Effects of fixed vs variable landmarks on learning image-location paired-associates

1. **Data collection. Have any data been collected for this study already?**

   No

2. **Hypothesis What's the main question being asked or hypothesis being tested in this study?**

   When learning image-location paired-associates on a 2-dimensional grid, does the number of fixed landmarks improve the speed of learning? Conversely, does the number of moving landmarks cause distraction and thus hinder learning?

3. **Dependent variable Describe the key dependent variable(s) specifying how they will be measured.**

   The participants will have to learn image-location associations (paired-associates, i.e. PAs) on various 2D boards (grids). On each trial, they guess the location for a particular PA by clicking on the screen. There will be 2 blocks of 4 trials for each association, on each of the 2D boards.

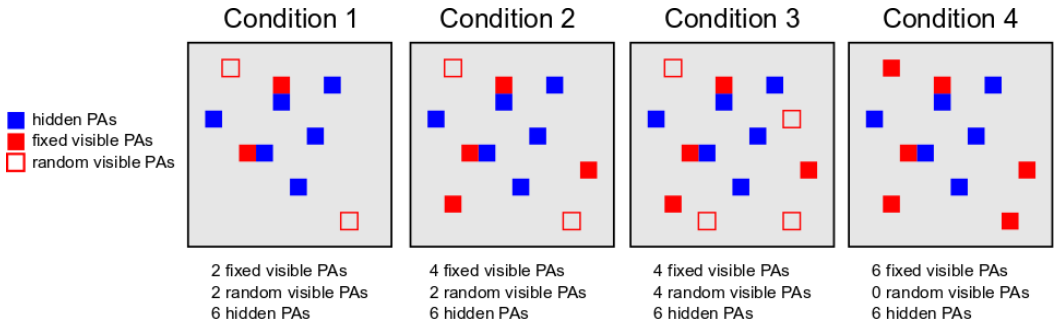
   Trial error: On each trial, error is measured as the Euclidean distance between the mouse click coordinate and the centre of the correct PA.

   Average block-2 error: For each participant and each condition, we will estimate the speed of learning by averaging the error in the 2nd block, i.e. the last 4 repetitions of each of the PAs.

   The average block-2 error will be visually inspected for normality. Appropriate data transformation will be performed if necessary for normalization. The measure will be computed separately for the near-PAs and far-PAs (see below), in addition to a combined score for all near-PAs and far-PAs together.

4. **Conditions. How many and which conditions will participants be assigned to?**

   There will be 4 within-participant learning conditions, each of which will contain a square board. Each board will contain 6 hidden items (the PAs), located at specific spots on the board. In addition to the hidden items, a number of visible items (i.e. landmarks) will be shown on the board. Some of these visible PAs will be fixed at specific locations across trials while others will move randomly anywhere on the board on every trial. The number of fixed vs random visible PAs will vary depending on the condition. See a schematic depiction below of the 4 conditions.



   On each trial of each condition, the visible PAs will be displayed on the board. Then, the visible PAs disappear and the participants will have to guess the location of a prompted hidden PA. The

trial ends with feedback showing the correct location of the hidden PA along with all the visible PAs showing up on the board again.

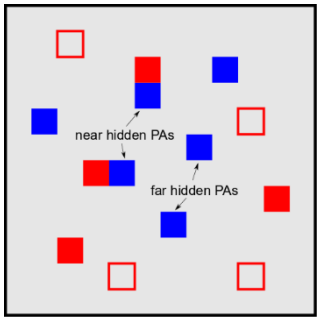
The hidden PA locations will always remain the same across trials, for every board.

For the visible PAs:

- Condition 1: 2 visible PAs will remain fixed across trials while 2 others will move anywhere on the board.
- Condition 2: 4 visible PAs will remain fixed across trials while 2 others will move anywhere on the board.
- Condition 3: 4 visible PAs will remain fixed across trials while 4 others will move anywhere on the board.
- Condition 4: All of the 6 visible PAs will remain fixed across trials.

<u>Far vs near PAs:</u>

In each condition, 2 of the hidden PAs (called “near-PAs”) will be located adjacent to visible PAs that remain stable across trials. These 2 hidden “near-PAs” will have corresponding 2 hidden “far-PAs” which are equally distant from the border of the board but which have no adjacent visible PAs that stay fixed across trials. The remaining 2 hidden PAs might or might not have adjacent visible PAs. See an example board on the right, with an example arrangement of the visible and hidden PAs.



