Supplemental Materials for the manuscript

Knowing before doing: Review and mega-analysis of action understanding in prereaching infants

Shari Liu & Melyssa Almeida

For data and code required to reproduce these figures and results, see https://osf.io/rkxjn.
Please direct questions to Shari Liu, shariliu@jhu.edu.

Contents:

Meta-analytic selection methods

Eligibility for study inclusion. We specified the following inclusion criteria: (1) all literature, journal papers, theses, and proceedings papers in (2) typically developing infants between 2 and 4 months of age that reported (3) looking responses towards individual video or live displays of the Woodward or Gergely task (hereafter referred to as "goals task" and "constraints task"), or responses to causal agency (e.g. entrainment and launching). Because we only identified 2 papers that met the criteria for studies of causal agency, we have decided to exclude them from the present analysis and focus only on the causes and goals tasks.

Information sources and search strategy. We followed the PRISMA statement (Moher, Liberati, Tetzlaff, Altmann, & The PRISMA Group, 2009) for selecting and reporting on the studies to be included in our meta-analysis. We started with the seed paper Sommerville et al. (2005) and other follow-up studies generated through expert knowledge that focus on 3-month-old infants' understanding of action. Studies were located using "3-month-old action understanding", "sticky mittens training", "action training infant" in September-October 2020 as search terms in Google Scholar, Proquest, and PubMed. Hand searches of the reference sections of all retrieved journal articles, book chapters, books, dissertations, and unpublished papers were also examined to locate additional studies. We also emailed two listservs (Cognitive Development Society, and Infant Studies) to collect more papers and datasets. Studies were included if: the infants were under 4 months old but not newborns, the methods used looking time and measured responses to single displays, the study followed the logic of Woodward (1998) (agent changes their goal) or Gergely et al. (1995) (agent performs inefficient action) or Leslie (1982) (Michottean launching, entrainment). For individual datasets, we contacted the authors and asked them to send us de-identified datasets from past published and unpublished work.

Data management. All identified studies that fit the inclusion criteria were documented in a publicly accessible Google Sheet (copy available at https://osf.io/zwncg/), all articles under consideration were added to a publicly accessible Google Drive folder, and all unpublished content were added with the study author's explicit permission.

Selection process. Here we followed the protocols recommended by MetaLab (https://langcog.github.io/metalab/). A team lead by SL identified potentially relevant papers using the search strategy above, conducted the search over 2000 total records, first screening by title and then by abstract, and retrieved full-text to check for eligibility and added verified records to the meta-analysis. We also scanned the reference sections of review papers and key empirical papers. We have documented our decision making process, and all interactions with experts and authors, at the publicly accessible Google Sheet (copy available at https://osf.io/zwncg/).

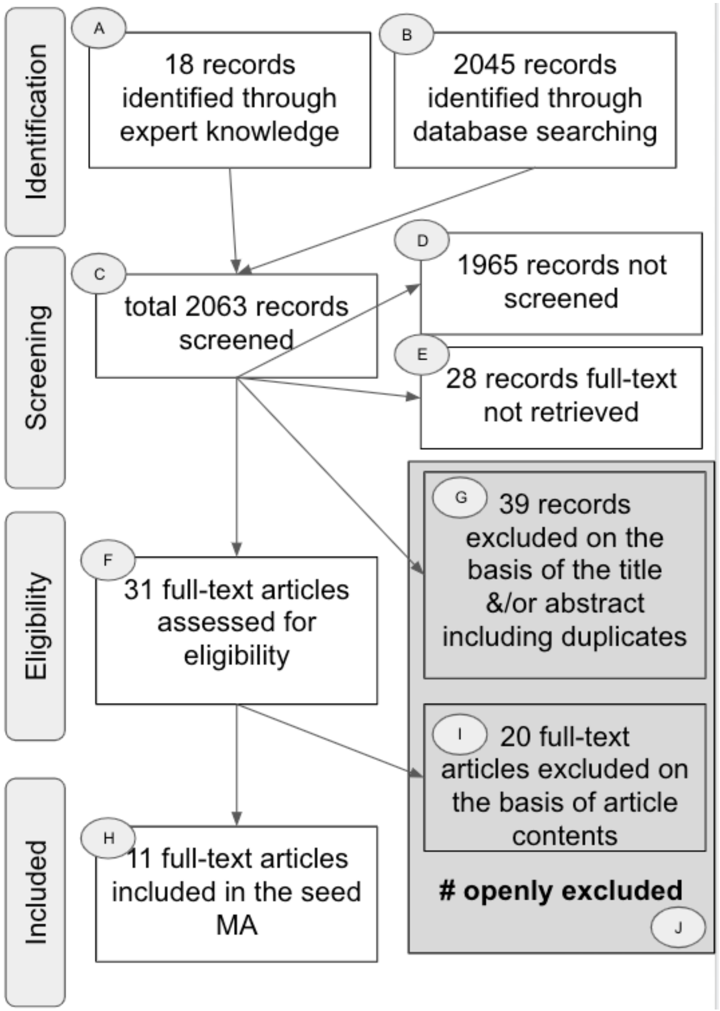

Figure S1. PRISMA flowchart for the current research. We identified a total of 2063 records through database searching and expert knowledge, and then used paper titles, abstracts, and full texts to screen for eligibility. Of these, 31 full-text articles or datasets passed the threshold for full-text screening, and 11 records met the criteria for inclusion in the final analysis.

Data collection process. SL contacted experts and solicited paper recommendations from the ICIS and CDS email listservs, and conducted the search process. The team randomly assigned themselves to look through relevant papers including supplemental materials (with SL double-checking every entry and resolving disagreements). Where extract values were not provided, or other ambiguities (e.g. numbers reported in the paper differ from the numbers calculated using the raw data), the team contacted authors to try and address, and also used the tool WebplotDigitizer (https://automeris.io/WebPlotDigitizer/) to extract estimated values from figures. If there were discrepancies between the paper, figures or raw data, we prioritized the data sources in the following way: the values from the raw data if available, then author correspondence, then paper, then estimates from figures.

For individual datasets, authors were asked to provide their data plus a codebook, and were asked for permission to share their stimuli and data publicly on OSF. Of 9 papers (33 conditions), authors were able to find and provide original data for 8 papers (8 papers, 30 conditions total). Data from all 30 conditions and stimuli from 13 conditions (either actual study videos, or example stimuli) are publically available at https://osf.io/zwncg/.

Stopping rule. We continued to search for and add studies that meet the selection criteria to the spreadsheet. We included all eligible studies in the analyses reported in this paper at the time of pre-registration, prior to the analysis. During analysis, a new study was completed (Woo et al., unpublished, Experiment 3) and we decided to add this study to the pool, because it met the inclusion criteria and there are so few studies in this topic area. The decision to include this additional study was made after pre-registration, but was not revisited after viewing the results.

Data items. The following data were extracted from eligible studies (see the tab “CodeBook” in the spreadsheet for details).

- General paper info: citations and peer review information, lab group information
- Methods: experiment and condition info, whether infants were familiarized or habituated, the dependent measure, study design (within or between subjects), whether trials were infant-controlled, number of familiarization or habituation and test trials
- Participant characteristics: whether infants were typically developing, mean age, age range, number of excluded infants, proportion and number of female infants
- Looking time data: where available, means, SD/SE of looking to each test event
- Inferential statistics: where available, t and F values, Cohen’s D, correlation between looks (if within-participant design across two test events)
- Data source: whether data primarily came from authors, papers, or figures, plus detailed comments about which data came from which source
- Data and stimuli availability (including URLS of open-access datasets)
- Moderators: including variables like which task the current condition falls into, whether the action was causal, what kind of agent performed the action, etc. see Codebook for details.

