

1 **Title**

2 Human infant EEG recordings for 200 object images presented in rapid visual streams.

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15 **Abstract**

16 Understanding the neural basis of human object recognition and semantic knowledge has
17 been a significant area of exploration, with recent focus aiming to reveal the developmental
18 trajectory of this core brain function. At present, however, there is limited access to high-
19 quality neuroimaging data obtained from human infants. Addressing this gap, we present a
20 dataset comprising electroencephalography responses from 42 human infants obtained in
21 response to visual presentations of various objects. Leveraging a rapid serial visual
22 presentation paradigm, 42 infants between 2 and 12 months of age viewed 200 images
23 spanning 50 distinct objects, with as many repetitions as possible tailored to individual infants
24 comfort. Our technical validation demonstrates discernible neural responses to both
25 individual objects and categorical distinctions, affirming the dataset's robustness and utility
26 for exploring the neural underpinnings of visual object recognition in infancy. Building upon
27 insights gained from adult studies, our findings suggest that fast presentation paradigms hold
28 promise for efficiently capturing electrophysiological responses to a large array of visual
29 stimuli in human infants. This dataset represents a valuable resource for advancing our
30 understanding of the developmental trajectory of object recognition and semantic knowledge
31 in the early stages of human life.

32 **Background & Summary**

33 Our daily lives involve rapid and accurate visual recognition of a vast array of different objects
34 – faces, cars, trees, structures, animals, and many more. We are adept at recognising individual
35 objects even in cluttered visual environments (e.g., a messy kitchen), and in the face of
36 dramatic differences in an object's retinal projection caused by lighting conditions or viewing
37 angle. Understanding the neural basis of this impressive capacity has been a core theme in
38 cognitive neuroscience research¹⁻⁴, with an increasing number of papers aimed at
39 understanding how these capabilities develop during the earliest stages of life – human
40 infancy⁵⁻⁹. While early findings in these neuroimaging infant studies have been promising,
41 stimulus set sizes and sample sizes have been relatively modest, and infant neural data is often
42 not publicly available. This is a barrier to progress in the field, particularly since the often noisy
43 quality of infant neuroimaging data necessitates a higher degree of preprocessing than
44 corresponding adult data would^{5,10,11}, and developing optimised preprocessing pipelines relies
45 on open data availability. Therefore, there is a pressing need for high-quality open-access
46 neuroimaging data associated with infant object recognition.

47

48 Collecting neurophysiological datasets on infants presents several challenges: Typically, classic
49 object vision experiments present around one image per second^{12–14}. Thus, obtaining multiple
50 trials for many images can thus take many hours, which is infeasible to achieve with infants
51 who cannot tolerate long experiments. However, we have recently shown in adult participants
52 that it is possible to uncover detailed information about visual stimuli presented in rapid serial
53 visual presentation (RSVP) streams using electroencephalography (EEG)^{15–18}. In these studies,
54 5 minutes of EEG recording can comprise more than 1000 visual object presentations
55 appearing at a rate of 5 images per second. Multivariate pattern classification analysis of this
56 data revealed detailed temporal dynamics of object processing that are similar to those
57 documented by studies using slower presentation speeds. Therefore, fast presentation
58 paradigms may be highly suitable for collecting neural responses to large numbers of visual
59 object stimuli in infant populations.

