# Exp. 1 Revised Analysis

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#### Reviewer 2

There is another concern about the data analysis that I'd like to raise. The trial-level inclusion criterion of a minimum of 500 ms during the analysis window seems extremely liberal, particularly since the window is 3500 ms long.

However, a subsequent PNAS paper by Bergelson & Aslin (2017), also cited in the manuscript, used a more conservative criterion: 'Trials were excluded if infants did not look at either image for at least 1/3 of the target window. This 10 1/3 criterion was also used by Bergelson & Swingley (2017). The 1/3 choice 11 seems like a much more reasonable inclusion criterion than the 1/7 used in the current study, which seems like it could lead to a lot of noise.

It is also standard to exclude infants who do not provide data for at least half of the test trials (cf. Bergelson & Swingley, 2017). I understand that this is a very difficult-to-test sample, and that the authors want to retain as many infants in the sample as possible, but there is a tradeoff between data retention and interpretability of the effects. In particular, the 1/7 data retention criterion seems quite problematic.

#### Adopting (3133/3)ms looking-time threshhold for trial inclusion

```
## exclusions
cn_r2\sexclusions <- cn_r2\skeep
cn_r2$exclusions[cn_r2$keep=='keep'] <- ''</pre>
cn_r2$exclusions[cn_r2$exclusions %in% c(
  'infant not paying attention', 'infant crying')] <-
  'restive_infant'
cn r2$exclusions[cn r2$pre looking sum ms == 0] <-
  'zero pre looking'
cn_r2$exclusions[cn_r2$post1_looking_sum_ms < (3133/3)] <-</pre>
  'under_third_window_looking'
```

```
cn r2$exclusions[cn r2$exclusions=='mom interference'] <-</pre>
     'mom_error'
   cn_r2$exclusions[cn_r2$exclusions=='discard'] <-</pre>
   TOTAL_EXCLUDED_TRIALS <- nrow(cn_r2[cn_r2$exclusions %in%
                                            c('restive_infant', 'zero_pre_looking',
                                              'mom_error',
                                              'under_third_window_looking'),])
  + 3 # mom_errors flagged in Datavyu export script:
  ## [1] 3
   # 'Invalid number of wordWindow cells' (because of mom not speaking prompt)'
   cn_exclusions_tab <- cn_r2 %>%
     filter(exclusions!='trial_was_recycled',
            exclusions!='old trial type') %>%
     group_by(subject_id) %>%
     summarize(excluded_trials=sum(exclusions!='')) %>%
     ungroup() %>%
     summarize(children_w_excl_trials=sum(excluded_trials>0),
               min_excl_trials=min(excluded_trials),
               max_excl_trials=max(excluded_trials),
               mean_excl_trials=mean(excluded_trials))
   xtable2kable(cn_exclusions_tab)
  ## # A tibble: 1 x 4
        children w excl trials min excl trials max excl trials mean excl trials
  ##
23
  ##
                          <int>
                                           <int>
                                                             <int>
                                                                               <dbl>
24
  ## 1
                              20
                                                                16
                                                                                4.52
25
        Excluded test trials came from 20 infants who had between 0 and 16 excluded trials; all
26
  infants provided usable data for at least half of the test trials. If we instead adopt the criteria
```

Excluded test trials came from 20 infants who had between 0 and 16 excluded trials; all infants provided usable data for at least half of the test trials. If we instead adopt the criteria that infants should provide data for at least half of the difference score calculations, then one subject ('J94252'), with 16 test trials, but only two calculable difference scores, should be excluded (see next section—'EXCLUSION CRITERIA 2'—for revised mean difference score analyses, which use this criterion).

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```
## # A tibble: 3 x 11
  ##
        min_good_trials min_n max_good_trials max_n mean_good_trials
                                                                            med
33
  ##
                   <dbl> <dbl>
                                          <dbl> <dbl>
                                                                    <dbl> <dbl>
34
  ## 1
                      16
                              3
                                              32
                                                                    25.1
                                                                             26
                                                     1
35
                      16
                              3
                                              32
                                                                    25.1
  ## 2
                                                     1
                                                                             26
36
                              3
  ## 3
                      16
                                              32
                                                     1
                                                                    25.1
                                                                             26
37
  ## # i 5 more variables: mode_good_trials <dbl>, mode_n <dbl>,
          min_good_prop <dbl>, max_good_prop <dbl>, mean_good_prop <dbl>
  ## #
```

A total of 93 trials from 20 infants were excluded because the infant never looked to the displays during the pre-naming period (n=14), looked for less than one-third of the analysis window (n=72), was distracted or crying (n=3), or because the caregiver erred or interfered (n=7). All infants contributed at least half (16) of test trials (range= c(16,16,16)-c(32,32,32), c(16,16,16)-c(32,32,32), c(16,16,16)-c(32,32,32), c(16,16,16)-c(32,32,32), c(16,16,16)-c(32,32,32), c(16,16,16)-c(32,32,32), c(16,16)-c(32,32,32), c(16,16)-c(32,32), c(16,16)-c(32,32)

#### **EXCLUSION CRITERIA 1**

```
MIN_AGE <- min(cn_fin_pp_df$bebe_meses)

MAX_AGE <- max(cn_fin_pp_df$bebe_meses)

MEAN_AGE <- mean(cn_fin_pp_df$bebe_meses)

SD_AGE <- sd(cn_fin_pp_df$bebe_meses)

We report on data from 21 infants (5.33 - 15.43mos, Mage = 10.96mos, SD_age = 2.71mos).

MOT_M_AGE <- na.mean(cn_fin_pp_df$mama_edad)

MOT_MIN_AGE <- min(cn_fin_pp_df$mama_edad, na.rm=T)

MOT_MAX_AGE <- max(cn_fin_pp_df$mama_edad, na.rm=T)

MOT_SD_AGE <- sd(cn_fin_pp_df$mama_edad, na.rm=T)
```

Mothers ranged in age from 14 to 44yrs ( $M_{age} = 26.85yrs$ ,  $SD_{age} = 8.36yrs$ )

# 49 Mean Difference Score Analysis

```
## specific image pairs (which of two image-pairs for each noun-pair)
# want to know the pairs of values that go together for the B&S 2012 calculation,
# which means the specific instances of each noun-pair where, e.g., baby is on L
# and corn is on R
cn_fin$trial_name_short <- gsub('^[0-9]*[-]', '', cn_fin$old_trial_name)</pre>
cn fin$stimulus set <- ''
# baby left, corn right = 'A'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'babcor-baby-L', 'babcor-corn-R',
  'BABY-corn', 'baby-CORN',
  'corbab-corn-R', 'corbab-baby-L')] <- 'A'
# corn left, baby right = 'B'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'babcor-baby-R', 'babcor-corn-L',
  'corbab-baby-R', 'corbab-corn-L',
  'corn-BABY', 'CORN-baby')] <- 'B'</pre>
# car left, shoe right = 'C'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'carsho-car-L', 'carsho-shoe-R',
  'CAR-shoe', 'car-SHOE')] <- 'C'
# shoe left, car right = 'D'
```

```
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'carsho-car-R', 'carsho-shoe-L',
  'shocar-shoe-L', 'shocar-car-R',
  'SHOE-car', 'shoe-CAR', 'carshow-car-R')] <- 'D'
# chayote left, cow right = 'E'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'chacow-chayote-L', 'chacow-cow-R',
  'chayote-COW', 'CHAYOTE-cow')] <- 'E'</pre>
# cow left, chayote right = 'F'
cn fin$stimulus set[cn fin$trial name short %in% c(
  'chacow-chayote-R', 'chacow-cow-L',
  'cowcha-cow-L', 'cowcha-chayote-R',
  'COW-chayote', 'cow-CHAYOTE')] <- 'F'
# dog left, fire right = 'G'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'dogfir-dog-L', 'dogfir-fire-R',
  'DOG-fire', 'dog-FIRE',
  'firdog-dog-L', 'firdog-fire-R')] <- 'G'
# fire left, dog right = 'H'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'dogfir-dog-R', 'dogfir-fire-L',
  'fire-DOG', 'FIRE-dog',
  'firdog-dog-R', 'firdog-fire-L')] <- 'H'
# horse left, soda right = 'I'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'horsod-horse-L', 'horsod-soda-R',
  'HORSE-soda', 'horse-SODA',
  'sodhor-horse-L', 'sodhor-soda-R')] <- 'I'</pre>
# soda left, horse right = 'J'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'horsod-horse-R', 'horsod-soda-L',
  'SODA-horse', 'soda-HORSE',
  'sodhor-horse-R', 'sodhor-soda-L')] <- 'J'</pre>
# rabbit left, soup right = 'K'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'rabsou-rabbit-L', 'rabsou-soup-R',
  'RABBIT-soup', 'rabbit-SOUP',
```

```
'sourab-rabbit-L', 'sourab-soup-R')] <- 'K'</pre>
# soup left, rabbit right = 'L'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'rabsou-rabbit-R', 'rabsou-soup-L',
  'sourab-rabbit-R', 'sourab-soup-L',
  'SOUP-rabbit', 'soup-RABBIT')] <- 'L'
# sheep left, water right = 'M'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'shewat-sheep-L', 'shewat-water-R',
  'sheep-WATER', 'SHEEP-water',
  'watshe-sheep-L', 'watshe-water-R')] <- 'M'
# water left, sheep right = 'N'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'shewat-sheep-R', 'shewat-water-L',
  'watshe-water-L', 'watshe-sheep-R',
  'water-SHEEP', 'WATER-sheep')] <- 'N'
# chicken left, tortilla right = '0'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'chitor-chicken-L', 'chitor-tortilla-R',
  'chicken-TORTILLA', 'CHICKEN-tortilla',
  'torchi-chicken-L', 'torchi-tortilla-R')] <- '0'
# tortilla left, chicken right = 'P'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'chitor-chicken-R', 'chitor-tortilla-L',
  'torchi-tortilla-L', 'torchi-chicken-R',
  'tortilla-CHICKEN', 'TORTILLA-chicken')] <- 'P'
# car left, squash right = 'Q'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'carsqu-car-L', 'carsqu-squash-R')] <- 'Q'</pre>
# squash left, car right = 'R'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'carsqu-squash-L', 'carsqu-car-R')] <- 'R'
# cow left, spoon right = 'S'
cn fin$stimulus set[cn fin$trial name short %in% c(
  'cowspo-cow-L', 'cowspo-spoon-R')] <- 'S'
```

