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Infants' brain responses to social interaction predict future language growth

Highlights

- Adults interact with human infants using a species-specific social ensemble
- Infant neural responses to social versus nonsocial interaction significantly differed
- Brain areas involved in attention activate more strongly for the social condition
- Individual variation in infant brain activation predicts language over 2 years later

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In brief

How early social interaction impacts language acquisition is not well understood. Using MEG brain imaging, Bosseler et al. show that 5-month-old infants' brain responses to social versus nonsocial interactions predict individual variation in their language skills more than 2 years later, suggesting a potent role for social interaction in language development.

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Infants' brain responses to social interaction predict future language growth

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SUMMARY

In face-to-face interactions with infants, human adults exhibit a species-specific communicative signal. Adults present a distinctive "social ensemble": they use infant-directed speech (parentese), respond contingently to infants' actions and vocalizations, and react positively through mutual eye-gaze and smiling. Studies suggest that this social ensemble is essential for initial language learning. Our hypothesis is that the social ensemble attracts attentional systems to speech and that sensorimotor systems prepare infants to respond vocally, both of which advance language learning. Using infant magnetoencephalography (MEG), we measure 5-month-old infants' neural responses during live verbal face-to-face (F2F) interaction with an adult (social condition) and during a control (nonsocial condition) in which the adult turns away from the infant to speak to another person. Using a longitudinal design, we tested whether infants' brain responses to these conditions at 5 months of age predicted their language growth at five future time points. Brain areas involved in attention (right hemisphere inferior frontal, right hemisphere superior temporal, and right hemisphere inferior parietal) show significantly higher theta activity in the social versus nonsocial condition. Critical to theory, we found that infants' neural activity in response to F2F interaction in attentional and sensorimotor regions significantly predicted future language development into the third year of life, more than 2 years after the initial measurements. We develop a view of early language acquisition that underscores the centrality of the social ensemble, and we offer new insight into the neurobiological components that link infants' language learning to their early brain functioning during social interaction.

INTRODUCTION

Prior to producing their first words, infants learn the sound patterns that distinguish the words used in their native language(s). A "sensitive period" for phonetic learning occurs between 6 and 12 months of age, during which infants' initially universal phonetic capacities narrow and become specific to their native language.[1–4] Laboratory studies in which infants are experimentally presented with a new language between 9 and 11 months of age reveal that infant learning during this early period requires social interaction.[5,6] Human infants born in the US to English-speaking parents and exposed to Mandarin Chinese at 9 months of age, during live social interaction, learned speech sounds so rapidly and effectively that they performed equivalently to infants raised in Taiwan and exposed to Mandarin from birth.[5] Yet control conditions in this experiment showed that no phonetic learning occurred for infants exposed to the same information on the same schedule presented via a standard video screen.

We hypothesize that infants' neuro-cognitive systems—social attention and sensorimotor processing, which are engaged by adults' use of the species-specific social ensemble—support language learning. This hypothesis grows out of several lines of research. First, previous work has demonstrated that social attention increases during adult-child social interaction in toddlers,[7,8] which in turn is correlated with language learning[9] (for review, see Werker et al.[10]). Moreover, studies of young children at risk for autism spectrum disorder (ASD) show that a failure to attend to a social stimulus predicts ASD subtypes.[11] The degree of disinterest in parents' speech by toddlers with ASD has been shown to be associated with the degree of autism symptom severity.[12,13]

Neural sensorimotor system engagement would also be expected to advance language development. In neurobiological research with songbirds, species capable of vocal learning, the social cues provided by an adult bird singing trigger events that aid the encoding of communicative information.[14] For example, in zebra finch, songbirds that require a social stimulus to learn species-typical song, social cues generated by the tutor bird activate neurons in the midbrain of the baby bird. These neurons release dopamine in a sensorimotor circuit that is shown to enhance the encoding of tutor song representations.[14] Thus, the social context enhances the initial encoding of the information needed in sensorimotor brain areas to imitate the tutor bird's