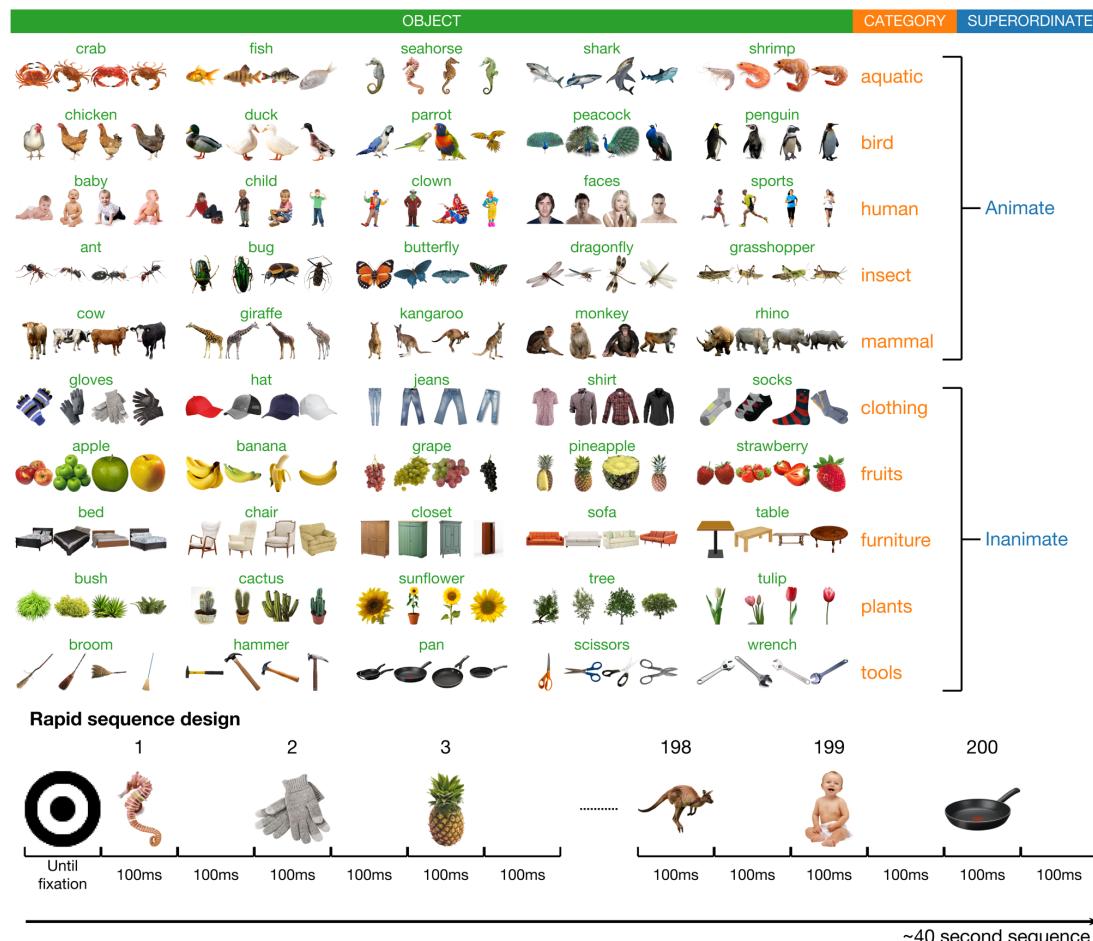
60
61 Here, we present a dataset of human infant (n=45) EEG responses to 200 object images
62 spanning 50 individual categories (e.g., dog, hammer, chair etc.). Each image was repeated at
63 least 3 times for each participant, with the experiment lasting as long as the infant participant
64 could comfortably comply. We used the same rapid serial visual presentation paradigm as a
65 previous adult study¹⁵. Technical validation results indicate distinguishable neural responses
66 to both specific objects and broader categories, demonstrating that the dataset can serve as
67 a high-quality resource for future investigations into the neural development of visual object
68 recognition.

69 Methods

70 A total of 42 infants took part in the experiment, recruited via the MARCS Institute BabyLab
71 database at Western Sydney University. Each caregiver was briefed on experimental
72 procedures and provided their informed consent prior to the start of the experiment.
73 Participants were 16 female and 26 male human infants, mean age 6.57 months (sd 3.02
74 months), age range 1.8 – 11.5 months. We recorded demographic information about each
75 participant's language and education background. All participants had been screened for
76 normal hearing and vision and had no known medical issues. There are 8 participants marked
77 for potential exclusion due to notably poor signal quality or equipment failure (marked in the
78 *participants.tsv* file). These participants are included in the release for completeness. All
79 aspects of the study were approved by the Western Sydney University ethics committee
80 (H14498).