Dependent variable. The dependent variable of interest is the difference of response measures between the expected and unexpected test events following habituation for all tasks, where a positive value indicates a novelty preference, i.e., longer looking at the unexpected action, and a negative value indicates a familiarity preference, i,e, longer looking at the expected action[1]. For simplicity, we will apply these labels regardless of whether the condition was an experimental or control condition. Specifically, for the goals task, the expected event is

[1] We considered other DVs as well, including proportion looks and log-transformed looking times. We chose this particular DV because it allows us to use the same measure across the meta-analysis and multilevel modeling approaches - most published papers report statistics over mean differences in untransformed looking times.

the one wherein the agent moves or reaches towards the old goal object, and the unexpected event is when the agent moves towards the new goal object. And for the cost task, the expected event is the one wherein the agent moves on a smooth straight path along the surface towards the goal, and the unexpected event is when the agent moves on a curved path towards the goal. See Figure 1.

Supplemental Figures and Tables

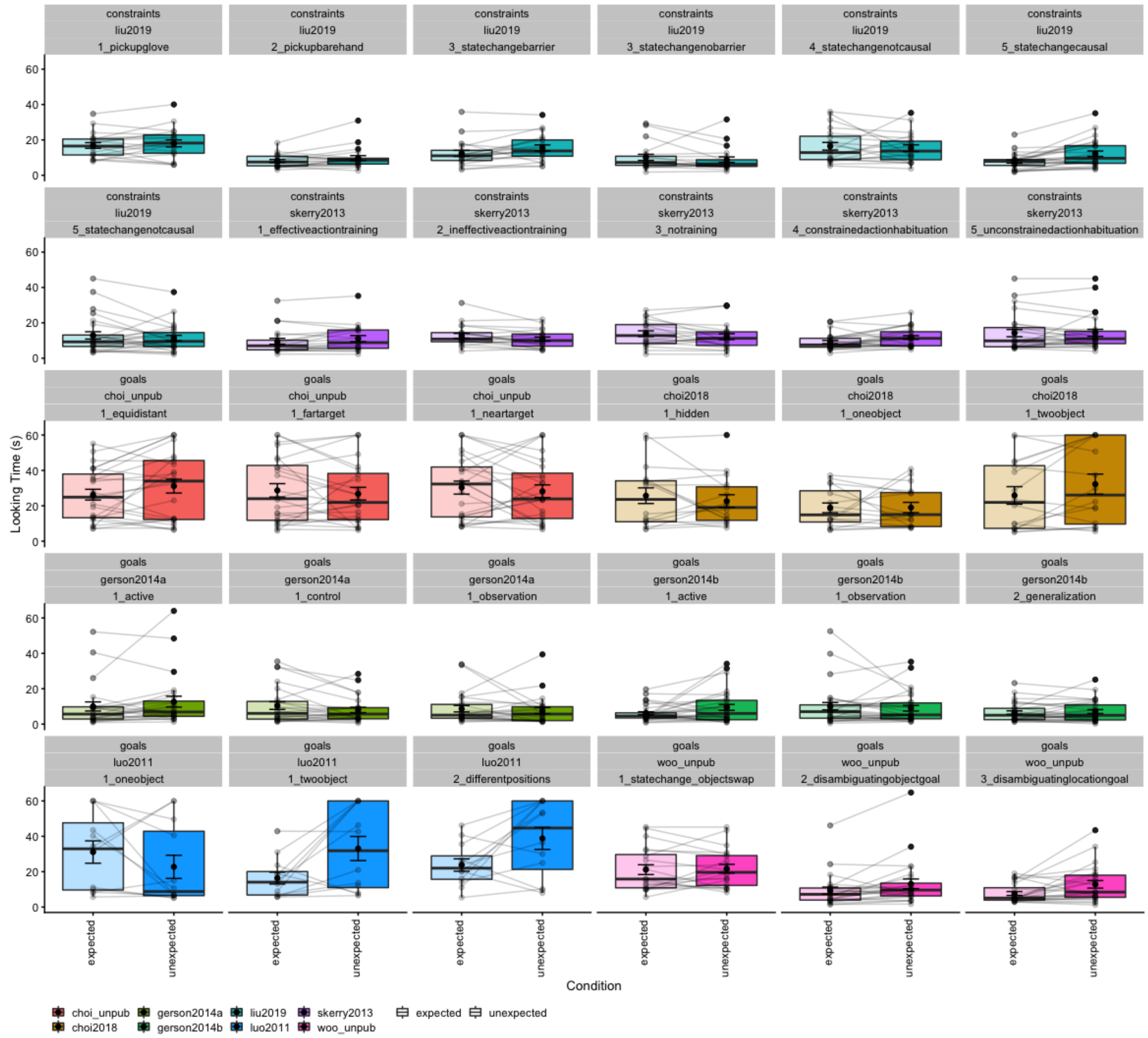

Figure S2. Looking times towards the expected and unexpected event for every condition included in the analysis. Data from individual babies are plotted as a pair of connected points. Black dots and error bars indicate means and standard errors.

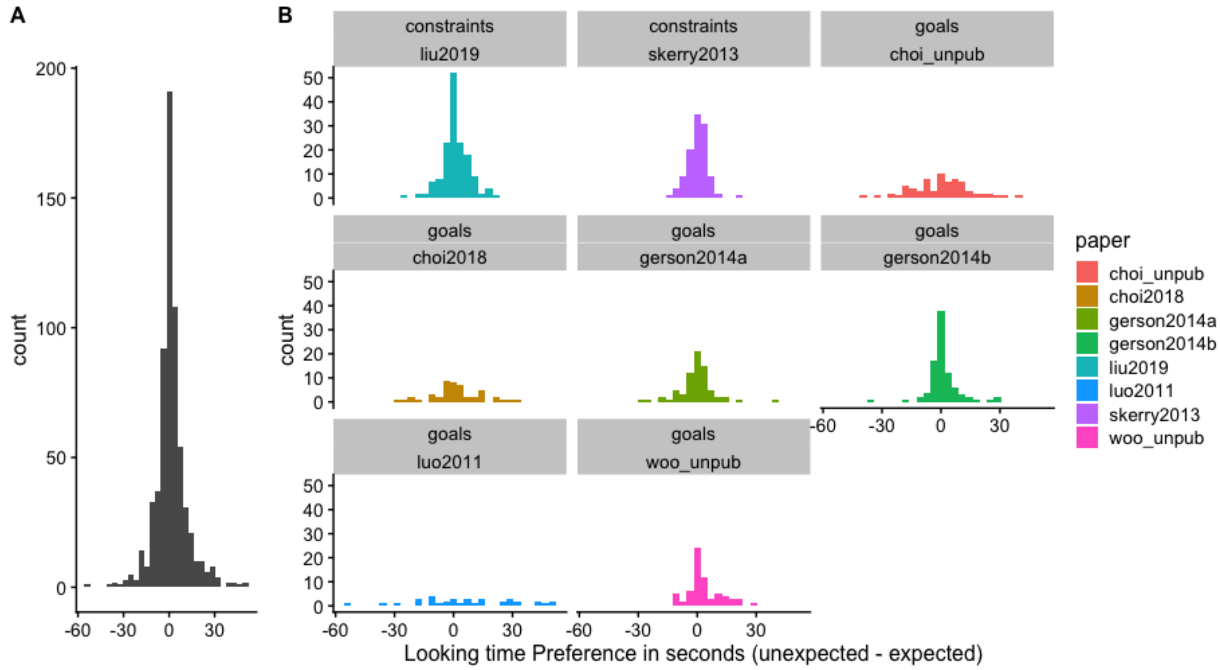

Figure S3. Violation-of-expectation effect (average looking to unexpected event - average looking to expected event) plotted as a histogram across all papers (A) and within each paper (B).