```
# spoon left, cow right = 'T'
cn_fin$stimulus_set[cn_fin$trial_name_short %in% c(
  'cowspo-spoon-L', 'cowspo-cow-R')] <- 'T'
cn_fin$target_stimulus <- paste(cn_fin$target_noun,</pre>
                                 cn_fin$stimulus_set, sep='')
cn_fin$non_target_stimulus <- paste(cn_fin$non_target_noun,</pre>
                                     cn_fin$stimulus_set, sep='')
cn_target_df <- cn_fin %>%
  dplyr::select(subject_id, target_noun, stimulus_set,
                target_stimulus,
                noun_pair, post1_target_prop,
                age centered, bebe meses, age group) %>%
  mutate(merge_on_noun = target_stimulus)
cn_non_target_df <- cn_fin %>%
  dplyr::select(subject_id, non_target_noun, stimulus_set,
                non_target_stimulus,
                noun_pair, post1_nontarget_prop,
                age_centered, bebe_meses, age_group) %>%
  mutate(merge_on_noun=non_target_stimulus)
cn_target_nontarget_props_df <- merge(</pre>
  cn_target_df, cn_non_target_df,
                                       by=c('subject_id',
                                            'noun_pair',
                                            'stimulus_set',
                                            'merge on noun',
                                            'age centered',
                                            'bebe_meses',
                                            'age_group'),
  all=T) %>%
  group_by(subject_id, noun_pair, stimulus_set, merge_on_noun,
           bebe_meses, age_centered, age_group) %>%
  summarize(post1_target_prop = na.mean(post1_target_prop),
            post1_nontarget_prop = na.mean(post1_nontarget_prop))
cn_diffs_df <- cn_target_nontarget_props_df %>%
  filter(noun_pair %in% noun_pairs) %>%
  dplyr::select(subject_id,
                bebe_meses, age_centered, age_group,
                noun_pair,
                stimulus_set, merge_on_noun,
```

```
num_scores_bypp_tab <- cn_diffs_df %>%
  filter(!is.na(noun_pair_diff)) %>%
  group_by(subject_id) %>%
  summarize(n_pairs=n()) %>%
  group_by(n_pairs) %>%
  summarize(n_subs = n())
```

We were able to calculate item-level scores for at least two noun-pairs for all subjects. There were eight subjects with calculable difference scores for all 8 noun-pairs, seven with calculable difference scores for 7/8, two with calculable scores for 6/8, one with calculable scores for 5/8, two with calculable scores for 4/8, and one with calculable scores for only 2/8.

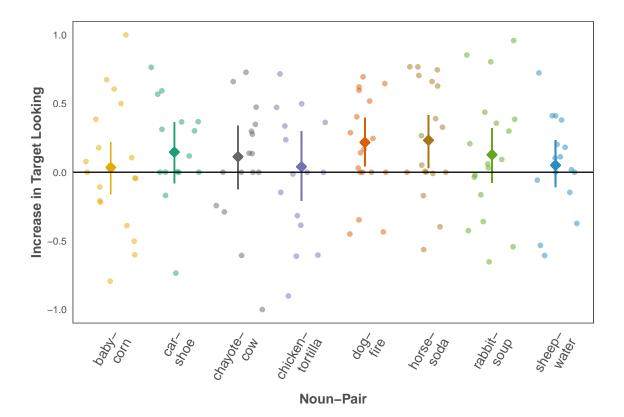
```
set.seed(36)
by_item_tab <- cn_diffs_df %>%
  group_by(noun_pair, subject_id) %>%
  summarize(subj_mean = na.mean(noun_pair_diff)) %>%
  ungroup() %>%
  group_by(noun_pair) %>%
  summarize(n = n(),
            M = na.mean(subj_mean),
            cil=M-ci.low(subj_mean),
            cih = M+ci.high(subj_mean),
            min=min(subj_mean, na.rm=T),
            max=max(subj_mean, na.rm=T))
ALL_ITEM_MEAN <- mean(by_item_tab$M)
ALL_ITEM_CIL <- ALL_ITEM_MEAN - ci.low(by_item_tab$M)
ALL_ITEM_CIH <- ALL_ITEM_MEAN + ci.high(by_item_tab$M)
ALL_ITEM_MIN <- min(by_item_tab$M)
ALL_ITEM_MAX <- max(by_item_tab$M)
N_ITEMS_POSITIVE <- sum(by_item_tab$M>0)
```

## Scores By Item.

```
## # A tibble: 8 x 7
       noun_pair
                                       cil
                                             cih
                                                    min
58 ##
                       <int> <dbl> <dbl> <dbl> <dbl> <dbl> <
       <chr>
                        21 0.0341 -0.160 0.219 -0.794 1
59 ## 1 baby-corn
60 ## 2 car-shoe
                         19 0.146 -0.0816 0.364 -1
61 ## 3 chayote-cow
                         19 0.113 -0.124 0.340 -1
^{62} ## 4 chicken-tortilla 21 0.0401 -0.208 0.299 -0.901 1
63 ## 5 dog-fire
                         21 0.217 0.0428 0.398 -0.450 1
64 ## 6 horse-soda
                         21 0.232 0.0304 0.416 -0.563 0.768
65 ## 7 rabbit-soup
                         21 0.127 -0.0767 0.321 -0.653 0.959
66 ## 8 sheep-water
                         21 0.0517 -0.108 0.233 -0.606 0.723
```

```
cn_item_wilcox <- wilcox.test(by_item_tab$M, mu=0,</pre>
                                   alternative='two.sided')
   CN_ITEM_P_WILCOX <- reportP(cn_item_wilcox$p.value)</pre>
   cn_item_binom <- binom.test(8, 8, p=.5)</pre>
   CN_ITEM_P_BINOM <- reportP(cn_item_binom$p.value)</pre>
   set.seed(36)
   # Bayes factor
   ttestBF(by_item_tab$M)
        Non-parametric tests.
  ## Bayes factor analysis
  ## -----
70 ## [1] Alt., r=0.707 : 17 ±0%
71 ##
72 ## Against denominator:
73 ##
       Null, mu = 0
74 ## ---
75 ## Bayes factor type: BFoneSample, JZS
   # Standard deviation
   stdev=sd(by_item_tab$M)
  mean_data=na.mean(by_item_tab$M)
   # Effect size
   CN_ITEM_D=abs(mean_data/stdev)
        When implementing this new, more stringent exclusion criteria suggested by R2, 8/8
76
77 noun-pairs showed a positive mean difference score (range: 0.03 - 0.23, M = 0.12 95% CI:
  [0.07, 0.17]; p < .01, Wilcoxon test, p < .01, binomial test, <math>d = 1.57).
   set.seed(36)
   cn_diffs_df$noun_pair_label <- gsub('-', '-\n', cn_diffs_df$noun_pair)</pre>
```

```
cn_diffs_df %>%
 group_by(noun_pair, noun_pair_label, subject_id) %>%
 summarize(subj_mean = na.mean(noun_pair_diff)) %>%
 ungroup() %>%
 group_by(noun_pair, noun_pair_label) %>%
 mutate(n_subjects = n(),
            item_mean = na.mean(subj_mean),
           min=min(subj_mean, na.rm=T),
           max=max(subj_mean, na.rm=T),
            ci.low=item_mean-ci.low(subj_mean),
            ci.high = item_mean+ci.high(subj_mean)) %>%
 ggplot(., aes(
   x=noun_pair_label, y=item_mean, color=noun_pair)) +
 geom_jitter(aes(y=subj_mean), alpha=.5) +
 geom_pointrange(aes(y=item_mean,
                      ymin=ci.low, ymax=ci.high,
                      fill=noun_pair), shape=23, size=0.5) +
 geom_hline(yintercept=0) +
 ylim(-1, 1) +
 sb.density.theme +
 theme(axis.text.x = element_text())
   angle=60, vjust=1, hjust=1, size=11),
       legend.position = 'none',
       axis.title = element_text(
          colour='gray30', size=11, face='bold')) +
 ylab('Increase in Target Looking') +
 xlab('Noun-Pair') +
 scale_discrete_manual(aesthetics=c('color', 'fill'),
                        values=noun_pair_fills)
```



```
sub_means_tab <- cn_diffs_df %>%
  filter(!is.na(noun_pair_diff)) %>%
  group_by(subject_id, bebe_meses) %>%
  summarize(n = n(),
    subj_mean = na.mean(noun_pair_diff))
positive_scorers_age_tab <- sub_means_tab %>%
  filter(subj_mean>0) %>%
  ungroup() %>%
  summarize(min=min(bebe_meses),
            max=max(bebe_meses),
            mean=mean(bebe_meses),
            sd=sd(bebe meses),
            ci.low=mean-ci.low(bebe meses),
            ci.high=mean+ci.high(bebe_meses))
N_SUBS_POSITIVE <- sum(sub_means_tab$subj_mean>0)
PS_MIN_AGE <- positive_scorers_age_tab$min</pre>
PS_MAX_AGE <- positive_scorers_age_tab$max</pre>
PS_MEAN_AGE <- positive_scorers_age_tab$mean
PS_CIL_AGE <- positive_scorers_age_tab$ci.low
PS_CIH_AGE <- positive_scorers_age_tab$ci.high
PS_SD_AGE <- positive_scorers_age_tab$sd
```

Scores By Subject.