81
82 Stimuli were taken from a previous object recognition study¹⁵ (Figure 1A), and consisted of
83 200 images spanning 50 object concepts. Each stimulus was associated with three levels of
84 labels – one corresponding to the individual object (e.g., dog, apple, hammer, etc.), one
85 corresponding to the category (e.g., mammal, fruit, tool, etc.) and one corresponding to the
86 superordinate category (e.g., animate or inanimate). The experiment was programmed in
87 Python (v3.7), using the Psychopy¹⁹ library (version 3.0.5). Images appeared in randomised
88 order in sequences at a rate of exactly 5Hz with a 50% duty cycle (Figure 1C), that is, each
89 image appeared for 100ms followed by a 100ms blank screen. Each 40 second sequence
90 contained one presentation of each unique stimulus. Participants sat on their caregiver's lap
91 in a dimly lit experiment booth approximately 57cm from the screen, so that each stimulus
92 subtended approximately 6 degrees visual angle. A fixation bullseye (0.5 degrees visual angle)
93 was overlaid at the centre of each image. To promote the infant's attention and engagement
94 to the screen, before each sequence, the bullseye alternately increased and decreased in size
95 until the experimenter manually started the sequence after verifying that the infant was
96 looking at the screen. The experiment was paused when the infant was looking away and
97 resumed when the infant's attention was directed back to the screen. The experiment lasted

98 between approximately 5 minutes to 20 minutes, depending on the infant's compliance. On
 99 average, infants completed 4.58 full sequences (sd 1.48).



101
 102 **Figure 1:** Stimuli, design, and EEG setup. Top: Stimulus set used in the experiment, adapted
 103 from¹⁵. Bottom: Rapid serial visual presentation design, showing part of a rapid sequence of
 104 stimuli.

105
 106 We used a BrainVision Liveamp EEG amplifier and Psychopy stimulus presentation with
 107 Labstreaminglayer connector protocol (<https://labstreaminglayer.org/>) for wireless EEG
 108 recording (Figure 1B). Specifically, a Brain Products Liveamp server software
 109 (<https://github.com/brain-products/LSL-LiveAmp>) was used on the EEG recording computer
 110 to wirelessly connect to the Liveamp amplifier. An event trigger coding for the stimulus
 111 number was sent for each image presentation using Psychopy on a stimulus presentation
 112 computer. On the EEG recording computer, a Labstreaminglayer recorder software
 113 (<https://github.com/labstreaminglayer/App-LabRecorder>) was used to wirelessly detect the
 114 signal streams from both the EEG amplifier and the stimulus presentation triggers, and
 115 visualise ongoing signals during EEG recording. We used BrainVision RNet caps with 32
 116 electrodes, arranged according to the international standard 10–10 system for electrode
 117 placement^{20,21}. The signal was digitised at a 500Hz sample rate.

118 We performed basic quality checks and technical validation for each subject individually using
 119 a standard time-series multivariate pattern analysis¹⁰. We applied the clean_rawdata
 120 preprocessing pipeline (see provided analysis code) from the EEGLab (v2023.0) toolbox²² in
 121 Matlab (R2023b). In addition, data were filtered using a Hamming windowed FIR filter with
 122 0.5Hz highpass and 40Hz lowpass filters, re-referenced to the average reference, and
 123 downsampled to 250Hz. Epochs were created for each individual stimulus presentation
 124 ranging from [-100 to 800ms] relative to stimulus onset. No further preprocessing steps were

125 applied for the technical validation analysis presented here. We then used the fieldtrip²³
 126 toolbox (version 20230926) to compute the power spectrum between 0-40 Hz using a Fast
 127 Fourier Transform (FFT) with a fixed length Hanning window of 0.8s yielding a frequency
 128 resolution of 1.25Hz. We averaged the frequency spectra across epochs for each infant, to
 129 examine their neural response at the 5Hz presentation rate and its corresponding harmonics.
 130

