What paradigms can webcam eye-tracking be used for? Attempted replications of 5

"classic" cognitive science experiments

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38   Abstract

39   ADD LATER

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⁴² What paradigms can webcam eye-tracking be used for? Attempted replications of 5

⁴³ "classic" cognitive science experiments

⁴⁴ The use of eye-tracking to study cognition took off when Alfred Yarbus used suction

⁴⁵ cups to affix a mirror system to the sclera of the eye in order to monitor eye position

⁴⁶ during the perception of images (Yarbus, 1967). In one study, participants viewed a

⁴⁷ painting depicting multiple people in a complex interaction inside of a 19th century

⁴⁸ Russian home. Yarbus showed, among other things, that the scan paths and locations of

⁴⁹ fixations were largely dependent on the instructions given to participants (e.g., View the

⁵⁰ picture freely vs. Remember the position of the people and objects in the room). In other

⁵¹ words, the cognitive processing that the individual is engaged in drives the visuo-motor

⁵² system. Since these findings, eye-tracking has become a central method in cognitive science

⁵³ research Rayner (1998). For example, gaze location during natural scene perception is used

⁵⁴ to test theories of visual attention (e.g., Henderson & Hayes, 2017). And eye-movements

⁵⁵ during auditory language comprehension, using the "visual world paradigm," demonstrated

⁵⁶ the context-dependent and incremental nature of language processing (e.g., Tanenhaus,

⁵⁷ Spivey-Knowlton, Eberhard, & Sedivy, 1995).

⁵⁸ An important limitation of the eye-tracking methodology is that it has typically

⁵⁹ required costly equipment (eye-trackers can range in price from a few thousand dollars to

⁶⁰ tens of thousands of dollars), particular laboratory conditions (a quiet room with

⁶¹ consistent indoor lighting conditions), and a substantial time investment (e.g., bringing

⁶² participants into a laboratory one at a time). This limits who can conduct eye-tracking

⁶³ research – not all researchers have the necessary resources – and who can participate in

⁶⁴ eye-tracking research. Most eye-tracking study participants are from western, educated,

⁶⁵ industrialized, rich, and democratic [WEIRD; Henrich, Heine, and Norenzayan (2010)]

⁶⁶ convenience samples (but see Ryskin, Salinas, Piantadosi, & Gibson, 2023), which

⁶⁷ diminishes the generalizability of the findings and the scope of conclusions that can be

68   drawn about human cognition.

69   Advances in software for online data collection (de Leeuw, 2015; Papoutsaki et al.,

70   2016) have the potential to address this shortcoming by expanding access to eye-tracking

71   technology for researchers and making it feasible to broaden and diversify the participant

72   samples. In particular, `Webgazer.js` (Papoutsaki et al., 2016) is a webcam-based

73   Javascript plug-in that works in the browser. It can be integrated with any Javascript web

74   interface. As a result, it can be used in conjunction with many existing platforms for online

75   behavioral data collection that are familiar to cognitive scientists, such as `jsPsych` (de

76   Leeuw, 2015), `Gorilla` (Anwyl-Irvine, Massonnié, Flitton, Kirkham, & Evershed, 2020), or

77   `lab.js` (Henninger, Shevchenko, Mertens, Kieslich, & Hilbig, 2021). However, the added

78   convenience comes at the cost of spatial and temporal resolution. The extent of this loss of

79   precision and its impact on the kinds of research questions that webcam eye-tracking is

80   appropriate for are not yet known.

81   A few previous studies have used webcam eye-tracking in the context of

82   behavioral/cognitive science experiments and reported on the quality of the data. In what

83   follows, we provide a brief review of the published work that we are aware of (note that we

84   focus on studies with adult participants as the considerations for eye-tracking of children

85   are substantially different, but see e.g., Bánki, Eccher, Falschlehner, Hoehl, & Markova,

86   2022).

87   Semmelmann and Weigelt (2018) compared eye-tracking results between in-lab

88   (n=29) and online (n=28) studies in three tasks: fixation, pursuit, and free viewing. They

89   used the `Webgazer.js` library (Papoutsaki et al., 2016) and programmed tasks in

90   HTML/Javascript directly. The first two tasks tested measurement of basic gaze

91   properties. In the fixation task, participants were asked to fixate a dot, and in the pursuit

92   task, they were asked to follow a dot with their eyes. In the free viewing task, the eye

93   movements may have been more semantically driven: participants were shown a picture of

94 a human face and asked to look wherever they wanted to on the image. Webgazer was

95 successful in accurately detecting fixation locations and saccades in all three tasks, though

96 online data (collected through a crowdsourcing platform) were slightly more variable and

97 delayed. The free viewing task replicated previously observed statistical patterns (e.g.,

98 more fixations on eyes than mouths).

99   Similarly, Yang and Krajbich (2021) used the `Webgazer.js` library (Papoutsaki et al.,

100 2016) combined with the `jsPsych` library for conducting behavioral experiments in a web

101 browser (de Leeuw, 2015), to replicate a well-established link between value-based

102 decision-making and eye gaze Krajbich, Armel, & Rangel (2010). Online participants

103 (n=38) first saw a series of images of 70 snack foods and rated how much they liked each

104 one. During the primary task, on each of 100 trials, two of the snack food images were

105 displayed on the left and right sides of the display and participants chose the one that they

106 preferred while their gaze was monitored. As in previous work, participants were biased to

107 choose the option they had spent more time looking at. The authors also implemented a

108 code modification to address temporal delays in `WebGazer`.

109   Several papers have used the `WebGazer.js` library (via different interfaces) to

110 replicate visual world paradigm studies. Slim and Hartsuiker (2022) used the `PCIbex`

111 online experiment platform (Zehr & Schwarz, 2018) to replicate a study in which

112 participants (n=90) listened to sentences (e.g., Mary reads a letter) while viewing four

113 pictures displayed across the four quadrants of the screen (e.g., a letter, a backpack, a car

114 and a wheelchair) (Dijkgraaf, Hartsuiker, & Duyck, 2017). When the verb in the sentence

115 was *constraining* (e.g., read) with respect to the display (only the letter would be an

116 appropriate continuation), listeners made more fixations to the target image (letter) than

117 when the verb was *neutral* (e.g., Mary steals a letter), as in previous work. However, they

118 observed a substantial delay of ~200ms in the onset of the effect relative to the in-lab study

119 with an infrared eyetracker and a reduction in effect size (despite a threefold increase in

120 sample size relative to the original). The authors noted that delay was particularly

problematic given that the purpose of the original study was to capture aspects of predictive or anticipatory processing: in the original study, but not in the web replication, the difference between *constraining* and *neutral* conditions emerged before the onset of the final noun (e.g., letter). Similarly, Degen, Kursat, and Leigh (2021) reported that effects of scalar implicature processing (comparing looks to the target in a four quadrant display for sentences such as "Click on the girl that has *some* apples" vs. "Click on the girl that has *three* apples") were smaller and delayed relative to those observed in the lab (Sun & Breheny, 2020).

In contrast, using the `Gorilla` experiment platform (Anwyl-Irvine et al., 2020), Prystauka, Altmann, and Rothman (2023) observed robust effects of verb semantics and lexical interference in similar time windows to previous in-lab studies (Altmann & Kamide, 1999; Kukona, Cho, Magnuson, & Tabor, 2014), though a direct comparison was not possible because their studies used different materials than the in-lab experiments they were conceptually replicating. Furthermore, using `jsPsych`, Vos, Minor, and Ramchand (2022) closely replicated the magnitude and timecourse of effects in a lab-based visual world paradigm where the regions of interest (ROIs) consisted of the left and right halves of the display, suggesting that the concerns about poor temporal resolution can be mitigated. Indeed, the eye-tracking plug-in in `jsPsych` uses a fork of `Webgazer.js` in which certain modifications have been made to minimize processing time. [1] Finally, Van der Cruyssen et al. (2023) used `WebGazer.js` in conjunction with `PsychoJS` to conceptually replicate three paradigms, one which is analogous to Yang and Krajbich (2021), another testing the novelty preference (tendency for learners to look more at an object that they have not yet studied), and a visual world paradigm study with 4 objects, similar to Prystauka et al. (2023). These replications were successful but they noted reductions in effect sizes relative to an in-lab dataset. (They did not address whether there were temporal delays.)

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[1] See discussion at https://github.com/jspsych/jsPsych/discussions/1892

In sum, webcam eye-tracking has been used to varying degrees of success across a small set of paradigms that are used in cognitive science research. One configuration, `jsPsych` with a modification of `WebGazer.js`, appears to have circumvented initial limitations in temporal precision (Krajbich et al., 2010; Vos et al., 2022) but has only been tested with paradigms with minimal requirements in terms of spatial precision (both experiments used the two sides of the display as the ROIs). Further, the extent to which noise in the measurement is due to the software and hardware limitations as opposed to the difference between the in-lab and online settings remains unclear. In the current work, we evaluate a broad variety of paradigms in terms of their suitability for webcam eye-tracking in order to provide guidance for cognitive scientists aiming to increase and diversify participation in their eye-tracking-based research.

Present work

In order to validate the online eyetracking methodology, with the particular configuration known to have the greatest temporal precision, `jsPsych` and a modification of `Webgazer`, we set out to reproduce five previously published studies representing a variety of questions, topics, and paradigms. The goal was to examine the strengths and weaknesses of webcam eye-tracking for common paradigms in cognitive science, across a broad range of research areas.

Selection of Studies

Studies with large effect sizes and which are known to replicate are ideal targets for further replication; otherwise, it can be difficult to distinguish a failure of the method from a failure of the original study to replicate. In practice, replications (successful or otherwise) have only been reported for a small number of studies, so we ultimately included some studies with unknown replicability. We addressed this in several ways. First, replicating five very different studies from different research traditions decreases our reliance on any

Table 1

Studies selected for replication attempts. Citation counts based on Google Scholar (August 2023).

Citation	Topic Area	Paradigm	Citations
Altmann & Kamide, 1999	Psycholinguistics	Natural Scenes	2,007
Johansson & Johansson, 2014	Memory	Four Quadrants	228
Manns, Stark, & Squire, 2000	Memory	Two Halves	131
Snedeker & Trueswell, 2004	Psycholinguistics	Four Quadrants	472
Shimojo et al., 2003	Decision Making	Two Halves	1,073

one study. Second, we include several ''sanity check" analyses, such as the correlation between calibration accuracy and effect size. (If the effect is real but there is noise from low-accuracy eyetracking, this correlation should be substantial.) Third, for two of the studies, we had comparison data collected in-lab either using `jsPsych` or a more traditional eyetracker technology, allowing us to directly assess the impact of differences in subject population and equipment/setting.

We chose five high-impact eyetracking studies involving adult subjects. (Given the additional difficulties of recruiting and retaining child participants, we excluded developmental studies.) Our goal was to include experiments from a range of topic areas (e.g., memory, decision making, psycholinguistics) and paradigms (two halves of the screen, visual world paradigm with four quadrants, visual world paradigm with "natural" scenes). As noted above, we had a preference for well-established findings that are known to replicate, though for sake of diversity this was not always possible. Table 1 provides an overview of the five studies we selected.

General Methods

Participants

Participants completed the experiment remotely and were recruited through the Prolific platform. In order to have access to the experiment, participants had to meet the following criteria: 18 years of age or older, fluency in English, and access to a webcam. All participants provided informed consent. The studies were approved by the Vassar College Institutional Review Board.

In addition, an in-person replication was conducted for Experiment 1. Information about the sample is given in the corresponding Method sections.

In order to have adequate statistical power and precision, we aimed for 2.5x the sample size of the original experiment, following the heuristic of Simonsohn (Simonsohn, 2015). In Experiment 5, the original sample size was so small that we opted to collect 5x the number of participants to increase precision. Because of budget and time constraints we were unable to replace the data for subjects who were excluded or whose data was missing due to technical failures.

Equipment

We used a fork of the `webgazer.js` library for webcam eyetracking (Papoutsaki et al., 2016), implemented in `jsPsych`, a Javascript library for running behavioral experiments in a web browser (de Leeuw, 2015). Our fork included changes to `webgazer.js` in order to improve data quality for experiments in which the precise timing of stimulus onsets is relevant. Specifically, we implemented a polling mode so that gaze predictions could be requested at a regular interval, which improved the sampling rate considerably in informal testing. This modification is similar to what Yang and Krajbich (2021) reported improved the sampling rate in their study of webgazer. We also adjusted

209 the mechanism for recording time stamps of each gaze prediction, so that the time stamp

210 reported by webgazer is based on when the video frame is received and not when the

211 computation of the gaze point is finished.

Eye-tracking Calibration and Validation

213   When participants began the experiment, they were notified the webcam would be

214 used for eye tracking but no video would be saved. They were asked to remove glasses if

215 possible, close any other tabs or apps, turn off notifications, and make sure their face was

216 lit from the front. The webcam's view of the participant popped up on the screen, and

217 participants were asked to center their face in the box and keep their head still. The

218 experiment window then expanded to full screen, and participants began the eye-tracking

219 calibration.

220   During the calibration, dots appeared on the screen one at a time in different

221 locations, and the participants had to fixate them and click on each one. Once they clicked

222 on a dot, it would disappear and a new one would appear in a different location on the

223 screen. The locations of calibration dots were specific to each experiment (details below)

224 and appeared in the areas of the screen where the visual stimuli would appear during the

225 main task in order to ensure that eye movements were accurately recorded in the relevant

226 regions of interest. After the calibration was completed, the validation began. Participants

227 were asked to go through the same steps as the calibration, except that they only fixated

228 the dots as they appeared in different locations on the screen. If accuracy on the validation

229 was too low (fewer than 50% of looks landed within a 200 px radius of the validation

230 points), participants were given an opportunity to re-start the calibration and validation

231 steps. If the second attempt also lead to low validation accuracy, participants were

232 informed that they could not participate in the study.

Pre-registration

These data were collected within the context of an undergraduate research methods course. Groups of students (co-authors) designed and programmed experiments in jsPsych, pre-registered their planned analyses, and collected data through Prolific under the supervision of the first author. The OSF repositories associated with these experiments are linked in the methods sections of each individual study. Note that in the current paper we expand on those pre-registered analyses (e.g., including analyses of the calibration quality). All analysis code underlying this paper can be found in the Github repository: https://github.com/jodeleeuw/219-2021-eyetracking-analysis

Data pre-processing

We used R (Version 4.4.0; R Core Team, 2021) and the R-packages *afex* (Version 1.3.1; Singmann, Bolker, Westfall, Aust, & Ben-Shachar, 2021), *broom.mixed* (Version 0.2.9.5; Bolker & Robinson, 2020), *dplyr* (Version 1.1.4; Wickham, François, Henry, & Müller, 2021), *forcats* (Version 1.0.0; Wickham, 2021a), *ggplot2* (Version 3.5.1; Wickham, 2016), *jsonlite* (Version 1.8.8; Ooms, 2014), *lme4* (Version 1.1.35.3; Bates, Mächler, Bolker, & Walker, 2015), *lmerTest* (Version 3.1.3; Kuznetsova, Brockhoff, & Christensen, 2017), *Matrix* (Version 1.7.0; Bates & Maechler, 2021), *papaja* (Version 0.1.2; Aust & Barth, 2020), *readr* (Version 2.1.5; Wickham & Hester, 2020), *shiny* (Chang et al., 2021), *stringr* (Version 1.5.1; Wickham, 2019), *tidyr* (Version 1.3.1; Wickham, 2021b), and *tinylabels* (Version 0.2.4; Barth, 2022) for all our analyses.

Experiment 1

The first study was a replication attempt of Altmann and Kamide (1999). Altmann and Kamide used the visual world eye-tracking paradigm (Tanenhaus et al., 1995) to show that meanings of verbs rapidly constrain the set of potential subsequent referents in

sentence processing. For example, when looking at the display in Figure 2 and listening to a sentence like "The boy will eat the...," participants are more likely to look at the cake than when they hear "The boy will move the...," in which case they tend to look at the train, presumably because cakes are edible and trains are not. Semantic information available at the verb is used to anticipate upcoming linguistic input.

We first collected data from participants via Prolific, then conducted a follow-up in-lab replication; both the original and the replication used WebGazer and identical materials and procedures.

Methods

All stimuli, experiment scripts, data, analysis scripts, and a pre-registration are available on the Open Science Framework at https://osf.io/s82kz.

Participants.

Remote sample. Sixty participants were paid $2.60 for their participation. Our sample size of participants was determined by the total run time of our experiment, ~10 minutes, and the allotted funding from the Vassar College Cognitive Science Department. From this information, we calculated a reasonable number of participants we could afford to compensate on Prolific. Note that the sample size of the original study was 24. For unknown reasons, 2 of the subjects' results were not recorded, so in the analysis, we worked with data collected from 58 participants.

In-lab sample. Forty-nine participants were AJ: help. Insert how they were compensated, relevant IRB/funding stuff, any other info.

Procedure. The task began with a 9-point eye-tracker calibration and validation (Figure 1). During the experiment, the participants were simultaneously presented with a visual image and a corresponding audio recording of a spoken sentence. Participants had to input a keyboard response indicating "yes" or "no" as to whether the sentence they heard

was feasible given the visual image. There were two practice trials to ensure that

participants understood the instructions before they undertook the main portion of the

experiment. Participants' reaction times, keyboard responses, and looks to objects in the

scene were recorded for each trial.

```
## Warning: A numeric 'legend.position' argument in 'theme()' was deprecated in ggplot2
## 3.5.0.
## i Please use the 'legend.position.inside' argument of 'theme()' instead.
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.
```
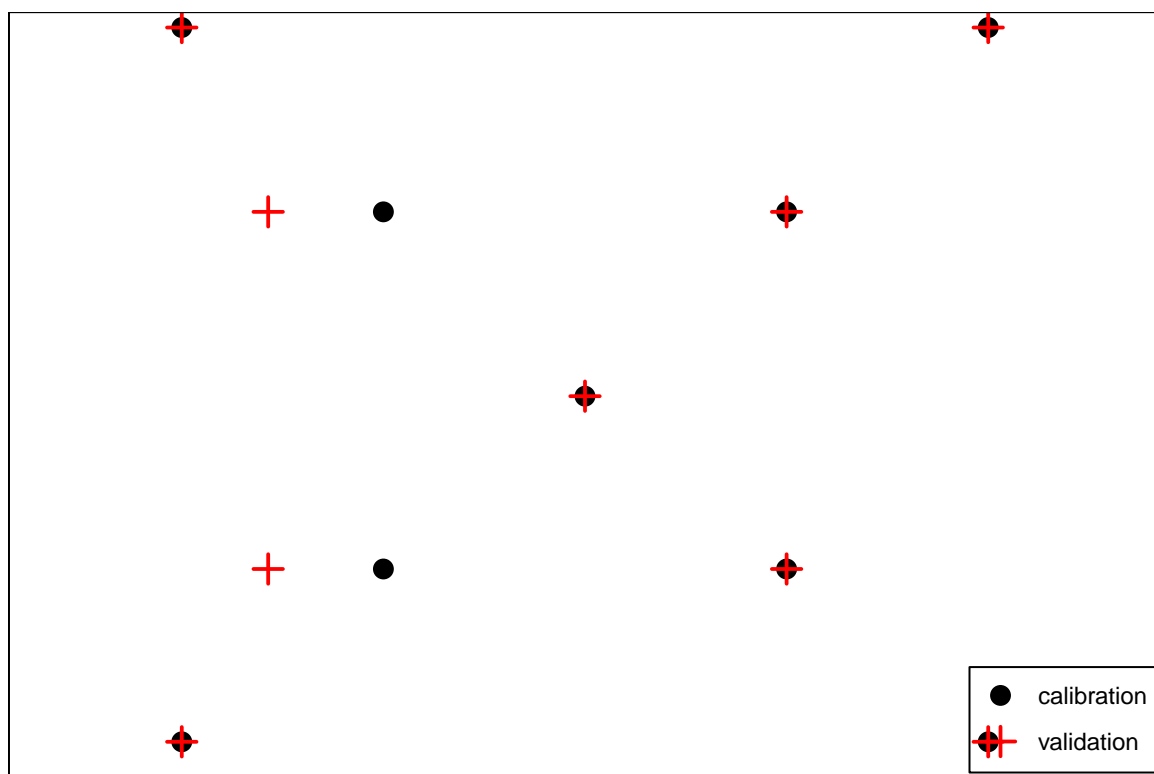

Figure 1. Calibration and validation point locations for Experiment 1. Black points were used for calibration. Red crosses were used for checking the accuracy of the calibration.