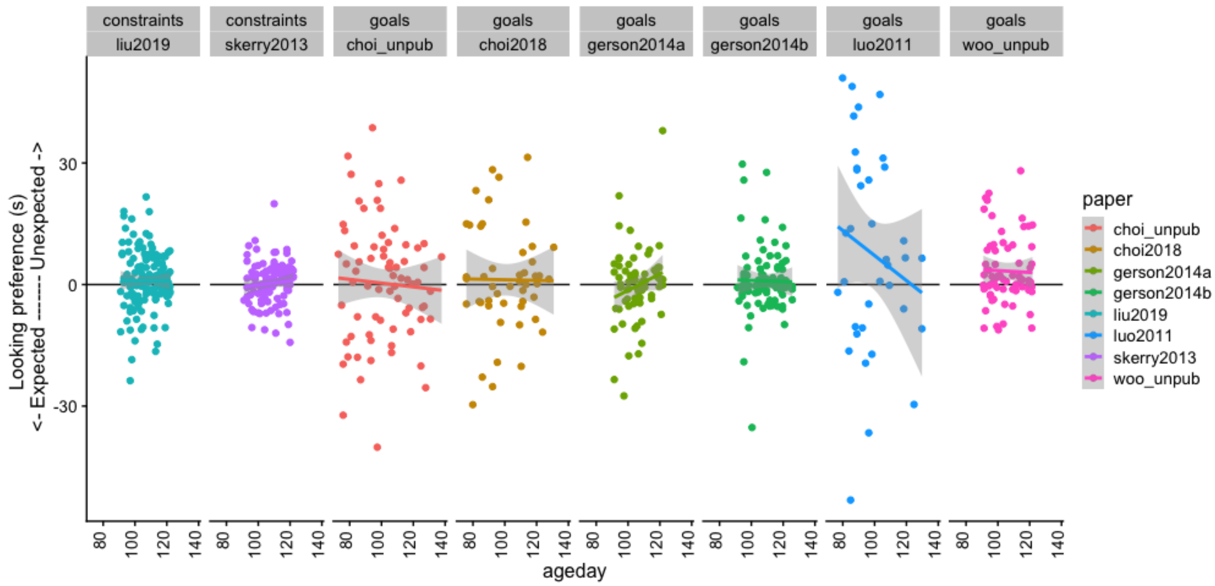

Figure S4. Violation-of-expectation effect (average looking to unexpected event - average looking to expected event) plotted against age in days, for all papers included in the analysis.

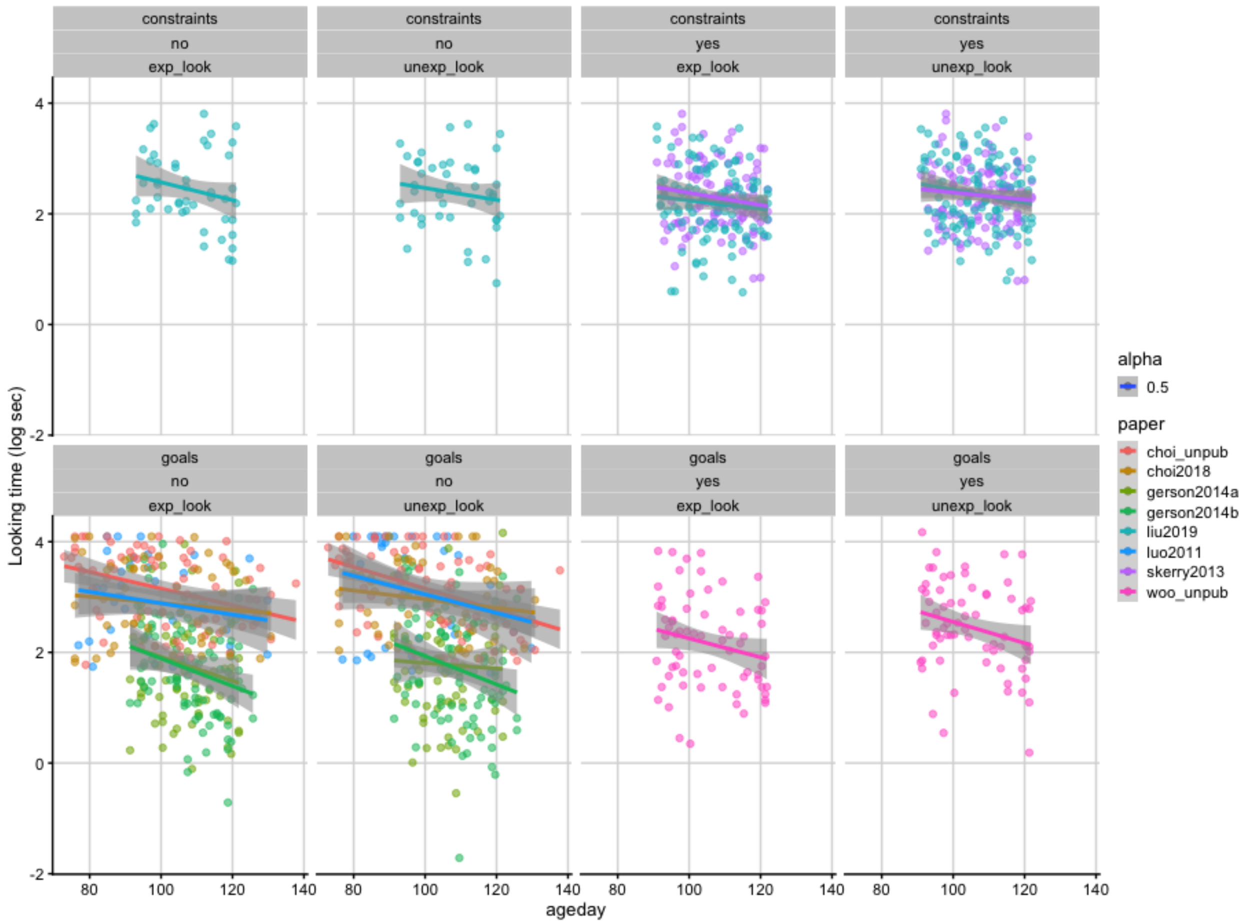

Figure S5. Looking time in log seconds towards the expected versus unexpected test events plotted against age for all 8 papers included in the mega-analysis, faceted by task (goals, constraints), and whether the actions were causal (no, yes). Each point indicates looking towards either the expected or unexpected event for one infant participant.

