

RESEARCH ARTICLE

Signal in the noise: Dimensions of predictability in the home auditory environment are associated with neurobehavioral measures of early infant sustained attention

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Abstract

The home auditory environment influences the development of early language abilities, and excessive noise exposure is increasingly linked with deficits in language and reading scores in children. However, fewer studies have considered the role of noise exposure in shaping the development of attentional processing in early infancy, a foundational neurocognitive skill relevant for learning. Here, we used passive at-home auditory recording to investigate how multiple dimensions of infants' home auditory environments, including both the quantity and the predictability of auditory input, impacts neural and behavioral measures of sustained attention in a sociodemographically diverse sample of 3-month-old infants ($N = 98$ infants, 62 males; age $M = 3.48$ months, $SD = 0.39$; 52% Hispanic/Latino). Results indicated that infants who were exposed to more predictable patterns of auditory input in the home demonstrated longer overall time in sustained attention during laboratory assessments. In addition, infants' who experienced more predictable auditory input also demonstrated greater relative increases in electroencephalography frontal theta power during periods of sustained attention, a neural marker relevant to information processing and attentional control. These findings provide novel evidence into the importance of the predictability of early environmental inputs in shaping developing cortical circuitry and attentional systems from the first months of postnatal life.

KEYWORDS

EEG, home environment, infancy, sustained attention

1 | INTRODUCTION

Variability in the early environment is increasingly recognized as an essential moderator of individual differences in brain and cognitive development. For instance, prior literature indicates that the home linguistic environment is associated with early language and cognitive abilities, with increases in the quantity and variability of linguistic exposure correlating with enhanced memory encoding and language development (Brito, 2017; Brito & Barr, 2012; Brito et al., 2020). Excessive ambient noise exposure in the home

is also increasingly linked with deficits in language and reading scores in children (Evans, 2006; Haines et al., 2001; Hygge et al., 2002; Simon et al., 2022). However, fewer studies have considered the role of the home auditory environment in shaping individual differences in trajectories of attentional processing in infancy, a foundational and early emerging neurocognitive skill relevant for learning. In this study, we used passive recording of infants' daily home environments to investigate whether moment-to-moment variations in auditory input in the naturalistic home environment impacts neural and behavioral measures of infant attentional processing.

Specifically, we used the Language Environment Analysis (LENA) system to quantify multiple dimensions of infants' home auditory environments, including both the quantity and the predictability of exposure to linguistic and nonlinguistic sounds throughout the day. We examine associations between these dimensions and individual differences in behavioral and neural measures of infant sustained attention at 3 months of age.

1.1 | Infant sustained attention

A core aspect of attention is to filter competing or distracting inputs and selectively bias our finite cognitive resources to a subset of those inputs (Amso & Scerif, 2015). The earliest manifestations of sustained attention are observable from the first months of postnatal life and shows rapid developmental change over infancy and early childhood (Colombo, 2001). Infant sustained attention has predominately been studied by the length of time spent attending to or interacting with a specific task or stimulus, or alternatively, by changes in heart rate derived from electrocardiogram (ECG) recordings (Reynolds & Richards, 2008). Using ECG measures, states of sustained attention can be identified by phases in which the infant's heart rate decelerates and remains significantly lower than a prestimulus baseline (Courage et al., 2006; Reynolds & Richards, 2008; Reynolds et al., 2010; Richards, 2010; Mallin and Richards, 2012). Infants' heart rate often accelerates to the baseline level over some period of time, signaling attention termination—a phase when the infant is no longer attentive even if they may continue to orient toward the stimulus. Prior studies indicate that infants respond differentially when they are in heart rate-defined phases of sustained attention relative to attention termination, including enhanced distractor suppression and superior memory encoding (Richards, Reynolds, & Courage, 2010).

The neural correlates of infant sustained attention have been studied using electroencephalography (EEG). In adults, EEG oscillations in the theta and alpha bands are thought to index tonic brain arousal and attentional allocations (Ergenoglu et al., 2004; Sauseng et al., 2005; 2007). Consistent with these findings, prior work in infants has found that engagement of sustained attention is accompanied by increases in theta power and attenuation of alpha power, which has been localized to regions of the frontal cortex (Xie et al., 2018). Moreover, these associations are observed to strengthen with age (Xie et al., 2019), consistent with the incremental improvement in infant sustained attention over the first year of infancy (Colombo, 2001).

Importantly, aspects of the early environment can have an impact on infant attention development. For instance, variations in family income are associated with developmental changes in infants' attention to visual features and whole objects over the first year of infancy (Werchan et al., 2019). Other work has found that, relative to their higher socioeconomic peers, infants from lower socioeconomic households exhibit greater levels of inattention and are less likely to modulate their attention based on the complexity of visual stimuli (Clearfield & Jedd, 2012). Global measures of infants' sustained attention at 7 and 15 months, measured using experimenter observations in the home, are

also negatively correlated with poverty-related risk factors (Brandes-Aitken et al., 2019). While the majority of studies have examined cumulative effects of environmental variability, there is also evidence that proximal environmental patterns can alter infant attention. For instance, interactions with caregivers have been shown to alter infant sustained attention in-the-moment (Wass et al., 2018; Yu & Smith, 2016). Prior studies also indicate that infants can extract visuospatial patterns from a proximal learning experience and use this information to guide attention to novel stimuli (Tummeltshammer & Amso, 2018; Werchan & Amso, 2020). Yet, fewer studies have considered how naturalistic variations in noise exposure shape early attentional processing, particularly in the first months of postnatal life when infants' auditory perceptual abilities are far more mature than their visual perceptual abilities (Aslin, 1987).