```
cn_subj_wilcox <- wilcox.test(sub_means_tab$subj_mean, mu=0,</pre>
                                  alternative='two.sided')
   CN_SUBJ_P_WILCOX <- reportP(cn_subj_wilcox$p.value)</pre>
   cn_subj_binom <- binom.test(N_SUBS_POSITIVE, 21, p=.5)</pre>
   CN_SUBJ_P_BINOM <- reportP(cn_subj_binom$p.value)</pre>
   set.seed(36)
   # Bayes factor
   ttestBF(sub_means_tab$subj_mean)
        Non-parametric tests.
82 ## Bayes factor analysis
  ## [1] Alt., r=0.707 : 5.8 \pm 0\%
85
  ## Against denominator:
86
87 ##
       Null, mu = 0
  ## Bayes factor type: BFoneSample, JZS
   ttestBF(sub_means_tab$subj_mean[sub_means_tab$bebe_meses<10])</pre>
90 ## Bayes factor analysis
91 ## -----
92 ## [1] Alt., r=0.707 : 0.42 ±0.01%
  ##
  ## Against denominator:
95 ## Null, mu = O
97 ## Bayes factor type: BFoneSample, JZS
```

```
ttestBF(sub_means_tab$subj_mean[sub_means_tab$bebe_meses>=10 &
                                       sub_means_tab$bebe_meses<14])</pre>
   ## Bayes factor analysis
   ## -----
   ## [1] Alt., r=0.707 : 2 ±0%
100
   ##
101
   ## Against denominator:
102
   ##
        Null, mu = 0
103
   ## ---
104
   ## Bayes factor type: BFoneSample, JZS
105
   ttestBF(sub_means_tab$subj_mean[sub_means_tab$bebe_meses>=14])
   ## Bayes factor analysis
107
   ## [1] Alt., r=0.707 : 1.1 ±0.04%
108
   ##
   ## Against denominator:
       Null, mu = 0
111 ##
112 ## ---
## Bayes factor type: BFoneSample, JZS
   # Standard deviation
   stdev=sd(sub_means_tab$subj_mean)
   # Mean
   mean_data=mean(sub_means_tab$subj_mean)
   # Effect size
   CN_SUBJ_D=abs(mean_data/stdev)
   set.seed(36)
   model0 <- lmer(noun_pair_diff ~ 0 + (1|subject_id), REML = FALSE,</pre>
                 cn_diffs_df)
   model1 <- lmer(noun_pair_diff ~ 1 + (1|subject_id), REML = FALSE,</pre>
                   cn_diffs_df)
   xtable2kable(summary(model1))
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
         method [lmerModLmerTest]
   ## Formula: noun_pair_diff ~ 1 + (1 | subject_id)
117
   ##
          Data: cn_diffs_df
118
   ##
119
   ##
            AIC
                      BIC
                            logLik deviance df.resid
120
   ##
            176
                      185
                               -85
                                         170
                                                   137
121
   ##
122
   ## Scaled residuals:
123
          Min
                  1Q Median
                                  3Q
                                        Max
124
   ## -2.533 -0.435 -0.107 0.618
                                      2.021
125
   ##
126
   ## Random effects:
127
   ##
        Groups
                                Variance Std.Dev.
                   Name
128
        subject_id (Intercept) 0.00301 0.0548
   ##
129
       Residual
                                0.19454 0.4411
   ##
   ## Number of obs: 140, groups: subject_id, 21
131
132
   ##
   ## Fixed effects:
133
                    Estimate Std. Error
                                              df t value Pr(>|t|)
134
   ## (Intercept)
                     0.1218
                                 0.0393 22.9081
                                                      3.1
                                                              0.005 **
135
   ## ---
136
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
137
   cn_b0_anova <- anova(model1, model0)</pre>
   CN_B0_CHISQ <- cn_b0_anova$Chisq[2]</pre>
   CN_BO_CHI_P <- reportP(cn_b0_anova$`Pr(>Chisq)`[2])
   all_subs_intercept <- as.data.frame(cbind(b=fixef(model1),
                               ci.low=confint(model1)[3,1],
                               ci.high=confint(model1)[3,2]))
   CN BO EST <- all subs intercept$b
   CN_BO_CIL <- all_subs_intercept$ci.low</pre>
   CN_BO_CIH <- all_subs_intercept$ci.high</pre>
   CN_BO_TT_DF <- as.numeric(unlist(summary(model1)['coefficients'])[3])</pre>
   CN_BO_TT_STAT <- as.numeric(unlist(summary(model1)['coefficients'])[4])</pre>
   CN_BO_TT_P <- reportP(as.numeric(unlist(summary(model1)['coefficients'])[5]))</pre>
   #noun pair not enough variance to warrant random intercept
   write(texreg(model1),
          file=here('supplement/tables/exp_1/cn_lmer0_tab.tex'))
```

The mean of infants' subject-level scores was also positive (range: -0.20 - 0.45,

M=0.11~95%~CI:~[0.04,~0.18],~p<.01,~Wilcoxon;~p<.01,~Cohen's~d=0.64),~ with a majority (17/21) of infants ( $M_{\rm age}=11.19mos,~SD_{\rm age}=2.74mos$ ) showing positive means across noun-pairs.

A linear mixed effects model with random intercepts for subjects indicates that these results were not driven by a few exceptional infants ( $\beta_0 = 0.12$ , 95% CI: [0.04, 0.20], t(22.91) = 3.10, p < .01;  $\chi^2(1) = 7.89$ , p < .01; d = 0.27).

Correlation with Age. Subject-level scores exhibited an insignificant positive correlation with infants' age in months ( $\tau = 0.25, p = 0.116$ ).

```
set.seed(36)

age_cor_test_no15mo <- cor.test(
   by_subj_age_tab[by_subj_age_tab$bebe_meses<15,]$bebe_meses,
   by_subj_age_tab[by_subj_age_tab$bebe_meses<15,]$subj_mean,
   method='kendall')

AGE_OLDEST_PP <- max(by_subj_age_tab$bebe_meses)
SCORE_OLDEST_PP <- op(by_subj_age_tab[
   by_subj_age_tab$bebe_meses==AGE_OLDEST_PP,]$subj_mean)
AGE_CORR_N015MO <- as.numeric(age_cor_test_no15mo$estimate)
AGE_CORR_P_N015MO <- reportP(age_cor_test_no15mo$p.value)
AGE_CORR_Z_N015MO <- as.numeric(age_cor_test_no15mo$statistic)</pre>
```

Excluding the one (oldest) participant (15.43 months) who showed notably low evidence of word recognition (mean difference score= 0.02), subject-level scores exhibited a significant ( $\alpha = 0.05$ ) positive correlation with infants' age in months ( $\tau = 0.33$ , p < .05).

```
age_lm <- lm(subj_mean ~ 1 + age_centered, by_subj_age_tab)
summary(age_lm)</pre>
```

```
##
150
   ## Call:
151
   ## lm(formula = subj_mean ~ 1 + age_centered, data = by_subj_age_tab)
152
   ##
153
   ## Residuals:
154
   ##
            Min
                       1Q
                             Median
                                           3Q
                                                    Max
155
    ## -0.24597 -0.14050
                           0.00887
                                     0.09741
                                               0.26630
156
   ##
157
   ##
      Coefficients:
158
                     Estimate Std. Error t value Pr(>|t|)
    ##
159
   ## (Intercept)
                       0.1170
                                   0.0372
                                              3.15
                                                      0.0053 **
160
   ## age_centered
                       0.0226
                                   0.0140
                                                      0.1241
                                              1.61
161
   ##
162
                        0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
163
164
   ## Residual standard error: 0.17 on 19 degrees of freedom
165
   ## Multiple R-squared: 0.12,
                                      Adjusted R-squared:
166
   ## F-statistic: 2.59 on 1 and 19 DF, p-value: 0.124
167
    write(texreg(age lm),
          file=here('supplement/tables/exp_1/cn_age_lm_tab.tex'))
```

**Results Section text.** All (8/8) noun-pairs showed positive mean scores, suggesting that the infants in our sample had knowledge of the nouns we tested, despite receiving very little directed speech (range:0.03-0.23, M=0.12, 95% bootstrapped CI: [0.07, 0.17];

The mean of infants' subject-level scores was also positive (range: -0.20 - 0.45, M = 0.11, 95% CI: [0.04, 0.18]; p < .01, Wilcoxon; p < .01, binomial; d = 0.64), with a majority (17/21) of infants ( $M_{\rm age} = 11.19mos$ ,  $SD_{\rm age} = 2.74mos$ ) showing positive means across noun-pairs (see Figure in Supplement).

A linear mixed effects model with random intercepts for subjects<sup>1</sup> indicates that these results were not driven by a few exceptional infants ( $\beta_0 = 0.12, 95\%$  CI: [0.04, 0.20],  $t(22.91) = 3.10, p < .01; \chi^2(1) = 7.89, p < .01; d = 0.27$ ).

p < .01, Wilcoxon; p < .01, binomial test; d = 1.57).

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<sup>&</sup>lt;sup>1</sup>A model which additionally included random intercepts for item failed to converge.

```
cn diffs df %>%
 filter(!is.na(noun_pair_diff)) %>%
 group_by(subject_id, bebe_meses) %>%
  summarize(subj_mean = na.mean(noun_pair_diff),
            n_{items} = n()) %>%
  filter(!is.na(subj_mean)) %>%
ggplot(.) +
  geom_point(aes(x=bebe_meses, y=subj_mean),
             color=sheeppink, alpha=.95, shape=21, size=2.5,
             fill=sheeppink) +
  geom_linerange(aes(x=bebe_meses,
                     ymin=0, ymax=subj_mean),
                 color=sheeppink) +
  geom hline(yintercept=0) +
  sb.density.theme +
  theme(
    axis.title = element_text(colour='gray30', size=11, face='bold'),
        axis.text = element_text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30')) +
  ylab('Increase in Target Looking') +
  xlab('Child Age (months)') +
 xlim(4.5, 16.0) +
  scale_x_continuous(breaks=c(4,5,6,7,8,9,10,11,12,13,14,15))+
 ylim(-.4, .6)
```

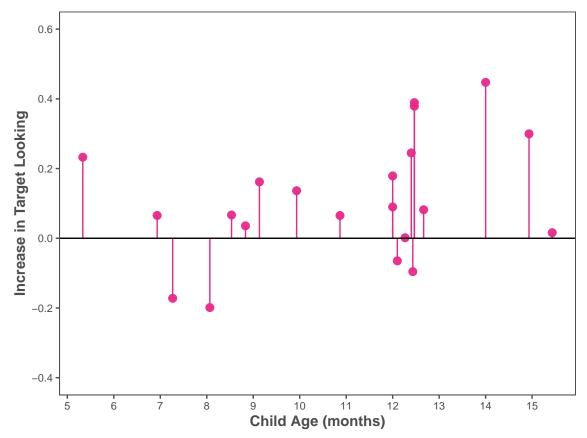


Figure 1

```
bysub_agegroup_means_df <-
    cn_diffs_df %>%
    group_by(subject_id, age_group) %>%
    summarize(subj_mean = na.mean(noun_pair_diff)) %>%
    group_by(age_group) %>%
    summarize(age_group_M=na.mean(subj_mean))

CN_SUBJ_MDIFF_6MOS <-
    bysub_agegroup_means_df$age_group_M[
        bysub_agegroup_means_df$age_group == '5-9 months']