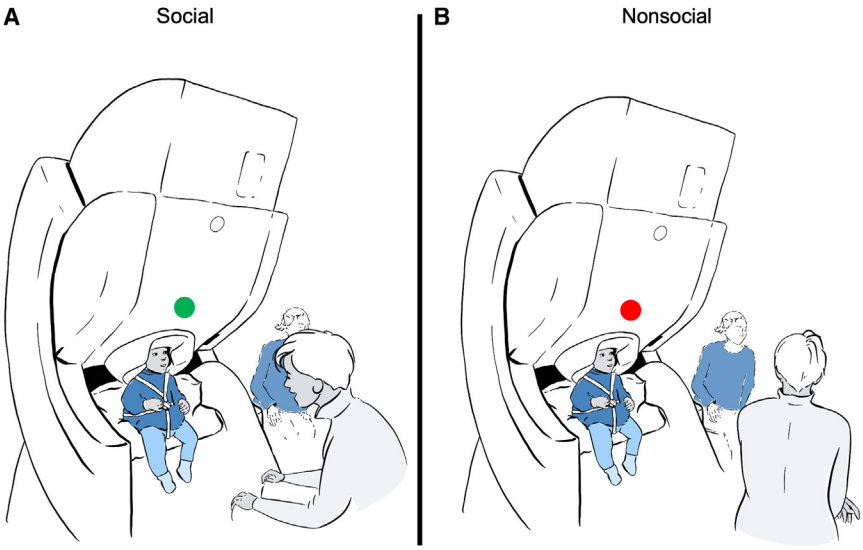

Figure 1. 5-month-old infant in an MEG brain-imaging device with social versus nonsocial conditions

(A) During the social condition, the experimenter, signaled by a green light, interacted with the infant by exhibiting the social ensemble of behaviors.

(B) During the nonsocial condition, the experimenter, signaled by a red light, turned 45 degrees toward an adult sitting out of view of the infant and spoke to them. For each infant, the conditions were presented randomly and separated by at least 7 s, with a minimum of 16 repetitions for each condition per infant. The recording session lasted about 13 min.

song. In humans, sensorimotor brain areas are activated during verbal social interaction with infants.[15] Hearing speech (but not nonspeech) activates sensorimotor brain areas when adults[16–18] and infants[19–21] listen to speech, and the nature and amount of language input from adults has been linked to the growth of sensorimotor connections in the young human brain.[22] Thus, we here hypothesized that adult-infant live face-to-face interaction would enhance activation in infant sensorimotor brain areas and predict future language learning.

The hypothesis tested in the current study is that individual variation in brain activation in areas of the brain related to attention and sensorimotor processing in response to the social ensemble predicts individual variation in language skills more than 2 years later. To test this hypothesis, we use infant whole-head magnetoencephalography (MEG) brain imaging to compare typically developing 5-month-old infants' neural activity during live interaction in a social versus a nonsocial situation (Figure 1), and we link individual differences in infants' brain response during this interaction to future language growth. Specifically, we examine brain activity elicited during F2F social interactions at 5 months of age, prior to the well-documented initial period for phonetic and word learning,[2,10] and test its predictive value for children's developing language skills. We hypothesize that infant attention to F2F social verbal interactions prior to this sensitive period may prepare infants for language learning when the sensitive period opens.

A brain-behavior, multi-time point longitudinal test of this type has not been done previously. Prior electroencephalogram (EEG) studies used video rather than live stimuli to examine infants' brain responses to social stimuli[23–25] or investigated live sung speech presented noncontingently with infant behavior.[26] An fNIRS hyperscanning study examined adult-infant interaction and found positive associations between (1) turn-taking behavior and adult-infant neural synchrony and (2) turn-taking behavior and infant brain maturity and 24-month vocabulary, but it did not directly link infants' brain activity to longitudinally measured language skills.[27]

The use of MEG brain imaging technology ensures spatial resolution (<3 mm) that is superior to that produced by EEG and temporal resolution (<1 ms) much greater than fNIRS. MEG is safe and noninvasive and has been maximized for infant testing.[28]

The experimental procedure entailed a within-subjects design, which included a social condition during which an adult female experimenter engaged the infant by speaking in parentese and reacted warmly and contingently to the infant, as well as a nonsocial condition during which the experimenter turned 45 degrees to speak (using adult-directed "standard" speech[29]) to an adult who was seated to the infants' left (out of view of the infant; Figure 1). Our intention was to capture, as much as possible in a brain-imaging experiment, typical social interactions that infants experience every day in their home environments. In both conditions, the adult spoke naturally, providing both auditory and visual speech stimulation to the infant brain for the same duration.

Following our hypothesis, we focused on brain regions related to attention (right inferior frontal, r-IF; right superior temporal, r-ST; and right inferior parietal, r-IP)[30–32] and those related to speech-motor processing (left inferior frontal, l-IF),[33,34] reasoning that differential activation in the social versus nonsocial condition in these areas would predict infants' future language skills. Given that infants heard auditory speech by the same adult experimenter speaking in both conditions, we did not expect differential activation to social versus nonsocial in the auditory speech processing area (left superior temporal, l-ST) or in the left inferior parietal area (l-IP), nor did we expect that activity in these areas would predict future language growth.