1.2 | Noise exposure and neurocognitive development

Increasing cross-species evidence suggests that variations in environmental noise exposure influence early brain and cognitive development. For instance, studies using parent report measures of household chaos have demonstrated that children who experience chronic ambient noise exposure show worse reading and language skills relative to matched peers, even when controlling for socioeconomic characteristics (Evans, 2006; Haines et al., 2001). Chronic noise exposure is also associated with reduced cortical thickness in language-related structures in 5–9-year-old children (Simon et al., 2022). Notably, another study found that children's language and reading skills improved following the closure of a nearby airport (Hygge et al., 2002). While there is less work examining noise exposure during infancy, one recent study found that 12-month infants who experience greater moment-to-moment fluctuations in environmental noise show more unstable autonomic arousal patterns, indicative of dysregulated stress physiology (Wass et al., 2019). Moreover, these infants also showed concomitant reductions in visual sustained attention measured during subsequent laboratory-based behavioral tasks. These correlational findings in humans are corroborated by rodent models, which indicate that the quantity and patterning of noise exposure directly impacts the development and organization of synaptic connections and cortical circuits across auditory, visual, and somatosensory cortical regions (Chang & Merzenich, 2003; Dornn et al., 2010; Espinosa & Stryker, 2012; Khazipov et al., 2004).

This work collectively indicates that noise exposure is an important dimension of the early environment. However, the majority of prior studies have focused on the total exposure to noise, without consideration of the *patterning* of auditory input (e.g., how predictable or unpredictable auditory input is over time). It is possible that the *predictability* of auditory input might be equally, if not more impactful, than the overall quantity of noise exposure. Indeed, variations in the predictability of environmental inputs, which can be quantified statistically using autocorrelations, is increasingly recognized as a key dimension of the early environment (Frankenhuis et al., 2016;

Young et al., 2020). Highly unpredictable early environments are thought to have an adverse impact on child development, potentially due to stress-related mechanisms (Young et al., 2020). Consistent with this idea, highly unpredictable maternal sensory signals, measured during in-laboratory mother–infant interactions, have been linked with worse cognitive outcomes in both human and animal models (Davis et al., 2017; Glynn & Baram, 2019; Molet et al., 2016).

In contrast, exposure to moderately predictable inputs is thought to promote attention, learning, and brain development in early life. Indeed, evidence from animal models indicates that the statistical patterning of sensory input also plays an important role in entraining developing cortical circuits (Chang & Merzenich, 2003; Dornn et al., 2010; Espinosa & Stryker, 2012; Khazipov et al., 2004). In human infants, prior behavioral work indicates that infants are biased to allocate their attention to both auditory and visual patterns of intermediate complexity and predictability (Kidd et al., 2012, 2014). Similarly, other findings show that infants can track the predictability of sensory input and use this information to guide learning and attention (Tummeltshammer & Kirkham, 2013; Tummeltshammer, Mareschal, et al., 2014; Tummeltshammer, Wu, et al., 2014b). Moreover, evidence from the statistical learning literature indicates that infants are highly adept at extracting the statistical properties of their early environments, which plays a key role in early language development (Saffran et al., 1996; Saffran & Kirkham, 2018).

Taken together, these findings suggest that the *patterning* of sensory input may play an important role in entraining developing neural circuits that support attention in early life. In particular, we hypothesize that highly unpredictable patterns of noise exposure may adversely impact infant attention, potentially due to stress-related mechanisms (Young et al., 2020; Wass et al., 2019). In contrast, we hypothesize that moderately predictable patterns of noise exposure may have a beneficial effect on early attention, potentially through the entrainment of developing cortical circuits relevant to attention and learning (Chang & Merzenich, 2003; Dornn et al., 2010; Espinosa & Stryker, 2012; Khazipov et al., 2004). Yet, virtually all prior studies examining associations between noise exposure and child development have focused on the overall level or quantity of noise exposure. Moreover, the majority of this literature has focused on older children and adults, rather than infants, who may be more susceptible to variations in sensory input during critical periods for sensory development in early infancy. As such, we currently lack empirical evidence on how moment-to-moment variations in the *patterning* of auditory input in infants' daily environments may impact neural and behavioral manifestations of sustained attention.