292   **Materials & Design.**   The visual stimuli were created through Canva and depicted

293   an agent accompanied by four to five objects in the scene (see Figure 2). On critical trials,

294   participants heard one of two sentences associated with the scene. In the restrictive

295   condition, the sentence (e.g., "The boy will eat the cake") contained a verb (e.g., "eat")

296   which restricts the set of possible subsequent referents (e.g., to edible things). Only the

297   target object (e.g., the cake) was semantically consistent with the verb's meaning. In the

298   non-restrictive condition, the sentence (e.g., "The boy will move the cake") contained a

299   verb (e.g., "move") which does not restrict the set of possible subsequent referents. The

300   target object (e.g., the cake) as well as the distractor objects (e.g., the train, the ball, etc.)

301   were semantically consistent with the verb's meaning. Both sentences were compatible

302   with the scene, such that the correct keyboard response for the critical trials was "yes."

303   Filler trials consisted of scenes that looked similar to critical scenes but were paired with

304   inappropriate sentences. The correct keyboard response for the filler trials was "no."

305   Each participant was presented with sixteen critical trials (eight in the restrictive

306   condition, eight in the non-restrictive condition) and sixteen fillers for a total of 32 trials.

307   The order of trials and the assignment of critical scene to condition was random on a

308   subject-by-subject basis.

309   **Data pre-processing and analysis.**   Looks to the objects in the scene were

310   time-locked to the onset of the verb, the offset of the verb, onset of the post-verbal

311   determiner, and onset of the target noun. ROIs were defined by creating boxes around each

312   object in the scene. The size of each box was determined by taking the height and width of

313   the given object and adding 20 pixels of padding. Each scene contained an agent region, a

314   target region, and three or four distractor regions.

315   **Results**

316   **Remote sample.**

Figure 2. Example trial from Experiment 1. Participants would hear a sentence (e.g., "The boy will eat the cake") and respond according to whether the sentence matched the picture.

Minimal Exclusion. The first set of analyses used minimal exclusion criteria. First, we eliminated participants with 0 percent of fixations in any ROIs. This resulted in the elimination of 1 participants. Second, we excluded participants with validation accuracy under 10 percent, resulting in an additional 5 excluded participants. The following analyses included 52 participants.

Cumulative Fixation Probabilities. For each sentence, the target time window began at the onset of the verb and ended 2000 milliseconds later. This window was then divided into 50-ms bins; for each participant and each trial, we recorded whether each

325   object was fixated during the 50-ms bin. Collapsing over trials and participants, and

326   averaging across distractors, we calculated the cumulative probability of fixation, shown in

327   Figure 3.
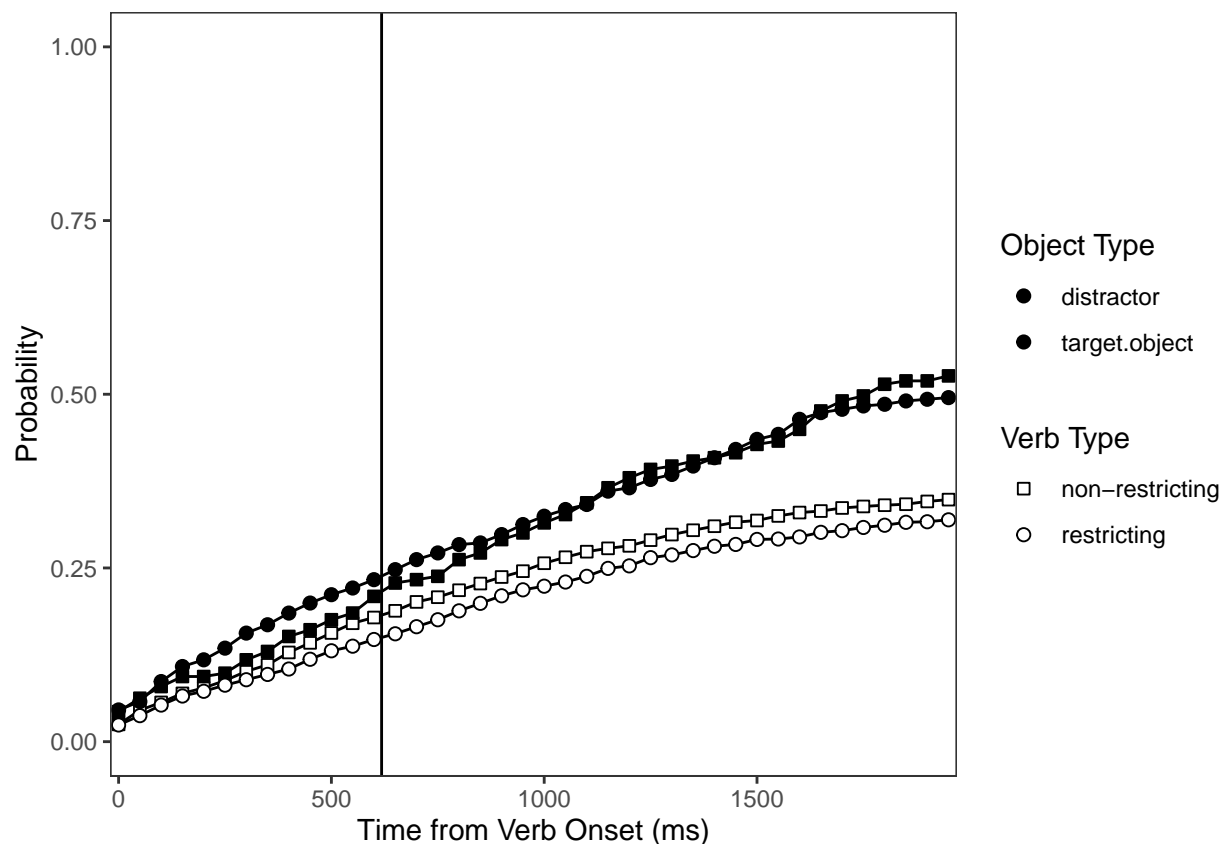
Figure 3. Cumulative probability of fixating distractor and target objects across conditions
over time, with 0 ms aligned to the verb onset time. The vertical line marks the mean noun
onset time across trials and conditions.

328   ***Pre-noun fixations.***   In our first two analyses, we ask whether participants looked

329   more to the target than to the distractor during the predictive time window, given that the

330   verb is restricting. The first model tested whether there were more fixations to the target

331   object than to the distractor in the time window before the onset of the target noun. We

332   ran a regression model predicting the cumulative fixation probability in the last 50-ms bin

333   before noun onset from the verb condition (restricting = 1 vs. non-restricting = 0), object

334 type (target = 1 vs. distractor = 0), and their interaction, along with random effects for

335 participants and images (with no covariance between random effects because the model

336 cannot converge with full covariance matrix). There were no significant effects, although

337 the critical interaction was in the right direction [bar graph?] ($b = 0.05$, $SE = 0.03$,

338 $p=0.15$).

339   ***Pre-verb-offset fixations.*** Altmann and Kamide tested a second model, aligning

340 the predictive time window with the offset of the verb rather than the onset of the noun as

341 above. When we do the same, we again see that the critical interaction is not significant

342 but numerically in the expected direction ($b = 0.05$, $SE = 0.03$, $p=0.20$).

343   ***First target fixations after verb.*** Finally, we address whether participants look

344 to the target faster in the restrictive vs. the non-restrictive condition, starting after the

345 onset of the verb. [TO-DO: On average, participants looked to the target 349 ms after the

346 noun onset in the restrictive condition (compared to) and 349 ms after the noun onset in

347 the non-restrictive condition (compared to)]. Thus, first fixations were not only delayed

348 relative to those in the previous studies compared here, but also showed a smaller

349 difference between conditions.

350   We ran a regression model predicting the timing of the first fixation to the target

351 object, relative to the onset of the noun, with verb condition as a predictor, mean-centered

352 verb duration as a covariate, and random intercepts and condition slopes for participants

353 and scenes. There were no significant effects; participants looked sooner at the target in the

354 restrictive condition, while accounting for verb duration and its interaction with condition,

355 but this was not a statistically significant effect ($b = -121.91$, $SE = 90.57$, $p=0.20$).

356   ***Aggressive Exclusion.*** The second set of analyses used more aggressive exclusion

357 criteria. First, we eliminated participants with 20 percent of fixations in any ROIs. This

358 resulted in the elimination of 15 participants. Second, we excluded participants with

359 validation accuracy under 50 percent, which eliminated an additional 35 participants. The

360 following analyses included 22 participants.

361   We tested the same three models under these more aggressive exclusion criteria. The

362 first two models, comparing target and distractor fixations in the predictive window,

363 produced very similar results; the critical interaction was not statistically significant

364 (Pre-noun-onset window: $b = 0.07$, $SE = 0.06$, $p=0.23$; Pre-verb-offset window: $b = 0.05$,

365 $SE = 0.05$, $p=0.28$). However, the final model, which tested the effect of verb condition on

366 saccades to the target, yielded a statistically significant result, unlike in the previous set of

367 analyses ($b = $ -193.35, $SE = 96.33$, $p=0.05$).

368   ***Calibration.***   Participants' calibration quality was measured as the mean

369 percentage of fixations that landed within 200 pixels of the calibration point. Calibration

370 quality varied widely, ranging from 3.16% to 98.87%.

371   We tested whether a participant's calibration quality was correlated with their effect

372 size. There were three effects of interest: the verb-by-object interaction in predicting

373 fixation probabilities, both in the (1) pre-noun-onset and (2) pre-verb-offset windows

374 (calculated as the difference in target-over-distractor preference between verb conditions),

375 and (3) the effect of verb on the timing of the first target fixation (calculated as the

376 difference in target latency between verb conditions). Across the three effects of interest,

377 calibration quality was not significantly correlated (Effect 1: Pearson's $r = 0.03$, $p = 0.83$,

378 Effect 2: Pearson's $r = $ -0.05, $p = 0.73$, Effect 3: Pearson's $r = 0.04$, $p = 0.78$. However,

379 when the two interaction effects are calculated as the target advantage in the restricting

380 condition only (i.e. rather than a difference of differences), we see a significant correlation

381 between target advantage and calibration quality in the wider pre-noun window (Pearson's

382 $r = 0.21$, $p = 0.14$).

383   **In-lab sample.**

384   ***Minimal Exclusion.***   As in the remote sample, we checked whether there were

385 participants with 0 percent of fixations in any ROIs and there were none. We then

excluded participants with validation accuracy under 10 percent, resulting in 2 excluded

participants. The following analyses included 47 participants.

Cumulative Fixation Probabilities. For each sentence, the target time window

began at the onset of the verb and ended 2000 milliseconds later. This window was then

divided into 50-ms bins; for each participant and each trial, we recorded whether each

object was fixated during the 50-ms bin. Collapsing over trials and participants, and

averaging across distractors, we calculated the cumulative probability of fixation, shown in

Figure 4.
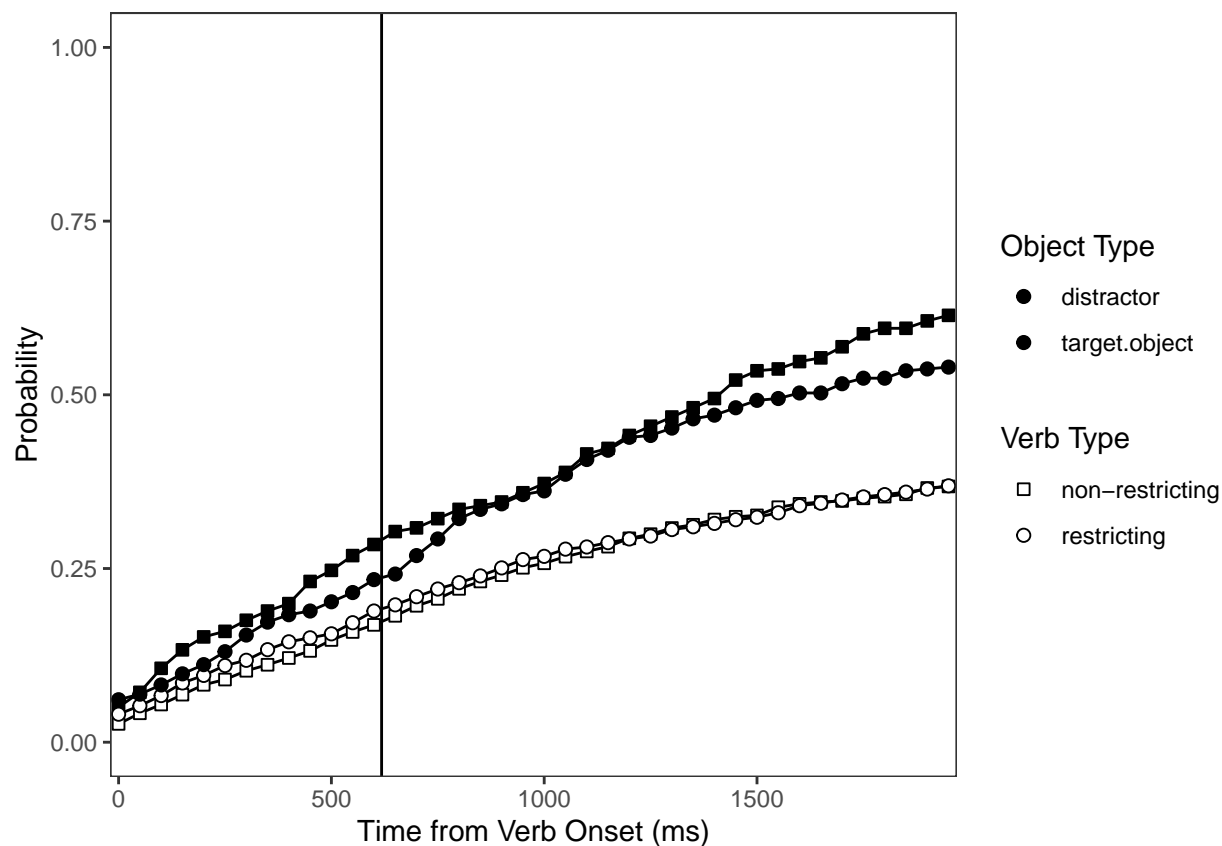
Figure 4. Cumulative probability of fixating distractor and target objects across conditions
over time, with 0 ms aligned to the verb onset time. The vertical line marks the mean noun
onset time across trials and conditions.

394 ***Pre-noun fixations.*** In our first two analyses, we ask whether participants looked

395 more to the target than to the distractor during the predictive time window, given that the

396 verb is restricting. The first model tested whether there were more fixations to the target

397 object than to the distractor in the time window before the onset of the target noun. We

398 ran a regression model predicting the cumulative fixation probability in the last 50-ms bin

399 before noun onset from the verb condition (restricting = 1 vs. non-restricting = 0), object

400 type (target = 1 vs. distractor = 0), and their interaction, along with random effects for

401 participants and images (with no covariance between random effects because the model

402 cannot converge with full covariance matrix). There were no significant effects, although

403 the critical interaction was in the right direction [bar graph?] (b = -0.05, SE = 0.05,

404 p=0.25).

405 ***Pre-verb-offset fixations.*** Altmann & Kamide tested a second model, aligning

406 the predictive time window with the offset of the verb rather than the onset of the noun as

407 above. When we do the same, we again see that the critical interaction is not significant

408 but numerically in the expected direction (b = -0.06, SE = 0.04, p=0.17).

409 ***First target fixations after verb.*** Finally, we address whether participants look

410 to the target faster in the restrictive vs. the non-restrictive condition, starting after the

411 onset of the verb. [TO-DO: On average, participants looked to the target X ms after (AK's

412 Table 1)..., I'll also want to say the lengths of the verbs. AK's Table 2] We ran a

413 regression model predicting the timing of the first fixation to the target object, relative to

414 the onset of the noun, with verb condition as a predictor, mean-centered verb duration as a

415 covariate, and random intercepts and condition slopes for participants and scenes. There

416 were no significant effects; participants looked sooner at the target in the restrictive

417 condition, while accounting for verb duration and its interaction with condition, but this

418 was not a statistically significant effect (b = 21.70, SE = 115.32, p=0.85).

419 ***Calibration.*** As before, participants' calibration quality was measured as the mean

420 percentage of fixations that landed within 200 pixels of the calibration point. Calibration

quality ranged from 5.13% to 97.89%.

We tested whether a participant's calibration quality was correlated with their effect size. Across the three condition effects of interest, calibration quality was not significantly correlated (Effect 1 (pre-noun-onset): Pearson's r = -0.24, p = 0.11, Effect 2 (pre-verb-offset): Pearson's r = -0.19, p = 0.20, Effect 3 (first fixation): Pearson's r = -0.12, p = 0.41. However, when the two interaction effects are calculated as the target advantage in the restricting condition only (i.e. rather than a difference of differences), we see a significant correlation between target advantage and calibration quality in the wider pre-noun window (Pearson's r = -0.16, p = 0.29).

Discussion

Experiment 2

The second study was a replication attempt of Johansson and Johansson (2014), which examined how visuospatial information is integrated into memory for objects. They found that, during memory retrieval, learners spontaneously look to blank screen locations where pictures were located during encoding (see Spivey & Geng, 2001) and that this spatial reinstatement facilitates retrieval of the picture.

Methods

All stimuli, experiment scripts, data, analysis scripts, and a pre-registration are available on the Open Science Framework at https://osf.io/xezfu/.

Participants. 60 participants were paid for their participation. The sample size was motivated in part by budget constraints, but was nonetheless 2.5x larger than the original sample size of 24). Data from 1 participant were not properly recorded due to unknown technical issues, so data from 59 participants were included in all analyses to follow.