We recorded MEG activity as the infant engaged in the social and nonsocial conditions and, in each region of interest (ROI), measured infants' oscillatory brain activity in the theta spectral band (4–8 Hz). We focus on the theta frequency band because previous studies in both adults and children implicate theta activity for sustained attention, active learning, cognitive load, and reward.[35–38] Moreover, EEG evidence indicates infant theta oscillations increase when processing positive social affect,[39] when listening to infant-directed speech,[40] and when viewing social versus nonsocial videos.[23,24]

The critical hypothesis for theory is that, at the level of individual participants, enhanced brain activation during the social condition would positively predict infants' prospective language skills. For each infant participant (n = 21), we collected longitudinal behavioral measures of productive vocabulary at five sequential 3-month intervals from 18 to 30 months of age. Vocabulary was measured using the standard MacArthur-Bates

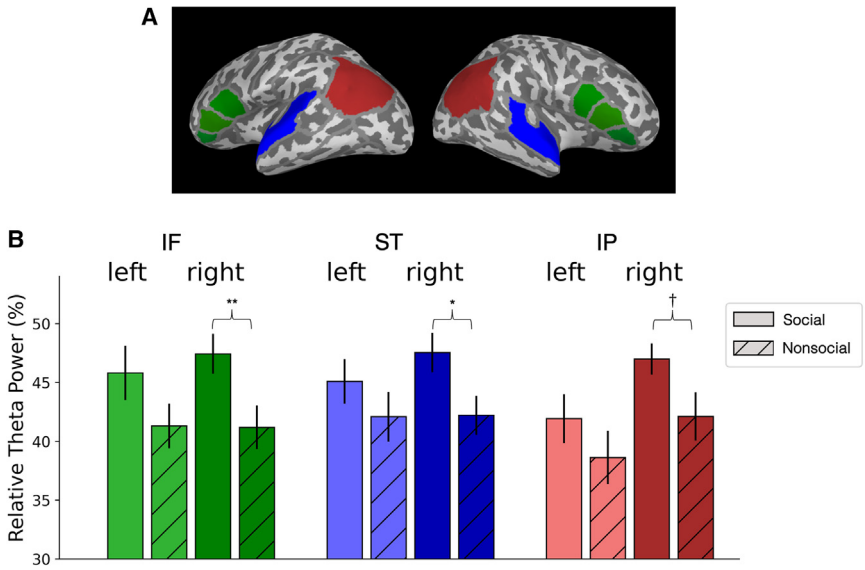

Figure 2. Mean neural activity during social and nonsocial conditions

(A) Brain map showing regions of interest (ROIs): inferior frontal (IF, green), superior temporal (ST, blue), and inferior parietal (IP, red) in the left and right hemispheres.

(B) Mean relative theta power (RTP), as a percentage of total power between 0 and 60 Hz, in each ROI for conditions and hemispheres. Error bar indicates ±1 standard error, **p ≤ 0.01, *p ≤ 0.05, and †p = 0.055; two-tailed paired t tests.

Communicative Development Inventories (CDI)-Words and Sentences,[41] a widely used and validated measure of children's language development. Growth curve models assessed the association between infants' brain responses and children's vocabulary growth (STAR Methods).

RESULTS

To test our hypothesis, we specified three brain ROIs and used *a priori* planned comparisons to test the predicted differences between the social and nonsocial conditions in each ROI and in each hemisphere, rather than conducting an overall ANOVA.[42] Figure 2A shows the cortical map of ROIs, and Figure 2B shows the mean relative theta power (RTP) as a function of condition (social versus nonsocial), ROI (IF, ST, and IP), and hemisphere (left and right).

Planned comparisons showed a significant effect of RTP in the social versus nonsocial condition in r-IF ($p = 0.01$, $t_{(20)} = 2.73$, effect size $\eta^2 = 0.60$) and r-ST ($p = 0.05$, $t_{(20)} = 2.05$, $\eta^2 = 0.45$) and a trend toward significance in r-IP ($p = 0.055$, $t_{(20)} = 2.04$, $\eta^2 = 0.44$). The effect in l-IF was not statistically significant (l-IF, $p = 0.10$). As expected, no significant effects were observed in l-ST or l-IP ($p = 0.26$ and $p = 0.08$, respectively).