1.3 | The current study

In this study, we aim to extend the developmental literature by examining associations between the patterning of auditory input in the home and infant sustained attention using both biobehavioral and EEG measures. We examine infants at approximately 3 months of age, given that sustained attention undergoes rapid change across the first half year of

TABLE 1 Sociodemographics

Variable	Mean (SD) or N (%)
Socioeconomic status	
Income-to-needs ratio	5.40 (5.57)
Maternal education (years)	15.47 (3.68)
Ethnicity	
Hispanic/Latine	51 (52%)
Not Hispanic/Latine	43 (44%)
Race	
Two or more/other	44 (45%)
White	27 (28%)
Black/African-American	16 (16%)
Asian	6 (6%)
Unreported	5 (5%)

life (Colombo, 2001). In addition, prior work has shown that environmental variability contributes to individual differences in attentional processing beginning in the first months of life (Werchan et al., 2019; Clearfield & Jedd, 2012; Brandes-Aitken et al., 2019). Thus, this age group represents an ideal developmental period to examine variability in attentional processing and the effects of early environmental input in moderating these differences. We estimate the *predictability* of infants' exposure to auditory input by measuring autocorrelations of daylong ambient recordings of infants' home environments. In addition to examining total auditory input (e.g., time without silence), we also examine whether exposure to linguistic versus nonlinguistic input may have differential effects on infant attention. In doing so, we aim to increase understanding of the nuanced patterns of sensory inputs in infants' daily environments that shape developing cortical circuitry and attentional systems.

2 | METHOD

2.1 | Participants

The initial sample consisted of 104 three-month-old infants drawn from a larger longitudinal study. Families were recruited (05/2018–12/2019) from community events, family services, health care providers, and flyers posted at local businesses around New York City. Participants were excluded from enrollment in the study on the basis of birth before 36 weeks' gestation or presence of developmental disorders. Six infants were missing data on the visual attention assessment and the home auditory environment and were thus excluded from the present analyses. Thus, the final sample in this study included 98 infants (62 males; age $M = 3.48$ months, $SD = 0.39$). Participant sociodemographics are reported in Table 1. Families were compensated for their time and transportation was provided to all families. All procedures were approved by the New York University Institutional Review Board.

2.2 | Measures

2.2.1 | Demographic questionnaire

Families completed demographic questionnaires to obtain information on maternal and infant age, race, and ethnicity. Caregivers also reported their highest level of education attained and annual household income. Family income-to-needs (ITN) ratio, which is the total household income divided by the federal poverty line for the corresponding number of adults and children in the home, was used as a proxy for socioeconomic status.

2.2.2 | ECG recording and heart rate-defined attention states

This study adapted the stimuli and procedure of Xie & Richards (2017) to measure sustained attention. Participants sat on their caregivers' lap while they were presented a dynamic Sesame Street video on a large computer monitor in a dimly lit room. A camera under the monitor recorded the infants' faces, while a camera behind the participants recorded the stimulus. The 281-s video consisted of several characters from *Sesame Street*, such as "Elmo" and "Big Bird," that moved from side to side, disappeared, sang, and danced. These videos have been demonstrated to elicit periods of sustained attention in young infants (Xie & Richards, 2017). Visual attention and fixation to stimuli were manually coded retroactively with the Net Station 5.1 software.

ECG data were recorded using two bipolar electrodes placed on the infant's chest. As in prior studies, ECG measures of heart rate deceleration were used to identify periods of sustained attention and attention termination in infants (Courage et al., 2006; Reynolds & Richards, 2008; Reynolds et al., 2010; Richards, 2010; Mallin and Richards, 2012). The interbeat interval (IBI) was computed by the latency period between the R waves of two heartbeats. The increase and decrease of the IBI correspond to the heart rate acceleration and deceleration, respectively. Following the methods of Xie et al. (2018), phases of attention were identified based on changes in the IBI during periods of infant looking. Specifically, sustained attention phases began when the infant was looking at the screen *and* the median of five consecutive IBI values was lower than the median of the preceding five IBIs. Sustained attention phases ended when the median of five consecutive IBI values was higher than the preceding five. As in past studies (Xie and Richards, 2016), the total duration of time in sustained attention (in seconds) was used as our measure of psychophysiological sustained attention.

2.2.3 | EEG data acquisition and processing

EEG data during the visual attention task data were acquired while the infants were seated on their caregivers' laps and followed methods used in prior infant work (Xie et al., 2018). EEG was recorded using a 64-channel HydroCel Geodesic Sensory Net (Electrical Geodesic, Inc., Eugene, OR) and amplifier (Electrical Geodesic, Inc., Eugene, OR; EB

NEURO S.p.A., Firenze, Italy). Electrode impedances were kept below 100 K Ω and the sampling rate was recorded at 1000 Hz.