⁴⁴⁵ **Procedure.** The task began with a 9-point eye-tracker calibration and validation
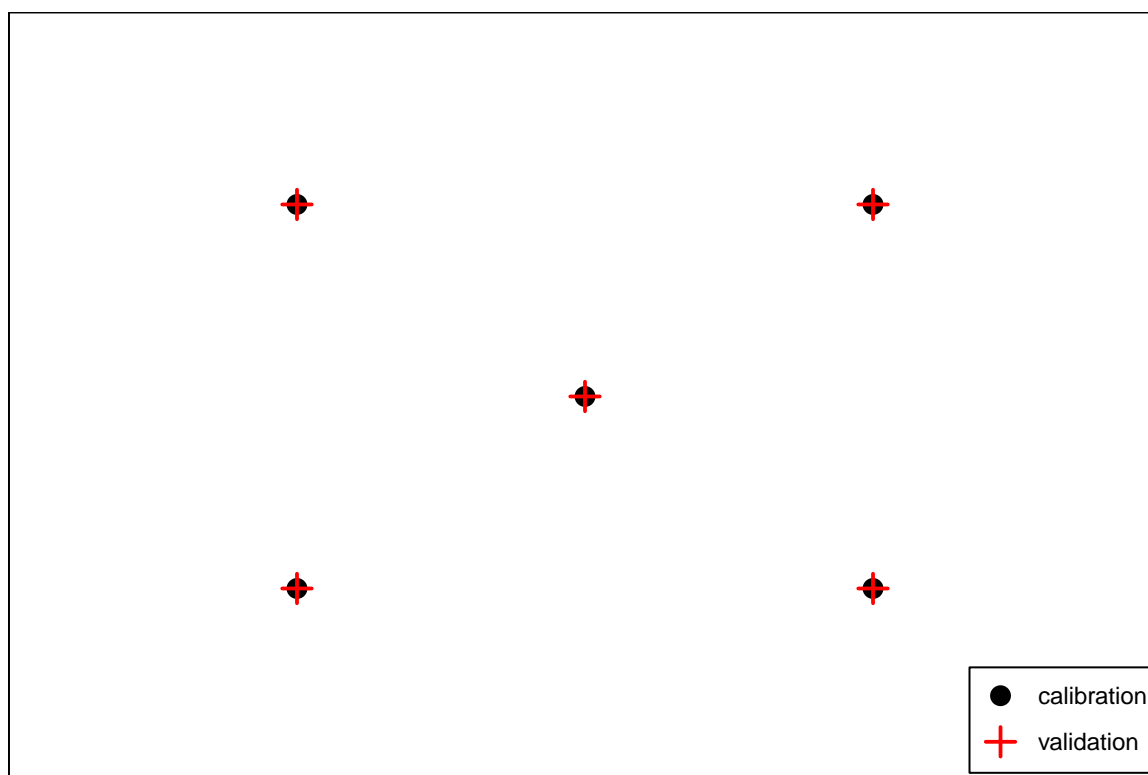
⁴⁴⁶ (Figure 5).

Figure 5. Calibration and validation point locations for Experiment 2. Black points were used for calibration. Red crosses were used for checking the accuracy of the calibration.(In this experiment all the same locations were used for both calibration and validation.)

⁴⁴⁷ The experiment consisted of two blocks each composed of an encoding phase and a

⁴⁴⁸ recall phase. During the encoding phase, participants saw a grid indicating the four

⁴⁴⁹ quadrants of the screen. Each quadrant contained six images of items belonging to the

⁴⁵⁰ same category (see Figure 6). The four categories were humanoids, household objects,

⁴⁵¹ animals, and methods of transportation. Each of the four quadrants was presented one at a

⁴⁵² time. First, a list of the items in the quadrant was shown, then the pictures of items were

⁴⁵³ displayed in the quadrant. For each item, participants used their arrow keys to indicate

⁴⁵⁴ whether the object was facing left or right. After the participant identified the direction of

⁴⁵⁵ each item, they would have an additional 30 seconds to encode the name and orientation of

456 each item in the quadrant. Finally, after all four quadrants were presented, participants

457 were shown the full grid of 24 items and had 60 seconds to further encode the name and

458 orientation of each item.

Figure 6. Example trial from Experiment 2.

459   During the recall phase, participants listened to statements and responded by

460 pressing the 'F' key for false statements and 'T' for true ones. Each statement fell into

461 either an interobject or intraobject condition. Interobject statements were those that

462 compared two different items in the grid (e.g. "The skeleton is to the left of the robot"),

463 while intraobject statements were those that asked about the orientation of a single item

464 (e.g. "The bus is facing right"). There were 48 total statements, with 24 interobject and 24

465 intraobject statements split evenly among the four quadrants. While listening to these

466 statements, in the free-viewing block, participants saw a blank screen and were allowed to

467 freely gaze around the screen. During the fixed-viewing block, participants were asked to

468 fixate a small cross in the center of the screen throughout the recall phase. In both cases,

469 the mouse was obscured from the screen. Participants were randomly assigned to see the

470 fixed-viewing or free-viewing block first. Different images were used in each block.

471 After completing both encoding-recall blocks, participants were asked to answer a few

472 survey questions (such as whether they wore glasses or encountered any distractions).

473 The primary methodological difference between this replication and Johansson and

474 Johansson's study was that the original study included two additional viewing conditions

475 that were omitted from this replication due to time constraints. In those two conditions,

476 participant were prompted to look to a specific quadrant (rather than free viewing or

477 central fixation) which either matched or mismatched the original location of the

478 to-be-remembered item.

Results

480 **Replication.   Eye-gaze**. Looks during the retrieval period were categorized as

481 belonging to one of four quadrants based on the x,y coordinates. The critical quadrant was

482 the one in which the to-be-retrieved object had been previously located during encoding.

483 The other three quadrants were semi-randomly labeled "first", "second," third" (e.g., when

484 the critical quadrant was in the top left, the "first" quadrant was the top right quadrant,

485 but when the critical quadrant was in the top right, "first" corresponded to bottom right,

486 etc.). In both the fixed- and free-viewing condition, participants directed a larger

487 proportion of looks to the critical quadrant (see Figure 7). This bias appeared larger in the

488 free-viewing condition, suggesting that the manipulation was (somewhat) effective.

489 The proportions of looks across quadrants in the free-viewing condition were analyzed

490 using a linear mixed-effects model with quadrant as the predictor (critical as the reference

491 level). The model included random intercepts and slopes for participants[2]. Proportions of

---

[2] `lme4` syntax: `lmer(proportion ~ quadrant + (1+quadrant|subject_id))`. Among other limitations, this approach violates the independence assumptions of the linear model because looks to the four locations are not independent. This analysis was chosen because it is analogous to the ANOVA analysis
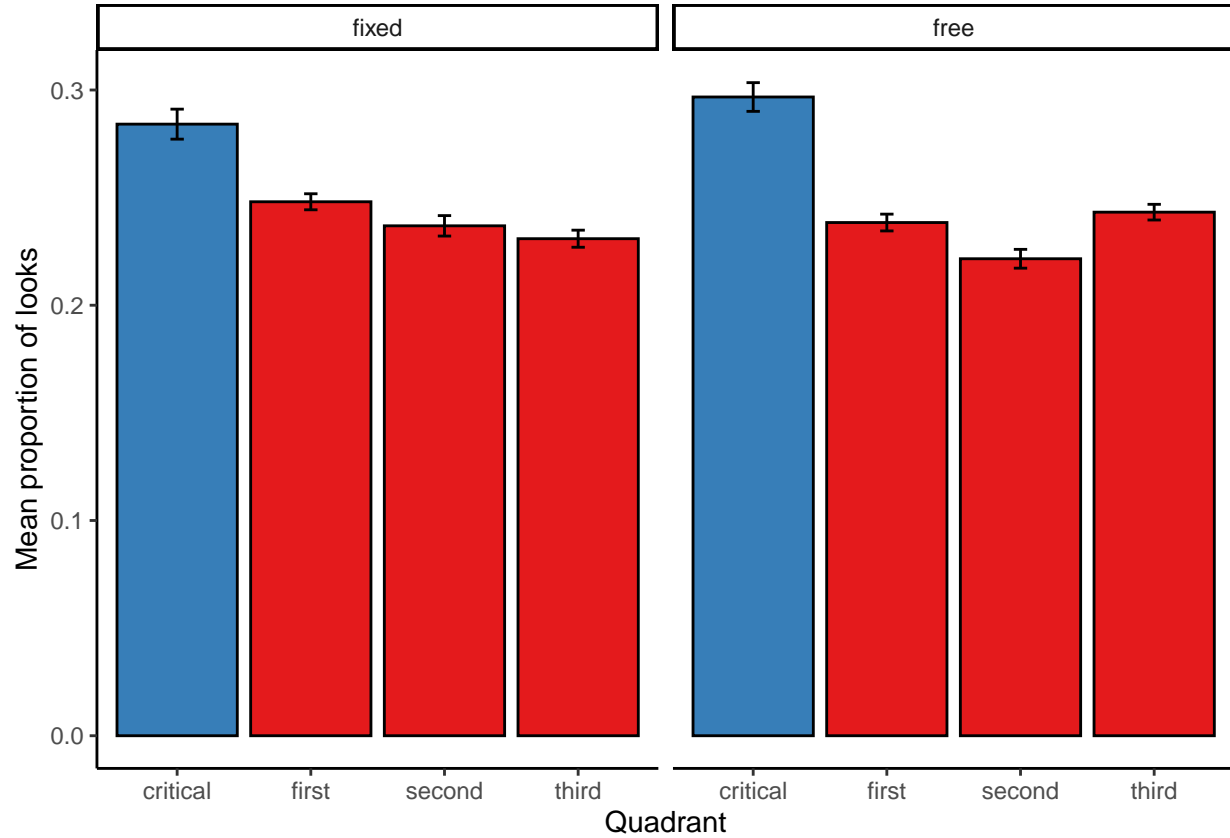
Figure 7. Proportion of eye-gaze to critical quadrant and other three quadrants during memory retrieval in a) fixed and b) free viewing conditions.

looks were significantly higher for the critical quadrant compared to the other three (first: $b = -0.06$, $SE = 0.01$, $p<0.001$, second: $b = -0.08$, $SE = 0.01$, $p<0.001$, third: $b = -0.05$, $SE = 0.01$, $p<0.001$)

Response Time and Accuracy. Participants' response times and accuracies on memory questions are summarized in Figure 8. Both dependent variables were analyzed with linear mixed-effects model with relation type (interobject = -0.5, intraobject=0.5) and viewing_condition (fixed = -0.5, free=0.5) and their interaction as the predictors. The model included random intercepts for participants[3]. Accuracy did not differ significantly

conducted in the original paper.

[3] lme4 syntax: `lmer(DV ~ relation_type*viewing_condition + (1|subject_id))`
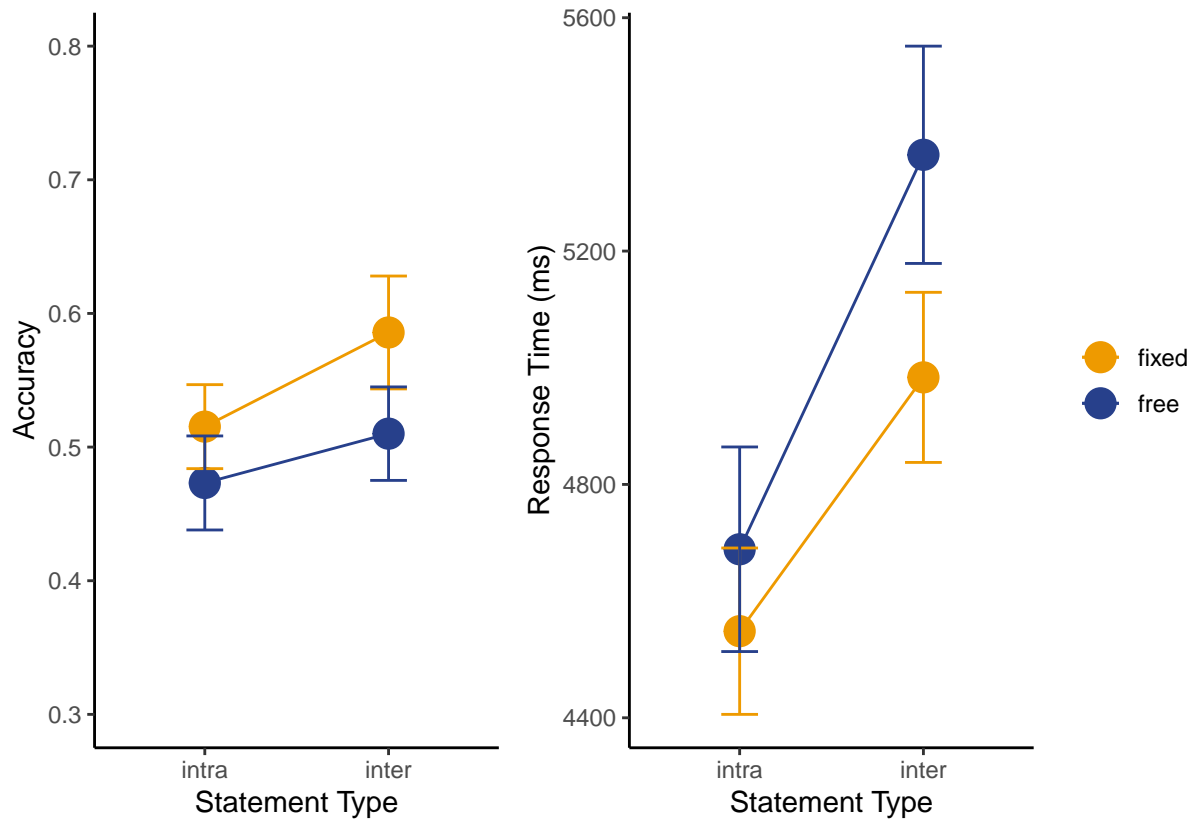
Figure 8. Accuracy and response times during memory retrieval.

between interobject and intraobject questions (b = -0.05, *SE* = 0.03, p=0.05). Participants were less accurate in the free viewing condition than the fixed condition (b = -0.06, *SE* = 0.03, p=0.03). Response times were slower for interobject (e.g., "The train is to the right of the taxi.") than intraobject (e.g., "The train is facing right.") questions (b = -555.60, *SE* = 105.24, p<0.001). Response times were slower in the free viewing condition than the fixed condition (b = 260.98, *SE* = 105.24, p<0.001). The interaction was not a significant predictor for response times or accuracy. These behavioral results are inconsistent with the original findings.

One possibility is that in-lab participants were much more compliant with the instruction to keep their gaze on central fixation (though these data are not reported in the original paper). When analyzing results from the subset of participants (N = 25) who were

most compliant during the fixed-viewing block (at least 25% of their looks fell within 20%
of the center of the display), the viewing condition effects and the interactions were not
signficant. Given the smaller sample size we do not interpret these results further.

Calibration.   Participants' calibration quality, measured as the mean percentage of
fixations that landed within 200 pixels of the calibration point, varied substantially
(between 17.78 and 100 %). The quality of a participant's calibration was not significantly
correlated with the participant's effect size (*Pearson's r*= 0.20, $p = 0.14$) as measured by
the difference between the proportion of looks to the critical quadrant minues the average
proportion of looks to the average of the other three quadrants.

Discussion

As in Johansson and Johansson (2014) and Spivey and Geng (2001), during memory
retrieval, learners spontaneously look to blank screen locations where pictures were located
during encoding, suggesting that visuospatial information is integrated into the memory for
objects. However, we did not observe a memory benefit, in terms of speed or accuracy, of
spatial reinstatement via gaze position during retrieval of the picture. We can speculate
that this may be due to the fact that participants struggled to maintain their gaze fixed in
the center in the fixed-viewing condition, such that the difference between the fixed- and
free-viewing conditions was minimal. Crucially for the current purposes, the webcam-based
eye-tracking measurements were successful in replicating the key eye-tracking results.

Experiment 3

The third study was a partial replication attempt of Manns, Stark, and Squire
(2000). This experiment used the visual paired-comparison, which involves presenting a
previously-viewed image and novel image together and measuring the proportion of time
spent looking at each image. The expected pattern of results is that participants will look

more at novel objects. They Manns et al. (2000) hypothesized that this pattern of

behavior could be used to measure the strength of memories. If a viewer has a weak

memory of the old image, then they may look at the old and new images roughly the same

amount of time. They tested this in two ways. First, they showed participants a set of

images, waited five minutes, and then paired those images with novel images. They found

that participants spent more time (58.8% of total time) looking at the novel images. They

then measured memory performance one day later and found that participants were more

likely to recall images that they had spent less time looking at during the visual

paired-comparison task the previous day.

Methods

The stimuli, experimental code, and data and analysis scripts can be found on the

Open Science Framework at https://osf.io/k63b9/. The pre-registration for the study can

be found at https://osf.io/48jsv . We inadvertently did not create a formal pre-registration

using the OSF registries tool, but this document contains the same information and is time

stamped prior to the start of data collection.

Participants.   Our pre-registered target was 50 participants. 51 participants

completed the first day of the experiment and 48 completed the second day. Following

Manns et al., we excluded 3 participants due to perfect performance on the recognition

memory test because this prevents comparison of gaze data for recalled vs. non-recalled

images. Our final sample size was 45 participants.

Procedure.   The task began with a 7-point eye-tracker calibration (each point was

presented 3 times in a random order) and validation with 3 points (each presented once).

The point locations were designed to focus calibration on the center of the screen and the

middle of the left and right halves of the screen (Figure 9).

The experiment was administered over the course of two consecutive days. It
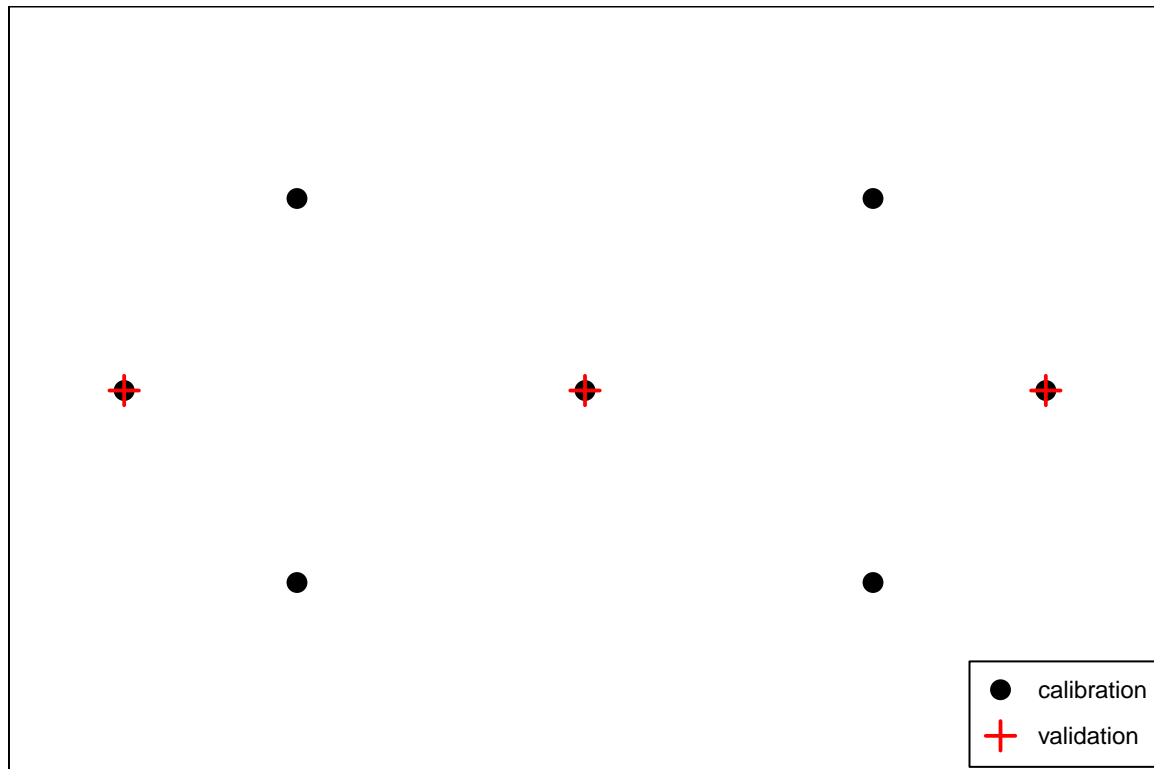
Figure 9. Calibration and validation point locations for Experiment 3. Black points were used for calibration. Red crosses were used for checking the accuracy of the calibration.

consisted of three sections: a presentation phase, a test phase, and a recognition test. The first two phases occurred on the first day, while the recognition test occurred on the second day.