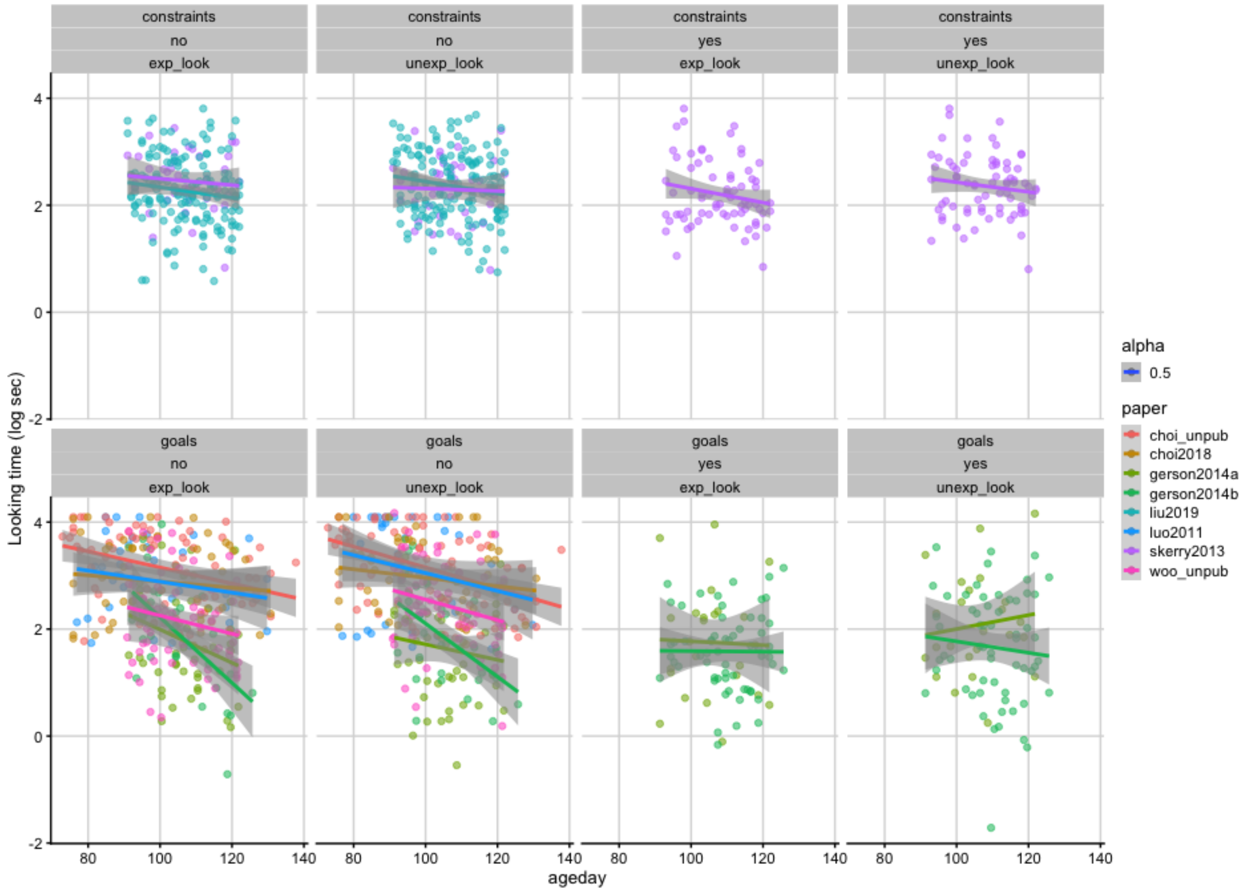

Figure S6. Looking time in log seconds towards the expected versus unexpected test events plotted against age for all 8 papers included in the mega-analysis, faceted by task (goals, constraints), and whether there was action training (no, yes). Each point indicates looking towards either the expected or unexpected event for one infant participant.

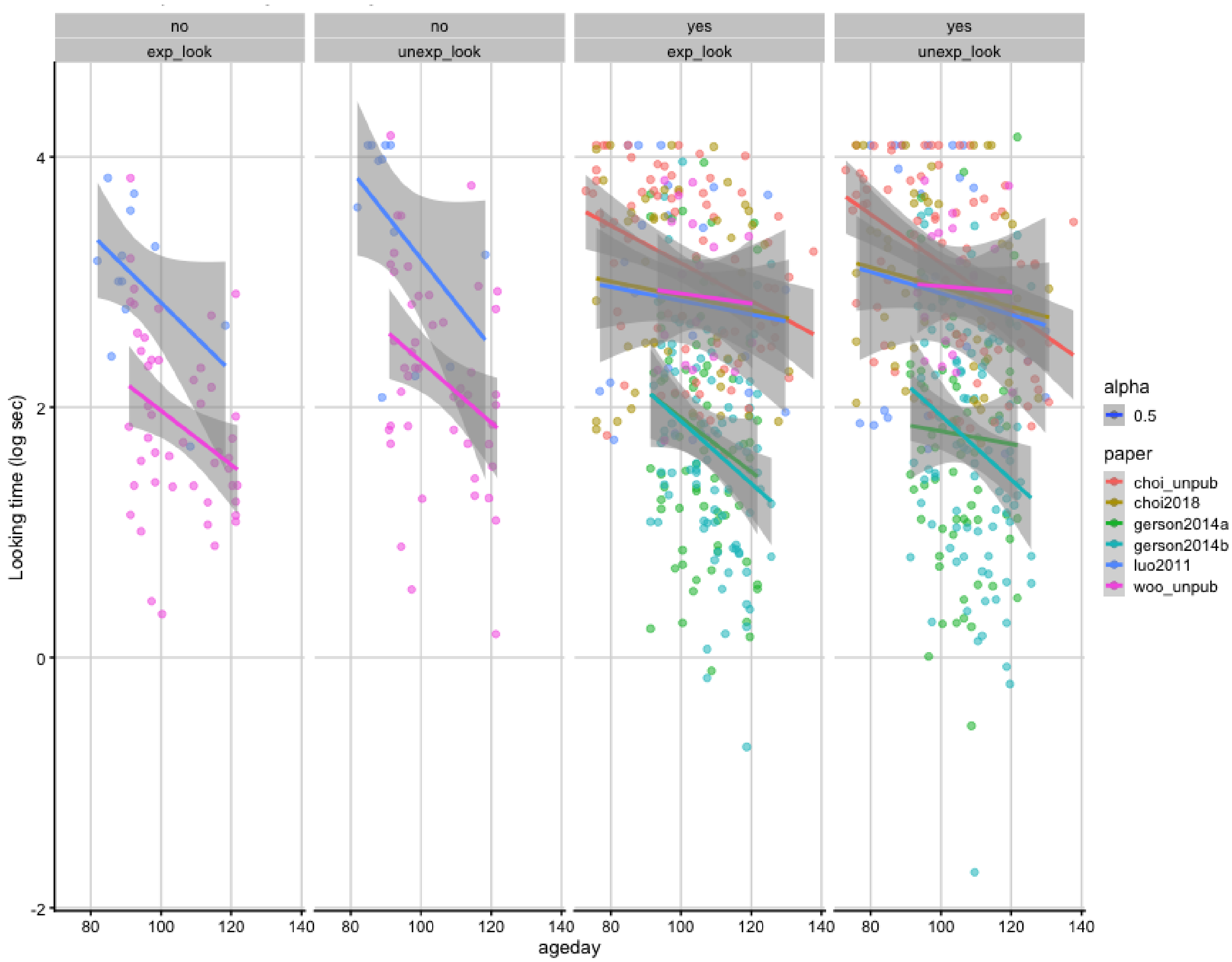

Figure S7. Looking time in log seconds for the goals task towards the expected versus unexpected test events plotted against age, faceted whether the goal of the action was ambiguous (no vs yes). Each point indicates looking towards either the expected or unexpected event for one infant participant.

