiters:

Language: English

Document Type: articles, conference papers, dissertations and theses