<u>PA arrangement and learning condition counterbalancing:</u>

There will be 4 pairs of arrangements of the visible and hidden PAs: A, B, C, and D. The assignment of learning conditions (1 through 4, as described above) and PA-arrangements (A through D) is shown by an example sequence of 5 subjects:

S1 A1 B2 C3 D4
S2 A2 B3 C4 D1
S3 A3 B4 C1 D2
S4 A4 B1 C2 D3

Thus, the order of conditions is fixed but each participant starts with the next one. The sequence of PA-arrangements is fixed across participants, as a result of which condition to PA-arrangement assignment is rotated.

5. **Analyses Specify exactly which analyses you will conduct to examine the main question/hypothesis.**

   The analysis and predictions below pertain to the combined error rates on the 4 invisible PAs in the centre of the board: the 2 near-PAs and the 2 far-PAs. The other 2 invisible PA error rates will not be analysed. The decision to focus on the combined error rates of these 4 PAs was driven by the outcome of a previous experiment documented here https://osf.io/w6fs7/

   Predicted outcomes:

The figure above depicts the relevant possible outcomes. We predict that the number of fixed items will have a facilitatory effect while the number of random items will have a distracting effect (i.e. the 3rd panel above). Thus, we predict the following key inequalities will hold for the error in the following conditions:

- Contrast 1: Condition 1 > Condition 2, since Condition 2 has more fixed items.
- Contrast 2: Condition 3 > Condition 2, since Condition 3 has more random items.

The difference scores between the above conditions will be subjected to a Bayesian two-sided one-sample t-test, using the ttestBF function provided by the BayesFactor package in R. Parameters:

- rscale = 'medium' (default).
- Criteria for BF_{10} and BF01 will be set to 6.

6. **Outliers and Exclusions Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.**

   Recruitment criteria on prolific.co:

   - Current country of residence: UK or Ireland.
   - Age: 18-40
   - Fluent languages: English
   - Vision: normal or corrected-to-normal
   - Approval rate on prolific: minimum 95%
   - Minimum number of previous submissions: 2

   A participant will be excluded if they fail any of the following post-experiment QC screenings:

   - For each condition, check that the total number of missed trials OR trials with RT < 350msec are not more than 20%.
   - Each break did not last for more than 10 minutes.
   - Indication during the debriefing survey of not having understood the instructions or failed to have followed them.
   - Indication during the debriefing survey of having encountered any technical error that interfered with the study.
   - Indication that they had display issues that interfered with proper conduction of the study, such as having to scroll to see the full board before making a response.

Performance-based exclusion criteria:

- A participant will be excluded if the overall accuracy in the 2nd block (i.e. last 4 repetitions of each hidden PA, across all 4 boards) is below the 95th percentile of their participant-specific permutation-based null distribution of accuracy scores. Such distribution will be computed by randomizing the mapping between the "correct response label" on each trial (i.e. which hidden PA was prompted to be found) and the participant responses. The 96 "correct response labels" will be shuffled while keeping the participant responses unchanged, maintaining any biases or trial-to-trial response-dependencies in participants' data. Mean accuracy will be computed for each such permutation. A total of 10,000 permutations will be performed for each participant.
- A participant will be excluded if the mean accuracy in the 2nd block across all the conditions is above the Q3 + 1.5xIQR or below Q1 - 1.5xIQR of group data.

7. Sample Size How many observations will be collected or what will determine sample size?
No need to justify decision, but be precise about <u>exactly</u> how the number will be determined.

We will use a sequential Bayesian design with maximal N for data acquisition. We will start with n=20, and calculate BF_{10} and BF_{01} for the two contrasts outlined above:

1. Contrast 1: error in Condition 1 vs Condition 2.
2. Contrast 2: error in Condition 2 vs Condition 3.

If for **both** contrasts, the Bayes factors exceed the threshold of 6 (whether in support of H0 or H1) we will stop data collection. Otherwise, we will add batches of 16 more successful participants and rerun Bayes factor analysis. This will continue until either we get decisive support for both contrasts or we reach a maximum of 116 successful participants per group. Successful participants are defined as passing the quality checks.