CN_SUBJ_MDIFF_10MOS <-
    bysub_agegroup_means_df$age_group_M[
        bysub_agegroup_means_df$age_group == '10-13 months']

CN_SUBJ_MDIFF_14MOS <-
    bysub_agegroup_means_df$age_group_M[
        bysub_agegroup_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_df$age_group_means_
```

```
byitem_agegroup_means_df <- cn_diffs_df %>%
  filter(noun_pair %in% noun_pairs) %>%
  group_by(age_group, noun_pair) %>%
  summarize(item_mean = na.mean(noun_pair_diff)) %>%
  group_by(age_group) %>%
  summarize(n = n(),
            age_group_M = na.mean(item_mean),
            cil = age_group_M - ci.low(item_mean),
            cih = age_group_M + ci.high(item_mean),
            min = min(item_mean, na.rm=T),
            max = max(item_mean, na.rm=T))
CN ITEM MDIFF 6MOS <-
  byitem_agegroup_means_df$age_group_M[
    byitem_agegroup_means_df$age_group == '5-9 months']
CN ITEM MDIFF 10MOS <-
  byitem_agegroup_means_df$age_group_M[
    byitem_agegroup_means_df$age_group == '10-13 months']
CN_ITEM_MDIFF_14MOS <-
  byitem_agegroup_means_df$age_group_M[
    byitem_agegroup_means_df\(^age_group == '14-16 months'\)
```

Comparison to B&S 2012. The evidence that Tseltal infants possessed knowledge of the words we probed is similarly strong to evidence that has been used to infer the presence of word knowledge among U.S. infants. For example, Bergelson and Swingley (2012) reported mean scores of 0.074 (over subjects) and 0.065 (over items) for 6- to 9-month-olds, 0.055 (over subjects) and 0.059 (over items) for 10- to 13-month-olds, and 0.29 (over subjects) and 0.28 (over items) for 14-16-month-olds.

We found: mean scores of 0.04 (over subjects) and 0.03 (over items) for 6- to 9-month-olds, 0.13 (over subjects) and 0.12 (over items) for 10- to 13-month-olds, and 0.25 (over subjects) and 0.26 (over items) for 14- to 16-month-olds.

#### EXCLUSION CRITERIA 2 (EC2)

#### Replicating Mean Difference Analysis (EC2)

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Including only infants affording calculation of at least half (4) of **difference scores** (rather than contributing half of all trials)

Under this criterion, total sample includes:

```
_ - 8 infants with calculable difference scores for all 8 noun-pairs_
_ - 7 infants with calculable difference scores for 7/8_
_ - 2 infants with calculable scores for 6/8_
```

```
    196 _- 1 infant with a calculable score for 5/8_
    197 _- 2 infants with calculable scores for 4/8_
```

- 1 EXCLUDED participant with calculable scores for only 2/8 (fewer than half of the set of noun-pairs).

N=20

```
set.seed(36)
by_item_tab2 <- cn_diffs_df %>%
  filter(subject_id!='J94252') %>%
  group_by(noun_pair, subject_id) %>%
  summarize(subj_mean = na.mean(noun_pair_diff)) %>%
 ungroup() %>%
  group_by(noun_pair) %>%
  summarize(n_subjects = n(),
            item mean = na.mean(subj mean),
            median = median(subj_mean, na.rm=T),
            ci.low=item_mean-ci.low(subj_mean),
            ci.high = item_mean+ci.high(subj_mean),
            min=min(subj_mean, na.rm=T),
            max=max(subj_mean, na.rm=T))
ALL_ITEM_MEAN2 <- mean(by_item_tab2$item_mean)
ALL_ITEM_CIL2 <- ALL_ITEM_MEAN - ci.low(by_item_tab2$item_mean)
ALL_ITEM_CIH2 <- ALL_ITEM_MEAN + ci.high(by_item_tab2$item_mean)
ALL_ITEM_MIN2 <- min(by_item_tab2$item_mean)
ALL_ITEM_MAX2 <- max(by_item_tab2\$item_mean)
N_ITEMS_POSITIVE2 <- sum(by_item_tab2$item_mean>0)
```

```
set.seed(36)
   by_item_tab2 <- cn_diffs_df %>%
     filter(subject_id!='J94252') %>%
     group_by(noun_pair, subject_id) %>%
     summarize(subj_mean = na.mean(noun_pair_diff)) %>%
     ungroup() %>%
     group_by(noun_pair) %>%
     summarize(n = n(),
               M = na.mean(subj_mean),
               cil=M-ci.low(subj_mean),
               cih = M+ci.high(subj_mean),
               min=min(subj_mean, na.rm=T),
               max=max(subj mean, na.rm=T))
   xtable2kable(by_item_tab2)
        Scores By Item (EC2).
   ## # A tibble: 8 x 7
202
   ##
       noun_pair
                                   Μ
                                         cil
                                               cih
                                                      min
203
                            n
                                                            max
        <chr>
                       <int> <dbl>
                                     <dbl> <dbl> <dbl> <dbl> <dbl>
  ##
                        20 0.0359 -0.183 0.251 -0.794 1
  ## 1 baby-corn
206 ## 2 car-shoe
                          18 0.146 -0.0860 0.359 -1
207 ## 3 chayote-cow 18 0.113 -0.108 0.335 -1
^{208} ## 4 chicken-tortilla \, 20 0.0401 -0.205 0.291 -0.901 1
209 ## 5 dog-fire
                        20 0.217 0.0374 0.394 -0.450 1
210 ## 6 horse-soda
                         211 ## 7 rabbit-soup
                         20 0.127 -0.0850 0.348 -0.653 0.959
212 ## 8 sheep-water
                          20 0.0517 -0.111 0.214 -0.606 0.723
   cn_item_wilcox2 <- wilcox.test(by_item_tab2$M, mu=0,</pre>
                                alternative='two.sided')
   CN_ITEM_P_WILCOX2 <- reportP(cn_item_wilcox2$p.value)</pre>
   cn_item_binom2 <- binom.test(N_ITEMS_POSITIVE2, 8, p=.5)</pre>
```

CN\_ITEM\_P\_BINOM2 <- reportP(cn\_item\_binom2\$p.value)</pre>

```
set.seed(36)
# Bayes factor
ttestBF(by_item_tab2$M)
```

### $Non-parametric\ Tests\ (EC2).$

```
214 ## Bayes factor analysis
215 ## ------
216 ## [1] Alt., r=0.707 : 13 ±0%
217 ##
218 ## Against denominator:
219 ## Null, mu = 0
220 ## ---
221 ## Bayes factor type: BFoneSample, JZS
```

```
# Standard deviation
stdev=sd(by_item_tab2$M)
# Mean
mean_data=mean(by_item_tab2$M)
# Effect size
CN_ITEM_D2=abs(mean_data/stdev)
```

When implementing this new, even more stringent exclusion criteria (leading us to drop an entire participant's data), 8/8 noun-pairs showed a positive mean difference score (0.04 – 0.27, M=0.12 95% CI: [0.06, 0.17]; p<.01, Wilcoxon test; p<.01, binomial test, d=1.47).

```
sub_means_tab2 <- cn_diffs_df %>%
  filter(!is.na(noun_pair_diff),
         subject_id != 'J94252') %>%
  group_by(subject_id, bebe_meses) %>%
  summarize(n = n(),
    subj_mean = na.mean(noun_pair_diff))
positive_scorers_age_tab2 <- sub_means_tab2 %>%
  filter(subj_mean>0) %>%
  ungroup() %>%
  summarize(min=min(bebe_meses),
            max=max(bebe_meses),
            mean=mean(bebe_meses),
            sd=sd(bebe_meses),
            ci.low=mean-ci.low(bebe_meses),
            ci.high=mean+ci.high(bebe_meses))
N2 <- length(unique(sub_means_tab2$subject_id))</pre>
N_SUBS_POSITIVE2 <- sum(sub_means_tab2$subj_mean>0)
PS_MIN_AGE2 <- positive_scorers_age_tab2$min
PS_MAX_AGE2 <- positive_scorers_age_tab2$max
PS_MEAN_AGE2 <- positive_scorers_age_tab2$mean
PS_CIL_AGE2 <- positive_scorers_age_tab2$ci.low
PS_CIH_AGE2 <- positive_scorers_age_tab2$ci.high
PS_SD_AGE2 <- positive_scorers_age_tab2$sd
```

Scores By Subject (EC2). 17/20 subjects showed a positive mean difference score (range: -10.10yrs,  $M_{age} = 11.19 95\%$  CI: [9.90, 12.33],  $SD_{age} = 2.74$ ).

```
by_sub_overall_tab2 <- cn_diffs_df %>%
filter(subject_id != 'J94252') %>%
group_by(subject_id) %>%
summarize(subj_mean = na.mean(noun_pair_diff)) %>%
ungroup() %>%
summarize(group_subject_mean = mean(subj_mean),
min=min(subj_mean),
max=max(subj_mean),
ci.low=group_subject_mean-ci.low(subj_mean),
ci.high = group_subject_mean+ci.high(subj_mean))
```