131 We performed time-resolved representational similarity analyses^{10,24} in Matlab using the
 132 CoSMoMVPA toolbox²⁵. First, we created RDMs for each infant by pca-transforming the
 133 baseline-corrected epochs, and averaging the evoked responses in posterior electrodes (C3
 134 ,CP5,CP1,Pz,P3,P7,P9,O1,Oz,O2,P10,P8,P4,CP2,CP6,C4,Cz) to each of the 200 images, and
 135 computing the dissimilarity (1-correlation) between each pair of images, separately for each
 136 time point in the epochs. This yielded a 200 by 200 representational dissimilarity matrix (RDM)
 137 for each time point for each infant. To estimate information in the infant data, we created
 138 model RDMs at three levels (object, category, and animacy) and correlated these with the
 139 neural RDM at each time point.

140
 141 Finally, we evaluated how well the structural overlap between our infant RDMs and an existing
 142 openly available adult EEG dataset¹⁵ derived from the same 200 object stimuli, using a similar
 143 5Hz rapid stimulus paradigm (for more details, see its associated publication¹⁵). For analysing
 144 the structural overlap between infant and adult data, we performed a time-time correlation
 145 between the mean infant RDMs and the mean adult RDMs at each pair of time points, resulting
 146 in a time-time correlation matrix. We then calculated cluster-based p-values by shuffling the
 147 RDMs 1000 times and re-computing the time-time correlations, applied a cluster-forming
 148 threshold of $p < 0.05$ and calculated the maximum cluster sum statistic for each permutation.
 149 We then reported the clusters in the original correlation result that exceeded 95% of the max-
 150 statistic permutation distribution.

151 Data Records

152 All data and code reported here are publicly available. The adult data can be found with the
 153 associated publication¹⁵. The raw infant EEG recordings are formatted according to the
 154 BIDS^{26,27} standard and hosted on OpenNeuro (<https://openneuro.org/datasets/ds005106>).
 155 The preprocessed (Matlab/EEGLAB²² format) data, individual RDMs, and RSA results are
 156 included for convenience, as well as the custom Matlab code to generate the figures in this
 157 paper. The data repository contains instructions and example code on how to get started with
 158 analyses.