During the presentation phase, participants viewed 24 pairs of identical color photographs depicting common objects. Each pair was presented for 5 seconds and an interval of 5 seconds elapsed before the next pair was shown. The order of the photographs was randomized and different for each participant. After completion of the presentation phase, participants were given a 5-minute break during which they could look away from the screen.

After the break, they were prompted to complete the eye-tracking calibration again before beginning the test phase. During this phase, participants again viewed 24 pairs of

photographs with an interstimulus duration of 5 seconds. In each pair, one photograph was previously seen during the presentation phase, while the other was new. Which pictures were old or new was counterbalanced across participants. For half of the participants in each counterbalancing group, the new and old photographs were reversed.

Approximately 24 hours after completing the first session, with a leeway interval of 12 hours to accommodate busy schedules, participants were given the recognition test. It consisted of 48 photographs, presented one at a time. Each was shown on the screen for 1 second, followed by a 1 second interstimulus interval. Half of the photographs had been viewed twice on the previous day and were deemed the "targets." The other half depicted an object with the same name as an object in one of the old photographs, but had not been viewed before, deemed "foils." Each photograph remained on the screen until the participants indicated whether or not they had seen it before by pressing 'y' for yes and 'n' for no. After they pressed one of the two keys, a prompt on the screen asked them to rate their confidence in their answer from 1 as a "pure guess" to 5 as "very sure." by clicking on the corresponding number on the screen. No feedback on their responses was given during the test.

The experimental design is visually depicted in Figure 10.

There were two modifications we made to the methods of the original experiment. As we were only replicating the declarative memory component of the original experiment, we did not have a "priming group." Therefore, we followed only the procedure for the "looking group." Additionally, for each section of the study, the stimuli were presented on a single screen instead of two screens due to the constraints of the online experiment format.
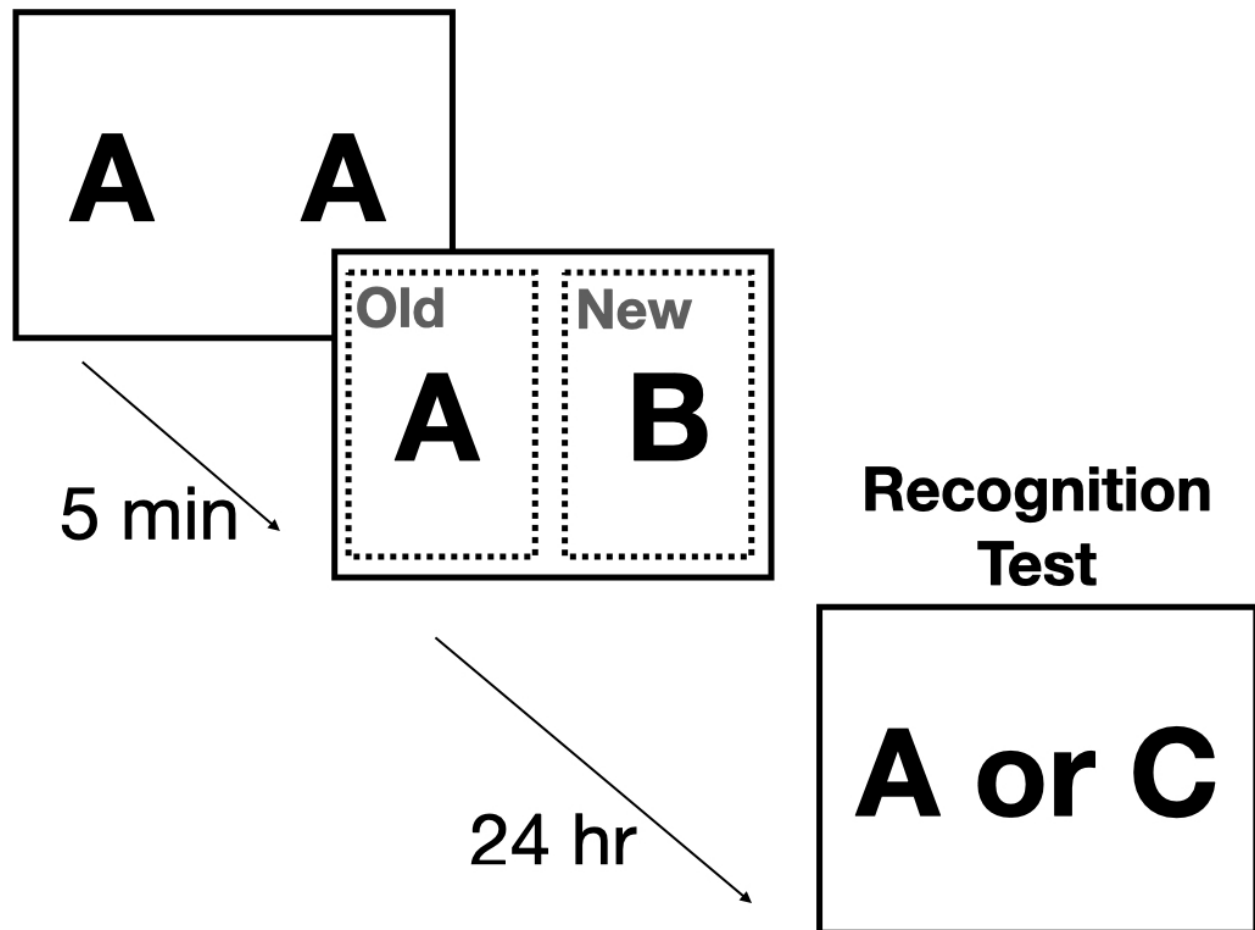
Materials.   Images were selected XXX...

Figure 10. Schematic of the design of Experiment 3

Results

Day 1.   During day 1 of the experiment, participants viewed pairs of images, one of which was always familiar and the other unfamiliar. We calculated a looking score for each participant, defined as the proportion of gaze samples in the ROI of the unfamiliar image out of all the gaze samples that were in either ROI. Gaze samples that were not in either ROI were not included in this analysis. A looking score of 0.5 indicates that participants looked equally often at the familiar and unfamiliar images, while a looking score above 0.5 indicates a preference for the unfamiliar object and a looking score below 0.5 indicate a preference for the familiar object.

603   Of the 1248 trials in the experiment, 78 had no fixations in either ROI, and so the

604   looking score was unknown. We removed these trials from this analysis.

605   The mean looking score was 0.55 ($SD = 0.10$). This significantly greater than 0.5,

606     $t(49) = 3.29$, $p = 0.00$, indicating that participants did show a preference for looking at the

607   novel objects.
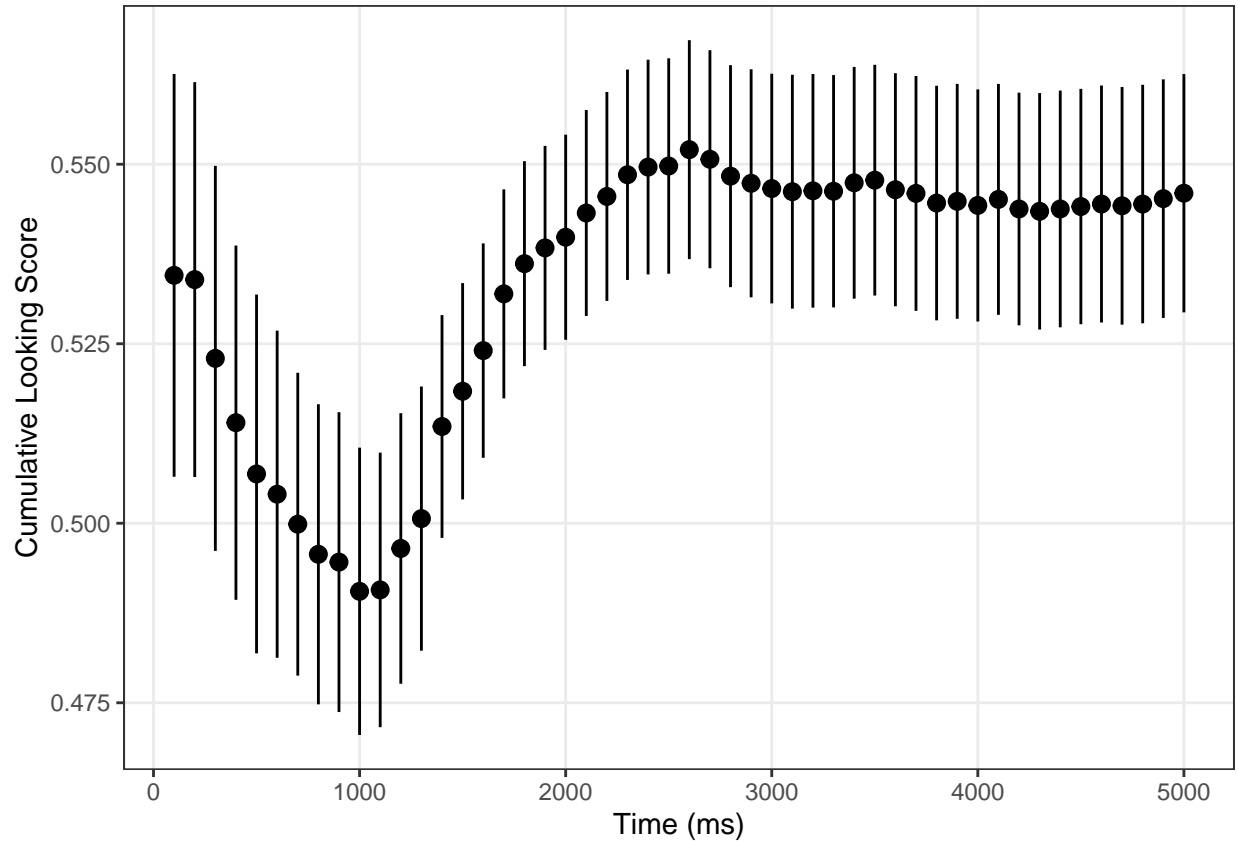
Figure 11. Cumulative looking score over the 5 second exposure during part 2 of day 1.
Error bars represent +/- 1 SEM.

608   ***Day 2.***   In all of these analyses, we excluded the 16 (out of 2304) trials where the

609   response time for the recognition judgment was greater than 10 seconds.

610   Participants correctly identified whether the image was familiar or unfamiliar 87.09%

611   ($SD = 10.49$) of the time. After excluding the 3 participants who responded correctly to all

612   images, the average confidence rating for correct responses (M = 3.51; SD = 0.41) was

613 significantly higher than their average confidence ratings for incorrect responses (M = 2.55;

614 SD = 0.75), t(44) = 9.36, p = 0.00 . Among the same subset of participants, response

615 times for correct responses (M = 1,443.49, SD = 413.94) were also significantly faster than

616 for incorrect responses (M = 2,212.65, SD = 1,733.76), t(44) = -3.43 , p = 0.00.

617   To see whether preferentially looking an the unfamiliar object on day 1 was

618 correlated with confidence and response time for correct responses on day 2, we computed

619 the correlation coefficient between day 1 looking scores and day 2 confidence/RT for each

620 participant. Following the original analysis, we transformed these values using the Fisher

621 p-to-z transformation. Using one-sample t-tests, we found no significant different from 0 for

622 the correlation between looking score and confidence ratings, t(38) = 0.46, p = 0.65

623 (excluding the subjects who gave the same confidence judgment for all images), nor the the

624 correlation between looking score and RT, t(46) = 0.49, p = 0.63.

625
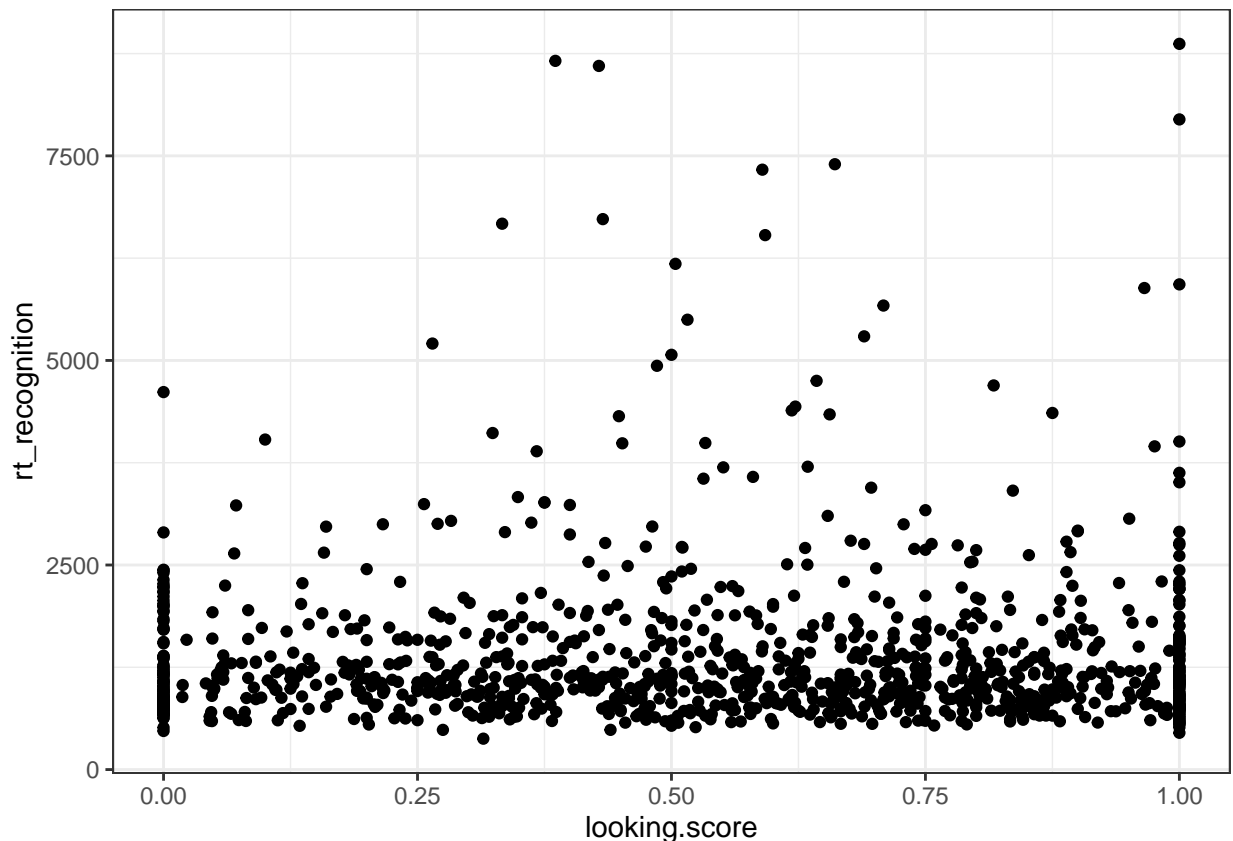
626   **Effects of ROIs.**   In the original experiment, the two objects on day 1 were

627 presented on two separate monitors and gaze was coded by manually coding video

628 recordings. In our replication analysis, we analyzed eye movement data using ROIs defined

629 around the two images. In this section we explore an alternative coding of the eye

630 movement data by coding simply left half vs. right half of the screen. The coarser coding

631 may be more appropriate for webcam-based eyetracking.

632   The correlation between looking scores using the ROI method and the halves method

633 is 0.76.
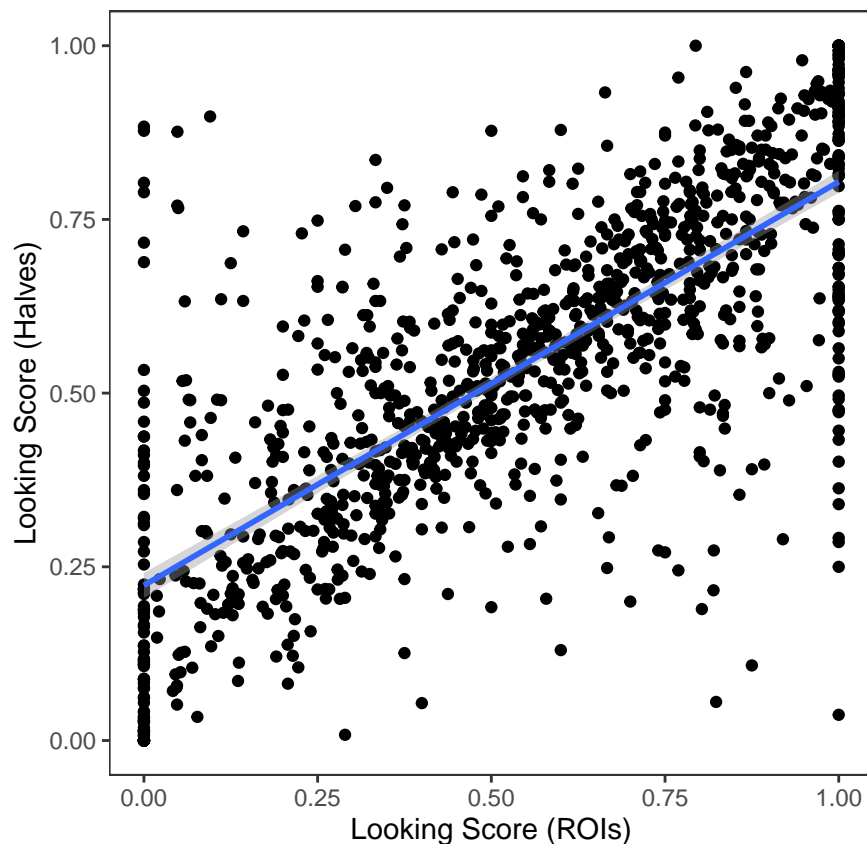
Figure 12. (#fig:E3-roi correlation of looking score)Correlation between looking scores cal-
culated using ROIs and using screen halves.