All EEG files were processed in batch electroencephalography automated processing platform software to ensure standardization in data processing and cleaning across all files (Levin et al., 2018). Continuous resting EEG files were converted from NetStation format to Matlab (2018b) format. Data preprocessing was carried out using the Harvard Automated Processing Pipeline for EEG (HAPPE), an automated preprocessing pipeline designed for infant EEG data (Gabard-Durnam et al., 2018). First, a 1 Hz high-pass and 100 Hz low-pass filter was applied to each EEG dataset. Second, the data, which was originally sampled at 1000 Hz, was resampled with interpolation to 250 Hz, following guidelines for further HAPPE processing. The third step involved artifact removal and included CleanLine's multitaper approach to removing 60 Hz electrical noise, bad channel rejection, and wavelet-enhanced independent component analysis (ICA) for artifact rejection with automated component rejection through the Multiple Artifact Rejection Algorithm (MARA) (Winkler et al., 2011) in EEGLAB. A subset of spatially distributed electrodes was selected for analysis with MARA: 2 3 5 6 8 9 10 11 12 13 14 18 20 24 25 28 30 31 34 35 39 40 42 44 48 50 52 57 58 59 60 (NetStation Geodesic 64-Channel Net). Bad channels that were initially rejected were repopulated using spherical interpolation to reduce bias in re-referencing and the signal was mean detrended. Finally, each EEG file was segmented into 1-s windows and each segment was assessed for remaining artifacts. Segment rejection thresholds were determined according to HAPPE's automated rejection criteria (Gabard-Durnam et al., 2018), which uses amplitude thresholding and assessment of segment likelihood using joint probability calculations. During these data cleaning procedures, the average percentage of independent components that were rejected was 44.0%, the average artifact probability for retained components after ICA was 18.6%, and the average percentage of segments that were rejected was 1.13%. These data loss metrics are in line with those reported in prior infant and adult EEG studies (Gabard-Durnam et al., 2018).

EEG power decomposition was accomplished using Matlab's fast Fourier transformation using hanning windowing to decompose into power for 1-s segments for each channel. The current study specifically focuses on oscillatory power in the Theta (4–6 Hz) and Alpha (6–9 Hz) frequency ranges. Summed power within each frequency band was averaged across all segments and normalized by a log base 10 transformation. Segments exceeding 3 SD \pm microvolts from the median were excluded from further analysis (Xie et al., 2018). Summed power was then averaged across all channels of interest in the frontal region (electrodes: 2, 3, 5, 6, 9, 10, 11, 12, 13, 14, 57, 59, 60) during phases of sustained attention and inattention. Change scores of EEG power calculated by subtracting power during sustained attention from power during inattention.

2.2.4 | Home auditory environment

Families were given a LENA digital recording device to take home following the laboratory visit. The LENA device and software is designed

to record the child's auditory environment. The device is placed within a specially designed shirt worn by infants, to ensure that only auditory input proximal to the infant is measured. The parent was instructed to have the infant wear the device within the shirt pocket for one full day when the typical caregivers were present. Once the device was returned, the recording was uploaded to a computer and analyzed by the LENA software. Sections of the recording with naps were identified by epochs in which (1) adult word count, child vocalizations, and conversational turns were not present and (2) at least 3 min of each 5-min epoch consisted only of silence or nonelectronic noise. These sections were filtered from the time series.

Automatic measures of hourly adult word count, hourly child vocalizations, and hourly conversational turns produced by the LENA analysis software were averaged separately. In addition, we used the raw time series data from the recording to calculate the predictability and exposure to total auditory input, linguistic input, and nonlinguistic input across all 5-min epochs. Overall auditory input in each 5-min epoch was derived by dividing the total number of seconds with noise by the total duration of each epoch (5-min, or 300-s). Linguistic input in each 5-min epoch was derived by dividing the total number of seconds with input identified by LENA analysis software as meaningful speech by the total duration of each epoch. Nonlinguistic input was derived by dividing the total number of seconds with input identified by LENA analysis software as nonspeech auditory input by the total duration of each epoch.

Exposure to total auditory input, linguistic input, and nonlinguistic input were calculated by averaging the proportion of exposure to each type of input across epochs. The predictability of exposure to each type of input was calculated by taking the autocorrelation of each series of epochs. Autocorrelations were calculated at a lag of one epoch (e.g., a 5-min lag) using the "acf" function in R version 4.0.5.

2.3 | Missing data and analytic plan

Of the $N = 98$ infants in the final sample, 29 infants did not have LENA data due to caregivers declining to participate ($n = 16$), not returning the device ($n = 1$), or returning the device without data ($n = 12$). In addition, 22 infants were missing EEG data due to poor data quality ($n = 5$), not attending to the task ($n = 3$), fussiness ($n = 10$), or technical error ($n = 4$). These data loss metrics align with the levels of data loss reported in similar infant EEG and home auditory recording studies (e.g., Brito et al., 2020). Little's missing completely at random (MCAR) test indicated that the data fit an MCAR pattern, $\chi^2(6) = 10.8, p = .21$, indicating that there were no systematic patterns in missing data. Full information maximum likelihood (FIML) was thus used to account for missing data in all analyses, as FIML produces unbiased parameter estimates when data are missing at random. Multiple linear regressions were used to test study hypotheses. Sensitivity power analyses indicated that our analytic approach and sample size yield 95% power to detect a minimum effect size of $f^2 = 0.13$ (or $\beta = 0.13$). All analyses were conducted using the "lavaan" package in R version 4.0.5.

3 | RESULTS

Descriptive statistics of all study variables are presented in Table 2, and correlations are presented in Table 3. For illustration purposes, representative examples of predictable and unpredictable patterns of auditory input are shown in Figure 1.