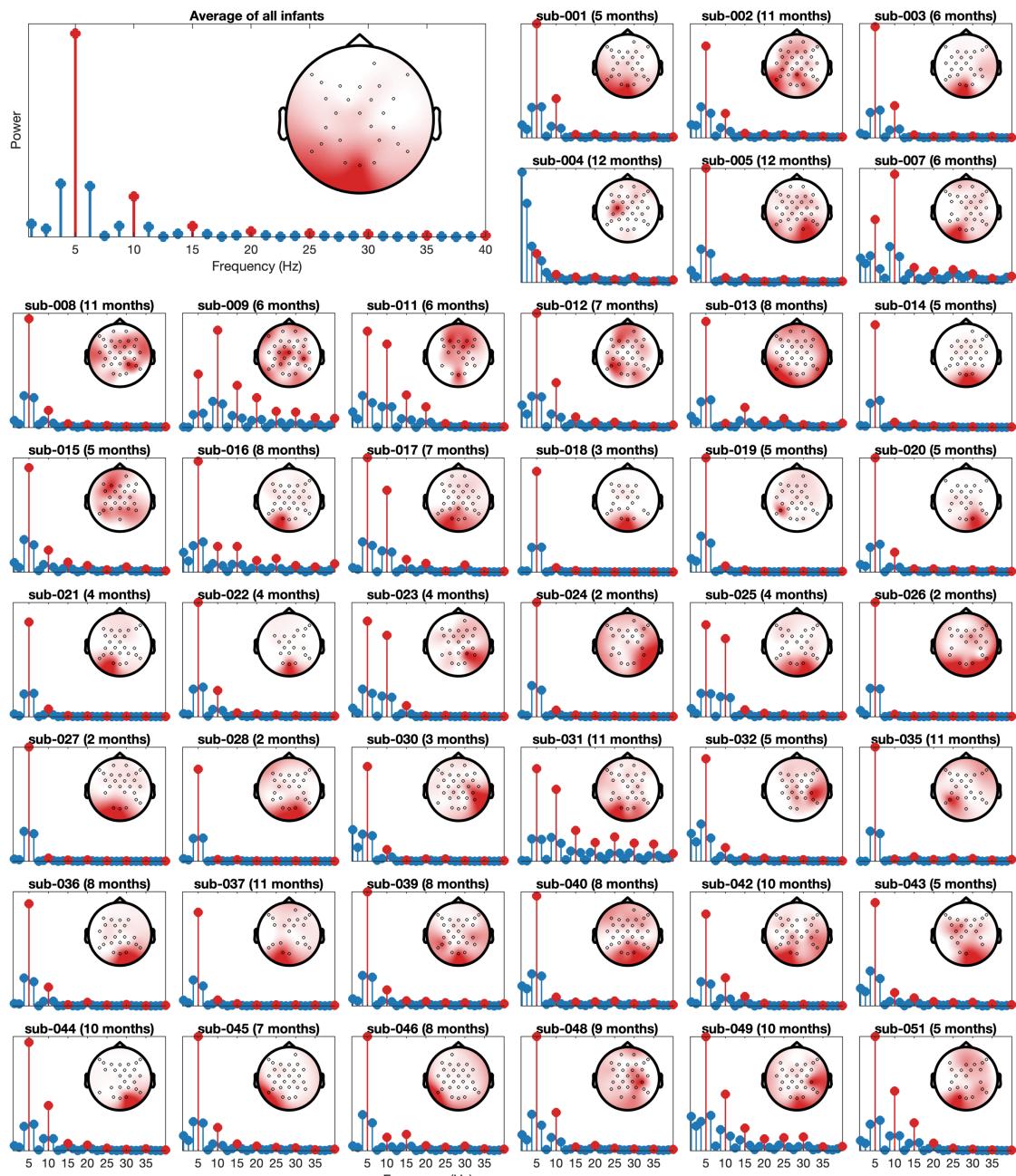
159 Technical Validation

160 To validate the quality of the data, we first measured the evoked steady state responses in
 161 each infant. As the 5Hz rapid presentation sequence should drive a visual signal in occipital
 162 electrodes at the presentation frequency and its harmonics, we performed a Fast Fourier
 163 Transform of the epoched data, and examined the spectral power per frequency (Figure 2). In
 164 the majority of infants, a strong 5Hz signal originating from occipital electrodes can be
 165 observed.

166

167 Next, to test the presence of object and category information in the evoked signals, we used
 168 time-varying representational similarity analysis¹⁰ to compare similarity neural responses to 3
 169 categorical levels of information from the EEG for the 200 images. Results indicated decodable
 170 information about the categorical levels (Figure 3), with comparable temporal dynamics to
 171 adult results obtained previously with a similar paradigm¹⁵. The infant RDMs were then directly
 172 compared to the adult RDM (Figure 3) for each pair of time points in the evoked responses,
 173 which showed a cluster of shared variance spanning approximately 200-500ms in the infant
 174 data to 100-250ms in the adult data.