```
ALL_SUB_MEAN2 <- by_sub_overall_tab2$group_subject_mean
ALL_SUB_CIL2 <- by_sub_overall_tab2$ci.low
ALL_SUB_CIH2 <- by_sub_overall_tab2$ci.high
ALL_SUB_MIN2 <- by_sub_overall_tab2$min
ALL_SUB_MAX2 <- by_sub_overall_tab2$max
```

#### $MLM\ Intercept\ (EC2).$

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
229
        method [lmerModLmerTest]
   ## Formula: noun_pair_diff ~ 1 + (1 | subject_id)
         Data: cn_diffs_df[cn_diffs_df$subject_id != "J94252", ]
   ##
232
   ##
233
   ##
           AIC
                     BIC
                           logLik deviance df.resid
234
           174
                     183
                               -84
                                        168
                                                  135
   ##
235
   ##
236
   ## Scaled residuals:
237
          Min
                    1Q Median
                                     3Q
                                            Max
238
   ## -2.5378 -0.4097 -0.0874 0.6331
                                        2.0047
239
240
   ##
   ## Random effects:
241
   ## Groups
                               Variance Std.Dev.
                   Name
242
       subject_id (Intercept) 0.00287 0.0535
243
   ## Residual
                                0.19546 0.4421
244
   ## Number of obs: 138, groups: subject_id, 20
245
   ##
   ## Fixed effects:
                                             df t value Pr(>|t|)
                   Estimate Std. Error
248
   ## (Intercept) 0.1269
                                0.0395 22.3564
                                                   3.21
                                                            0.004 **
249
250
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
```

```
cn b0 anova 2 <- anova(model1 2, model0 2)</pre>
   CN_BO_CHISQ2 <- cn_bO_anova_2$Chisq[2]</pre>
   CN_BO_CHI_P2 <- reportP(cn_b0_anova_2$`Pr(>Chisq)`[2])
   all_subs_intercept2 <- as.data.frame(cbind(b=fixef(model1_2),
                               ci.low=confint(model1_2)[3,1],
                               ci.high=confint(model1_2)[3,2]))
   CN_B0_EST2 <- all_subs_intercept2$b</pre>
   CN_BO_CIL2 <- all_subs_intercept2$ci.low</pre>
   CN_BO_CIH2 <- all_subs_intercept2$ci.high</pre>
   CN_BO_TT_DF2 <- as.numeric(unlist(summary(model1_2)['coefficients'])[3])</pre>
   CN BO TT STAT2 <- as.numeric(unlist(summary(model1 2)['coefficients'])[4])
   CN_BO_TT_P2 <- reportP(as.numeric(unlist(summary(model1_2)['coefficients'])[5]))</pre>
   cn subj wilcox2 <- wilcox.test(sub means tab2$subj mean, mu=0,
                                   alternative='two.sided')
   CN_SUBJ_P_WILCOX2 <- reportP(cn_subj_wilcox2$p.value)</pre>
   cn_subj_binom2 <- binom.test(N_SUBS_POSITIVE2, N2, p=0.5)</pre>
   CN_SUBJ_P_BINOM2 <- reportP(cn_subj_binom2$p.value)</pre>
   set.seed(36)
   # Bayes factor
   ttestBF(sub means tab2$subj mean)
         Non-parametric tests (EC2).
253 ## Bayes factor analysis
254 ## -----
255 ## [1] Alt., r=0.707 : 16 \pm 0\%
257 ## Against denominator:
       Null, mu = 0
258 ##
259 ## ---
260 ## Bayes factor type: BFoneSample, JZS
```

```
# Standard deviation
stdev=sd(sub_means_tab2$subj_mean)
# Mean
mean_data=mean(sub_means_tab2$subj_mean)
# Effect size
CN_SUBJ_D2=abs(mean_data/stdev)
```

Using this alternative interpretation of the reviewer's suggested exclusion criteria, the mean across all 20 subjects was positive (range: -0.17 - 0.45, M = 0.13 95% CI: [0.06, 0.20]; p < .01, Wilcoxon; p < .01, binomial, d = 0.77).

A linear mixed effects model with random intercepts for subjects suggests that these results were reliable across infants ( $\beta_0 = 0.13$ , 95% CI: [0.05, 0.21], t(22.36) = 3.21, p < .01;  $\chi^2(1) = 8.45$ , p < .01; d = 0.28).

```
set.seed(36)
by_subj_age_tab2 <- cn_diffs_df %>%
  filter(subject_id != 'J94252') %>%
  group_by(subject_id, bebe_meses, age_centered) %>%
  summarize(subj mean = na.mean(noun pair diff),
            n_{subjects} = n(),
            min = min(noun_pair_diff, na.rm=T),
            max = max(noun_pair_diff, na.rm=T),
            ci.low = subj_mean-ci.low(noun_pair_diff),
            ci.high = subj_mean+ci.high(noun_pair_diff))
age_cor_test2 <- cor.test(by_subj_age_tab2$age_centered,
                         by_subj_age_tab2\subj_mean,
                         method='kendall')
AGE_CORR2 <- as.numeric(age_cor_test2$estimate)
AGE_CORR_P2 <- as.numeric(age_cor_test2$p.value)
AGE_CORR_Z2 <- as.numeric(age_cor_test2$statistic)
```

Replicating Correlation with Age (EC2). Using this alternate exclusion criteria, children's age in months exhibited an insignificant positive correlation with their mean difference scores across items ( $\tau = 0.20$ , p = 0.22).

```
age_lm2 <- lm(subj_mean ~ 1 + age_centered, by_subj_age_tab2)
summary(age_lm2)</pre>
```

267

268

269

262

263

264

```
## Call:
   ## lm(formula = subj_mean ~ 1 + age_centered, data = by_subj_age_tab2)
273
   ## Residuals:
274
           Min
                           Median
                      10
                                         30
                                                 Max
275
   ## -0.24652 -0.09133 -0.00413 0.09738 0.26970
276
   ##
277
   ## Coefficients:
278
                    Estimate Std. Error t value Pr(>|t|)
   ##
                      0.1290
   ## (Intercept)
                                 0.0365
                                            3.53
                                                   0.0024 **
280
                                            1.23
                                                   0.2335
   ## age_centered
                      0.0171
                                 0.0139
281
282
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
283
   ##
284
   ## Residual standard error: 0.16 on 18 degrees of freedom
285
   ## Multiple R-squared: 0.0779, Adjusted R-squared:
   ## F-statistic: 1.52 on 1 and 18 DF, p-value: 0.234
```

# Pre/Post Looking Logit Model

Dueling exclusion criteria are not relevant here, as even participant 'J94252' contributed at least half (16) of all test trials.

```
cn_supp_pre <- cn_fin %>%
  select(pre_target_sum_ms, pre_nontarget_sum_ms,
         subject_id, bebe_meses, age_centered, noun_pair)
cn supp pre$phase <- 'pre-naming'</pre>
cn supp prestarget bins <- round(cn supp prespre target sum ms/20,0)
cn_supp_pre$nontarget_bins <- round(cn_supp_pre$pre_nontarget_sum_ms/20, 0)</pre>
cn_supp_pre <- cn_supp_pre %>%
  select(subject_id, bebe_meses, age_centered,
         noun_pair, phase, target_bins, nontarget_bins)
cn_supp_post <- cn_fin %>%
  select(post1_target_sum_ms, post1_nontarget_sum_ms,
         subject_id, bebe_meses, age_centered, noun_pair)
cn_supp_post$phase <- 'post-naming'</pre>
cn_supp_post$target_bins <- round(cn_supp_post$post1_target_sum_ms/20,0)</pre>
cn supp post$nontarget bins <- round(cn supp post$post1 nontarget sum ms/20,0)
cn_supp_post <- cn_supp_post %>%
  select(subject_id, bebe_meses, age_centered,
```

```
noun_pair, phase, target_bins, nontarget_bins)
   cn_supp_stacked_r2 <- rbind(cn_supp_pre, cn_supp_post)</pre>
   cn_supp_stacked_r2$phase <- as.factor(cn_supp_stacked_r2$phase)</pre>
   cn supp_stacked_r2$phase <- relevel(cn_supp_stacked_r2$phase, ref='pre-naming')</pre>
   cn_supp_stacked_r2 %>%
     group_by(subject_id, bebe_meses, age_centered, noun_pair, phase) %>%
     reframe(target_bins = target_bins,
               nontarget_bins = nontarget_bins) %>%
   write.csv(., here('data/r analysis dfs',
                      'cn_prepost_target_looking.csv')
   set.seed(36)
   cn_supp_glmer_null <- glmer(cbind(target_bins, nontarget_bins) ~</pre>
                             1 + (1|subject_id) + (1|noun_pair),
                            family=binomial, cn_supp_stacked_r2)
   cn_supp_glmer <- glmer(cbind(target_bins, nontarget_bins) ~</pre>
                             phase + (1|subject_id) + (1|noun_pair),
                            family=binomial, cn supp stacked r2)
   summary(cn supp glmer)
   ## Generalized linear mixed model fit by maximum likelihood (Laplace
        Approximation) [glmerMod]
   ##
       Family: binomial (logit)
   ## Formula: cbind(target_bins, nontarget_bins) ~ phase + (1 | subject_id) +
   ##
          (1 | noun_pair)
         Data: cn_supp_stacked_r2
   ##
   ##
   ##
           AIC
                     BIC
                           logLik deviance df.resid
   ##
        114954
                  114973
                           -57473
                                    114946
                                                1052
   ##
   ## Scaled residuals:
301
          Min
                    1Q Median
                                    3Q
   ##
                                           Max
   ## -20.196 -7.622 0.822 7.850 19.954
   ##
   ## Random effects:
       Groups
                   Name
                               Variance Std.Dev.
   ##
   ##
       subject_id (Intercept) 0.0327
                                        0.181
   ##
       noun_pair (Intercept) 0.0234
                                        0.153
```

291

292

293

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297

298

299

300

302

303

305

306

```
## Number of obs: 1056, groups: subject_id, 21; noun_pair, 8
   ##
310
   ## Fixed effects:
311
   ##
                        Estimate Std. Error z value Pr(>|z|)
312
   ## (Intercept)
                         0.02640
                                     0.06726
                                                 0.39
                                                          0.69
313
   ## phasepost-naming 0.24900
                                     0.00983
                                               25.32
                                                        <2e-16 ***
314
   ## ---
315
   ## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
   ## Correlation of Fixed Effects:
318
   ##
                   (Intr)
319
   ## phspst-nmng -0.059
320
   cn_supp_glmer_tab <- as.data.frame(</pre>
     cbind('OR'=op(exp(fixef(cn_supp_glmer))),
            'CIL'=op(exp(confint(cn_supp_glmer))[3:4,1]),
            'CIH'=op(exp(confint(cn_supp_glmer))[3:4,2])))
   POSTNAMING_OR <- cn_supp_glmer_tab$OR[2]</pre>
   POSTNAMING_CIL <- cn_supp_glmer_tab$CIL[2]</pre>
   POSTNAMING_CIH <- cn_supp_glmer_tab$CIH[2]</pre>
   PHASE_WALD_CHISQ <- Anova(cn_supp_glmer)['phase','Chisq']
   PHASE WALD P <- reportP(Anova(cn supp glmer)['phase', 'Pr(>Chisq)'])
   anova(cn supp glmer null, cn supp glmer)
   ## Data: cn_supp_stacked_r2
321
   ## Models:
322
   ## cn_supp_glmer_null: cbind(target_bins, nontarget_bins) ~ 1 + (1 | subject_id) + (1 | nou
323
   ## cn_supp_glmer: cbind(target_bins, nontarget_bins) ~ phase + (1 | subject_id) + (1 | noun
   ##
                                          BIC logLik deviance Chisq Df Pr(>Chisq)
                          npar
                                   AIC
325
   ## cn_supp_glmer_null
                             3 115594 115609 -57794
                                                        115588
   ## cn_supp_glmer
                             4 114953 114973 -57473
                                                        114945
                                                                 643 1
                                                                             <2e-16 ***
327
   ## ---
328
   ## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
   Anova(cn_supp_glmer)
   ## Analysis of Deviance Table (Type II Wald chisquare tests)
330
   ##
331
   ## Response: cbind(target_bins, nontarget_bins)
332
             Chisq Df Pr(>Chisq)
333
               641 1
                          <2e-16 ***
   ## phase
334
335
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
```