The hypothesis critical to theory is whether individual infants' brain measures at 5 months of age predict individual differences in vocabulary development between 18 and 30 months of age (see STAR Methods for vocabulary measurement details). We developed a series of linear mixed-effect models in each ROI of the left and right hemispheres, and for both the social and nonsocial conditions, to assess whether RTP at 5 months predicts growth in vocabulary from 18 to 30 months. As shown in Figure 3, productive vocabulary size measured at 18, 21, 24, 27, and 30 months shows typical growth trajectories for all infants.[43]

Figure 4 displays scatterplots relating RTP (in l-IF, r-IF, l-ST, r-ST, l-IP, and r-IP) to children's CDI vocabulary scores at 24 months (the age that corresponds to the intercept in the linear models) for the social and nonsocial conditions. In brain regions related to attention (r-IF, r-ST, and r-IP) and sensorimotor processing (l-IF), the magnitude of RTP during the social condition (all $p < 0.05$, Bonferroni corrected for multiple comparisons) showed a significant positive association with the size of the 24-month vocabulary measure (see STAR Methods for an additional analysis), as well as a significant association with vocabulary growth from 18 through 30 months (Table S1). In contrast, for the nonsocial condition, the same correlations were not significant (all $p > 0.05$, Bonferroni corrected; Table S2).

DISCUSSION

The findings show that at 5 months of age, live F2F social verbal interaction between an infant and an adult who is responsive to the infant's cues increases infants' brain activity significantly in the 4–8 Hz (theta) band in brain regions involved in attention compared with a nonsocial control condition. Moreover, and more critical for theory, we found that infants' individual levels of neural activation in both attention and sensorimotor brain areas during the social condition (but not the nonsocial condition) show a strong positive association with subsequent longitudinal measures of those same infants' prospective language skills at 18, 21, 24, 27, and 30 months of age.

These differential effects of the social and nonsocial conditions cannot be attributed simply to hearing speech alone, because each infant listened to the same adult speak for the same amount of time in the two conditions, in each case using language that is appropriate to their social partners in natural everyday settings. The results are therefore unlikely to be attributed simply to infants' brain processing of auditory speech in the two conditions. Instead, we argue that the results are attributable to infants' attention and engagement in response to the species-specific social ensemble that exists when adults address and interact with young infants during F2F encounters.

To our knowledge, this is the first use of infant MEG brain imaging to study the effects of F2F social interaction on infants' oscillatory brain activity. It is also the first study to link oscillatory activity during live natural social interaction with prospective measures of language growth at multiple time intervals in a longitudinal study. Our work fits with previous work showing larger theta activity to social stimuli during infancy.[24,26]

It is noteworthy that we measured infants' attention prior to the initial sensitive period that exists in early language learning to

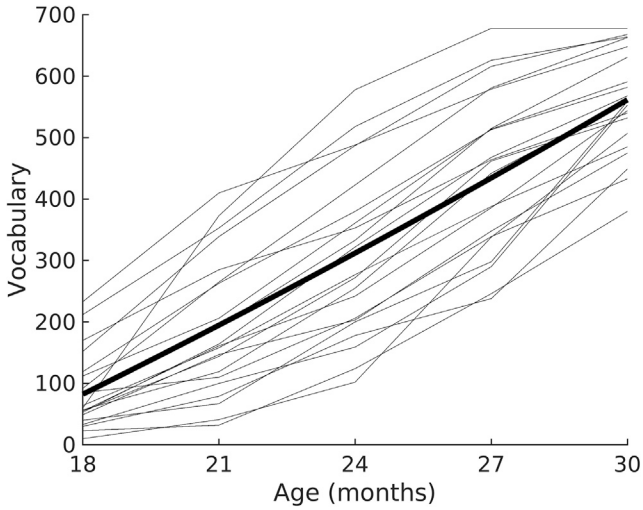

Figure 3. Vocabulary growth as a function of age

Vocabulary growth (STAR Methods) as a function of age for each of the 21 individual children (gray lines) and the mean vocabulary score for the group (bold). Age is shown in months and vocabulary in average words produced.

assess the potential link between infant attention and initial language learning. Selective attention to F2F social verbal interactions with an adult who responds naturally, adapting to the infant's behavior during this early period, may support language learning when the sensitive periods opens.