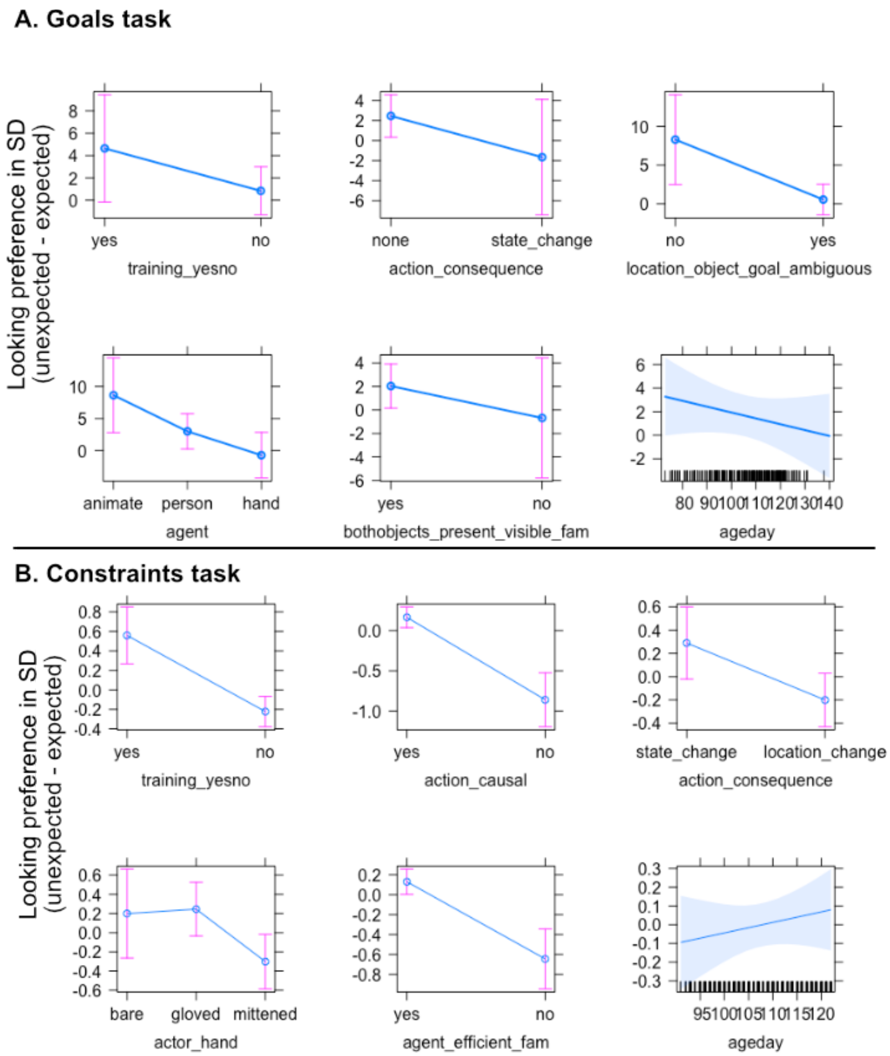

Figure S8. **Visualization of confirmatory results.** Y axis indicates violation-of-expectation response (looking at unexpected outcome - looking at expected outcome, in standard deviations). Each panel shows effects over all predictors in the goals task (A) and the constraints task (B), including data from 619 2- to 4-month-old infants (31 excluded based on Cook's Distance, see results for details). Note that the effects "bothobjects_present_visible_fam" (A) and "agent_efficient_fam" (B) are predictors included to account for standard control conditions in each respective task. Dots and error bars / error ribbons indicate the estimated effect and the 95% confidence interval.

Table S1. Overview of the conditions from the goals task, including experiment and condition names (e.g. choi_unpub refers to the paper Choi and Luo, unpublished; 1_equistant refers to Experiment 1, Equidistant Condition), sample sizes, age ranges, and the names and values of the predictors that entered the analyses.

Article	Condition	N	Min Age (days)	Max Age (days)	Sticky mittens training	Causal action	Consequence of action	Ambiguous goal	Both objects present and visible to agent	Agent
choi_unpub	14_equidistant	24	76	137	no	no	none	yes	yes	person
choi_unpub	1_fartarget	24	72	130	no	no	none	yes	yes	person
choi_unpub	1_neartarget	24	74	127	no	no	none	yes	yes	person
choi2018	1_hidden	16	75	121	no	no	none	yes	no	person
choi2018	1_oneobject	16	75	127	no	no	none	yes	no	person
choi2018	1_twoobject	16	77	130	no	no	none	yes	yes	person
gerson2014a	1_active	24	91	121	yes	no	none	yes	yes	hand
gerson2014a	1_control	24	91	120	no	no	none	yes	yes	hand
gerson2014a	1_observation	24	91	121	no	no	none	yes	yes	hand
gerson2014b	1_active	30	91	125	yes	no	none	yes	yes	hand
gerson2014b	1_observation	30	92	125	no	no	none	yes	yes	hand
gerson2014b	2_generalization	30	94	125	yes	no	none	yes	yes	hand
luo2011	1_oneobject	12	76	124	no	no	none	yes	no	animate
luo2011	1_twoobject	12	79	129	no	no	none	yes	yes	animate
luo2011	2_differentpositions	12	81	118	no	no	none	no	no	animate
woo_unpub	1_statechange_objectswap	20	93	120	no	yes	state change	yes	yes	person
woo_unpub	2_disambiguatingobjectgoal	24	91	121	no	yes	state change	no	yes	person
woo_unpub	3_disambiguatinglocationgoal	24	90	121	no	yes	state change	no	yes	person

Table S2. Overview of the conditions from the constraints task, including the condition names (e.g. 1_pickupglove refers to Experiment 1, condition involving a hand wearing a glove picking up an object), sample sizes, age ranges, and the names and values of the predictors that entered the analyses.

Article	Condition	N	Min Age (days)	Max Age (days)	Sticky mittens training	Causal action	Consequence of action	Agent efficient initially	Actor's hand
liu2019	1_pickupglove	20	92	122	no	yes	location change	yes	gloved
liu2019	2_pickupbarehand	20	93	120	no	yes	location change	yes	bare
liu2019	3_statechangebarrier	20	91	122	no	yes	state change	yes	gloved
liu2019	3_statechangenobarrier	20	91	122	no	yes	state change	no	gloved
liu2019	4_statechangenotcausal	20	93	121	no	no	state change	yes	gloved
liu2019	5_statechangecausal	26	92	121	no	yes	state change	yes	gloved
liu2019	5_statechangenotcausal	26	93	120	no	no	state change	yes	gloved
skerry2013	1_effectiveactiontraining	20	93	121	yes	yes	location change	yes	mittened
skerry2013	2_ineffectiveactiontraining	20	93	122	no	yes	location change	yes	mittened
skerry2013	3_notraining	20	91	121	no	yes	location change	yes	mittened
skerry2013	4_constrainedactionhabituation	26	93	120	yes	yes	location change	yes	mittened
skerry2013	5_unconstrainedactionhabituation	26	93	122	yes	yes	location change	no	mittened

Table S3. Distribution of influential observations in the constraints analysis, model formula:
`look_pref ~ training_yesno + action_causal + action_consequence + actor_hand + agent_efficient_fam + ageday + (1|condition) + (1|experiment) + (1|paper)`

Paper	Condition	Original N	N after exclusions	N excluded
liu2019	1_pickupglove	20	18	2
liu2019	2_pickupbarehand	20	19	1
liu2019	3_statechangebarrier	20	19	1
liu2019	3_statechangenobarrier	20	17	3
liu2019	4_statechangenotcausal	20	17	3
liu2019	5_statechangecausal	26	26	0
liu2019	5_statechangenotcausal	26	23	3
skerry2013	1_effectiveactiontraining	20	20	0
skerry2013	2_ineffectiveactiontraining	20	20	0
skerry2013	3_notraining	20	19	1
skerry2013	4_constrainedactionhabituation	26	26	0
skerry2013	5_unconstrainedactionhabituation	26	25	1