Model summary shows that model is fit on 1056 observations from 21 subjects (number of trials = 1056/2 = 528, as model is fit to data in 'long' form, where two rows for each trial: pre-naming and post-naming).

```
cn_supp_stacked_r2$ratio <- cn_supp_stacked_r2$target_bins/</pre>
     cn_supp_stacked_r2$nontarget_bins
   cn_supp_age_glmer <- glmer(cbind(target_bins, nontarget_bins) ~</pre>
                             phase + age centered +
                                (1|subject_id) + (1|noun_pair),
                            family=binomial, cn supp stacked r2)
   cn_pp_age_glmer_tab <- as.data.frame(</pre>
     cbind('OR'=op(exp(fixef(cn_supp_age_glmer))),
            'CIL'=op(exp(confint(cn_supp_age_glmer))[3:5,1]),
            'CIH'=op(exp(confint(cn_supp_age_glmer))[3:5,2])))
   anova(cn_supp_glmer, cn_supp_age_glmer)
   ## Data: cn_supp_stacked_r2
   ## Models:
341
   ## cn_supp_glmer: cbind(target_bins, nontarget_bins) ~ phase + (1 | subject_id) + (1 | noun
   ## cn_supp_age_glmer: cbind(target_bins, nontarget_bins) ~ phase + age_centered + (1 | subj
                                         BIC logLik deviance Chisq Df Pr(>Chisq)
   ##
344
   ## cn_supp_glmer
                            4 114953 114973 -57473
                                                       114945
345
   ## cn_supp_age_glmer
                            5 114955 114980 -57473
                                                       114945
                                                                0.1 1
                                                                              0.75
   Anova(cn_supp_age_glmer)
   ## Analysis of Deviance Table (Type II Wald chisquare tests)
347
   ##
348
   ## Response: cbind(target_bins, nontarget_bins)
349
                    Chisq Df Pr(>Chisq)
350
                    641.1
                                  <2e-16 ***
   ## phase
                           1
   ## age_centered
                      0.1 1
                                    0.75
352
353
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
   cn_supp_ageint_glmer <- glmer(cbind(target_bins, nontarget_bins) ~</pre>
                             phase*age_centered +
                                (1|subject_id) + (1|noun_pair),
                            family=binomial, cn_supp_stacked_r2)
```

```
cn_supp_ageint_glmer_tab <- as.data.frame(</pre>
  cbind('OR'=op(exp(fixef(cn_supp_ageint_glmer))),
         'CIL'=op(exp(confint(cn_supp_ageint_glmer))[3:6,1]),
         'CIH'=op(exp(confint(cn_supp_ageint_glmer))[3:6,2])))
## reporting effect of trial phase
POST_AGE_INT_PHASE_OR <- cn_supp_ageint_glmer_tab$OR[2]</pre>
POST_AGE_INT_PHASE_CIL <- cn_supp_ageint_glmer_tab$CIL[2]
POST_AGE_INT_PHASE_CIH <- cn_supp_ageint_glmer_tab$CIH[2]
POST_AGE_INT_PHASE_WALD_CHISQ <-
  Anova(cn_supp_ageint_glmer)['phase','Chisq']
POST AGE INT PHASE WALD P <-
  reportP(Anova(cn_supp_ageint_glmer)['phase', 'Pr(>Chisq)'])
## reporting interaction between phase and age
POST_AGE_INT_OR <- cn_supp_ageint_glmer_tab$OR[4]</pre>
POST_AGE_INT_CIL <- cn_supp_ageint_glmer_tab$CIL[4]</pre>
POST_AGE_INT_CIH <- cn_supp_ageint_glmer_tab$CIH[4]</pre>
POST_AGE_INT_WALD_CHISQ <-
  Anova(cn_supp_ageint_glmer)['phase:age_centered','Chisq']
POST AGE INT WALD P <-
  reportP(Anova(cn_supp_ageint_glmer)['phase:age_centered', 'Pr(>Chisq)'])
## comparing interaction model to model with phase alone
cn_supp_ageint anova <- anova(cn_supp_glmer, cn_supp_ageint_glmer)</pre>
POST AGE INT DF <- cn supp ageint anova$Df[2]
POST AGE INT CHISQ <- cn supp ageint anova$Chisq[2]
POST AGE INT P <- reportP(cn supp ageint anova$`Pr(>Chisq)`[2])
## print summary, model comparison, type 2 tests
summary(cn_supp_ageint_glmer)
## Generalized linear mixed model fit by maximum likelihood (Laplace
     Approximation) [glmerMod]
## Family: binomial (logit)
## Formula: cbind(target_bins, nontarget_bins) ~ phase * age_centered + (1 |
       subject_id) + (1 | noun_pair)
##
##
      Data: cn_supp_stacked_r2
##
##
        AIC
                        logLik deviance df.resid
                  BIC
               114585 -57272 114544
##
     114556
                                             1050
## Scaled residuals:
```

355

356

357

358

359

361

362

```
##
          Min
                    1Q Median
                                     30
                                            Max
   ## -19.818 -7.472
                         0.582
                                 7.865
                                        19.878
   ##
368
   ## Random effects:
369
       Groups
                                Variance Std.Dev.
                   Name
370
       subject_id (Intercept) 0.0320
                                         0.179
371
   ## noun_pair (Intercept) 0.0235
                                         0.153
372
   ## Number of obs: 1056, groups: subject_id, 21; noun_pair, 8
   ##
375
   ## Fixed effects:
                                      Estimate Std. Error z value Pr(>|z|)
   ##
376
   ## (Intercept)
                                       0.02609
                                                  0.06713
                                                              0.39
                                                                      0.698
377
   ## phasepost-naming
                                       0.25195
                                                  0.00985
                                                             25.58
                                                                     <2e-16 ***
378
   ## age_centered
                                      -0.02692
                                                  0.01499
                                                             -1.80
                                                                      0.072 .
379
   ## phasepost-naming:age_centered 0.07640
                                                0.00381
                                                             20.03
                                                                     <2e-16 ***
380
   ## ---
381
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
382
383
   ##
   ## Correlation of Fixed Effects:
384
                   (Intr) phsps- ag_cnt
385
   ## phspst-nmng -0.059
386
   ## age_centerd 0.045 -0.001
   ## phspst-nm:_ -0.001 0.018 -0.106
   anova(cn_supp_glmer, cn_supp_ageint_glmer)
   ## Data: cn_supp_stacked_r2
   ## Models:
   ## cn_supp_glmer: cbind(target_bins, nontarget_bins) ~ phase + (1 | subject_id) + (1 | noun
391
   ## cn_supp_ageint_glmer: cbind(target_bins, nontarget_bins) ~ phase * age_centered + (1 | s
392
                                            BIC logLik deviance Chisq Df Pr(>Chisq)
                            npar
                                     AIC
393
                                4 114953 114973 -57473
                                                          114945
   ## cn_supp_glmer
304
                                                          114544
   ## cn_supp_ageint_glmer
                                6 114556 114585 -57272
                                                                   402 2
                                                                               <2e-16 ***
395
396
   ## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
   Anova(cn_supp_ageint_glmer)
   ## Analysis of Deviance Table (Type II Wald chisquare tests)
   ## Response: cbind(target_bins, nontarget_bins)
400
   ##
                          Chisq Df Pr(>Chisq)
401
   ## phase
                          635.8 1
                                        <2e-16 ***
402
   ## age_centered
                            0.1 1
                                          0.75
```

The odds ratio for trial phase (POST-NAMING OR=1.28, 95% CI: [1.26, 1.31]) indicates that infants dedicated a significantly greater share of their visual attention to the target image *after* hearing it labeled than *before* hearing it labeled, controlling for subjectand item–level variability ( $Wald \chi^2(1) = 641.07, p < .001, d = 1.05$ ; see Supplement).

A model which additionally included infant age and its interaction with trial phase resulted in a significantly better fit ( $\chi^2(2)=401.95,\ p<.001$ ), showing a reliable effect of trial phase (POST-NAMING  $OR=1.29,\ 95\%$  CI: [1.26, 1.31],  $Wald\ \chi^2(1)=635.84,\ p<.001,\ d=1.07$ ) and interaction with age, such that older children showed a greater increase in the ratio of targe to non-target looking after hearing the target word ( $OR=1.08,\ 95\%$  CI: [1.07, 1.09],  $Wald\ \chi^2(1)=401.02,\ p<.001,\ d=0.32$ ).