The pattern of findings suggests that infants' attention to the social ensemble when adults are in face-to-face social communication with them may play a more important role in language acquisition than previously acknowledged.[44] We hypothesize that the social ensemble initially helps capture infant attention. Caregivers' animated faces, parentese speech, and their tendencies to respond contingently—the package that makes up the uniquely human social ensemble—attracts and holds infants' attention, motivating them to learn, and may provide the initial impetus and opportunity for learning aspects of language. In the absence of children's early attention to social speech stimuli, as is common in young children with ASD, language learning may be limited (see Pierce et al.,[11] Stavropoulos et al.,[45] Stavropoulos et al.,[46] and Dawson et al.[47] for data and discussion).

The current data contribute to several ongoing theoretical discussions about the role that the l-IF area plays in speech processing. We show that infants' responses in the l-IF area during the social condition are a strong predictor of future language development. Previous reports show that infants activate the l-IF in response to hearing speech, but not nonspeech, as early as 2 months of age.[19–21,48] This could indicate activation of speech-motor planning (though studies show that activation in motor brain regions can also be attributed to sensitivity to acoustic features of speech[49]). Moreover, behavioral studies have demonstrated that infants specifically map between auditory and motor instantiations of speech early in development: 5-month-old infants imitate the vowels they hear[50] and detect the match between visually and auditorily presented vowel sounds.[51] Studies also show that somatosensory information can influence infants' perception of speech.[52] Taken together, all of this work suggests that infants' speech perception is deeply linked to sensorimotor representations. Additional studies will be necessary to understand the precise role that IF brain areas play in initial language learning prior to speech production by infants,[53,54] but our results tentatively suggest that social encounters involving speech not only activate infants' inferior frontal areas (which include Broca's area) but also that the degree of activation in individual infants is strongly predictive of that infant's prospective language abilities, as shown by the longitudinal findings reported here.

In this study, we examine infants' brain responses to the entire social ensemble, reflecting infants' everyday experiences. Individual components of the social ensemble, such as infant-directed speech,[55–58] contingency,[59] and parental sensitivity,[60] have been associated with future language abilities, but in older infants. Future neuroscience studies can isolate components of the ensemble and examine how each affects infant attention, now that the current results establish that the composite social ensemble evokes brain responses in infants as young as 5 months of age that predict future language development.

Finally, we note that our results are compatible with extant two-person neuroscience studies in which both people are simultaneously measured by brain-imaging equipment while engaged in face-to-face exchanges. Dual-EEG, dual-fNIRS, and dual-MEG experiments show that neural regions in two brains engaged in social interaction activate in neural synchrony (see Lin et al.[61] and Endevelt-Shapira et al.[62] for reviews). These studies have suggested that neural synchrony may be a marker of attuned human social interaction, even during infancy.[61,63]

In summary, the current study shows that brain activity elicited during face-to-face, language-rich social interactions between 5-month-old infants and an adult, prior to the initial sensitive period for phonetic and word learning, is predictive of children's developing language skills, as measured using longitudinal assessments in individual children. In typically developing children, attention to a social partner is advantageous and bidirectional and may itself be rooted in the quality of one-on-one interactions between caregivers and their infants. Sensorimotor brain activation may prompt and be prompted by early conversational turn-taking, which is significantly linked to future language as well as white matter growth in neural pathways that support the language network.[22] Social interactions in infancy may thus influence multiple aspects of development, including children's later language, social, emotional, and cognitive development.[55,60,64] Further studies will be needed to advance our understanding of the neurobiological mechanisms that link infants' language development to their social brains.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
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- EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