3.1 | Total auditory input

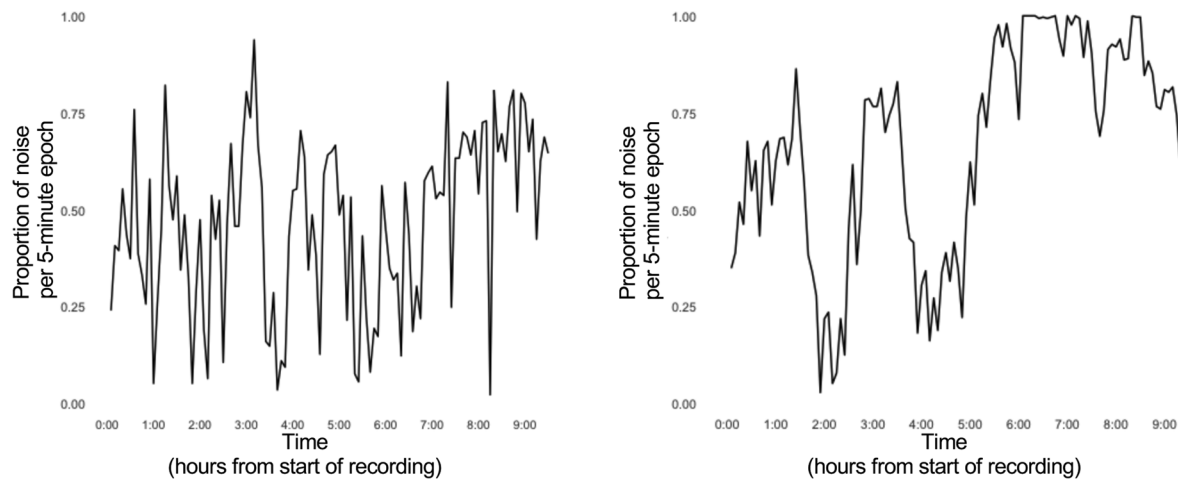
We first examined associations between infants' overall exposure to noise throughout the day (i.e., the proportion of recorded time awake with auditory input) and neural and behavioral measures of infant attention. All analyses controlled for income-to-needs, infant sex, infant age, and infant gestational age at birth. Results indicated that there was no association between exposure to total auditory input and the change in frontal theta power during sustained attention relative to inattention, $\beta = -.20, p = .11$. Similarly, there were no impacts of exposure to total auditory input on the change in frontal alpha power, $\beta = .09, p = .57$, nor on the total duration of time spent in heart rate-defined phases of sustained attention, $\beta = -.15, p = .28$. Family ITN ratio was not a significant predictor of any outcome variables, β s $< .09, p$ s $> .54$.

Next, we evaluated whether the *patterning* of overall noise exposure (e.g., the predictability or unpredictability of total auditory input throughout the day) impacted infant attention. Results indicated that there was a significant positive association between the predictability of total auditory input and the change in frontal theta power, $\beta = .32, p = .02$, such that more predictable patterns of auditory input were associated with a greater increase in theta power during sustained attention relative (Figure 2a). Similarly, more predictable patterns of auditory input were also associated with longer durations of sustained attention, $\beta = .39, p = .002$ (Figure 2b). However, we observed no associations between the predictability of auditory input and the change in frontal alpha power during attentive relative to inattentive states, $\beta = -.08, p = .60$. In addition, ITN ratio was not significant in all models, β s $< .08, p$ s $> .50$.

As a robustness check, we also evaluated whether associations between the predictability of total auditory input and infant attention remained significant while additionally controlling for relevant LENA language metrics (average adult word count, child vocalizations, and conversational turns) and total auditory input. Mirroring the above findings, there was still a significant effect of the predictability of total auditory input on frontal theta, $\beta = .32, p = .03$, and the duration of time in sustained attention, $\beta = .40, p < .001$. Average adult word count was also significantly associated with the duration of time in sustained attention, $\beta = .63, p = .002$. However, there were no other effects of adult word count, child vocalizations, conversational turns, or income-to-needs on neural or behavioral measures of infant attention, β s $< .09, p$ s $> .40$. Full multivariate regression results are reported in Table S1.

TABLE 2 Descriptive statistics

Variable	Mean (or N)	SD (or %)	Min	Max	Skewness
Demographics					
Income-to-needs ratio	5.40	5.57	.09	24.06	1.67
Infant sex (male)	63	64%	-	-	-
Infant age (months)	3.48	.39	2.20	4.37	.10
Sustained attention					
Theta power change	.03	.06	-.11	.21	.49
Alpha power change	-.67	.20	-1.20	-.19	-.32
Total time attending (s)	39.89	52.00	4.73	276.00	3.03
Home auditory environment					
Total auditory input	.67	.15	.39	.94	-.04
Linguistic input	.19	.06	.06	.34	.10
Nonlinguistic input	.48	.16	.20	.81	.17
Total auditory predictability	.64	.12	.31	.86	-.47
Linguistic predictability	.57	.10	.31	.76	-.40
Nonlinguistic predictability	.71	.10	.50	.90	-.24
LENA metrics					
Average hourly adult word count	1473.0	717.0	160	3009.5	.38
Average hourly child vocalizations	104.4	79.41	10.73	648.5	4.81
Average hourly conversational turns	27.78	15.48	4.50	72.0	.81