# GLMERs by Age Group. From B&S 2012:

A separate hierarchical logistic regression model was created for each group of children (6–9 mo, 10–13 mo, 14–16 mo, and 18–20 mo) for each trial type (paired-picture and scene). Phase of trial (pretarget utterance vs. posttarget utterance) was included as a fixed-effect predictor, and subject and item were included as random effects. Each model predicts (the log of) the ratio of target to distracter looking, as calculated by counting time bins.

```
phase + (1|subject_id) + (1|noun_pair),
family=binomial, cn_supp_stacked_r2[
    cn_supp_stacked_r2$bebe_meses>=14 &
    cn_supp_stacked_r2$bebe_meses<17,])</pre>
```

```
write(texreg(list(
  cn_phase_6_9_glmer, cn_phase_10_13_glmer, cn_phase_14_16_glmer),
  custom.model.names=c('5-9 months', '10-13 months', '14-16 months')),
  here('supplement/tables/exp_1/age_binned', 'cn_prepost_agegroup_glmers.tex')
  ) # 3 columns for age
# individual tables for each age group
phase_glmer_6_9mos_tab <-</pre>
  cbind('Estimate'=summary(cn_phase_6_9_glmer)$coefficients[,'Estimate'],
      'Standard Error'= summary(cn_phase_6_9_glmer)$coefficients[,'Std. Error'],
      'P value'=summary(cn_phase_6_9_glmer)$coefficients[,'Pr(>|z|)'])
phase_glmer_10_13mos_tab <-</pre>
  cbind('Estimate'=summary(cn_phase_10_13_glmer)$coefficients[,'Estimate'],
      'Standard Error'= summary(cn_phase_10_13_glmer)$coefficients[,'Std. Error'],
      'P value'=summary(cn_phase_10_13_glmer)$coefficients[,'Pr(>|z|)'])
phase_glmer_14_16mos_tab <-</pre>
  cbind('Estimate'=summary(cn_phase_14_16_glmer)$coefficients[,'Estimate'],
      'Standard Error'= summary(cn_phase_14_16_glmer)$coefficients[,'Std. Error'],
      'P value'=summary(cn phase 14 16 glmer)$coefficients[,'Pr(>|z|)'])
# write to tex
write(apa_table(phase_glmer_6_9mos_tab,
                caption='5--9 month-olds'),
      here('supplement/tables/exp_1/age_binned', 'cn_phase_6mos_tab.tex')
      )
write(apa_table(phase_glmer_10_13mos_tab,
                caption='10--13 month-olds'),
      here('supplement/tables/exp_1/age_binned', 'cn_phase_10_13mos_tab.tex')
write(apa_table(phase_glmer_14_16mos_tab,
                caption='14--16 month-olds'),
      here('supplement/tables/exp 1/age binned', 'cn phase 14 16mos tab.tex')
      )
# replicate final table in B&S 2012 SI:
```

```
write(apa table(
     rbind(
       phase_glmer_6_9mos_tab,
       phase_glmer_10_13mos_tab,
       phase_glmer_14_16mos_tab)),
         here('supplement/tables/exp_1/age_binned', 'cn_phase_agegroups_bsrep_tab.tex')
     )
   # will add midrules in tex for ease
   cn_fin %>%
     group_by(age_group) %>%
     summarize(pre_prop = na.mean(pre_target_prop),
               post_prop = na.mean(post_target_prop))
   ## # A tibble: 3 x 3
        age_group
                   pre_prop post_prop
425
   ##
        <fct>
                         <dbl>
                                   <dbl>
426
   ## 1 5-9 months
                         0.526
                                   0.482
427
   ## 2 10-13 months
                         0.498
                                   0.541
428
   ## 3 14-16 months
                         0.500
                                   0.560
```

## Trial Counts Across Analyses

430

How many more trials were we able to analyze in the pre-/post-looking analysis, relative to the paired difference score calculation, where so many trials with otherwise useable data had to be dropped?

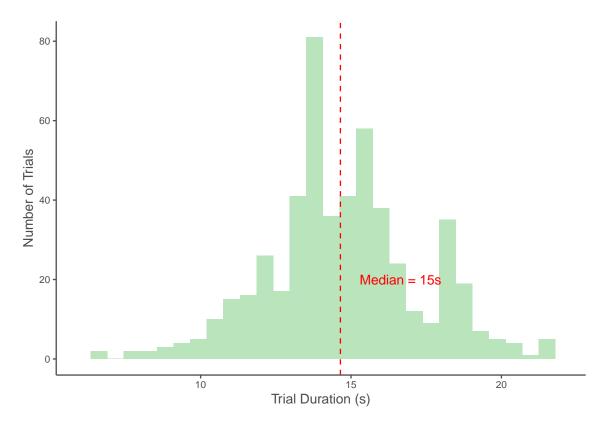
mean stimdiffs=mean(n),

```
med_stimdiffs=median(n),
               mode stimdiffs=DescTools::Mode(n))
   #stim_diffs_summary_tab$min_stimdiffs
   #stim_diffs_summary_tab$max_stimdiffs
   #stim_diffs_summary_tab$mean_stimdiffs
   \#stim\_diffs\_summary\_tab\$mode\_stimdiffs
   \#stim\_diffs\_summary\_tab\$med\_stimdiffs
   TOTAL_TRIALS_N <- nrow(cn_fin)
   MEAN_DIFF_TRIALS_N <- cn_target_nontarget_props_df %>%
     dplyr::select(subject_id, age_centered,
                    noun_pair, stimulus_set, merge_on_noun,
                    post1_target_prop,
                    post1_nontarget_prop) %>%
     mutate(diff = post1_target_prop - post1_nontarget_prop) %>%
     group_by(
       subject_id, age_centered, noun_pair, stimulus_set
     ) %>%
     summarize(stim_pair_diff = mean(diff)) %>%
     filter(!is.na(stim_pair_diff)) %>%
     nrow(.) * 2
   TRIALS_DROPPED_FOR_DIFF_CALC <- TOTAL_TRIALS_N - MEAN_DIFF_TRIALS_N
   TRIALS_DROPPED_FOR_DIFF_CALC/TOTAL_TRIALS_N
434 ## [1] 0.18
        94 trials lost (out of 528), or 17.80% of non-excluded trials.
   cn_supp_stacked_r2 %>%
     group_by(subject_id) %>%
     summarize(trials=n()/2) %>%
     ungroup() %>%
     summarize(min=min(trials),
               max=max(trials),
               mean=mean(trials),
               med=median(trials),
               mode=DescTools::Mode(trials))
436 ## # A tibble: 3 x 5
```

```
##
           min
                              med mode
437
                 max mean
         <dbl> <dbl> <dbl> <dbl> <dbl> <
   ##
438
                  32 25.1
                               26
   ## 1
            16
                                      16
439
   ## 2
            16
                  32 25.1
                               26
                                      25
440
                  32 25.1
  ## 3
            16
                               26
                                     31
441
```

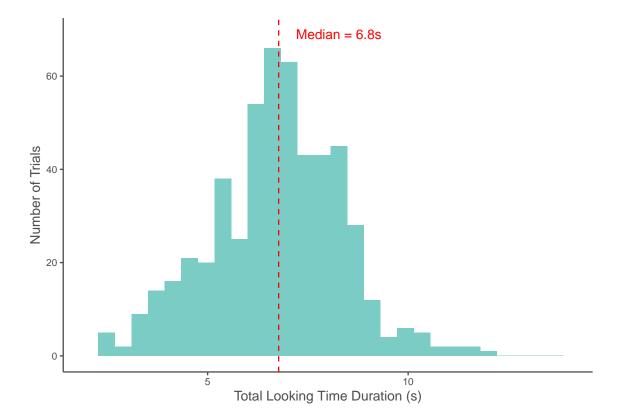
442 Trial Durations

```
CN MED_TRIAL_DUR_S <- median(cn_fin$trialtolookingoffset_dur_s)
CN MIN TRIAL DUR S <- min(cn fin[cn fin$trial dur s<30,]$trialtolookingoffset dur s)
CN MAX TRIAL DUR S <- max(cn_fin[cn_fin$trial_dur_s<30,]$trialtolookingoffset_dur_s)
CN_MEAN_TRIAL_DUR_S <- mean(</pre>
  cn_fin[cn_fin$trial_dur_s<30,]$trialtolookingoffset_dur_s)</pre>
CN_CIL_TRIAL_DUR_S <- CN_MEAN_TRIAL_DUR_S -</pre>
  ci.low(cn_fin[cn_fin$trial_dur_s<30,]$trialtolookingoffset_dur_s)</pre>
CN_CIH_TRIAL_DUR_S <- CN_MEAN_TRIAL_DUR_S +</pre>
  ci.high(cn_fin[cn_fin$trial_dur_s<30,]$trialtolookingoffset_dur_s)</pre>
ggplot(cn fin, aes(x=trialtolookingoffset dur s)) +
  geom_histogram(fill='#bae4bc') +
  sb.density.theme +
  geom_vline(xintercept=CN_MED_TRIAL_DUR_S, color='red', lty=2) +
  xlim(6,22) +
  xlab('Trial Duration (s)') +
  vlab('Number of Trials') +
  theme(axis.title = element_text(colour='gray30', size=11),
        axis.text = element_text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30'),
        plot.background = element_blank() ,
        panel.grid.major = element_blank() ,
        panel.grid.minor = element_blank() ,
        panel.border = element_blank() ,
        panel.background = element_blank(),
        axis.line = element line(color = 'gray30')) +
  annotate(
    'text', label = 'Median = 15s',
    x = CN_MED_TRIAL_DUR_S+2, y = 20, size = 4, colour = 'red')
```

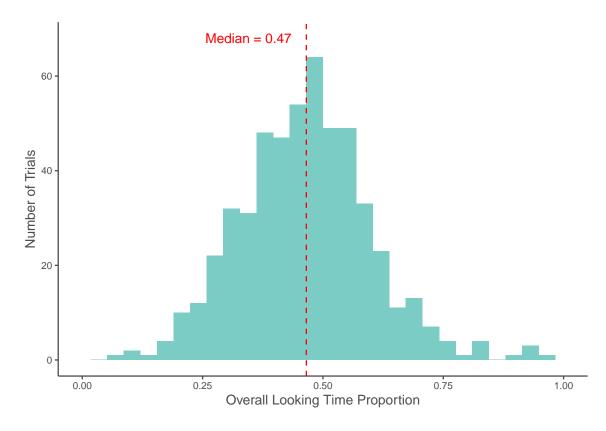


```
CN_MED_TRIAL_LOOKING_S <- median(</pre>
  cn_fin$totaltrialtime_looking_sum_s)
CN_MIN_TRIAL_LOOKING_S <-</pre>
  min(cn_fin$totaltrialtime_looking_sum_s)
CN_MAX_TRIAL_LOOKING_S <-</pre>
  max(cn_fin$totaltrialtime_looking_sum_s)
CN_MEAN_TRIAL_LOOKING_S <-</pre>
  mean(cn_fin$totaltrialtime_looking_sum_s)
CN_CIL_TRIAL_LOOKING_S <- CN_MEAN_TRIAL_LOOKING_S -</pre>
  ci.low(cn_fin$totaltrialtime_looking_sum_s)
CN_CIH_TRIAL_LOOKING_S <- CN_MEAN_TRIAL_LOOKING_S +</pre>
  ci.high(cn_fin$totaltrialtime_looking_sum_s)
ggplot(cn_fin, aes(x=totaltrialtime_looking_sum_s)) +
  geom_histogram(fill='#7bccc4') +
  sb.density.theme +
  geom_vline(xintercept=CN_MED_TRIAL_LOOKING_S,
```

```
color='red', lty=2) +
xlim(2,14) +
xlab('Total Looking Time Duration (s)') +
ylab('Number of Trials') +
theme(axis.title = element_text(colour='gray30', size=11),
      axis.text = element_text(colour='gray30', size=11),
      axis.ticks = element_line(colour='gray30'),
     plot.background = element_blank(),
     panel.grid.major = element_blank(),
     panel.grid.minor = element_blank(),
     panel.border = element_blank(),
     panel.background = element blank(),
     axis.line = element_line(color = 'gray30')) +
annotate(
  'text', label = 'Median = 6.8s',
 x = CN_MED_TRIAL_LOOKING_S+1.5, y = 69, size = 4, colour = 'red')
```