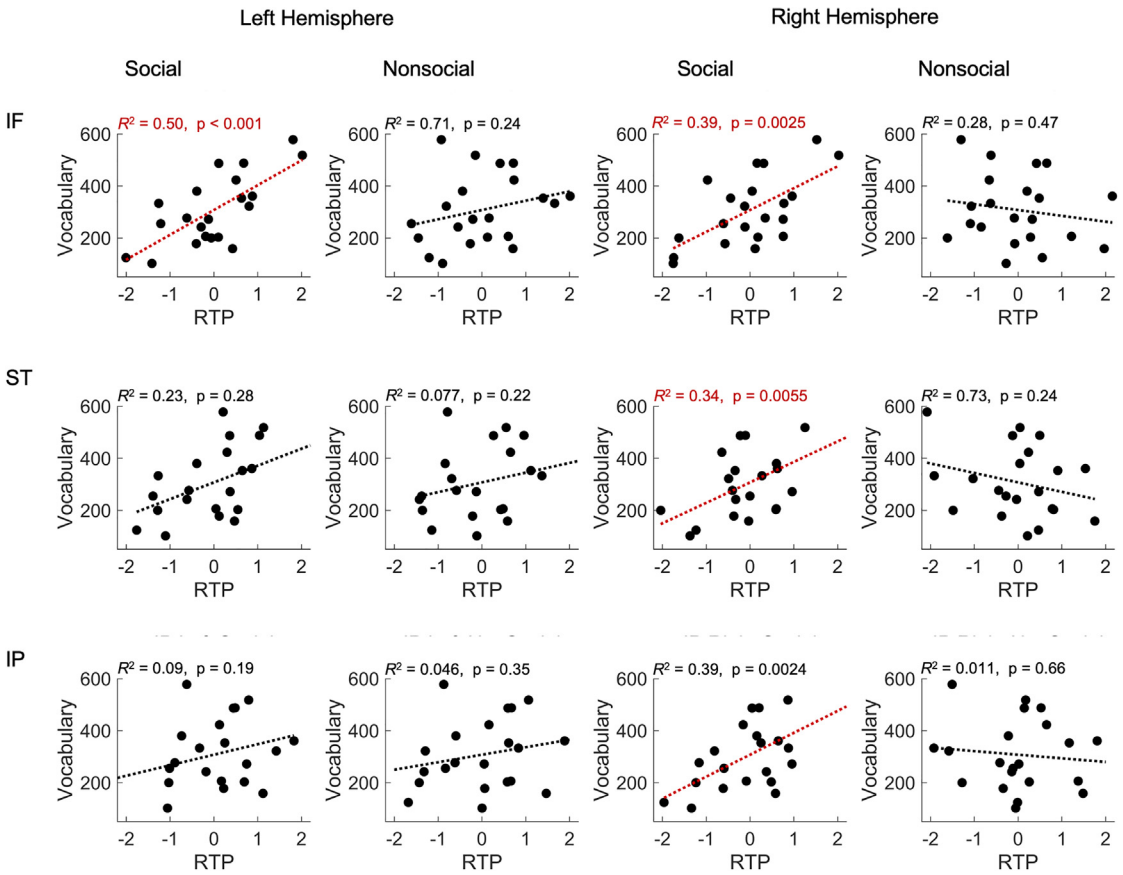

Figure 4. Scatterplots showing the correlation between neural activity during social and nonsocial conditions at 5 months of age and children's later language skills at 24 months of age

Left: two columns show RTP for the social and nonsocial conditions in relation to children's productive vocabulary score at 24 months for the left hemisphere: inferior frontal (IF), superior temporal (ST), and inferior parietal (IP). Right: two columns show the same information for the right hemisphere. Each point represents a single child participant. The x axis values reflect standardized RTP. Lines are simple linear regression fits, with the variance explained (R^2) and p values indicated (Bonferroni corrected $p < 0.05$). Significant effects that exceed correction for multiple comparisons are shown in red.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.cub.2024.03.020.

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AUTHOR CONTRIBUTIONS

P.K.K. and A.N.M. developed the concept. A.N.B. and J.C.M. designed the paradigm, and A.N.B. administered the experiment. A.N.B., S.B., E.H., E.L., and S.T. analyzed the data. A.N.B. and P.K.K. interpreted the data. A.N.B., P.K.K, A.N.M., S.B., J.C.M., E.H., and Y.E.-S. prepared the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
eSSS	Helle et al.[65]	N/A
FreeSurfer	Desikan et al.[66]	RRID: SCR_001847
JASP Version 0.18.1	JASP Team	http://www.jasp-stats.org; RRID: SCR_015823
MATLAB R2023a	Mathworks	https://www.mathworks.com/; RRID: SCR_001622
MNE-Python Version 1.0.3	Gramfort et al.[67] and Gramfort et al.[68]	https://mne.tools; RRID: SCR_005972
sLORETA	Pascual-Marqui[69]	RRID: SCR_013829
SSP	Uusitalo and Ilmoniemi[70]	N/A
Tucker-Davis RZ6	https://www.tdt.com/component/rz6-multi-i-o-processor/	RRID: SCR_018153
tSSS	Taulu and Simola[71]	N/A
Other		
Custom analysis scripts	This paper	GitHub: https://bit.ly/2023-Infants-Brain
Current Designs Fiber Optic Response Pad	https://www.curdes.com/mainforp/responsedevices/hhsc-2x4-c.html	SKU#: HHSC-2x4-C
I-LABS MEG Brain Imaging Center	https://ilabs.uw.edu/meg-brain-imaging/	RRID: SCR_024836
Polhemus Fastrak	Polhemus, Colchester, VT, USA	Electromagnetic digitizer

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Patricia K. Kuhl (pkkuhl@uw.edu).

