Methods

Participants

We retrieved data from 90 participants: 24 from Santolin & Saffran (2019) (26 tested in Wisconsin, the replication study [Santolin et al. (2019); 24] tested in Barcelona, and 40 from Saffran & Wilson (2003), tested in Wisconsin. Two datapoints were available for each participant: one for the mean looking time in "familiar" trials, and one for the mean looking time in "novel" trials. A total of 180 datapoints were included in the analysis. Participants included in our analysis were those included in the final version of both studies.

Studies

Both studies compared looking times in novel and familiar trials, and revealed that infants displayed a preference toward one of the trial types. The direction of the preference, however, was different.

Data analysis

This model included looking time (LT) as response variable, trial type ($TrialType$ = familiar/novel), the number of HeadTurn Preference Procedure experiments completed by infants (HPP), and their interaction ($TrialType \times HPP$) as fixed effects. *Familiar* trials were set as the baseline. Participant ($Participant$) and study ($Study$) were included as random effects. The model included a by-participant and by-study random intercepts, and a random slope of HPP by $Study$.

This model accounts for across-participants variability in overall looking time (i.e. some infants are long lookers, some are short lookers), and for across-studies differences in overall looking time, and allows the effect of HPP to vary across studies. Although including data from only two studies is not an optimal practice when specifiying $Study$ as a random effect, there are two strong reasons to include the said by-study random intercept, and a random slope of HPP by study. First, participants from different linguistic/cultural environments were included in both studies. This may have led to participants in one of the locations to looking longer in average than those from the other location. Second, in spite of their similarity both studies were not identical, which could also have led to differences in overall looking time.

Term	Coefficient	95% CI	t	df	p
Intercept	7218.974	6498.11-7939.84	-	-	-
Trial type	-318.405	-734.26-97.45	2.252	89.999	0.137
HPP	-584.607	-1136.36–32.85	0.962	63.831	0.330
Trial type * HPP	665.558	213.32-1117.8	8.320	89.999	0.005

We found a statistically significant interaction term, $t(90) = 8.32$, $p = 0.005$, 95% CI = 213.32-1117.8, suggesting that the effect of trial type on looking time was influenced by the number of HPP experiments each participant participated in. The interaction shows that experience with a higher number of HPP experiments is associated with a stronger novelty preference.