Max n of 116 was decided based on simulating "power" for supporting one of the three following possibilities:

1. Scenario 1: existence of a true medium sized effect (Cohen's $d_1 = 0.5$) for contrast 1 and no effect ($d_2 = 0$) for contrast 2. This would support the hypothesis that only the fixed landmarks have a positive influence.
2. Scenario 2: no effect for contrast 1 ($d_1 = 0$), and a medium sized effect for contrast 2 ($d_2 = 0.5$). This would support the hypothesis that only the random landmarks have a distraction effect.
3. Scenario 3: existence of true medium sized effect for both contrast 1 and contrast 2 (i.e. $d_1 = 0.5$ & $d_2 = 0.5$).

For each of the above scenarios, we performed 10,000 simulations of our Bayesian sequential design.

The table below illustrates the frequencies of various outcomes from the simulations for Scenario 1, i.e. when $d_1 = 0.5$ and $d_2 = 0$. Note that Scenario 1 and 2 above are symmetrical, so our procedure has the same power to make the correct inference of existence of effects in both scenarios.

If Scenario 1, i.e. when $d_1 = 0.5$ and $d_2 = 0$:

For contrast 1 supports:	For contrast 2 supports:	Percent of simulations:
H1	H0	80.05%
H1	Undecided	17.64%
H1	H1	1.66%
Undecided	H1	0.01%
Undecided	H0	0.25%
H0	H0	0%
Undecided	Undecided	0.39%
H0	H1	0%
Total:		**100%**

Thus, we have 80% "power" to correctly support H1 for contrast 1 when $d_1 = 0.5$ and to correctly support H0 for contrast 2 when $d_2 = 0$. Likewise, we have 80% "power" to correctly support H0 for contrast 1 when $d_1 = 0$ and to correctly support H1 for contrast 2 when $d_2 = 0.5$.

If Scenario 3, i.e. $d_1 = 0.5$ & $d_2 = 0.5$:

For contrast 1 supports:	For contrast 2 supports:	Percent of simulations:
H1	H1	98.97%
H0	H0	0.01%
H0	H1	0.02%
H1	Undecided	0.5%
Undecided	H1	0.43%
H0	H0	0%
Undecided	Undecided	0.07%
H0	H1	0%
Total:		**100%**

Thus, we have 99% "power" to correctly support H1 for contrast 1 when $d_1 = 0.5$ and H1 for contrast 2 when $d_2 = 0.5$.

8. **Anything else you would like to pre-register?**
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

Variables for secondary analysis:

- In case the "block-2 error" is too coarse, we will also estimate learning rate from fitting an exponential function to the error across all 8 trials per condition per participant. We will fit a 2-parameter model as described below.
    - Model formula: $y = a * e^{-c*(t-1)}$ where y is the error, *t* is the trial number, *c* is the learning rate, and *a* is the intercept.
    - *a* and *b* will be bounded between 0 and maximum possible error, while *c* will have an upper bound of 4.09 determined through the procedure described below.
    - Determining the upper bound of learning rate *c*: We simulated a hypothetical learning data across the 8 repetitions, starting with the maximum possible error (~620 pixels) on the 1st repetition and immediately dropping to an error of 10 pixels (to account for the motor error in responding with a mouse) on the 2nd repetition. Fitting the 2-parameter model to such learning data resulted in the learning parameter estimate of *c*=4.09. This indicates that larger learning curve estimates will not provide substantially better fits to even a perfect learner scenario, but they would introduce skewness in the distribution of learning estimates.
    - If fitting does not converge, the fit will be visually inspected. The estimate of c will be included if the fit looks reasonable, and excluded otherwise.
    - If a participant misses trials such that no data point can be calculated for the 1st repetition of the PAs, the participant's data will be excluded.
- We will conduct similar analysis on reaction times (RTs) across trials

Contrasts for other secondary analyses:

- Within Condition 4 (6 fixed, 0 random), we will compare the performance between the 2 "near" and the 2 "far" hidden-PAs in the attempt to replicate the previous finding of near-PAs being learned faster than far-PAs (see https://osf.io/w6fs7/)

9. **Name Give a title for this AsPredicted pre-registration**
Suggestion: use the name of the project, followed by study description.

Effects of fixed vs variable landmarks on learning image-location paired-associates