634   **_Looking Scores._**   When looking scores are coded as left vs. right half of the screen,

635 we find that participants looked more at the novel object. The mean looking score was 0.54

636 ($SD = 0.08$). This was significantly greater than 0.5, $t(50) = 3.51$, $p = 0.00$.
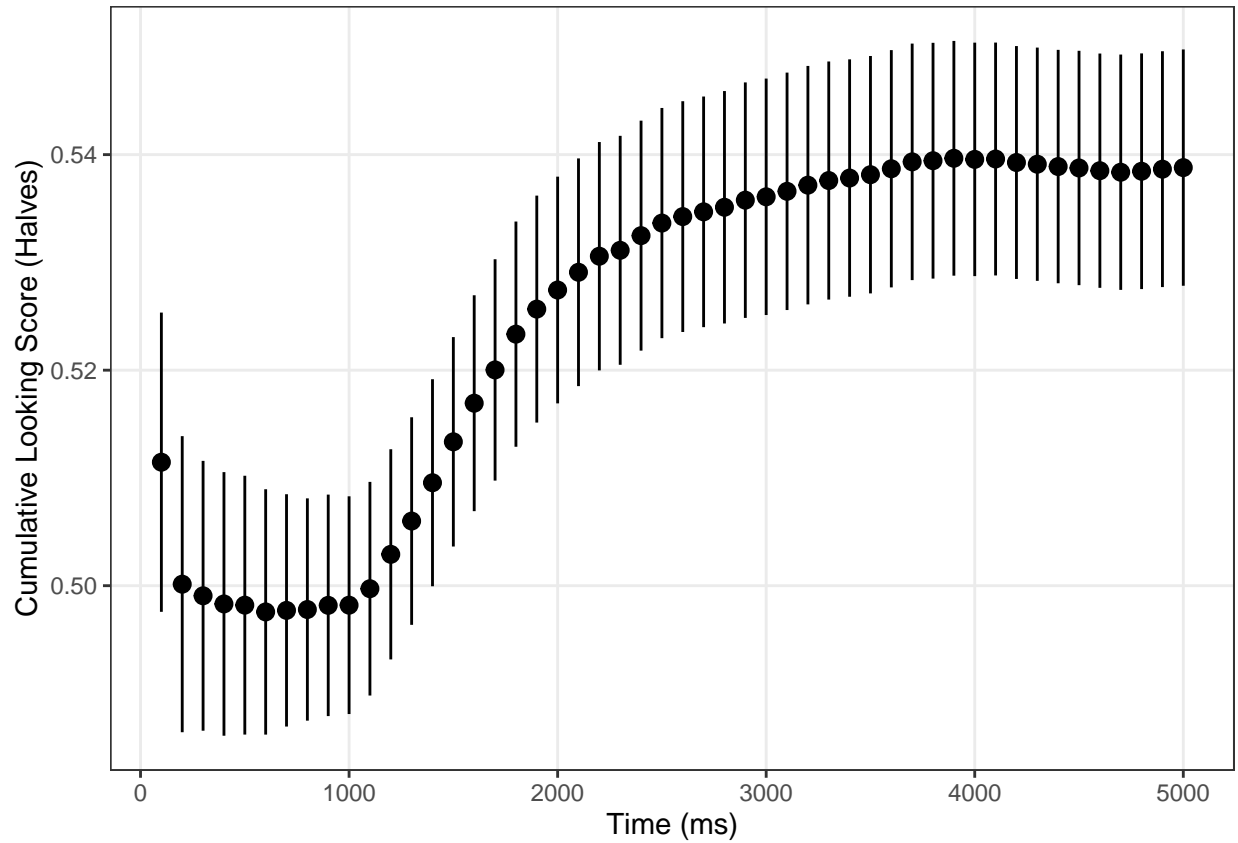
Figure 13. (#fig:E3-roi Plot of cumulative looking score)Cumulative looking score over the 5 second exposure during part 2 of day 1. Error bars represent +/- 1 SEM.

637 ***Correlations with Day 2 Performance.*** Performance on day 2 remained

638 uncorrelated with day 1 looking scores after switching the coding of gaze. We found no

639 significant different from 0 for the correlation between looking score and confidence ratings,

640 $t(39) = 0.74$, p = 0.47 (excluding the subjects who gave the same confidence judgment for

641 all images), nor the the correlation between looking score and RT, $t(47) = 0.28$, p = 0.78.

642 **Calibration.**

643   *Calibration Accuracy.*

Calibration Accuracy
(% of samples within 200px of calibration point)

644
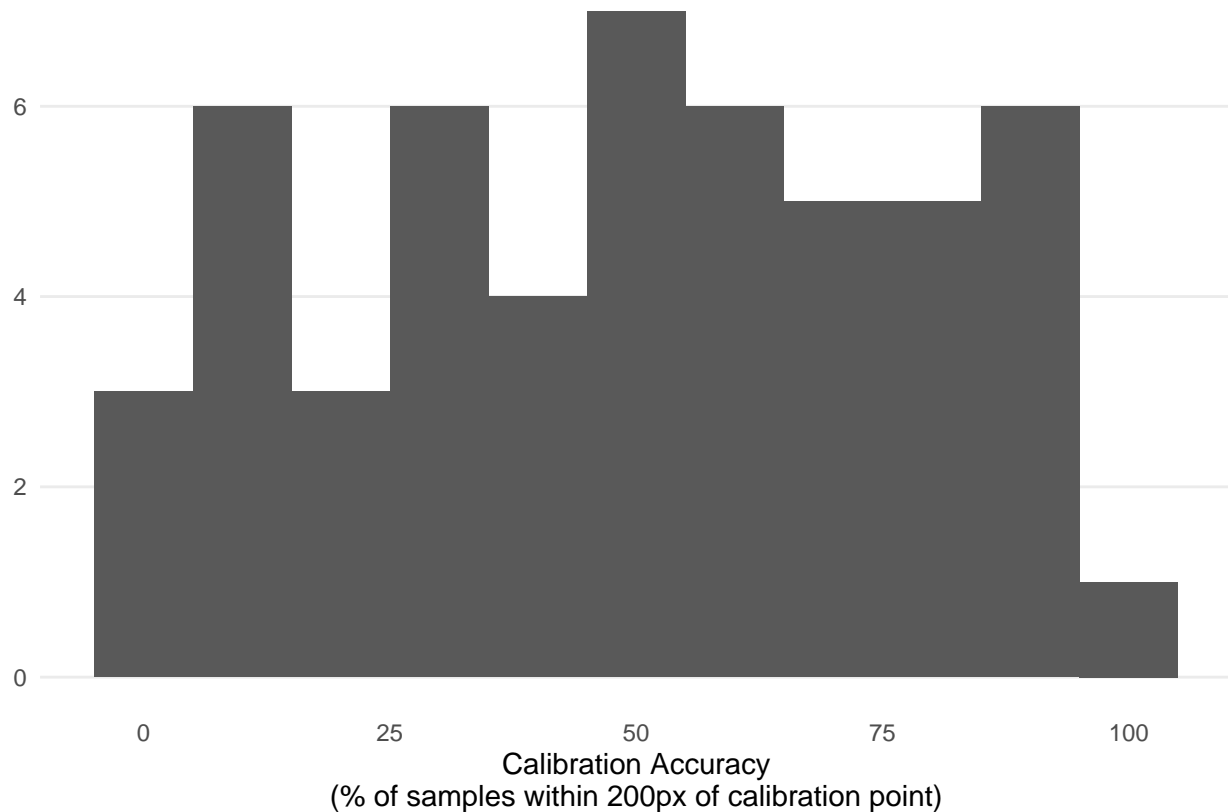
645   *Correlation with Effects.*   To see if calibration success is correlated with the eye

646   tracking effects, we calculated a calibration score for each participant. The calibration

647   score was the average proportion of samples within 200 pixels of the validation points

648   during the final validation phase before the eye tracking is performed.

649   Calibration scores were not correlated with looking scores, regardless of which

650   method was used to calculate looking scores.

651
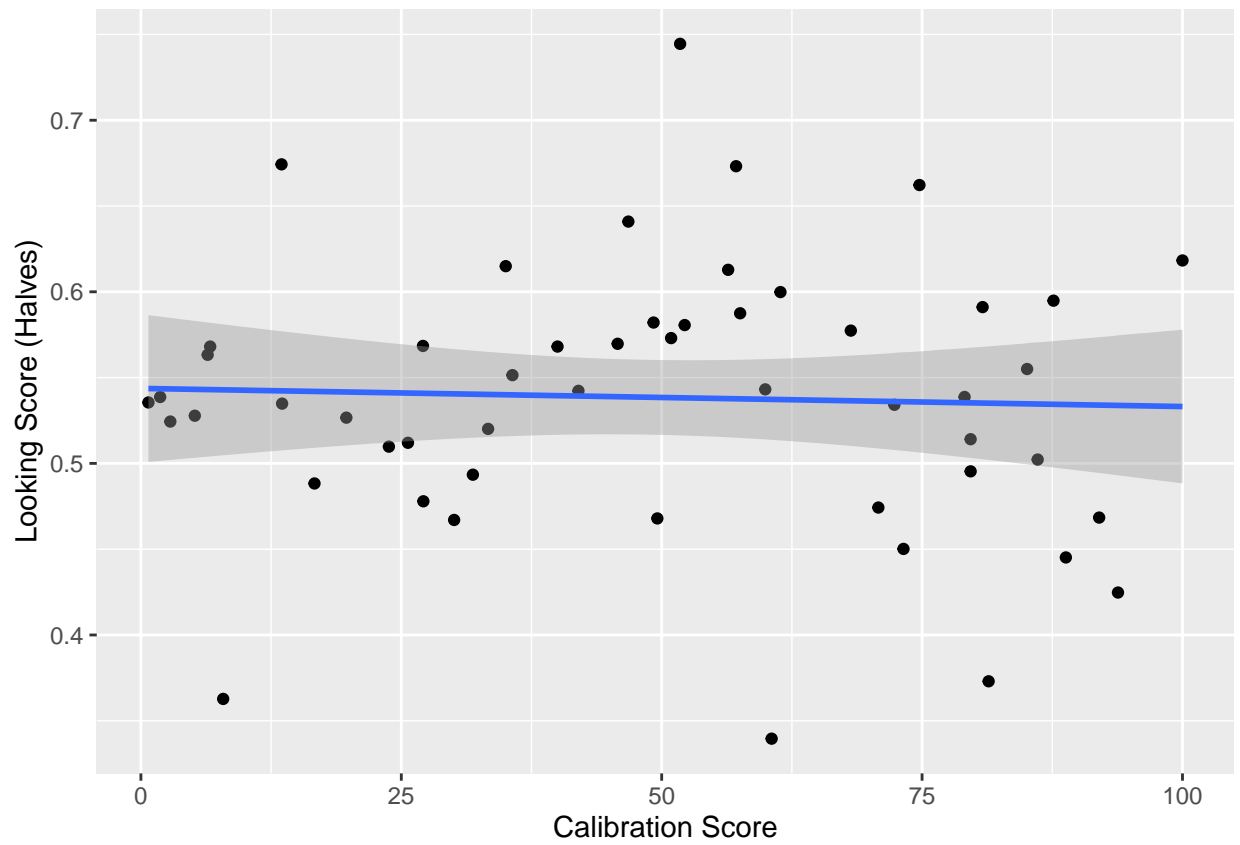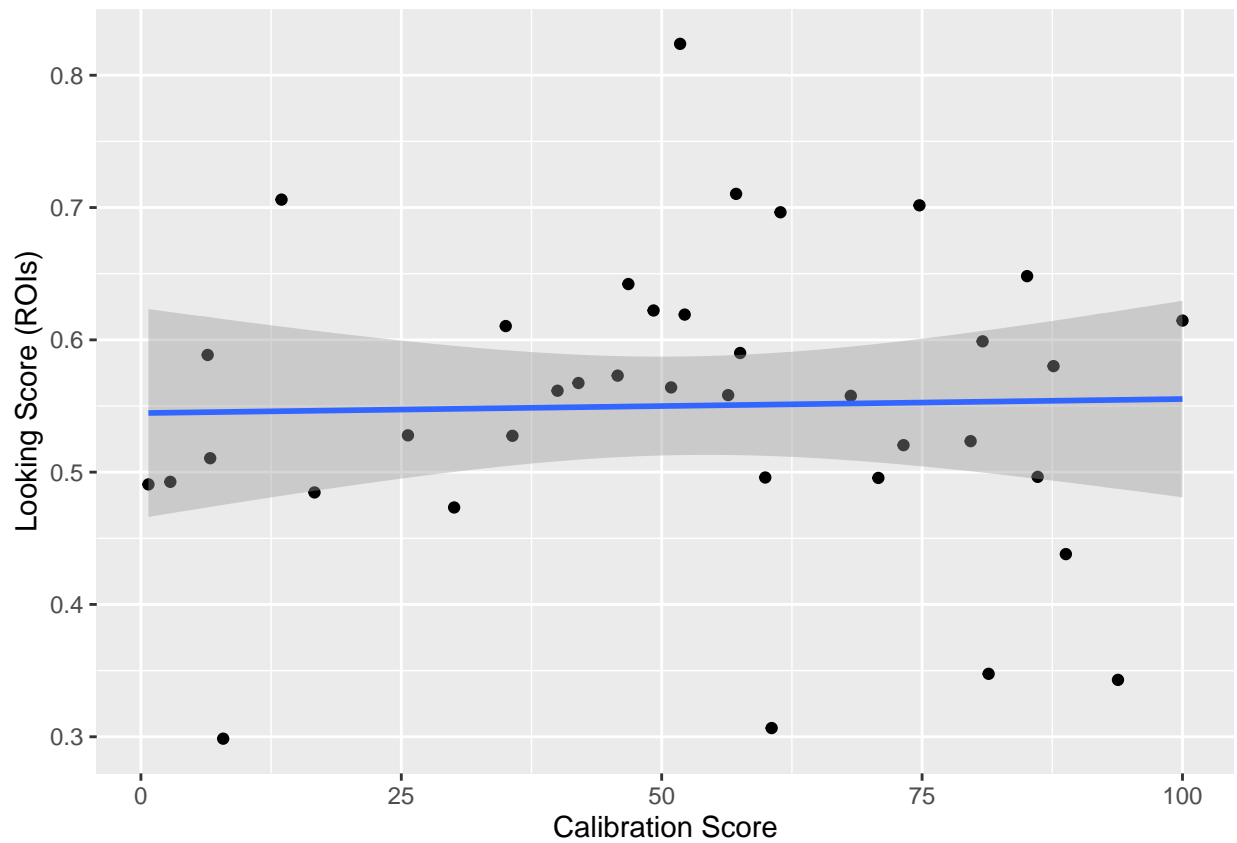
653   We then looked at the correlation of calibration scores with the correlation between

654 day 2 memory performance and day 1 looking scores for both kinds of behavioral and

655 looking measures. None of the four relationships showed a significant correlation.
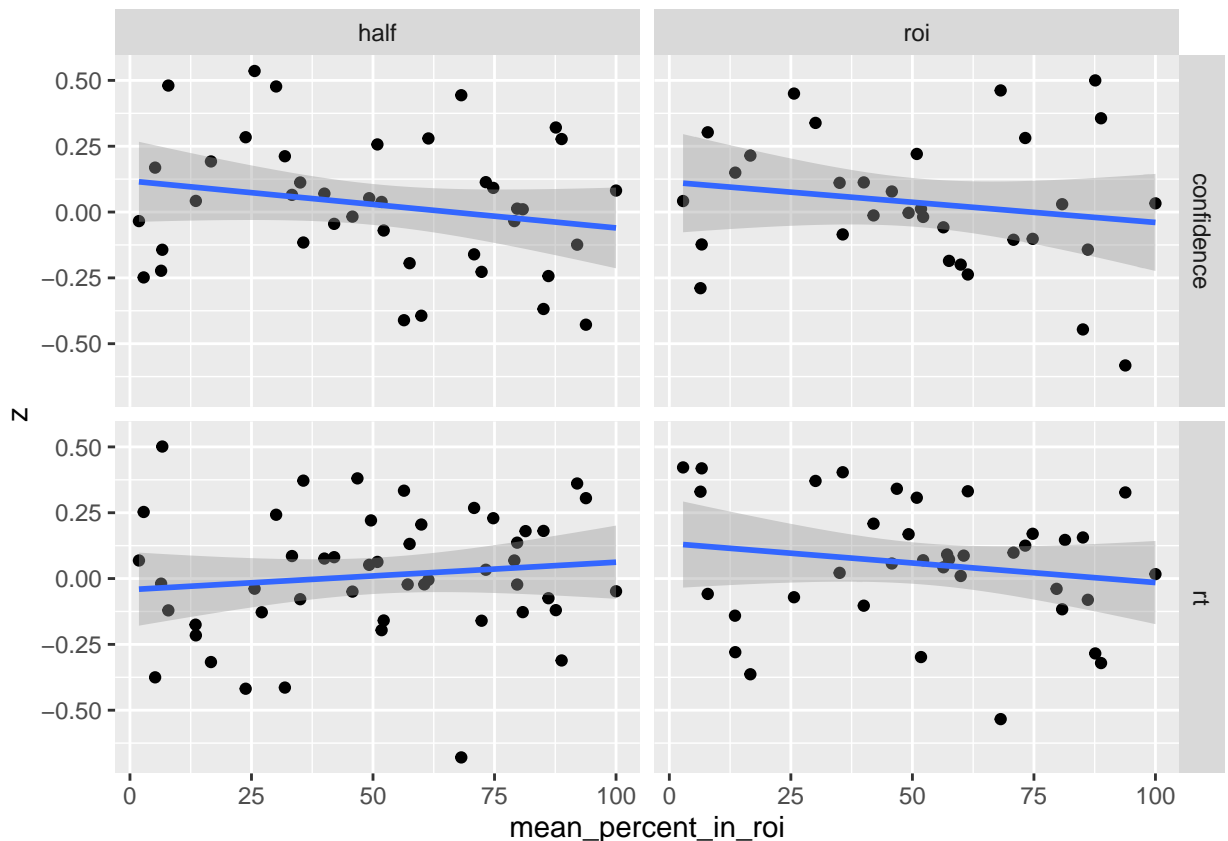
Discussion

As in Manns et al. (2000), participants looked more at novel images than previously seen images. This effect was consistent for ROIs based on the images and for the coarser ROIs based on two halves of the display. A day later, participants were also able to discriminate the images they had seen from foil images they had not seen during the previous session. However, there was no evidence that memory performance on day 2 was related to looking time on day 1. Calibration quality did not appear to impact this relationship.

Experiment 4

The fourth study was a replication attempt of Experiment 1 in Ryskin, Qi, Duff, and Brown-Schmidt (2017), which was closely modeled on Snedeker and Trueswell (2004).

668 These studies used the visual world paradigm to show that listeners use knowledge of the

669 co-occurrence statistics of verbs and syntactic structures to resolve ambiguity. For

670 example, in a sentence like "Feel the frog with the feather," the phrase "with the feather"

671 could be describing the frog, or it could be describing the instrument that should be used

672 to do the "feeling." When both options (a frog holding a feather and a feather by itself) are

673 available in the visual display, listeners rely on the verb's "bias" (statistical co-occurrence

674 either in norming or corpora) to rapidly choose an action while the sentence is unfolding. .

Methods

676 The stimuli, experimental code, and data and original analysis scripts can be found

677 on the Open Science Framework at the following link, https://osf.io/x3c49/. The

678 pre-registration for the study can be found at https://osf.io/3v4pg.

679 **Participants.** 57 participants were paid $2.50 for their participation. A sample size

680 of 60 was initially chosen (but not reached in time) because we wanted to replicate the

681 experiment with greater statistical power. Note that the original study had a sample size of

682 24.

683 **Procedure.** After the eye-tracking calibration and validation (Figure 14),

684 participants went through an audio test so they could adjust the audio on their computer

685 to a comfortable level. Before beginning the experiment, they were given instructions that

686 four objects would appear, an audio prompt would play, and they should do their best to

687 use their mouse to act out the instructions. They then went through three practice trials

688 which were followed by 54 critical trials and 24 filler trials presented in a random order.