Table S4. Distribution of influential observations in the goals analysis, model formula: `look_pref ~ training_yesno  + action_consequence + location_object_goal_ambiguous + agent + bothobjects_present_visible_fam + ageday + (1|condition) + (1|experiment) + (1|paper)`

paper	condition	n	n_cooks	n_excluded
choi_unpub	1_equidistant	24	24	0
choi_unpub	1_fartarget	24	24	0
choi_unpub	1_neartarget	24	23	1
choi2018	1_hidden	16	15	1
choi2018	1_oneobject	16	16	0
choi2018	1_twoobject	16	16	0
gerson2014a	1_active	24	24	0
gerson2014a	1_control	24	24	0
gerson2014a	1_observation	24	24	0
gerson2014b	1_active	30	30	0
gerson2014b	1_observation	30	30	0
gerson2014b	2_generalization	30	30	0
luo2011	1_oneobject	12	8	4
luo2011	1_twoobject	12	7	5
luo2011	2_differentpositions	12	7	5
woo_unpub	1_statechange_objectswap	20	20	0
woo_unpub	2_disambiguatingobjectgoal	24	24	0
woo_unpub	3_disambiguatinglocationgoal	24	24	0

Exploratory Bayesian analysis using brms

All models had this general format: `brm(formula = look_pref ~ [fixed effects] + [random effects], data = [constraints or goals], warmup = 1000, iter = 5000, family = student`[2]`(link = "identity"), chains = 6, thin = 2, seed = 429, save_all_pars = TRUE, sample_prior = TRUE, control = list(adapt_delta = 0.98)`. For both the goals and constraints tasks, we fit 3 models: a null model with rich random effects, a full model (with the same fixed effects as the frequentist models) with complex random effects, and a full model with simple random effects. In models with complex random effects, we took into account that conditions were nested within experiments, and experiments were nested within papers, i.e. `(1|condition) + (1+condition|experiment) + (1+condition|paper)`, as originally intended in the pre-registration. In models with simple random effects, we fit the same random intercepts as the frequentist models reported above, i.e. `(1|condition) + (1|experiment) + (1|paper)`. We performed model diagnostics by inspecting the trace plots of all parameters, the distributions of R_hat, effective sample size, and Monte Carlo standard error, autocorrelation plots across chains, PSIS diagnostic plots (which can reveal outliers), and plots of the posterior predictive density using 100 draws. We then compared the estimates and equivalents of Bayes Factors (evidence ratios, computed via the Savage-Dickey density ratio method) for the hypothesis that each fixed effect of interest had an effect greater than 0. Results of the full model with complex random effects provide estimates that take into account correlated design decisions within papers. By comparing the evidence ratios, estimates, and confidence intervals in the estimates, between the full model with simple versus complex random effects, we can assess the impact of accounting for this structure in the data. Finally, we computed the Bayes Factor between the full model with complex versus simple random effects to assess which model provides the best fit to the data overall.

Goals task. The intercept only model (`look_pref ~ 1 + ageday + (1|condition) + (1+condition|experiment) + (1+condition|paper)`) provided moderate evidence for looking preference larger than 0 (evidence ratio = Estimate = 4.7 [-4.145, 14.008], Evidence Ratio = 4.291, Posterior Probability = 0.811). The full model with complex random effects (`look_pref ~ training_yesno + action_consequence + location_object_goal_ambiguous + agent + bothobjects_present_visible_fam + ageday + (1|condition) + (1+condition|experiment) + (1+experiment|paper)`)

---

[2] We also tried using family = gaussian, but this provided far weaker fits during visual inspection of the posterior predictive checks, for all models. All models (both executable and saved .Rds objects) are available at https://osf.io/zwncg/.

yielded some similar results to the frequentist model, but also some differences: of all the predictors, there was moderate evidence that seeing unambiguous evidence for someone's goal (Estimate = 4.797 [-3.75, 13.553], Evidence Ratio = 5.015, Posterior Probability = 0.834) mattered for infants' looking preferences, as did infant age (Estimate = -0.03 [-0.098, 0.036], Evidence Ratio = 3.405, Posterior Probability = 0.773), with older babies showing smaller effects than younger babies. These effects were substantially smaller than the full Bayesian model with simpler random effects, and all confidence intervals included 0, suggesting that substantial variance in the data is accounted for by shared methodological considerations within experiments and papers. As in the constraints task, the Bayes Factor between the full models with identical fixed effects and varying (simple vs complex) random effects strongly favored the simple random effects structure (BF = 819.758). These results suggest that although adding random slopes for conditions and experiments accounted for variance in infants' looking behavior, the simple random effects structure represented in the frequentist analysis better accounted for this data. In the Bayesian version of this model, the only effect with posterior probability greater than 0.95 was seeing unambiguous evidence for someone's goal (Estimate = 3.362 [0.641, 6.454], Evidence Ratio = 42.478, Posterior Probability = 0.977), which largely agrees with the findings from the frequentist analysis. See Tables S5-S6.

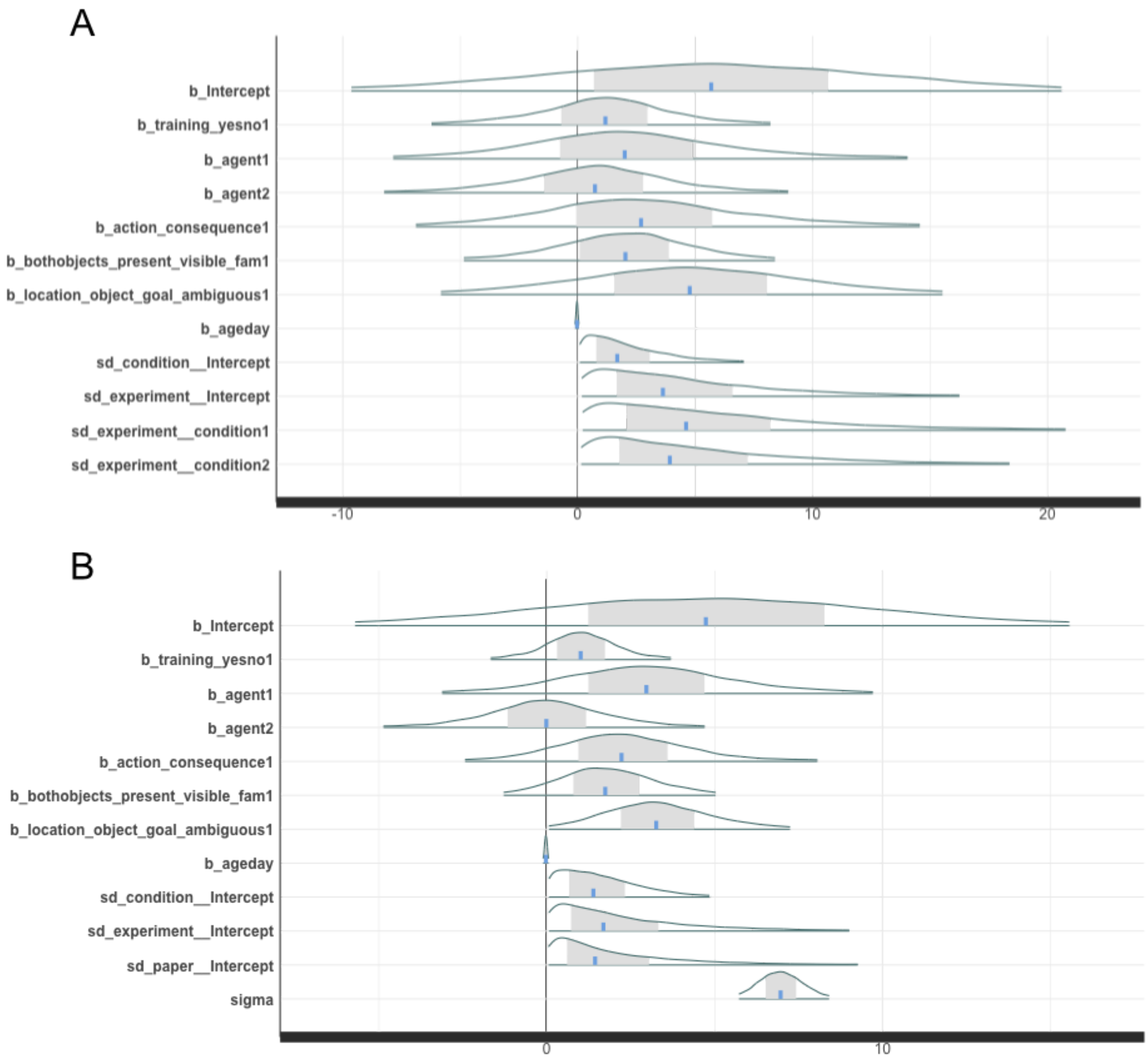

Figure S9. Parameter estimates for the goals model with complex (A) verus simple (B) random effects, including kernel density estimates, median point estimates, and the 50% posterior interval (shaded region), for each parameter.