(a) Unpredictable noise exposure (low autocorrelation) (b) Predictable noise exposure (high autocorrelation)**FIGURE 1** Representative examples of an unpredictable pattern of auditory input (a) and a predictable pattern of auditory input (b)

3.2 | Linguistic versus nonlinguistic noise exposure

In the prior analyses, we examined total noise exposure, which combined measures of both meaningful auditory input (e.g., linguistic noise) as well as ambient auditory input (e.g., nonlinguistic noise). However, it is possible that the *type* of auditory input may be relevant when considering the effects of noise predictability on infant attention. In particular, unpredictable temporal patterns of *nonlinguistic* input may have a greater impact on infant attention relative to unpredictable

temporal patterns of *linguistic* input, given the inherent value of linguistic input for learning. As such, we next examined whether the patterning of linguistic and nonlinguistic noise had differential effects on infant attention.

Controlling for infant demographics and family ITN ratio, we found no effects of the total exposure to linguistic input on the change in frontal theta, $\beta = -.02, p = .87$, frontal alpha, $\beta = .01, p = .93$, nor on the total duration of sustained attention, $\beta = .16, p = .27$. Mirroring these results, we also observed no associations between the predictability of

TABLE 3 Bivariate correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Income-to-needs	1															
2. Infant sex (male)	-.04	1														
3. Infant age (days)	-.17 [±]	.09	1													
4. Infant gestational age	-.10	-.22*	-.26**	1												
5. Theta power change	.01	-.28*	-.24*	.01	1											
6. Alpha power change	-.07	-.13	-.05	.15	.23*	1										
7. Total time attending	-.01	-.12	-.20 [±]	.16	.28**	.13	1									
8. Total auditory input	-.22 [±]	-.01	-.02	.23 [±]	-.17	.14	-.13	1								
9. Linguistic input	.13	-.02	-.11	.19	-.02	.03	.18	.00	1							
10. Nonlinguistic input	-.26*	.00	.02	.13	-.15	.12	-.18	.92**	-.39**	1						
11. Total auditory predictability	.02	-.09	-.10	-.16	.33*	-.09	.38*	-.08	-.37**	.07	1					
12. Linguistic predictability	-.09	.01	-.31**	-.02	-.15	-.10	-.03	.11	-.06	.12	.22 [±]	1				
13. Nonlinguistic predictability	-.11	-.02	-.06	-.04	.26 [±]	-.14	.14	-.01	-.36**	.13	.70**	.34**	1			
14. Adult word count	.23 [±]	-.15	-.26*	.21 [±]	.08	.10	.42**	.04	.81**	-.28*	-.25*	.12	-.25*	1		
15. Child vocalizations	-.08	.16	.03	-.03	-.11	-.04	-.23	-.28*	.28*	-.37**	-.27*	-.18	-.15	-.08	1	
16. Conversational turns	.23 [±]	.04	-.01	.01	.06	.10	.17	-.25*	.73**	-.51**	-.34**	-.01	-.27*	.68**	.28*	1

[±]*p* < .10.

**p* < .05.

***p* < .01.

(a) Noise predictability and frontal theta EEG power (b) Noise predictability and time in sustained attention

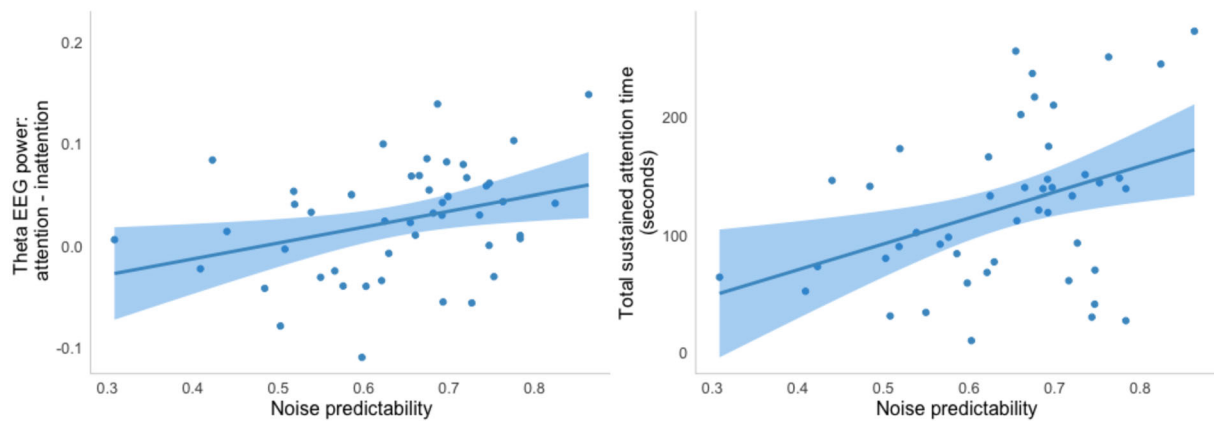


FIGURE 2 Associations between the predictability of noise and the change in frontal theta power (a) and the average duration of time in sustained attention (b)