689 During a trial, four pictures were displayed (target animal, target instrument,

690 distractor animal, distractor instrument), one in each corner of the screen, and participants

691 heard an audio prompt that contained instructions about the action they needed to act out
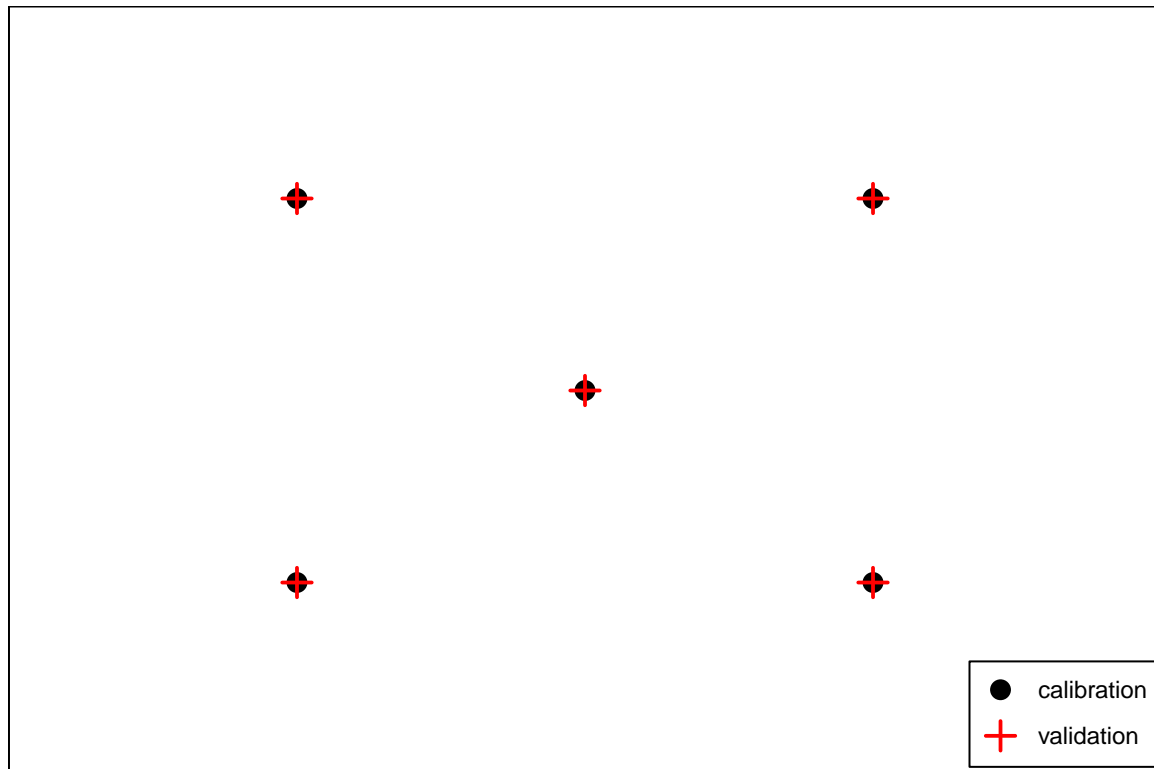
Figure 14. Calibration and validation point locations for Experiment 4. Black points were used for calibration. Red crosses were used for checking the accuracy of the calibration.(In this experiment all the same locations were used for both calibration and validation.)

692 (e.g., "Rub the butterfly with the crayon"; see Figure 15)[4]. Using their cursor, participants

693 could act out the instructions by clicking on objects and moving them or motioning over

694 the objects[5]. After the action was completed, the participants were instructed to press the

695 space bar which led to a screen that said "Click Here" in the middle in order to remove

696 bias in the eye and mouse movements from the previous trial. The experiment only allowed

697 the participants to move on to the next trial once the audio was completely done playing

---

[4] In the original study, the pictures appeared one by one on the screen and their names were played as they appeared. We removed this introductory portion of the trial to save time

[5] As opposed to the original study we recorded mouse movement instead of clicking behavior since not all of the audio prompts required clicking. For example, the sentence "locate the camel with the straw" may not involve any clicking but rather only mousing over the camel.

and the mouse had been moved over at least one object.

Figure 15. An example of a critical trial from Experiment 4 for the sentence "Rub the butterfly with the crayon." The butterfly is the target animal, the panda is the distractor animal, the crayon is the target instrument, and the violin is the distractor instrument.

Materials. The images and audios presented to the participants were the same stimuli used in the original study (available here). The critical trials were divided into modifier-biased, instrument-biased, and equibiased conditions, and the filler trials did not contain ambiguous instructions. Two lists of critical trials were made with different verb and instrument combinations (e.g., "rub" could be paired with "panda" and "crayon" in one list and "panda" and "violin" in the second list). Within each list, the same verb was presented twice but each time with a different target instrument and animal. The lists were randomly assigned to the participants to make sure the effects were not caused by the properties of the animal or instrument images used. The list of verbs used can be found in Appendix A of the original study.

₇₀₉ **Results**

₇₁₀   **Replication.**   The location of initial mouse movements was used to assess whether

₇₁₁ the final interpretation of ambiguous sentences was biased by the verb. Figure 16 suggests

₇₁₂ that listeners were more likely to move their mouse first over the target instrument when

₇₁₃ the verb was equi-biased than when the verb was modifier-biased and even more so when

₇₁₄ the verb was instrument-biased. The opposite graded pattern can be observed for mouse

₇₁₅ movements over the target animal.
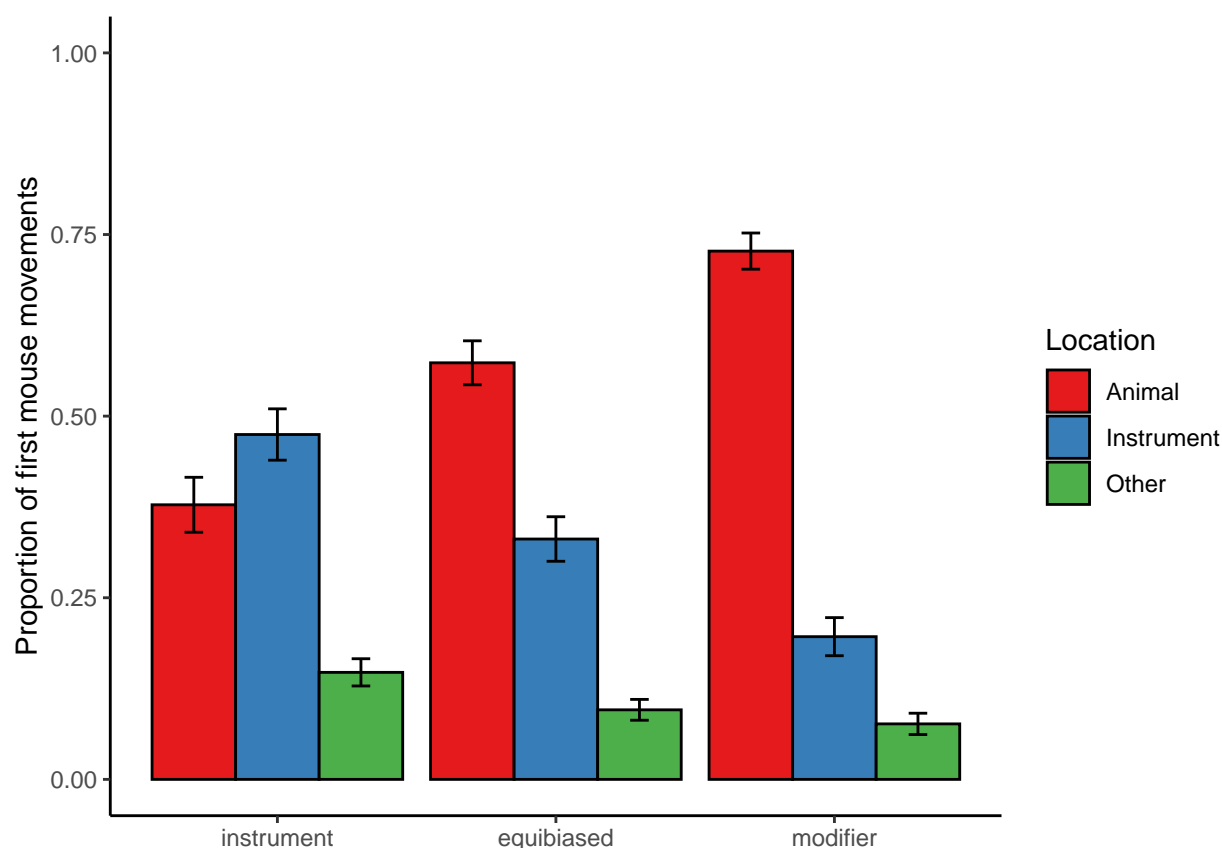
Figure 16. Proportion of first mouse movements by location and verb bias.

₇₁₆   A mixed-effects logistic regression model was used to predict whether the first

₇₁₇ movement was on the target instrument with the verb bias condition as an orthogonally

₇₁₈ contrast-coded (instrument vs. equi & modifier: inst = -2/3, equi = 1/3, mod = 1/3; equi

₇₁₉ vs. modifier: inst = 0, equi = -1/2, mod = 1/2) fixed effect. Participants and items were

entered as varying intercepts with by-participant varying slopes for verb bias condition[6].

Participants were more likely to first move their mouse over target instruments in the

instrument-biased condition relative to the equi-biased and modifier-biased condition ($b =$

-1.50, $SE = 0.25$, $p < 0.01$). Further, participants were more likely to first move their

mouse over target instruments in the equi-biased condition relative to the modifier-biased

condition ($b =$ -1.10, $SE = 0.29$, $p < 0.01$)

Gaze fixations were time-locked to the auditory stimulus on a trial by trial basis and

categorized as being directed towards one of the four items in the display if the x, y

coordinates fell within a rectangle containing the image. Figure 17 suggests that the

participants made more fixations to the target animal when the verb was modifier-biased

compared to when the the verb was equi-biased and they looked at the target animal least

when the verb was instrument-biased. The pattern was reversed for looks to the target

instrument.

In order to assess how verb bias impacted sentence disambiguation as the sentence

unfolded, the proportion of fixations was computed in three time windows: the

verb-to-animal window (from verb onset + 200 ms to animal onset + 200 ms), the

animal-to-instrument window (from animal onset + 200 ms to instrument onset + 200 ms),

and the post-instrument window (from instrument onset + 200 ms to instrument onset +

1500ms + 200 ms). Mixed-effects linear regression models were used to predict the

proportions of fixations to the target animal within each time window with the verb bias

condition as an orthogonally contrast-coded (instrument vs. equi & modifier: inst = -2/3,

equi = 1/3, mod = 1/3; equi vs. modifier: inst = 0, equi = -1/2, mod = 1/2) fixed effect.

Participants and items were entered as varying intercepts[7]. In the *verb-to-noun* window,

_____

[6] `lme4` syntax: `glmer(is.mouse.over.instrument ~ verb_bias + (1 + verb_bias | participant) +`
`(1 | item), family="binomial", data=d)`

[7] `lme4` syntax: `lmer(prop.fix.target.animal ~ verb_bias + (1 + verb_bias | participant) + (1`
`| item), data=d)`. A model with by-participant varying slopes for verb bias condition was first attempted
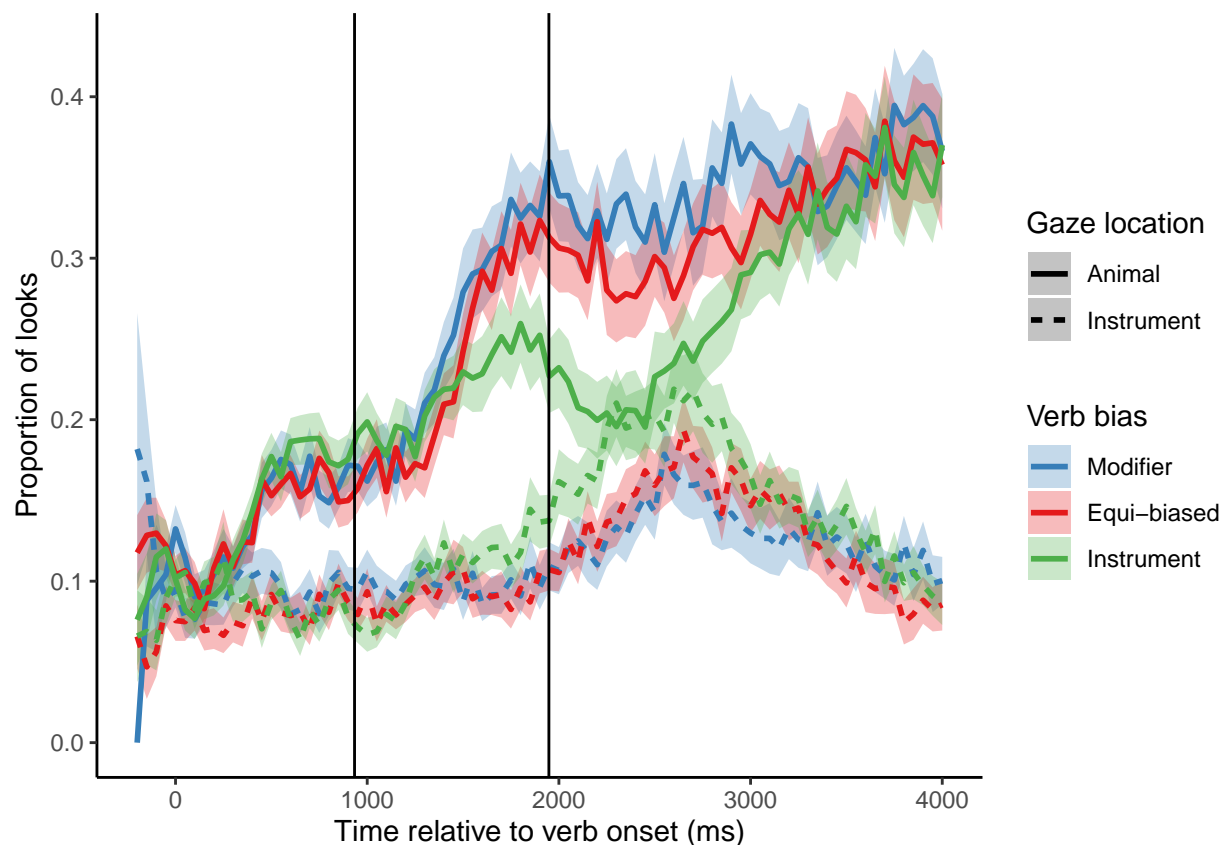
Figure 17. Timecourse of eye-gaze to target animal and target instrument by verb bias condition. Vertical lines indicate average onsets of animal and instrument offset by 200ms.

743 participants did not look more at the target animal in any of the verb bias conditions

744 (Instrument vs. Equi and Modifier: b = -0.01, $SE = 0.02$, $p = 0.59$; Equi vs. Modifier: $b =$

745 0, $SE = 0.02$, $p = 1$). In the *noun-to-instrument* window, participants looked more at the

746 target animal in the modifier-biased condition and equi-biased conditions relative to the

747 instrument-biased condition ($b = 0.03$, $SE = 0.01$, $p < 0.01$) and in the modifier biased

748 relative to the equi-biased condition ($b = 0.02$, $SE = 0.01$, $p < 0.05$). In the

749 *post-instrument* window, participants looked more at the target animal in the

750 modifier-biased condition and the equi-biased conditions relative to the instrument-biased

751 condition ($b = 0.08$, $SE = 0.02$, $p < 0.01$) but not significantly so in the modifier biased

———

but did not converge.

752 condition relative to the equi-biased condition ($b = 0.03$, $SE = 0.02$, $p = 0.15$).

753   **Comparison to in-lab data.**   The web version of the study qualitatively replicates

754 the action and eye-tracking results of the original dataset (Ryskin et al., 2017). The mouse

755 click results from both studies are summarized in Figure 18. The quantitative patterns of

756 clicks were similar to those observed in the original dataset, though for Instrument-biased

757 verbs, clicks were closer to evenly split between the animal and the instrument relative to

758 the in-lab study where they were very clearly biased toward the instrument.
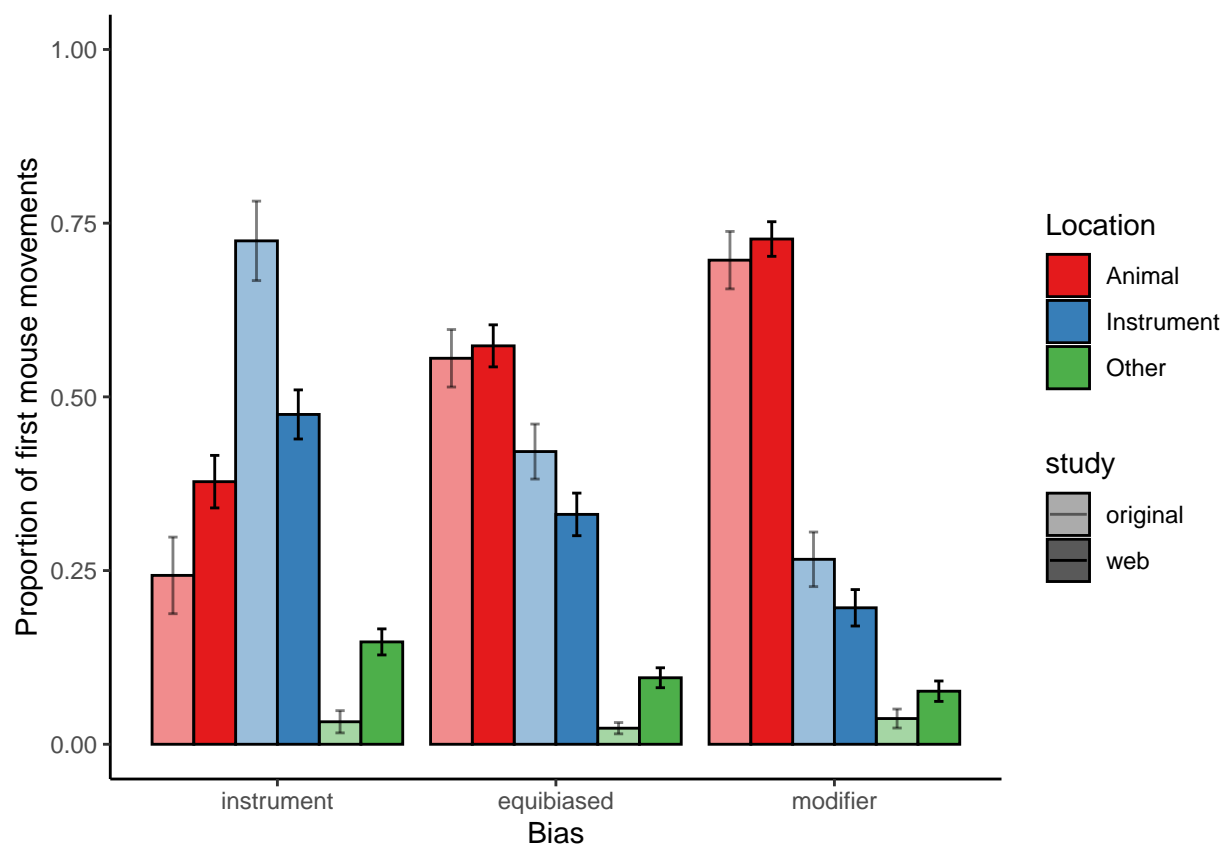
Figure 18. Proportion of first mouse movements by location and verb bias in the original
dataset (Ryskin et al., 2017) and the current data collected online.