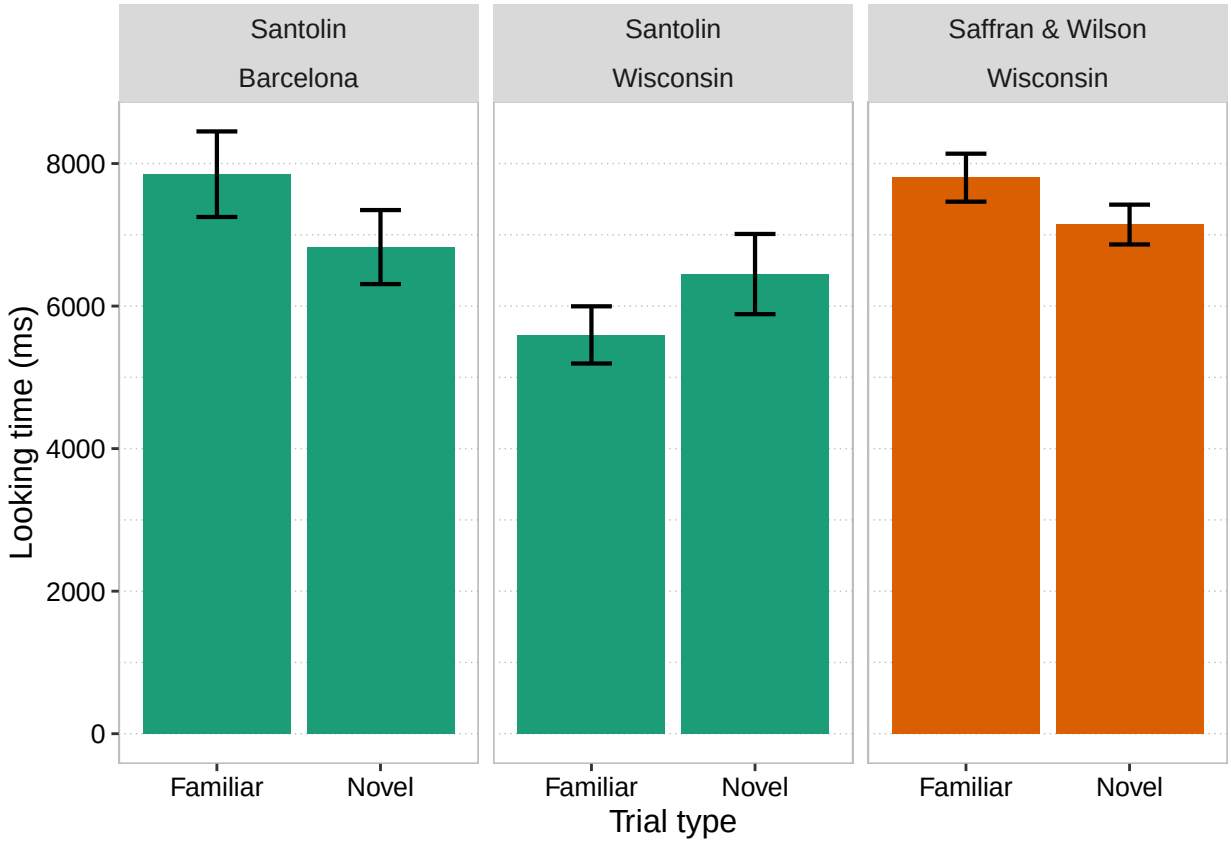


Figure 1: Looking time (ms) in familiar and novel trials split by Study and Location. Whiskers indicate the standard error of the mean, respectively. Grey lines indicate participant level mean looking times.