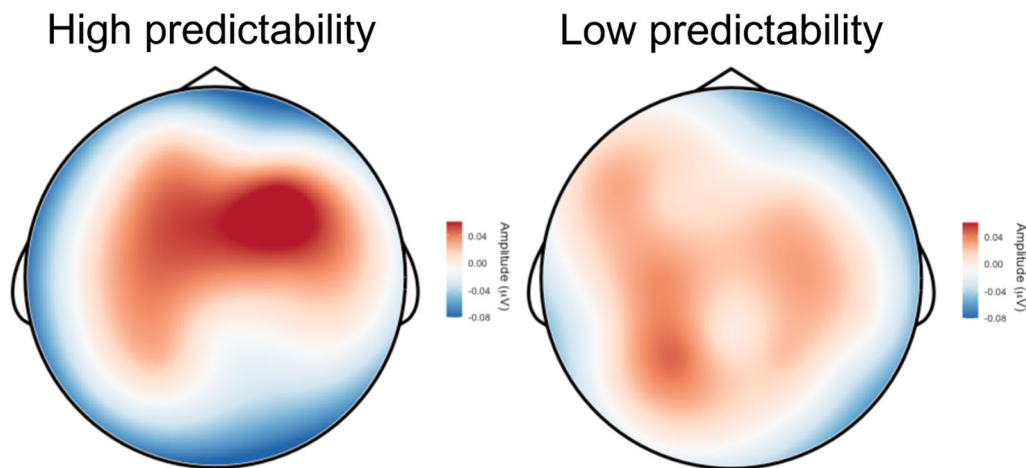


FIGURE 3 For illustration purposes, topo plots of theta EEG power during sustained attention relative to inattention are shown for the 10 infants with the highest and lowest predictability scores for nonlinguistic input.

linguistic input throughout the day and any metrics of infant attention, $\beta s < -.19, ps > .27$. When examining infants' total relative exposure to nonlinguistic input, we again observed no significant effects on neural or behavioral measures of infant attention, $\beta < -.18, p > .17$. When examining the predictability of nonlinguistic input, we found no significant effects on frontal alpha power, $\beta = -.16, p = .29$, nor on the total duration of sustained attention, $\beta = .16, p = .28$. In contrast, however, we observed that the predictability of nonlinguistic input was associated with a greater change in frontal theta power during sustained attention, $\beta = .26, p = .04$ (Figure 3). As a robustness check, a multivariate regression model was used to assess whether this effect remained significant while also controlling for average adult word count, child vocalizations, conversational turns, nonlinguistic input, linguistic input, and the predictability of linguistic input. Results from this analysis indicated that the effect of nonlinguistic predictability on the change in frontal theta power remained significant, $\beta = .32, p = .02$.

Full results from the multivariate regression analysis are reported in Table S2.

4 | DISCUSSION

The aim of this study was to examine whether variations in infants' exposure to auditory input in their daily lives are meaningfully associated with neural and behavioral measures of sustained attention. We used the LENA digital recording device and software to collect and analyze naturalistic measures of infants' home auditory environments, including both the *quantity* and the *predictability* of auditory input throughout the day. The total time in sustained attention, as well as changes in EEG power, were evaluated by measuring heart rate-defined phases of sustained attention during stimulus presentation in laboratory assessments. In addition, exploratory analyses also

evaluated whether there were differential effects of *linguistic* input relative to *nonlinguistic* input on neural and behavioral indices of infant attention.

Our results indicated that infants who were exposed to more predictable patterns of auditory input in the home (combining across linguistic and nonlinguistic input) demonstrated longer overall time in sustained attention during laboratory assessments. In addition, infants' who experienced more predictable auditory input also demonstrated greater relative increases in absolute theta power during periods of sustained attention relative to inattention. This pattern of neural activation is consistent with prior findings demonstrating associations between theta oscillations and attention and information processing in both infants (Orehova, 1999; Xie et al., 2018, 2019) and adults (Ergenoglu et al., 2004; Sauseng et al., 2005; Sauseng et al., 2007). Moreover, it is also consistent with prior work demonstrating associations between theta oscillations and general cognitive ability and task engagement in infants (Anderson et al., 2022; Braithwaite et al., 2020; Jones et al., 2020), children (Adam et al., 2020; Meyer et al., 2019), and adults (Cavanagh & Frank, 2014; Klimesch, 1999; Narayanan et al., 2013). Notably, associations between attention and the predictability of auditory input were robust even when controlling for demographic variables previously shown to impact infant EEG activity, including family ITN ratio, age at test, gestational age at birth, and sex. Furthermore, these findings also remained significant after controlling for relevant metrics of language exposure produced by LENA analysis software, including average hourly adult word count, child vocalizations, and conversational turns.