Materials availability

The study did not produce new materials.

Data and code availability

- Original data reported in this paper is available in the folder 2024-F2F-MEG at OSF: https://osf.io/2xf4y/.
- Custom analysis scripts are available at GitHub: https://bit.ly/2023-Infants-Brain.
- Data reported in this paper will be shared by the lead contact upon request.

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

Forty-one typically developing English-learning infants participated in the MEG portion of the study. All participants were recruited through a university-wide Developmental Participants' Pool at 5 months of age (M = 5.19, SD = 0.16; 22 male). The infants had no history of ear infections or other hearing difficulties, were born full term (39–42 weeks gestational age), had normal birth weights (6–10 lbs), and had no older siblings (first-born children). We obtained ethical approval from the University of Washington Human Subjects Division. The parents or legal guardians of all participants provided informed written consent as per the principles of the Declaration of Helsinki. Data from three infants were not deemed useable due to fussiness during the nonsocial condition of MEG session and data collection was stopped and the data were not processed. These infants were not invited to complete the longitudinal portion of the language measure. Seventeen additional infants were not included in the final analysis because they left the longitudinal portion of the study (n = 1), had too few trials after data preprocessing (n = 6), had a later diagnosis of speech delay (n = 4) or developmental delay (n = 2), or technical error during recording and data could not be processed (n = 4). Twenty-one (13 male) had sufficient artifact-free MEG data, and completed all scheduled CDI questionnaires to be included in the analysis.

METHOD DETAILS

MEG Recording and Behavioral Procedures

Whole-head magnetic field recordings were made with a SQUID-sensor MEG system (Neuromag - Elekta Oy, Helsinki, Finland), consisting of 204 planar gradiometers and 102 magnetometers. Prior to recording, five head position indicator (HPI) coils attached to a nylon cap were placed on the infant's head. Positions of the coils, nasion and periauricular fiducial points as well as approximately 100 additional points across the head surface were marked using a digitizer system (Fastrak Polhemus - Colchester, VT, USA) for subsequent head movement tracking and anatomical reconstruction. A set of ECG electrodes was also affixed to the infant to measure magnetic fields produced by heart activity. Once the infant was seated under the MEG sensor helmet, field data were recorded continuously at a sampling rate of 3109 Hz and analog filtered between 0.03 and 1025 Hz while the infant sat face-to-face with an adult female experimenter. During the *social* condition (Figure 1A), the experimenter interacted naturally with the infant, talking and responding positively. During the *nonsocial* condition (Figure 1B), the experimenter turned 45 degrees away from the infant and interacted naturally with another adult, who was sitting out of view of the infant. The experimenter was cued about which condition was in effect by the color of an LED light controlled by an Arduino based minicomputer that was mounted on the front of the MEG device, visible to the adult experimenter but not the infant (Figure 1). Tucker-Davis RZ6 delivered triggers and allowed for communication between the triggers and the Arduino. Conditions were randomized, separated by 7 s, and a minimum of 16 trials occurred for each condition. The session lasted about 13 min.

Productive Vocabulary Assessment

Productive vocabulary was assessed when participants were 18, 21, 24, 27, and 30 months of age using the MacArthur-Bates CDI, specifically, the 680-word checklist, 'Words and Sentences,' a validated language inventory for research.[72,73] Using the CDI, parents reported the number of words produced by their child based on the 680-word checklist section of the CDI when their child reached the target age.

QUANTIFICATION AND STATISTICAL ANALYSIS

MEG Data Analysis

MEG data were analyzed with custom software based on the MNE-Python package.[67,68] Several preprocessing steps were implemented to minimize noise and artifacts and prepare the MEG data for source reconstruction.[28] First, sensor channels were rejected if they were flat, excessively noisy, or contained numerous transients, using an automated process complemented by manual inspection. Interference external to the helmet was then suppressed using temporal signal space separation (tSSS) with a 4-s buffer,[71,74] modified to incorporate a 3-component noise projection from the empty room recording[65] ('extended' tSSS). The process reconstructed bad channels and transformed the MEG signals to account for head movements.[75] Finally, the signal space projection method[70] (SSP) was applied to remove heartbeat artifact based on the ECG signal (or a proxy gradiometer channel when a robust ECG signal could not be obtained) followed by lowpass filtering at 80 Hz.