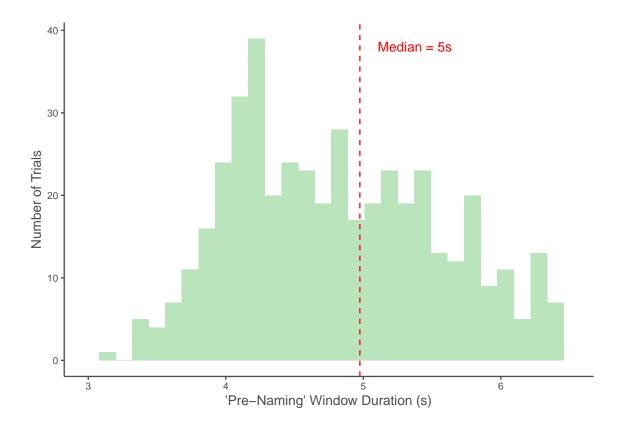


```
CN MED LOOKING PROP <- median(
  cn_fin$trialtolookingoffset_prop)
CN_MIN_LOOKING_PROP <- min(</pre>
  cn_fin$trialtolookingoffset_prop)
CN_MAX_LOOKING_PROP <- max(</pre>
  cn_fin$trialtolookingoffset_prop)
CN_MEAN_LOOKING_PROP <- mean(</pre>
  cn_fin$trialtolookingoffset_prop)
CN_CIL_LOOKING_PROP <- CN_MEAN_LOOKING_PROP - ci.low(</pre>
  cn_fin$trialtolookingoffset_prop)
CN_CIH_LOOKING_PROP <- CN_MEAN_LOOKING_PROP +ci.high(</pre>
  cn fin$trialtolookingoffset prop)
ggplot(cn_fin, aes(x=trialtolookingoffset_prop)) +
  geom_histogram(fill='#7bccc4') +
  sb.density.theme +
  geom_vline(xintercept=CN_MED_LOOKING_PROP, color='red', lty=2) +
 xlim(0,1) +
  xlab('Overall Looking Time Proportion') +
  ylab('Number of Trials') +
  theme(axis.title = element_text(colour='gray30', size=11),
        axis.text = element_text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30'),
        plot.background = element_blank() ,
        panel.grid.major = element_blank() ,
        panel.grid.minor = element_blank() ,
        panel.border = element blank() ,
        panel.background = element_blank(),
        axis.line = element_line(color = 'gray30')) +
  annotate(
    'text', label = 'Median = 0.47',
    x = CN_MED_LOOKING_PROP-.12, y = 68, size = 4, colour = 'red')
```

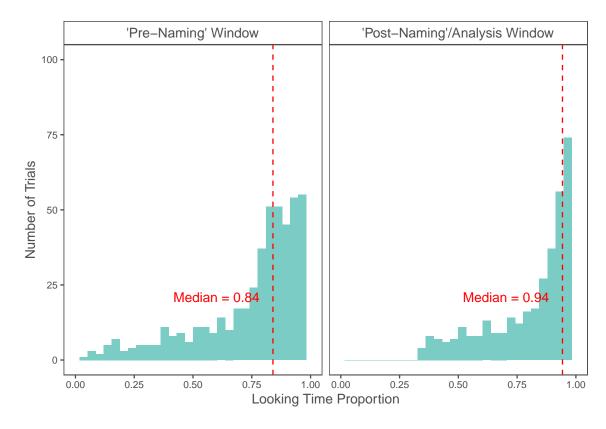


```
CN_MED_PRE_DUR_S <- median(cn_fin\pre_dur_ms/1000)</pre>
CN_MIN_PRE_DUR_S <- min(cn_fin$pre_dur_ms/1000)</pre>
CN_MAX_PRE_DUR_S <- max(cn_fin[cn_fin$pre_dur_ms<10000,]$pre_dur_ms/1000)</pre>
CN_MEAN_PRE_DUR_S <- mean(cn_fin[cn_fin$pre_dur_ms<10000,]$pre_dur_ms/1000)</pre>
ggplot(cn_fin, aes(x=pre_dur_ms/1000))+
  geom_histogram(fill='#bae4bc') +
  sb.density.theme +
  geom vline(xintercept=CN MED PRE DUR S, color='red', lty=2) +
  #geom_vline(xintercept = 3.133, color='red') +
  xlim(3,6.5)+
  xlab("'Pre-Naming' Window Duration (s)") +
  ylab('Number of Trials') +
  theme(axis.title = element_text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30'),
        plot.background = element_blank() ,
        panel.grid.major = element_blank() ,
```

```
panel.grid.minor = element_blank() ,
    panel.border = element_blank() ,
    panel.background = element_blank(),
    axis.line = element_line(color = 'gray30')) +
annotate(
    'text', label = 'Median = 5s',
    x = CN_MED_PRE_DUR_S+.4, y = 38, size = 4, colour = 'red')
```



```
mutate(window = "'Post-Naming'/Analysis Window",
         looking_prop = post1_looking_sum_ms/post1_dur_ms,
         median = median(looking prop),
         mean = mean(looking_prop)) %>%
  dplyr::select('subject_id', 'window', 'looking_prop', 'median', 'mean')
CN_POST_MIN_PROP <- min(postlookingprop_df$looking_prop)</pre>
CN_POST_MAX_PROP <- max(postlookingprop_df$looking_prop)</pre>
CN_POST_MEAN_PROP <- mean(postlookingprop_df$looking_prop)</pre>
CN_POST_MEDIAN_PROP <- median(postlookingprop_df$looking_prop)</pre>
prepost_lookingprop_df <- rbind(prelookingprop_df, postlookingprop_df)</pre>
prepost_lookingprop_df$window <-</pre>
  factor(prepost lookingprop df$window, levels=c(
    "'Pre-Naming' Window","'Post-Naming'/Analysis Window"), ordered=T)
prepost_lookingprop_label_df <- prepost_lookingprop_df %>%
  group by(window) %>%
  summarize(median=median(median),
            label=paste('Median =', round(median, 2), sep=' '))
ggplot(prepost_lookingprop_df, aes(x=looking_prop)) +
  geom_histogram(fill='#7bccc4') +
  sb.density.theme +
  geom_vline(aes(xintercept=median), color='red', lty=2) +
  xlim(0,1) +
  ylim(0,100) +
  xlab('Looking Time Proportion') +
  ylab('Number of Trials') +
  theme(axis.title = element_text(colour='gray30', size=11),
        axis.text = element_text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30'),
        plot.background = element_blank(),
        strip.text.x = element_text(colour='gray30', size=11))+
  facet_wrap(~window) +
  geom_text(data=prepost_lookingprop_label_df,
            aes(x=median-.24, label=label), y=21,
            color='red', size=4)
```



```
dplyr::select('subject_id', 'window', 'looking_dur', 'median', 'mean')
CN_POST_MIN_DUR <- min(postlookingdur_df$looking_dur)</pre>
CN_POST_MAX_DUR <- max(postlookingdur_df$looking_dur)</pre>
CN_POST_MEAN_DUR <- mean(postlookingdur_df$looking_dur)</pre>
CN_POST_MEDIAN_DUR <- median(postlookingdur_df$looking_dur)</pre>
prepost_lookingdur_df <- rbind(prelookingdur_df, postlookingdur_df)</pre>
prepost_lookingdur_df$window <-</pre>
  factor(prepost_lookingdur_df$window, levels=c(
    "'Pre-Naming' Window", "'Post-Naming'/Analysis Window"), ordered=T)
prepost_lookingdur_label_df <- prepost_lookingdur_df %>%
  group by (window) %>%
  summarize(median=median(median),
            label=paste('Median =', round(median, 2), sep=' '))
cn pp durs <- ggplot(prepost lookingdur df, aes(x=looking dur)) +</pre>
  geom_histogram(fill='#7bccc4') +
  sb.density.theme +
  geom_vline(aes(xintercept=median), color='red', lty=2) +
  xlim(0,9) +
  #ylim(0,100) +
  xlab('Looking Time Duration (s)') +
  ylab('Number of Trials') +
  theme(axis.title = element_text(colour='gray30', size=11),
        axis.text = element text(colour='gray30', size=11),
        axis.ticks = element_line(colour='gray30'),
        plot.background = element blank(),
        strip.text.x = element_text(colour='gray30', size=11))+
  facet wrap(~window) +
  geom_text(data=prepost_lookingdur_label_df,
            aes(x=median+2, label=label), y=250,
            color='red', size=4)
ggsave(here('supplement/plots/exp_1/pdfs', 'cn_lookingdurs_prepost.pdf'),
       device='pdf', width=2.75, height=1.5, units='in', scale=2.5)
ggsave(here('supplement/plots/exp_1/pngs', 'cn_lookingdurs_prepost.png'),
       device='png', width=2.75, height=1.5, units='in', scale=2.5)
```

Trials in Experiment 1 were 14.86s [14.60, 15.13] long on average (range: 5.42-24.82s,  $M_{\rm dur}=14.86s$ , Med=14.65s), and infants spent an average of 6.70s [6.55, 6.84] total looking at the displays (range: 1.97-12.17s, Med=6.77s, or between 0.07 and 0.99 of the total trial duration; M=0.46 [0.45, 0.48]).

The pre-naming window was between 3.12 and 9.44s (M = 5.22s, Med = 4.97s).

The children in our final sample spent similar proportions of time looking at the displays during the pre- and post-naming periods (PRE-NAMING range: 0.03-1, M=0.77, Med=0.84; POST-NAMING range: 0.34-1, M=0.87, Med=0.94).