759   The eye-tracking results from both studies are summarized in Figure 19. For

760 simplicity, and to reflect the dependent variable used in analyses, we average the

761 proportion of fixations to the target animal within each time window. Though the

⁷⁶² qualitative patterns are replicated, proportions of fixations to the target animal were much

⁷⁶³ lower in the web version of the study. This may reflect the fact that participants in the web

⁷⁶⁴ study are less attentive and/or the quality of the webgazer eye-tracking system is lower,

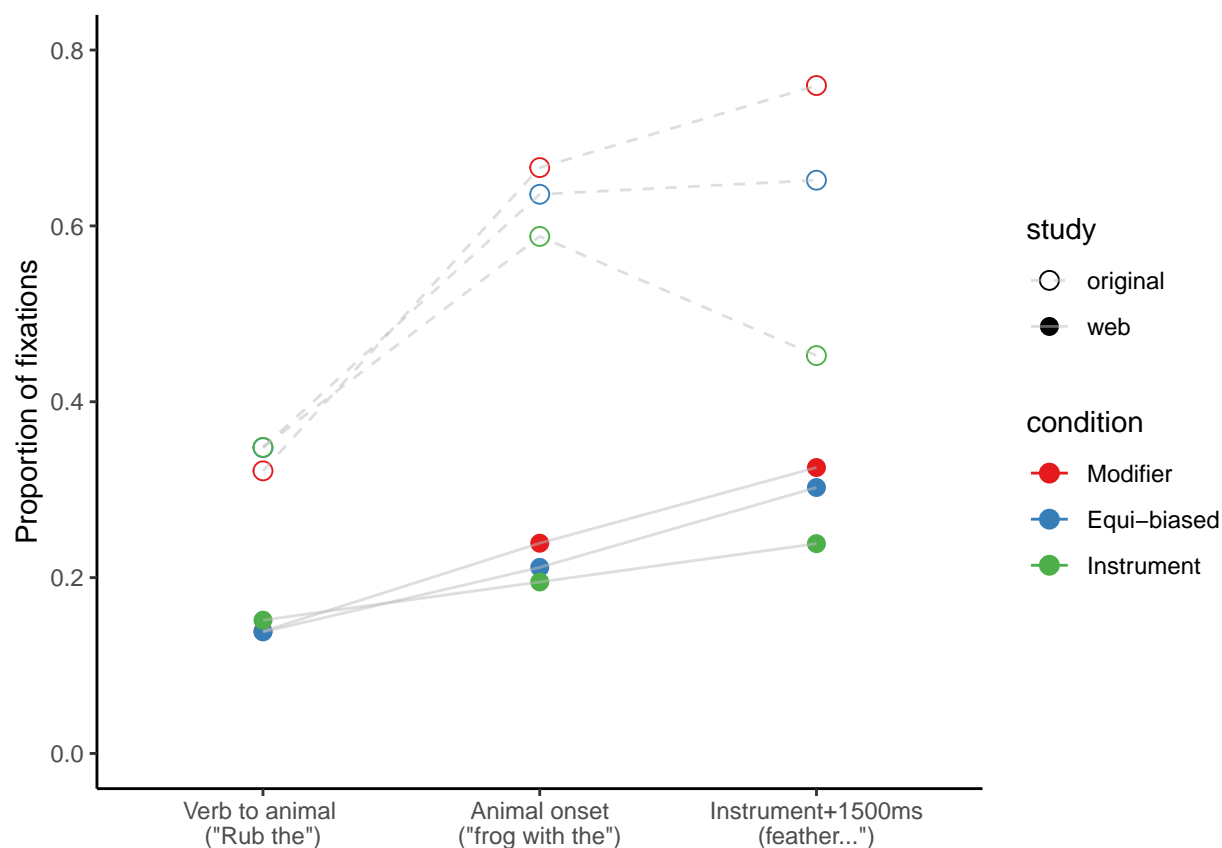⁷⁶⁵ relative to the Eyelink 1000 which was used for the original study.

Figure 19. Proportion of target fixations by verb bias in the original dataset (Ryskin et al.,
2017) and the current data collected online. Error bars reflect bootstrapped 95% CIs over
subject means

⁷⁶⁶ **Calibration.** Participants' calibration quality, measured as the mean percentage of

⁷⁶⁷ fixations that landed within 200 pixels of the calibration point, varied substantially

⁷⁶⁸ (between 2.22 and 97.36 %). The quality of a participant's calibration significantly

⁷⁶⁹ correlated with the participant's effect size (*Pearson's r*= 0.29, $p < 0.05$). The difference

⁷⁷⁰ in target animal fixation proportions between modifier and instrument conditions was

771   higher for participants with better calibration

772   Replicating the linear mixed-effects analysis (in the post-instrument onset time

773   window only) on a subset of 35 participants with calibration quality >50% suggests that

774   the effect of verb bias condition was larger in this subset than in the full dataset.

775   Participants looked more at the target animal in the modifier-biased condition and the

776   equi-biased conditions relative to the instrument-biased condition ($b = 0.10$, $SE = 0.02$, p

777   < 0.001) but not significantly so in the modifier biased condition relative to the equi-biased

778   condition ($b = 0.02$, $SE = 0.02$, $p = 0.29$).

779   Replicating the linear mixed-effects analysis (in the post-instrument onset time

780   window only) on a subset of 19 participants with calibration quality >75% suggests that

781   the effect of verb bias condition was larger in this subset than in the full dataset.

782   Participants looked more at the target animal in the modifier-biased condition and the

783   equi-biased conditions relative to the instrument-biased condition ($b = 0.11$, $SE = 0.03$, p

784   < 0.001) but not significantly so in the modifier biased condition relative to the equi-biased

785   condition ($b = 0.05$, $SE = 0.03$, $p = 0.13$).

786   **Effects of ROIs.**   Eye-tracking on the web differs critically from in-lab eye-tracking

787   in that the size of the display differs across participants. Thus the size of the ROIs differs

788   across participants. The current version of the web experiment used a bounding box around

789   each image to determine the ROI. This approach is flexible and accomodates variability in

790   image size, but may exclude looks that are directed at the image but fall outside of the

791   image (due to participant or eye-tracker noise) as show in Figure 20a. Alternatively, The

792   display can be split into 4 quadrants which jointly cover the entire screen (see Figure 20b).

793   Categorizing gaze location based on which of the four quadrants of the screen the

794   coordinates fell in, increases the overall proportions of fixations (see Figure 21). In the

795   *post-instrument* window, participants looked more at the target animal in the

796   modifier-biased condition and the equi-biased conditions relative to the instrument-biased
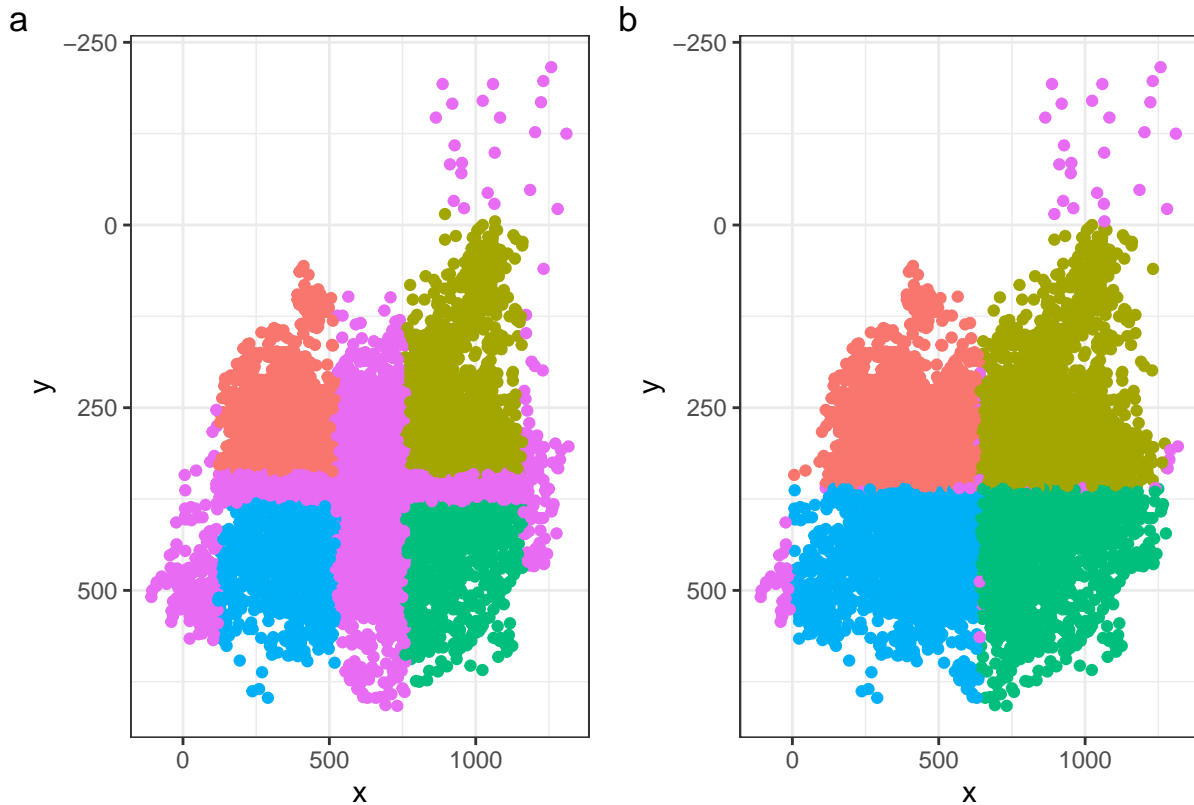
Figure 20. Example participant's gaze coordinates categorized into ROIs based on a) image bounding boxes and b) screen quadrants. Magenta points indicate looks that were not categorized into an ROI

condition ($b = 0.08$, $SE = 0.02$, $p < 0.01$) and marginally so in the modifier biased condition relative to the equi-biased condition ($b = 0.04$, $SE = 0.02$, $p = 0.05$). Effect size estimates appeared somewhat larger and noise was somewhat reduced when using the quadrant categorization relative to the bounding box-based ROIs.

Discussion

As in Ryskin et al. (2017) and Snedeker and Trueswell (2004), listeners' gaze patterns during sentences with globally ambiguous syntactic interpretations differed depending on the bias of the verb (i.e., modifier, instrument or equi). For modifier-biased verbs,
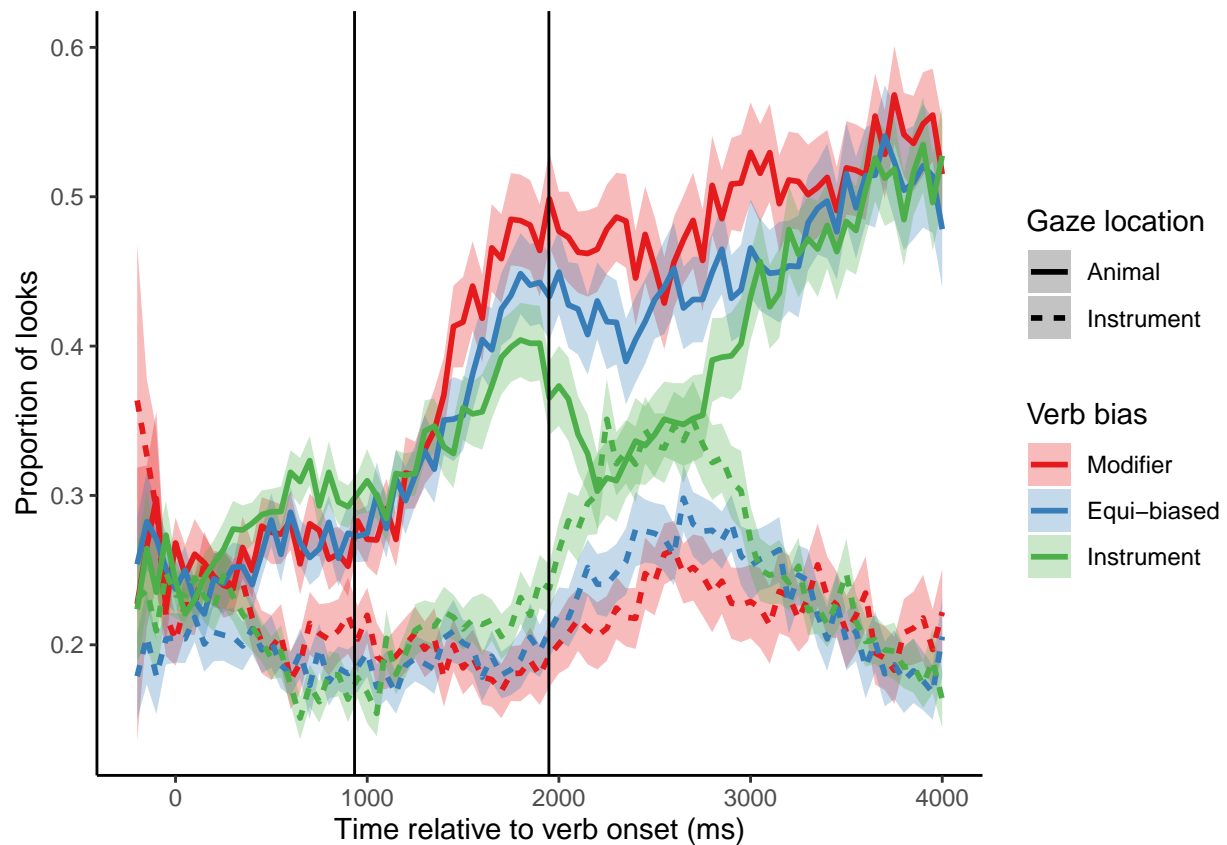
Figure 21. Timecourse of eye-gaze to target animal and target instrument by verb bias condition with gaze categorized based on which quadrant of the screen the coordinates fall in (as opposed to a bounding box around the image). Vertical lines indicate average onsets of animal and instrument offset by 200ms.

participants looked more quickly at the target animal and less at the potential instrument than for instrument-biased verbs (and equi-biased verbs elicited a gaze pattern between these extremes). This pattern was stronger for those who achieved higher calibration accuracy and when quadrant-based ROIs were used compared to image-based ROIs.

Experiment 5

The fifth study was a replication attempt of Shimojo et al. (2003), which found that human gaze is actively involved in preference formation. Separate sets of participants were

shown pairs of human faces and asked either to choose which one they found more

attractive or which they felt was rounder. Prior to making their explicit selection,

participants were increasingly likely to be fixating the face they ultimately chose, though

this effect was significantly weaker for roundness discrimination.

Note that Shimojo and colleagues compare five conditions, of which we replicate only
the two that figure most prominently in their conclusions: the "face-attractiveness-difficult
task" and the "face-roundness task".

Methods

All stimuli, experiment scripts, data, and analysis scripts are available on the Open
Science Framework at https://osf.io/eubsc/. The study pre-registration is available at
https://osf.io/tv57s.

Participants.   50 participants for the main task were recruited on Prolific and were
paid $10/hour. 8 subjects, 4 from the attractiveness task group and 4 from the roundness
task group, were excluded for incorrect validations. After this data exclusion, we ended up
with 21 participants each for the attractiveness task and the roundness task. The original
sample size in Shimojo et al. (2003) was 10 participants total.

Procedure and Design.   At the beginning of the experimental task, participants
completed a 9-point eye-tracker calibration (each point appeared 3 times in random order)
and 3-point validation. The validation point appeared once at center, middle left, and
middle right locations in random order (see Figure 22).

During each trial of the main task, two faces were displayed on the two halves of the
screen, one on the left and one on the right (as in Figure 23). Participants were randomly
assigned to one of two tasks: attractiveness or shape judgment. In the attractiveness task,
participants were asked to chose the more attractice face in the pair and in the shape
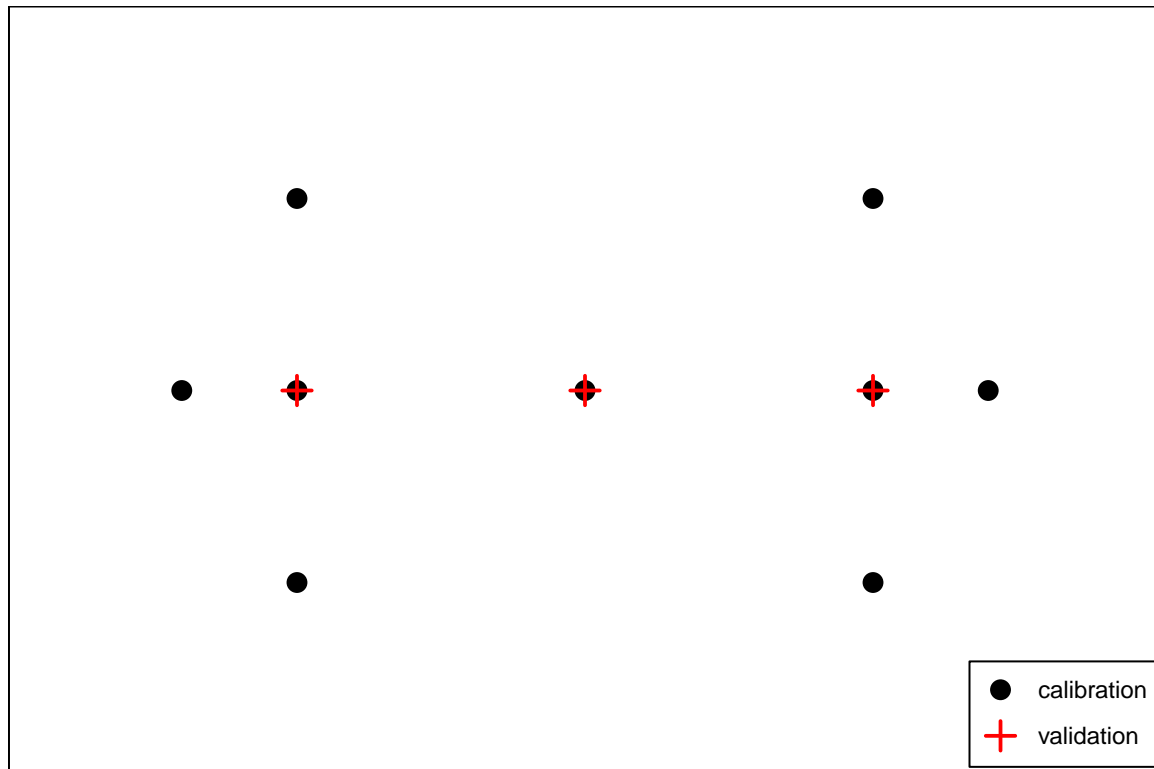judgment task participants were asked to pick the face that appeared rounder. They

Figure 22. Calibration and validation point locations for Experiment 5. Black points were used for calibration. Red crosses were used for checking the accuracy of the calibration.

pressed the "a" key on their keyboard to select the face on the left and the "d" key to select the face on the right. A fixation cross appeared in the center of the screen between each set of faces. Participants were asked to look at this fixation cross in order to reset their gaze in between trials. The order of the 19 face pairs was random for each participant.