Table S5. Hypothesis table for goals brms model including full random effects, `look_pref ~ training_yesno + action_consequence + location_object_goal_ambiguous + agent + bothobjects_present_visible_fam + ageday + (1|condition) + (1+condition|experiment) + (1+experiment|paper)`

Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob
(ageday) < 0	-0.0305	0.0409	-0.0979	0.0361	3.405	0.7730
(training_yesno1) > 0	1.1114	3.4628	-4.4831	6.6605	2.053	0.6725
(location_object_goal_ambiguous1) > 0	4.7971	5.3897	-3.7498	13.5534	5.015	0.8338
(action_consequence1) > 0	2.9948	5.2689	-4.8005	11.9329	2.906	0.7440
(agent1) > 0	2.2503	5.3811	-5.6864	11.3187	2.221	0.6896
(agent2) > 0	0.6285	4.1461	-5.7784	6.8591	1.477	0.5963
(bothobjects_present_visible_fam1) > 0	1.9612	3.2511	-3.4528	7.1290	3.128	0.7577

'CI': 90%-CI for one-sided and 95%-CI for two-sided hypotheses.
* For one-sided hypotheses, the posterior probability exceeds 95%; for two-sided hypotheses, the value tested against lies outside the 95%-CI. Posterior probabilities of point hypotheses assume equal prior probabilities.

Table S6. Hypothesis table for goals brms model including simple random effects, `look_pref ~ training_yesno + action_consequence + location_object_goal_ambiguous + agent + bothobjects_present_visible_fam + ageday + (1|condition) + (1|experiment) + (1|paper)`

Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob
(ageday) < 0	-0.0257	0.0409	-0.0943	0.0409	2.7152	0.7308
(training_yesno1) > 0	1.0165	1.3263	-1.0207	3.1027	4.8910	0.8302
(location_object_goal_ambiguous1) > 0	3.3618	1.8229	0.6408	6.4544	42.4783	0.9770*
(action_consequence1) > 0	2.3451	2.6280	-1.2419	6.5523	6.8792	0.8731
(agent1) > 0	3.0375	3.2804	-1.7158	8.1477	7.0429	0.8757
(agent2) > 0	0.0164	2.4794	-3.4888	3.4689	0.9874	0.4968
(bothobjects_present_visible_fam1) > 0	1.7882	1.5856	-0.6941	4.4398	7.9219	0.8879

'CI': 90%-CI for one-sided hypotheses and 95%-CI for two-sided hypotheses.

* For one-sided hypotheses, the posterior probability exceeds 95%; for two-sided hypotheses, the value tested against lies outside the 95%-CI. Posterior probabilities of point hypotheses assume equal prior probabilities.

Constraints task.The intercept only model (`look_pref ~ 1 + ageday + (1|condition) + (1+condition|experiment) + (1+condition|paper)`) provided moderate against the hypothesis that there is a looking preference than 0 Estimate = -5.409 [-13.024, 2.357], Evidence Ratio = 0.138, Posterior Probability = 0.122. The full model with complex random effects (`look_pref ~ training_yesno + action_causal + action_consequence + actor_hand + agent_efficient_fam + ageday + (1|condition) + (1+condition|experiment) + (1+experiment|paper)`) yielded qualitatively similar results to the frequentist model (see Table x): of all the predictors, infant age (Estimate = 0.056 [-0.007, 0.118], Evidence Ratio = 13.184, Posterior Probability = 0.929), and seeing an action that caused an observable outcome on contact (Estimate = 2.316 [-1.107, 5.687], Evidence Ratio = 8.057, Posterior Probability = 0.89) had the highest predictive power on infants' looking behavior, followed by a manipulation that picked out control conditions (Estimate = 2.233 [-2.441, 6.909], Evidence Ratio = 4.54, Posterior Probability = 0.82), and then sticky mittens training (Estimate = 1.667 [-2.087, 5.395], Evidence Ratio = 3.994, Posterior Probability = 0.8). However, like in the goals task, the confidence interval over these estimates included 0, and the size of the evidence ratios were substantially smaller than the Bayes Factors from the frequentist model, and smaller than the evidence ratios from the full Bayesian model with simpler random effects (see TableS6), suggesting that substantial variance in the data is accounted for by shared methodological decisions within experiments and papers. (Note that the 26 conditions from this task came from just 2 papers). Nevertheless, the Bayes Factor between these two full models with identical fixed effects and varying (simple vs complex) random effects substantially favored the simple random effects structure (BF = 70.2845). Altogether, these results suggest that although adding random slopes for conditions and experiments accounted for variance in infants' looking behavior, simple random effects structure presented in the frequentist analysis better accounts for the data. (One caveat to this interpretation is that the number of conditions and papers were limited - only 2 papers with 7 and 5 conditions each.) In the Bayesian version of this model, the only effects with posterior probabilities greater than 0.95 were sticky mittens training (Estimate = 1.815 [0.344, 3.284], Evidence Ratio = 35.923, Posterior Probability = 0.973), causal action (Estimate = 2.198 [0.906, 3.527], Evidence Ratio = 121.449, Posterior Probability = 0.992), and seeing a constraint agent during habituation (Estimate = 1.822 [0.711, 2.957], Evidence Ratio = 105.195, Posterior

Probability = 0.991), which accord with the findings from the frequentist analysis. See Tables S7-S8.