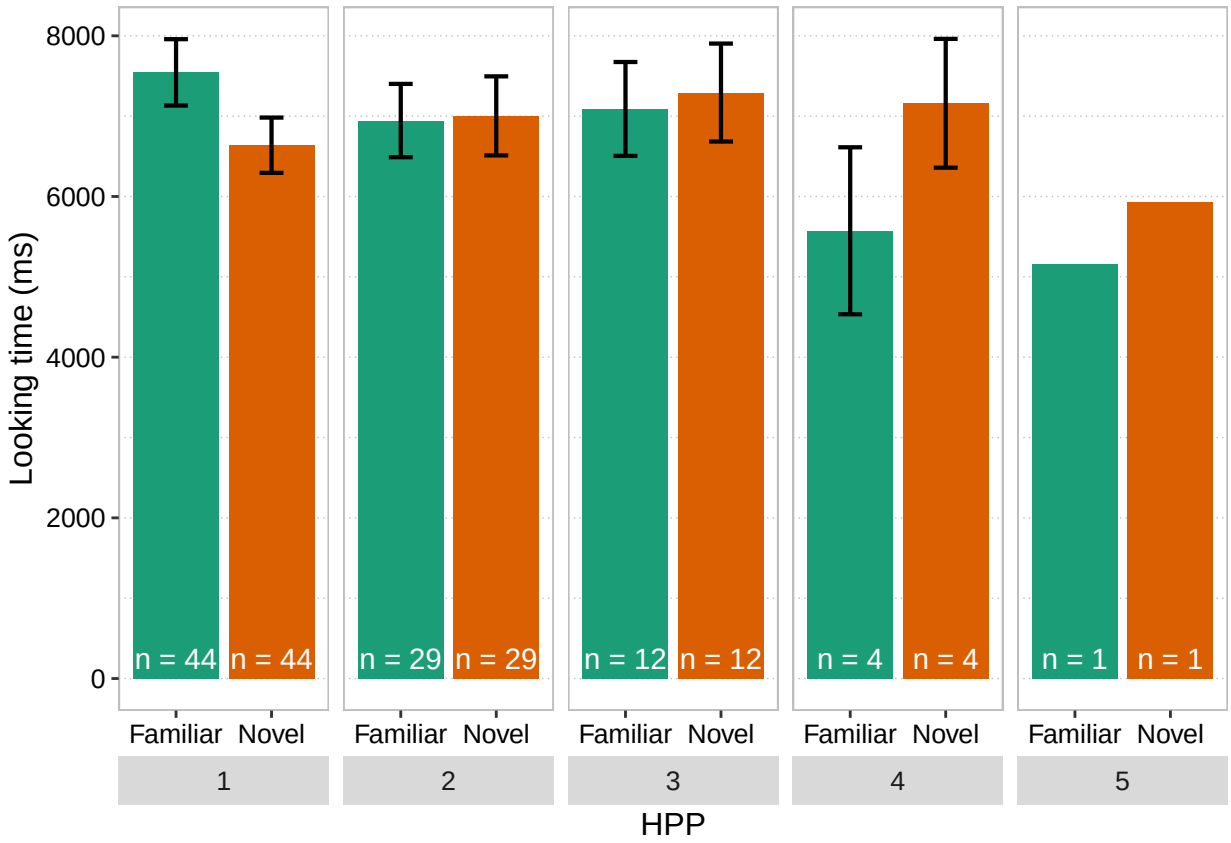


Figure 2: Looking times of familiar and novel trials, split by number of HeadTurn Preference Procedure experiments. Black points and whiskers represent the group-level mean looking time and SEM, respectively. Grey lines represent participant-level mean looking time.