Materials and Norming.   The faces in our replication were selected from a set of 1,000 faces within the Flickr-Faces-HQ Dataset. (The face images used in Shimojo et al. were from the Ekman face database and the AR face database.) These images were chosen because the person in each image was looking at the camera with a fairly neutral facial expression and appeared to be over the age of 18. 27 participants were recruited on Prolific to participate in stimulus norming (for attractiveness). They each viewed all 172 faces and were asked to rate them on a scale from 1 (less attractive) to 7 (more attractive) using a slider. Faces were presented one at a time and in a random order for each
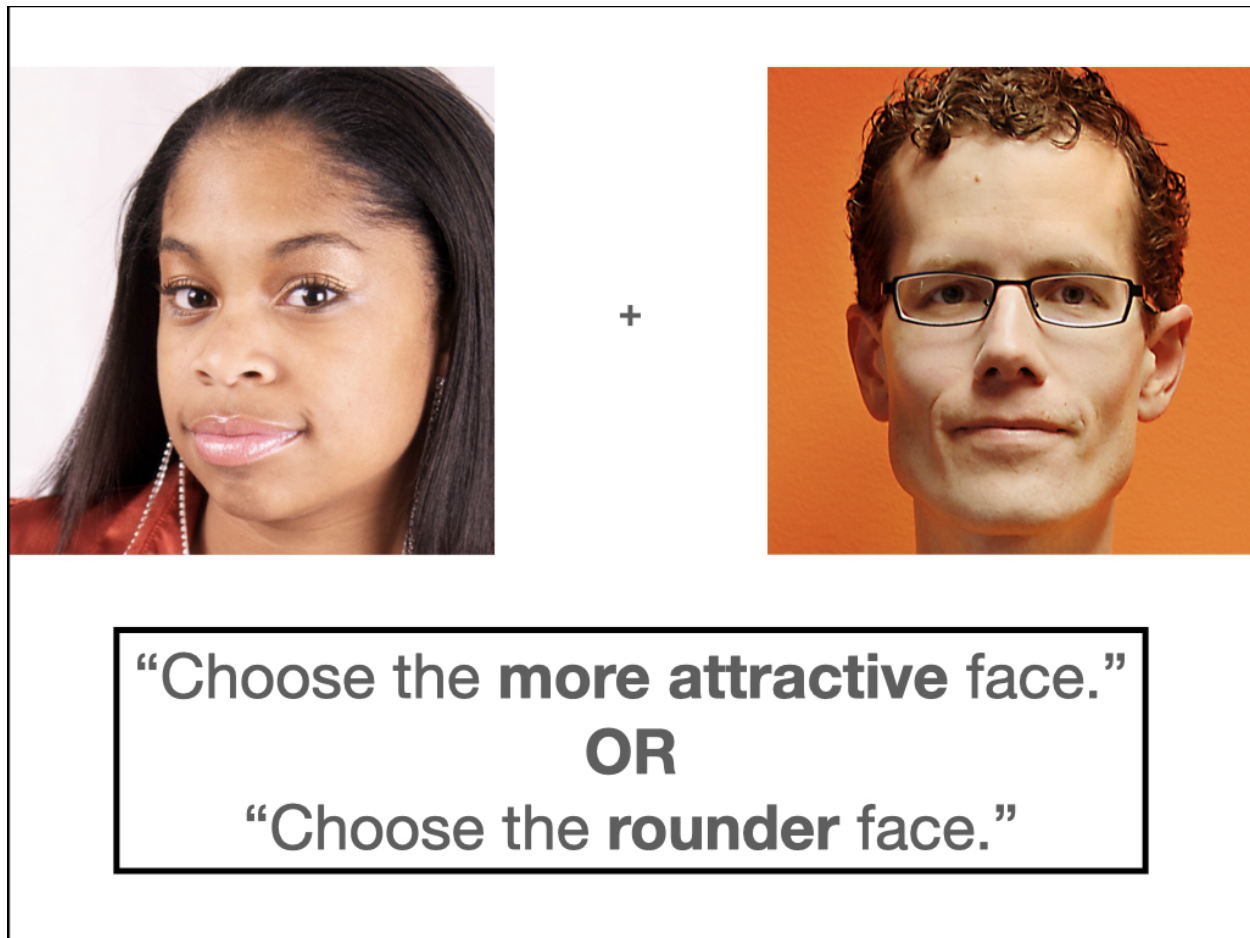
Figure 23. An example of a critical trial from Experiment 5. (Text did not appear on each screen.)

participant. Data from 3 participants were excluded because their mode response made up more than 50% of their total responses, for a total of 24 participants in the norming.

Following Shimojo et al., 19 face pairs were selected by identifying two faces that 1) had a difference in mean attractiveness ratings that was 0.25 points or lower and 2) matched in gender, race, and age group (young adult, adult, or older adult).

Data analysis. In the original study, a video-based eye tracker was used. The eye movements of participants were recorded with a digital camera downsampled to 33.3 Hz, with eye position was then determined automatically with MediaAnalyzer software. In our study, subjects supplied their own cameras, so hardware sampling rate varied. However,

data was collected at 20 Hz.[TODO - CONFIRM]

Results

Due to large variation in response time latency, Shimojo and colleagues analyzed eye gaze for the 1.67 seconds prior to the response. This duration was one standard deviation of the mean response time, ensuring that all timepoints analyzed have data from at least 67% of trials. In our dataset, one standard deviation amounts to 1.85 seconds. We then binned eyegaze data into 50 ms bins rather than the 30 ms bins used by Shimojo and colleagues, reflecting the different sampling rates.

Following Shimojo and colleagues, data for each condition were fit using a four-parameter sigmoid (Fig. 24). These fit less well than in the original paper for both the attractiveness judgment ($R^2 = 0.84$ vs. 0.91) and the roundness judgment ($R^2 = 0.54$ vs. 0.91).

From these curves, Shimojo and colleagues focus on two qualitative findings. First, they note a higher asymptote for the attractiveness discrimination task relative to roundness discrimination. Qualitatively, this appears to replicate. However, their statistical analysis – a Kolmogorov-Smirnov test for distance between two distributions – is not significant ($D = 0.19$, $p = 0.53$), though it should be noted that this is a very indirect statistical test of the hypothesis and probably not very sensitive.

The second qualitative finding they note is that the curve for the roundness judgment "saturates" (asymptotes) earlier than the curve for the attractiveness judgment. They do not present any statistical analyses, but it is clear qualitatively that the result does not replicate.

Calibration. As in the previous experiments, calibration score was defined as the average proportion of samples within 200 pixels of the validation point during the final validation phase before the eye tracking is performed. The distribution across participants
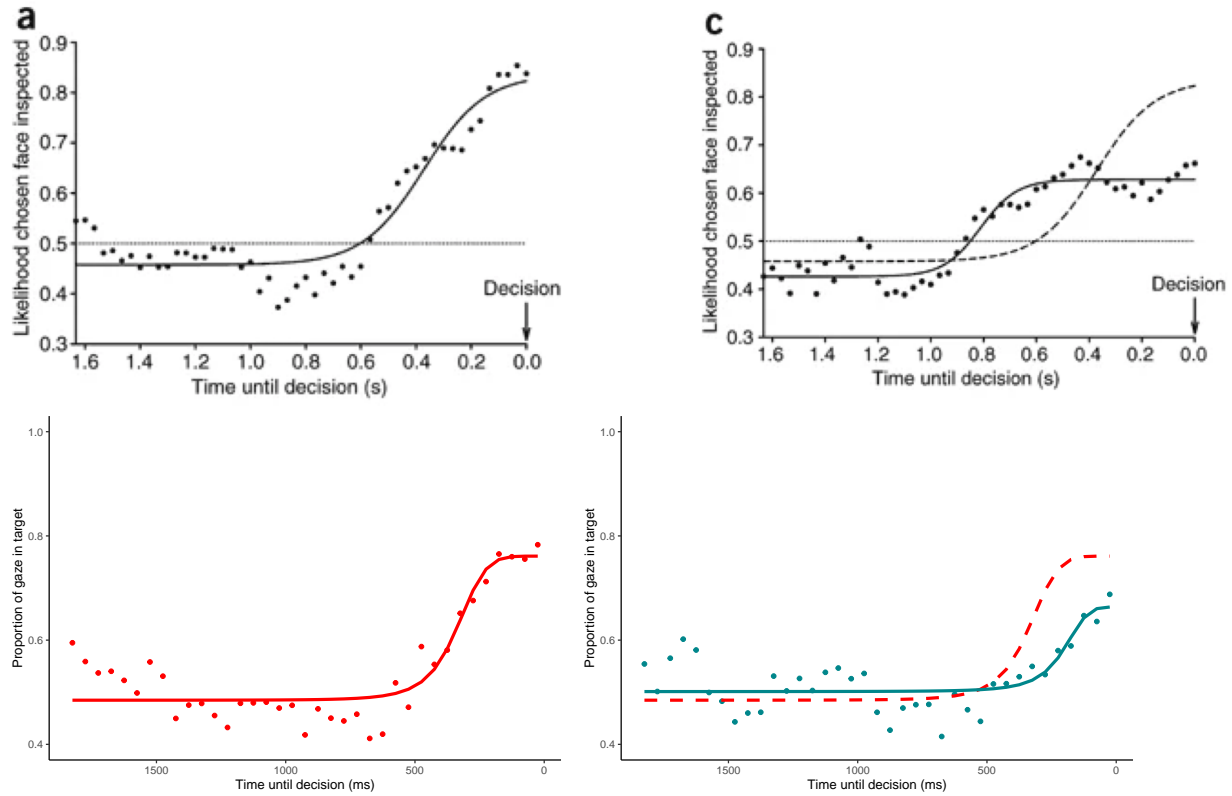
Figure 24. Primary results from Exp. 5. *Top* shows the original results from Shimojo and colleagues (Figures reprinted with permission[TODO]). The attractiveness judgment along with the best-fitting sigmoid is shown in the *top left*. Results for the roundness judgment are show in the *top right*, with the best-fitting sigmoid for the attractiveness judgment depicted in a dashed line for comparison (*top right*). (*Bottom*) shows the analogous results from the replication, with the attractiveness judgments on the *bottom left* and the roundness judgments on the *bottom right*. Again, the best-fitting sigmoid for the attractiveness judgments are plotted with a dashed line alongside the roundness results, for purposes of comparison.

883 is shown in Fig. 25.
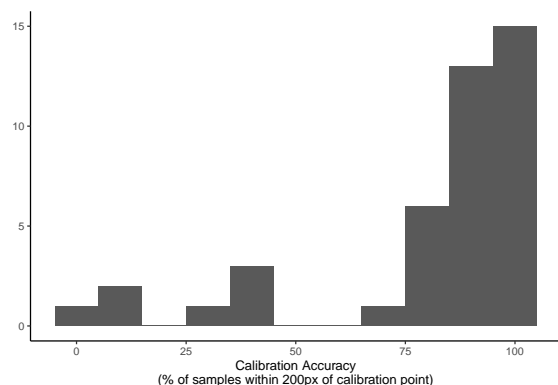
Figure 25. Histogram of calibration success in Exp. 5. Where participants required more than one calibration (N=8), only the final calibration was considered.

884   To determine whether calibration accuracy influenced our key effects, we calculated

885 the percentage of samples during the task in which the participant was fixating the face

886 they ultimately chose. There was a significant correlation for both the attractiveness

887 judgments (r = 0.47 [0.04, 0.75], p = 0.03) and the roundness judgments (r = 0.60 [0.23,

888 0.82], p = 0). Inspection of Fig. 26 reveals that this correlation is due to a handful of

889 particpiants with calibration values below 50%.

890   Thus, we re-analyzed the data, removing the participants whose calibration accuracy

891 was not greater than 50%. This slightly improved the fits of the sigmoids (Attractiveness:

892 $R^2 = 0.79$; Roundness: $R^2 = 0.60$). However, the difference between sigmoids remained

893 non-significant using the Kolmogorov-Smirnov test (D = 0.22, p = 0.36). Descriptively, the

894 results do not look substantially different (Fig. 27).

895   **Effects of ROIs.** In the original experiment, eye gazes that did not directly fixate

896 one or other of the faces were excluded. In this section we explore an alternative coding of

897 the eye movement data by coding simply left half vs. right half of the screen. The coarser

898 coding may be more appropriate for webcam-based eyetracking.

899   Only a small percentage of samples (7.00%) involved looks to anything other than
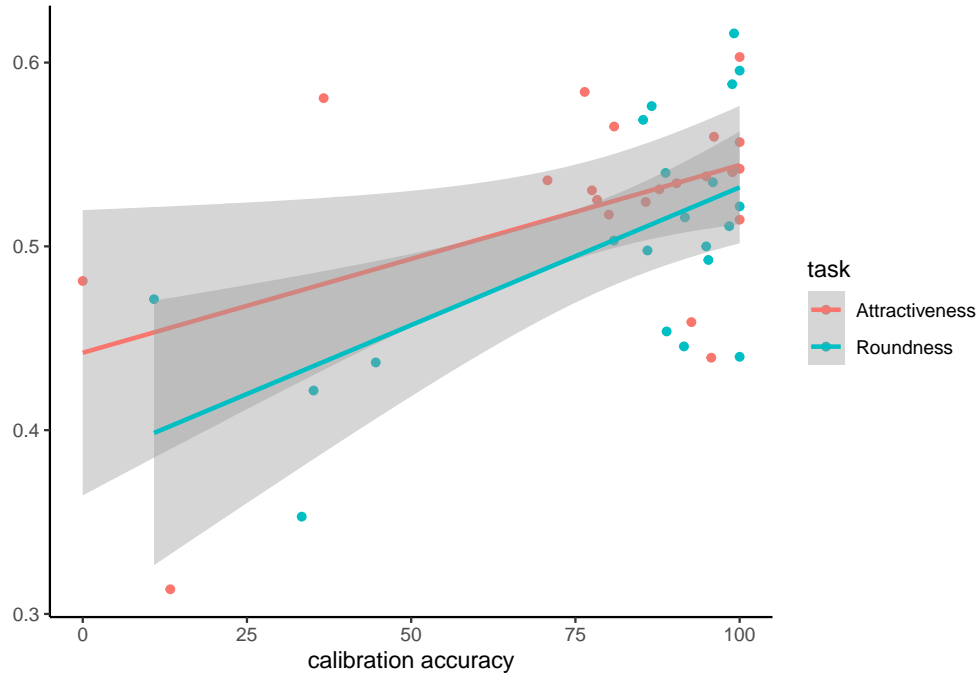
Figure 26. Correlation between calibration accuracy (x-axis) and percentage of samples fixating target (y-axis) in Exp. 5.
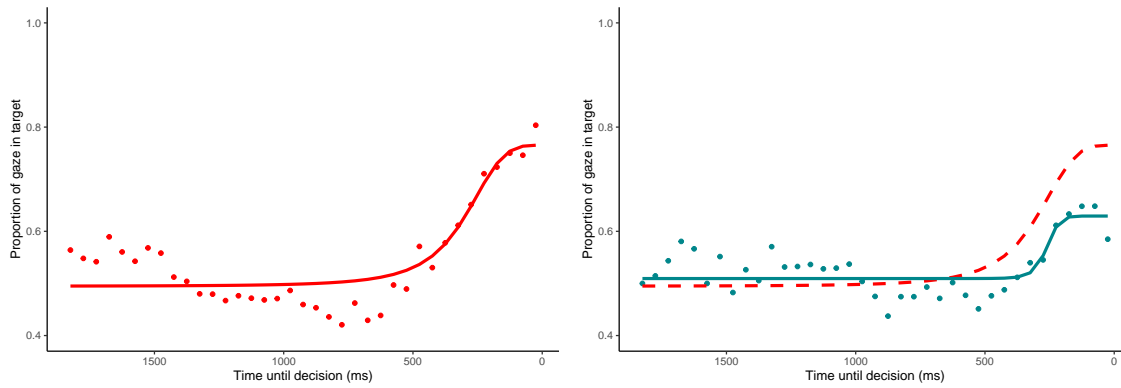

Figure 27. Revised results for Exp. 5 after removing low-calibration accuracy participants. *Left*: Eyegaze during attractiveness judgments, along with the best-fitting sigmoid. *Right*: Eyegze during roundness judgments, along with best-fitting sigmoid (best-fitting sigmoid for attractiveness is re-plotted with a dashed line for comparison).

one of the two faces. Thus, not surprisingly, the correlation between percentage of time spent fixating the to-be-chosen face using the ROI method and the halves method was near ceiling (r = 0.97 [0.97, 0.98], p = 0). Since the choice of method had almost no effect on whether participants were coded as fixating one face or the other, we did not further investigate the effect of method choice on the analytic results.

Discussion

Qualitatively, the results are similar to those of Shimojo et al., such that participants look more at the face that they ultimately choose. This gaze bias appears to be stronger for decisions about face attractiveness than shape, though this is not supported by the statistical analysis approach used in the original paper. The gaze patterns remained consistent for participants with better calibration accuracy.

<div align="center">

General Discussion

</div>

We conducted 5 attempted replication studies using different experimental paradigms from across the cognitive sciences. All were successfully implemented in `jsPsych` using the `webgazer` plugin, but replication success was mixed. Experiment 1 had the smallest ROIs due to the use of an integrated visual scene with 5 to 6 ROIs of varying size per scene, as opposed to ROIs corresponding to display halves or quadrants. Both attempts to replicate Altmann and Kamide (1999) were unsuccessful, despite the success of previous in-lab replications using infrared eye-tracking (James, Minnihan, & Watson, 2023). A previous conceptual replication of this paradigm using webcam-based eye-tracking (Prystauka et al., 2023) was successful but used a 4-quadrant visual world paradigm, rather than the "naturalistic" scenes used in the original study and in the current replication attempts. It is worth noting that removing variability related to participant environments (by conducting the webcam-tracking study in the lab) did not appear to improve the sensitivity of the paradigm. The primary limitation is likely to be the size of the ROIs.

Experiment 2 used the 4 quadrants of the participant's screen as ROIs. As in Johansson and Johansson (2014) and Spivey and Geng (2001), participants spontaneously looked to blank ROIs which previously contained to-be-remembered pictures. These results appeared to be robust to calibration quality. An additional manipulation, instructing participants to keep gaze fixed on a central point, was not successful. One possibility is that participants are less motivated to follow such instructions when an experimenter is not present in the same room with them. It may be possible to improve performance by emphasizing that this is an important aspect of the experiment or by providing additional training/practice in keeping the eyes still on one particular point.

Experiment 3 used 2 large ROIs (halves of the display in one analysis) and successfully replicated the novelty preference in terms of gaze duration shown in Manns et al. (2000). However, the subtler relationship between gaze duration and recognition memory on day 2 was not replicated, despite the fact that participants were able to discriminate pictures they had seen from those they hadn't seen during that delayed test. Calibration quality did not appear to impact this relationship. More work is needed to understand whether delay manipulations can be practically combined with webcam eye-tracking.

Experiment 4 used the 4 quadrants of the participant's screen as ROIs. As in Ryskin et al. (2017), listeners used knowledge of the co-occurrence statistics of verbs and syntactic structures to resolve ambiguous linguistic input ("Rub the frog with the mitten"). Across multiple time windows, participants looked more at potential instruments (mitten), when the verb (rub) was one that was more likely to be followed by a prepositional phrase describing an instrument with which to perform the action , as opposed to describing the recipient of the action (frog). Despite the qualitative replication of past findings, the overall rates of looks to various objects were much lower than in an in-lab study using infrared eye-tracking. This reduction may be related to measurement quality: effect sizes were greater for participants with higher calibration accuracy. Using the full quadrants as

ROIs, rather than bounding boxes around the four images, also appeared to improve the measurement of the effect. Crucially, there was no evidence of a delay in the onset of effects relative to in-lab work, indicating that the modifications to `webgazer` that are made within the `jsPsych` plug-in successfully address the issues noted by Dijkgraaf et al. (2017) and suggesting that this methodology can be fruitfully used to investigate research questions related to the timecourse of processing.

Experiment 5, similar to Experiment 3, used 2 large ROIs (or halves of the display). As in Shimojo et al. (2003) and in the recent webcam-based replication by Yang and Krajbich (2021), participants (qualitatively) look more at the face that they ultimately choose. This gaze bias appears to be stronger for decisions about face attractiveness than shape, though this is not supported by the statistical analysis approach used in the original paper. The gaze patterns remained consistent for participants with better calibration accuracy.

In sum, the `webgazer` plug-in for `jsPsych` can be fruitfully used to conduct a variety of cognitive science experiments on the web, provided the limitations of the methodology are carefully considered. Studies with ROIs that take up half or a quarter of the participant's display, which encompasses a large number of common paradigms, are very likely to be successful, even when testing questions related to the timecourse of processing. However, the smaller the ROIs, the more important the calibration becomes. For instance, studies with 4 ROIs may want to exclude data from participants with less than 75% validation accuracy, whereas studies using 2 halves of the display as ROIs may not need to be so conservative. Studies with smaller ROIs (see Experiment 1) may not be appropriate for webcam eye-tracking in its current form.

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