For source analysis, the sensor data was subsampled to 310.9 Hz and divided into 1-s epochs, overlapping by 0.5 s and spanning the first 7 s of every *social* and *nonsocial* condition. Individual epochs were rejected if fewer than 3 head coils were active, head motion was greater than 0.1 m/s translation or 10 deg/s rotation, or the amplitude was above or below criterion levels determined by an automated procedure.[76] The first 210 valid epochs for each condition were retained. Sources were localized to a high-resolution MRI template brain of a 14-month-old infant, spatially warped and aligned to the digitized head metrics of the individual subjects. The source space consisted of 4098 points per hemisphere, distributed uniformly across the gray-white matter boundary.[77] Source activity for each epoch was estimated using the sLORETA method,[69] yielding covariance-normalized temporal waveforms at every source point. Finally, the power spectral density (PSD) of each epoch's estimated source activity was calculated using the multi-taper approach with a bandwidth parameter of 2 Hz. The power was summed into four bands (theta: 4–8 Hz, alpha: 8–12 Hz, beta: 12–28 Hz, gamma: 28–60 Hz) then normalized point-by-point by the average total power across epochs between 0 and 60 Hz. The values were transformed to log units, resulting in an approximately Gaussian distribution of power, then averaged across the respective epochs resulting in separate relative theta power values (RTP) for the *social* and *nonsocial* conditions at each point of the discrete source space.

Regions of Interest and Statistical Analyses

The cortical source space was parcellated into 34 cortical regions in each hemisphere according to the Desikan-Killiany anatomical atlas available from FreeSurfer.[66] From these, the three ROIs of each hemisphere were defined (Figure 2A). The ST and IP ROIs were defined from the single Aparc regions of the same name. The IF ROIs were defined by combining the pars orbitalis, triangularis, and opercularis regions. Combining anatomical regions was intended to mitigate localization errors incurred by imperfect head movement compensation and subject-to-subject variability in cortical topography, and the use of a surrogate MRI template for anatomical registration.

Statistical analysis was performed on RTP values averaged across all source points within each ROI then transformed from log units to a linear percentage scale. *A priori* planned comparisons were used to test for differences between response magnitudes during *social* and *nonsocial* conditions within each ROI and are two-tailed, α set at $p < 0.05$ and Cohen's *d* reported as effect

size. Preliminary independent sample two-tailed t-tests comparing RTP across ROIs with sex as the between group factor indicated no significant effects of sex for any of the ROIs (all ps > 0.13, with the exception of r-IF, p = 0.07). Thus, sex was excluded as a variable in subsequent analyses. Statistical calculations were conducted with the statistical computing package JASP (JASP Team, 2023. JASP Version 0.18.1 [Computer software], BibTeX).

Linear Modeling of Vocabulary Growth and Relation to RTP

Multivariate linear mixed effects models were developed to evaluate the relation between RTP levels at age 5 months and growth in language scores from 18 to 30 months. A baseline model included fixed and random effects for the intercept, slope (growth as function of age, in months, mean centered and standardized), and acceleration (age x age) terms. The acceleration term was included to capture non-linear growth in measured vocabulary, which was observed in the current sample and is expected for the CDI vocabulary measure at these ages.[72,73] Model comparisons indicated that the model including age provided a better fit to the data than either a model including only a linear growth term, or one including an additional cubic term (age). All fittings were carried out using custom software written in MATLAB (R2023a) and the MathWorks Statistics and Machine Learning toolbox.

After fitting the baseline model, a second set of models were developed to test the interaction between vocabulary development and RTP within each ROI and hemisphere, for the social and nonsocial conditions. Prior to fitting, RTP scores were mean centered and standardized within ROIs. For each ROI model, significance of the fixed coefficients was assessed after Bonferroni correction based on the number of models considered (6 in total: 3 ROIs and 2 hemispheres, see also Tables S1 and S2). The impact and significance of adding variables beyond the baseline model was assessed on the basis of *R*-squared values and by comparison of likelihood ratios and the Bayesian Information Criterion (BIC). The residuals of all models exhibited acceptable homoskedasticity and approximately normal distributions according to the Shapiro test (p > 0.05 for all models).

An additional analysis compared the coefficients obtained for the social and nonsocial conditions in each ROI.[78] The results indicated significant differences between conditions in the l-IF, $z_{(1.98)}$, p = .024, r-IF, $z_{(2.93)}$, p = .002, r-ST $z_{(2.74)}$, p = 0.003, r-IP $z_{(2.44)}$, p = 0.007. Differences were not significant in l-ST $z_{(0.90)}$, p = 0.19 or in l-IP, $z_{(0.47)}$, p = 0.32.