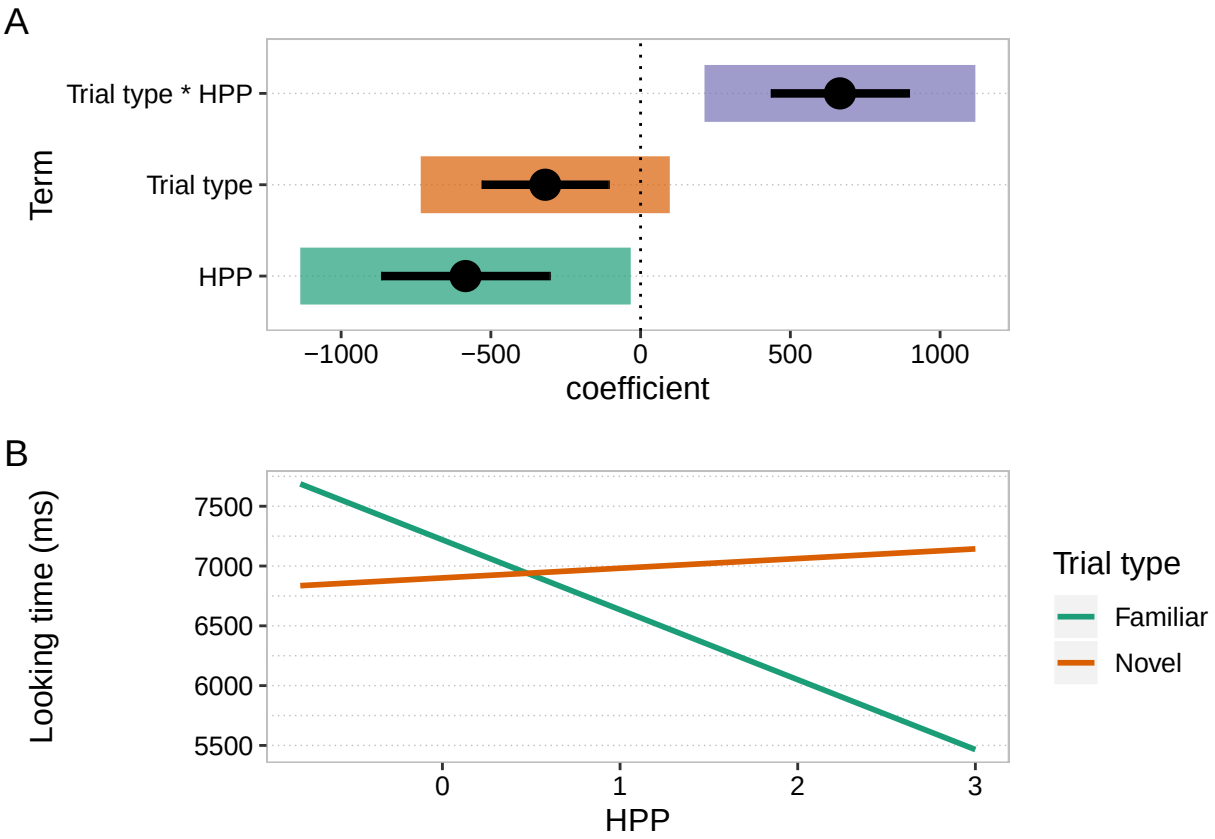


Figure 3: (A) Coefficients of the fixed effects. Dots, whiskers, and shaded boxes represent the estimated coefficients, standard error, and 95 percent Wald confidence intervals, respectively. (B) Predicted looking times plotted against HPP, split by study. The HPP variable was centered.

Appendices

Appendix 1: Linear Mixed Model

Following Barr, Levy, Scheepers, & Tily (2013) guidelines, we initially specified a maximal random structure, including random intercepts for *Participant* and *Study*, and random slopes for $TrialType$, HPP, and $TrialType \times HPP$, by *Participant* and *Study*. Due to lack of convergence, the random structure was simplified until the model fit was no longer singular. The code and formula of the mode are presented below:

```
lookingTime ~ TrialType * HPP + (1 | Participant) + (1 | Study) + (1 + HPP | Study)
```

$$
\begin{aligned}
LT_{ips} = \\
&\beta_0 + Participant_{0p} + Study_{0s} + \\
&(\beta_1 + Study_s)HPP_i + \\
&\beta_2 TrialType_i + \\
&(\beta_3 + Study_s)HPP \times TrialType_i + \\
&e_{ips}, e_{ips} \sim N(0, \sigma^2), Participant_{0p} \sim N(0, \tau^2_{00}), Study_{0p} \sim N(0, \quad \omega^2_{00})
\end{aligned}
$$

Where:

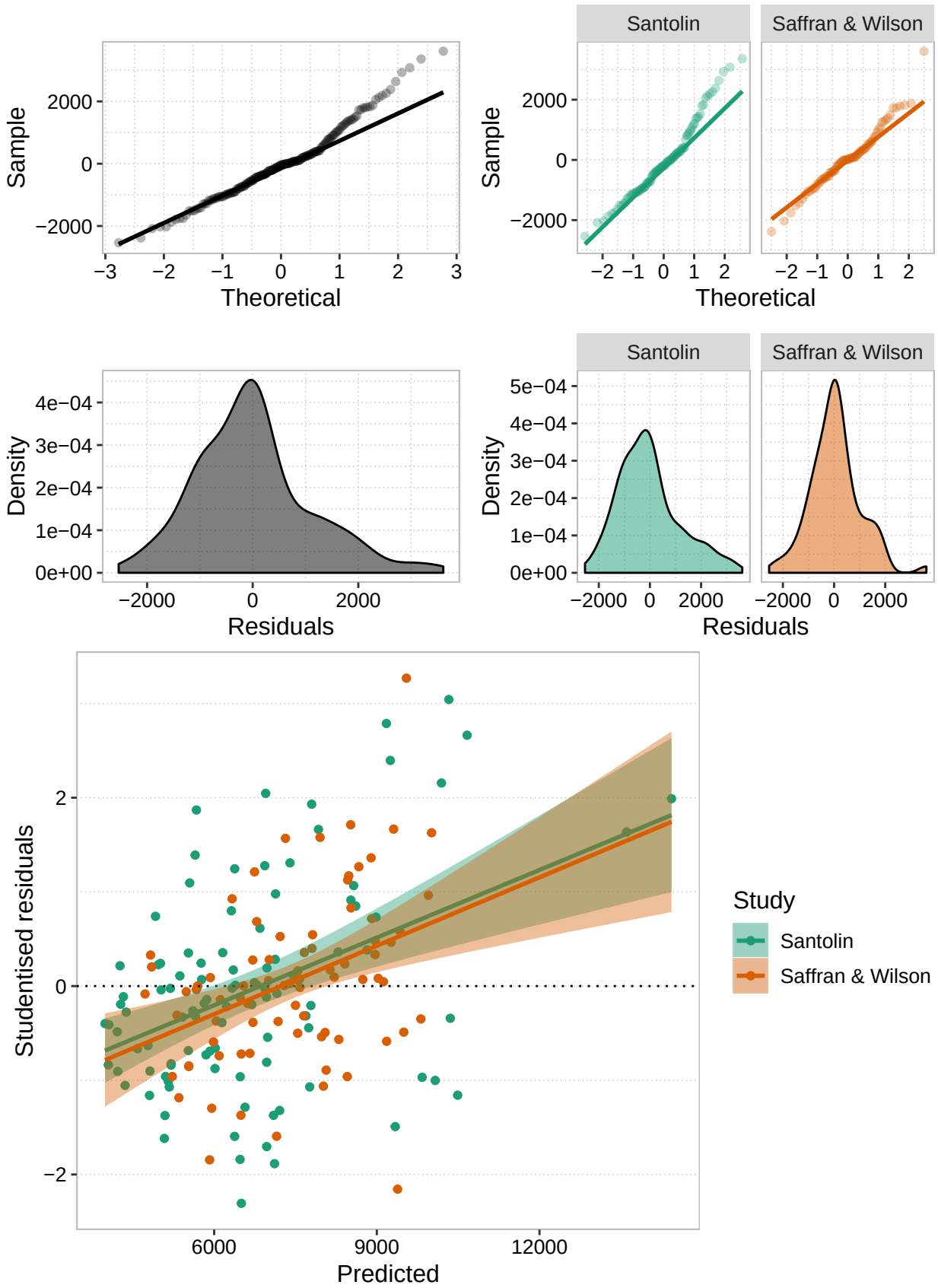
- LT_{ips} is the looking time in trial i, in participant p from study s.
- β_0 is the fixed intercept (the grand mean of all looking times from all trials).
- $Participant_{0p}$ is the by-participant random intercept (the overall looking time of participant p, assumed to have been sampled from a normal distribution with mean 0 and variance τ^2_{00}.
- $Study_{0s}$ is the by-study random intercept (the overall looking time in study s, assumed to have been sampled from a normal distribution with mean 0 and variance ω^2_{00}.
- β_1 is the coefficient of the fixed effect of the HPP predictor.
- β_2 is the coefficient of the fixed effect of the $TrialType$ predictor.
- β_3 is the coefficient of the fixed effect of the $TrialType \times HPP$ interaction.
- e_{ips} is the error of the model in trial i, of participant p from study s, assumed to be normally distributed with mean 0 and variance σ^2.

Before fitting the model, we group mean-centered the HPP predictor.The model was fitted using the `lme4` R package (Bates, Mächler, Bolker, & Walker, 2015). We used Maximum Likelihood criterion to estimate the coefficients, assuming an unstructured variance-covariance structure. We used the `lmerTest` package (Kuznetsova, Brockhoff, & Christensen, 2017) to compute p-values using the Satterthwaite's approximation to degrees of freedom (Satterthwaite, 1946).

Posterior predicted simulations (Gelman & Hill, 2006) indicated that the coefficients obtained by our model are plausible: The observed inter-quartile range (IQR) of looking times lied within the IQR obtained from 1000 simulated datasets generated from the model in more than 95% of the simulations ($p = 0.484$).

Appendix 2: Checking assumptions of the Linear Mixed Model

Residuals seem to approximate a normal distribution, though the some scores in the Santolin & Saffran (2019) and Santolin et al. (2019) studies seem to be somewhat shifted.


Sample
Theoretical
Santolin
Saffran & Wilson
Density
Residuals
Studentised residuals
Predicted
Study
Santolin
Saffran & Wilson

We observed little evidence of multicollinearity in the predictors we included in the model:

	VIF	Tolerance
Trial type	1.0	1.00
HPP	1.2	0.83
Trial type * HPP	1.2	0.83

References

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*, *68*(3), 255–278. https://doi.org/10.1016/j.jml.2012.11.001

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

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Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Saffran, J. R., & Wilson, D. P. (2003). From Syllables to Syntax: Multilevel Statistical Learning by 12-Month-Old Infants. *Infancy*, *4*(2), 273–284. https://doi.org/10.1207/S15327078IN0402_07

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