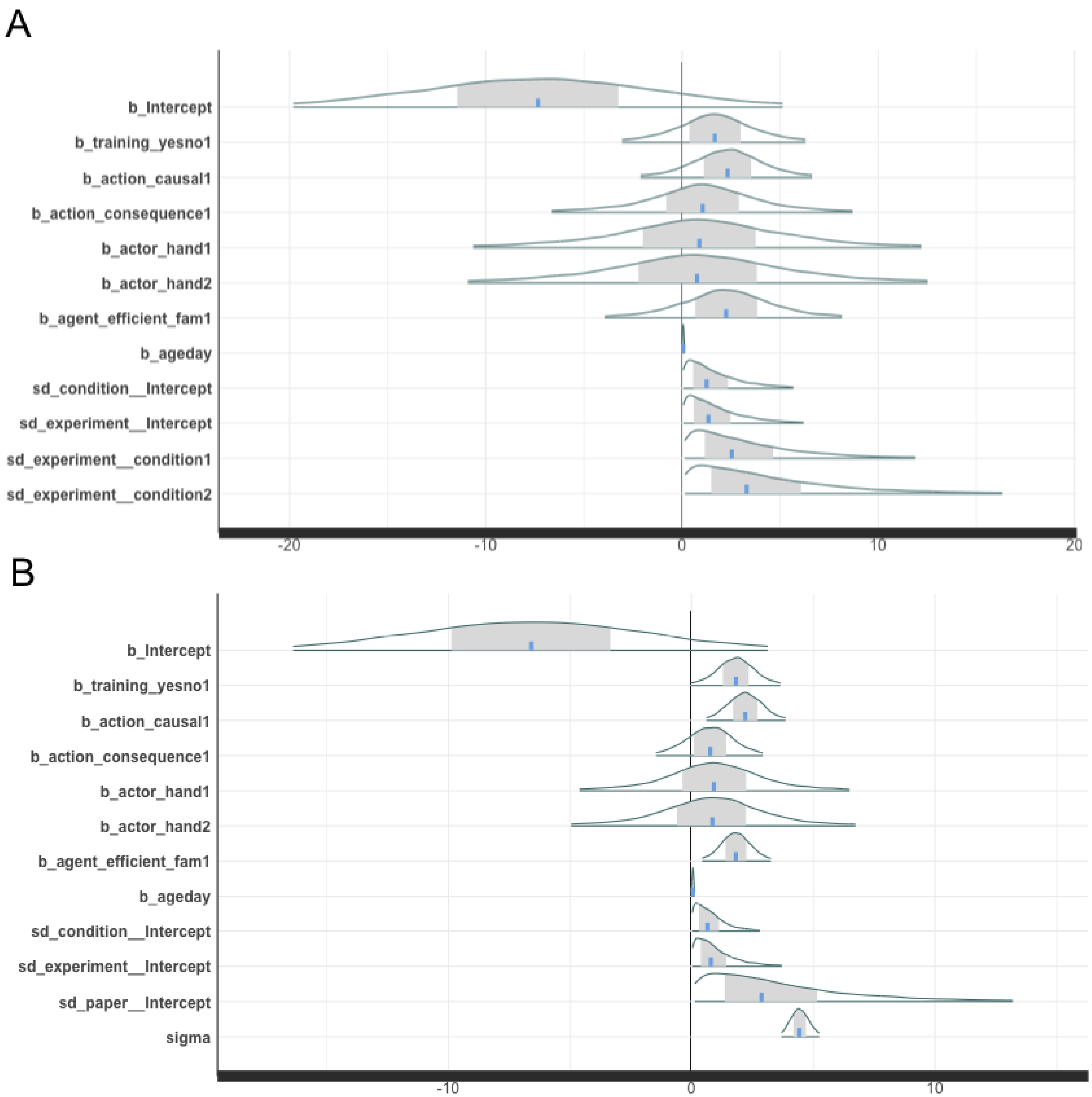

Figure S10. Parameter estimates for the constraints model with complex (A) verus simple (B) random effects, including kernel density estimates, median point estimates, and the 50% posterior interval (shaded region), for each parameter.

Table S7. Hypothesis table for constraints brms model including complex random effects, `look_pref ~ training_yesno + action_causal + action_consequence + actor_hand + agent_efficient_fam + ageday + (1|condition) + (1+condition|experiment) + (1+experiment|paper)`

Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob
(ageday) > 0	0.0558	0.0379	-0.0069	0.1182	13.184	0.9295
(training_yesno1) > 0	1.6674	2.3111	-2.0868	5.3950	3.994	0.7998
(action_causal1) > 0	2.3164	2.1193	-1.1074	5.6866	8.057	0.8896
(action_consequence1) > 0	1.0226	3.7318	-4.8642	6.7179	1.912	0.6566
(actor_hand1) > 0	0.8818	5.4982	-7.8344	9.5696	1.425	0.5876
(actor_hand2) > 0	0.8077	5.7737	-8.2251	9.9956	1.341	0.5728
(agent_efficient_fam1) > 0	2.2333	2.9437	-2.4412	6.9092	4.540	0.8195

'CI': 90%-CI for one-sided hypotheses and 95%-CI for two-sided hypotheses. * For one-sided hypotheses, the posterior probability exceeds 95%; for two-sided hypotheses, the value tested against lies outside the 95%-CI. Posterior probabilities of point hypotheses assume equal prior probabilities.

Table S8. Hypothesis table for constraints brms model including simple random effects, `look_pref ~ training_yesno + action_causal + action_consequence + actor_hand + agent_efficient_fam + ageday + (1|condition) + (1|experiment) + (1|paper).`

Hypothesis	Estimate	Est.Error	CI.Lower	CI.Upper	Evid.Ratio	Post.Prob
(ageday) > 0	0.0531	0.0373	-0.0077	0.1155	11.698	0.9212
(training_yesno1) > 0	1.8147	0.9199	0.3436	3.2843	35.923	0.9729*
(action_causal1) > 0	2.1985	0.8409	0.9061	3.5267	121.449	0.9918*
(action_consequence1) > 0	0.7475	1.1238	-1.0188	2.5010	3.417	0.7736
(actor_hand1) > 0	0.9176	2.6849	-3.2750	5.0812	2.175	0.6850
(actor_hand2) > 0	0.8293	2.8026	-3.5769	5.1792	1.926	0.6582
(agent_efficient_fam1) > 0	1.8224	0.7294	0.7108	2.9571	105.195	0.9906*

'CI': 90%-CI for one-sided hypotheses and 95%-CI for two-sided hypotheses. * For one-sided hypotheses, the posterior probability exceeds 95%; for two-sided hypotheses, the value tested against lies outside the 95%-CI. Posterior probabilities of point hypotheses assume equal prior probabilities.

References

Bürkner, P.-C. (2018). Advanced Bayesian Multilevel Modeling with the R Package brms. *The R Journal*, *10*(1), 395.

Choi, Y.J. & Luo, Y. (unpublished). Three-month-old infants' understanding of a human agent's preference

Choi, Y.-J., Mou, Y., & Luo, Y. (2018). How do 3-month-old infants attribute preferences to a human agent? *Journal of Experimental Child Psychology*, *172*, 96–106.

Gergely, G., Nádasdy, Z., Csibra, G., & Bíró, S. (1995). Taking the intentional stance at 12 months of age. *Cognition*, *56*(2), 165–193.

Gerson, S. A., & Woodward, A. L. (2014a). The joint role of trained, untrained, and observed actions at the origins of goal recognition. *Infant Behavior & Development, 37*(1), 94–104.

Gerson, S. A., & Woodward, A. L. (2014b). Learning from their own actions: the unique effect of producing actions on infants' action understanding. *Child Development, 85*(1), 264–277.

Leslie, A. M. (1982). The perception of causality in infants. *Perception*, *11*(2), 173–186.

Liu, S., Brooks, N. B., & Spelke, E. S. (2019). Origins of the concepts cause, cost, and goal in prereaching infants. *Proceedings of the National Academy of Sciences of the United States of America, 116*(36), 17747–17752.

Luo, Y. (2011). Three-month-old infants attribute goals to a non-human agent. *Developmental Science, 14*(2), 453–460.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA Statement. *Open Medicine: A Peer-Reviewed, Independent, Open-Access Journal*, *3*(3), e123–e130.

Skerry, A. E., Carey, S. E., & Spelke, E. S. (2013). First-person action experience reveals sensitivity to action efficiency in prereaching infants. *Proceedings of the National Academy of Sciences of the United States of America, 110*(46), 18728–18733.

Sommerville, J. A., Woodward, A. L., & Needham, A. (2005). Action experience alters 3-month-old infants' perception of others' actions. *Cognition*, *96*(1), 1–11.

Woo, B. M., Liu, S., & Spelke, E. (2021). Open-minded, not naïve: Three-month-old infants encode objects as the goals of other people's reaches. *Proceedings of the 43rd Annual Meeting of the Cognitive Science Society.*

Woodward, A. L. (1998). Infants selectively encode the goal object of an actor's reach. *Cognition, 69*(1), 1–34.