175



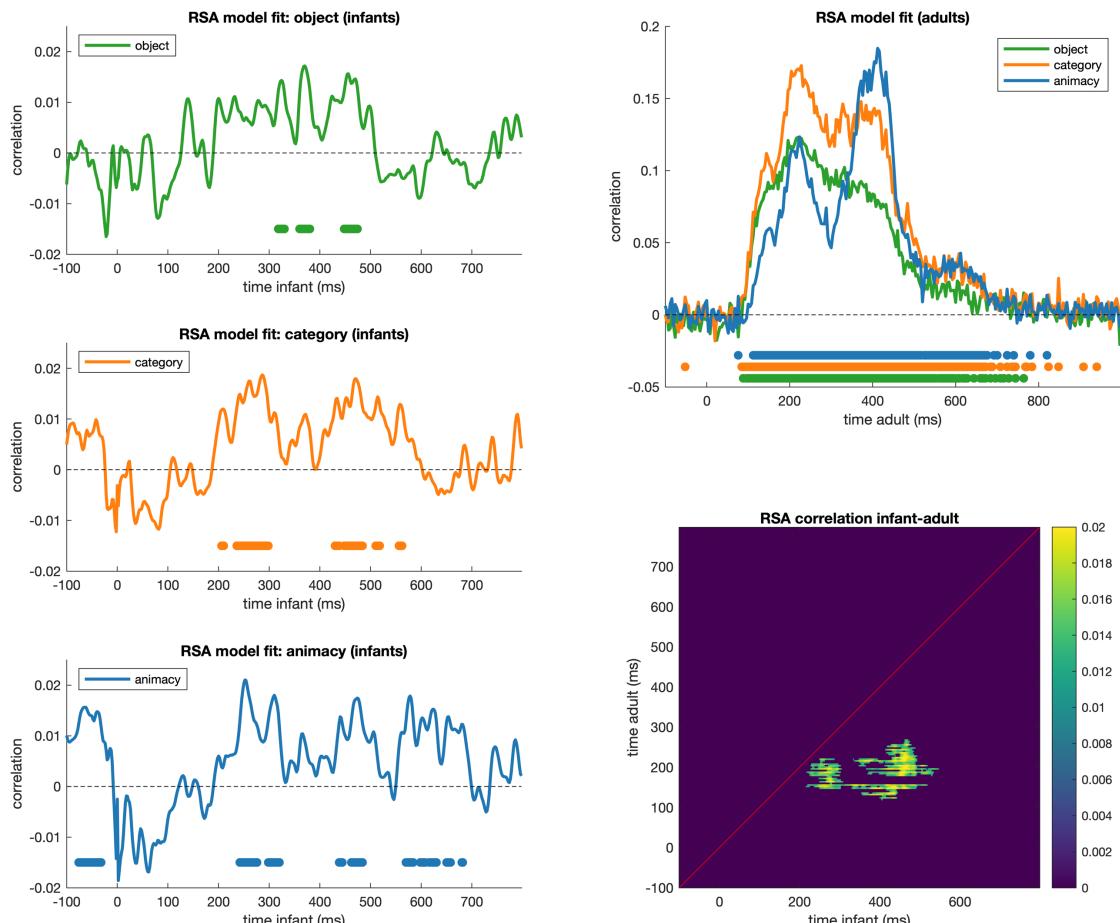
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Figure 2: Averaged (top left) and individual spectral power. The 5Hz presentation frequency and harmonics (10Hz, 15Hz, 20Hz, etc) shown in red. Inset in each plot are the channel topographies of the 5Hz signal.



180
181 **Figure 3:** Technical validation results. Left: RSA model fits for the infant RDM for 3 categorical
182 levels. Marks above the x-axis indicate $p < 0.05$ (uncorr.). Top-right: RSA model fits for the adult
183 RDMs for comparison marks above the x-axis indicate $p < 0.05$ (uncorr.). Bottom-right: Time-
184 time correlation matrix between the infant and adult RDMs, thresholded at $p < 0.05$ (cluster-
185 corrected). Significant clusters below the diagonal suggest that object representations arising
186 during later stages of the infant response (200-600ms) correspond well to an early stage of
187 the adult neural response (100-200ms).

188 **Code Availability**

189 Code and detailed instructions to reproduce the technical validation analyses and figures
190 presented in this manuscript are available in the “code” directory in the abovementioned
191 OpenNeuro repository.

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194 **Author contributions**

195 GQ: Conceptualization, Methodology, Investigation, Formal analysis, Data Curation, Writing –
196 Original Draft, Writing – Review & Editing.
197 ZZ: Investigation, Data Curation, Writing – Review & Editing.
198 MV: Methodology, Writing – Review & Editing, Funding Acquisition.
199 TG: Conceptualization, Methodology, Software, Investigation, Formal analysis, Visualization,
200 Data Curation, Writing – Original Draft, Writing – Review & Editing, Project administration,
201 Funding Acquisition.

202 **Competing interests**

203 The authors declare no competing interests.

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