Analogous patterns of results were found when examining infants' exposure to nonlinguistic auditory input. In contrast, however, we found that neither the predictability nor total exposure to *linguistic* input was associated with neural or behavioral measures of infant attention. There are several potential explanations for this null result. First, linguistic input may have differential value for attention relative to nonlinguistic input, given the inherent value of linguistic information for human learning. For example, prior literature on statistical learning and language development indicates that infants extract statistical patterns of linguistic input at the level of individual syllables (Saffran et al., 1996; Saffran & Kirkham, 2018). In contrast, the current study analyzed patterns at a macroscale (e.g., the patterning of auditory input across five-minute epochs throughout the course of a typical day). As such, it is possible that effects of the predictability of linguistic input may only be observed when examining statistical patterning at a smaller scale. In addition, while speech itself is inherently predictable, prior studies also show that infant-directed speech has a prosodic rhythm that is less predictable than adult-directed speech (MacDonald et al., 2020). Finally, prior research has found that effects of language input on EEG activity is modulated by chaos and disorganization in the home environment (Brito et al., 2020). Specifically, this study found that among children living in high-chaos households, *increased* language input was linked to *reduced* EEG activity, whereas there were no associations between language input and EEG activity among children living in low-chaos homes. As such, it is possible that effects of linguistic input on neurobehavioral measures of attention

could be modulated by other dynamics of the home environment, such as household chaos. Although the current study did not have measures of household chaos, this is an intriguing question to examine in future work.

In general, our finding that exposure to more predictable patterns of auditory input was associated with more robust neural and behavioral measures of sustained attention is consistent with prior work examining variations in the periodicity of early environments. Indeed, children's early life environments vary greatly in predictability (Glynn et al., 2021; Papadimitriou et al., 2021), which are observable across a variety of scales and measures, including daily routines (Roche & Ghazarian, 2012), patterns of social interactions (Feldman, 2007), and early language exposure (Narayan & McDermott, 2016). As such, the predictability of auditory stimulation may be tied with other periodic aspects of the early environment, including factors within the family's control (e.g., daily routines) and factors outside of the family's control (e.g., ambient environmental noise). Importantly, prior work suggests associations between the periodicity of early environments and long-term neurocognitive outcomes. For instance, questionnaire ratings of household chaos predict long-term cognitive outcomes, such as measures of effortful control in children (Evans & Wachs, 2010; Marsh et al., 2020; Martin et al., 2012). Our findings extend this literature by demonstrating that moment-to-moment variations in auditory input in infants' daily environments impact cognition and brain development as early as 3 months of age.

While our results suggest robust correlations between the predictability of exposure to auditory input and attention development, we cannot directly speak to the mechanisms underlying these associations. There are likely multiple overlapping pathways through which these effects may influence early development. For instance, seminal rodent research shows that rearing rat pups in environments with continuous, moderate noise delays the topographic organization and response selectivity of the primary auditory cortex (Chang & Merzenich, 2003). In contrast, exposure to structured patterns of sensory inputs has been found to shape the development of brain synapses and circuits across auditory, visual, and somatosensory cortical regions (Dornn et al., 2010; Espinosa & Stryker, 2012; Khazipov et al., 2004). As such, predictable environmental inputs may shape early attention development through the entrainment of cortical circuitry to oscillations experienced in the external environment (Wass et al., 2022). In contrast, *unpredictable* noise exposure has been linked with unstable patterns of autonomic arousal, indicative of dysregulated stress physiology in infants (Wass et al., 2019). Given the adverse effects of stress exposure on early brain and cognitive development (Blair & Raver, 2012), exposure to unpredictable auditory input may additionally impact early brain and behavioral development through stress-related mechanisms. Future experimental and animal work is needed to tease apart the mechanistic pathways through which naturalistic patterns of auditory stimulation impact neurocognitive development.

In addition, it is important to note that the current findings were drawn from a sample of infants tested at one point in time and at a relatively early period of infancy—a time in which there is substantial variability in trajectories of attention development. Thus,

associations between the predictability of noise exposure and infant attention observed in the current study should not be interpreted as delays or deficits, but rather as normative variability in trajectories of early attention development. Moreover, it is also critical to replicate and extend these findings in future studies using repeat measures and longitudinal designs to determine the robustness, reliability, and predictive value of these observed associations for long-term developmental outcomes. Finally, future work would also benefit from using multiple indices of infant sustained attention. For instance, prior work suggests that the amplitude of the heart rate change may be a stronger indicator of the *quality* of sustained attention, as shown by differences in memory encoding and distractibility (Richards, 2010). Thus, using physiological indices of the quality of sustained attention, alongside behavioral measures such as the duration of sustained attention, may support greater power and reliability in future studies.

In sum, here we examined how naturalistic moment-to-moment variations in infants' exposure to noise in their daily lives may impact the development of sustained attention. While our results should be replicated in future research, our findings suggest that the predictability of noise exposure is robustly associated with greater time spent in sustained attention. Moreover, we also demonstrate that the predictability of noise exposure is linked with greater increases in frontal theta power during sustained attention, a pattern of neural activity indicative of enhanced information processing and attentional control. This work increases our understanding of the nuanced patterns of sensory inputs that shape developing cortical circuitry and attentional systems. Importantly, these findings underscore the importance of considering the predictability of early environmental inputs for shaping foundational neurocognitive systems from the first months of postnatal life.

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DATA AVAILABILITY STATEMENT

The data and analysis scripts that support the findings of this study are available on request from the corresponding author.

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

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