**Introduction**

A principal tenet of motor learning is that skillful action requires practice, and a key component of practice is repetition.

- Talk about how after a motor skill is acquired, practice may still play an important role

- For instance, recent work has shed light on some of the effects of repetition, e.g., faster preparation time (Mawase and Haith), biasing of future movements towards repeated pattern, etc.

- Now bring in golfer example: “This may explain why our golfer continues to take thousands of practice shots long after her swing has become fundamentally sound—presumably, repetition biases her future shots towards movement patterns that increase her chances of task success…However, since no two movements can ever be identical, how consistent must the golfer’s movements be during practice to engage a repetition-based learning process?

Use-dependent learning biases future movements in the direction past movements (Classen et al., 1998; Diedrichsen et al., 2010). It is a form of Hebbian learning occurring in the motor cortex (Classen et al., 1998; Orban de Xivry et al., 2011). Use-dependent bias has been observed in reaching direction (Diedrichsen et al., 2010; Verstynen and Sabes, 2011), reaction time during reaching (Wong et al., 2017), movement speed during reaching (Hammerbeck et al., 2014), upper extremity strength training (Selvanayagam et al., 2016), hand path direction during obstacle avoidance (Jax and Rosenbaum, 2007) and walking (Huynh et al., 2014; Ochoa et al., 2017) (source).

The vast majority of studies of UDP have examined the phenomenon during upper-extremity movements. The relatively sparse literature on UDP in locomotion is surprising, given the repetitive nature of walking . Locomotion is, by definition, the repetition of a cyclical movement pattern until arriving at the desired destination. On the other hand, reaching for an object, such as a glass of water, is discrete and is usually accomplished in one movement.

The cyclical, repetitive nature of walking creates an excellent opportunity to study the use-dependent learning process. Our recent study used visual targets to guide participants into walking with an asymmetry(i.e. a limp). The asymmetric walking pattern was induced by gradually [whatever you did], and use-dependent biases were assessed throughout training during catch trials, in which all visual feedback was removed and participants were instructed to “walk normally”, as well as during a long washout phase. Use-dependent biases increased throughout the training block and persisted well into the late stages of the washout block. However, as the asymmetry was gradually introduced, we were unable to determine if the smaller use-dependent biases we observed early in training were due to less practice time or less repetition of the same movement pattern (Orban de Xivry et al., 2011; Orban de Xivry and Lefèvre, 2015).

Here, through computational modeling, simulations, and a series of behavioral experiments, we directly tackle the question of how the consistency of movement patterns impacts use-dependent learning. We first provide two distinct computational accounts of how UDP arises. In our Bayesian model, adopted from a study of reaching (Verstynen), UDP is framed as a process of combining quickly adapting prior probabilities of target (step) locations with current sensory estimates of where to step. Thus, the magnitude of use-dependent biases is directly related to the consistency of the environment, or target locations. Our second model involves two processes acting in parallel: a strategic learning process that is active when the goal is to match step lengths to visual targets (process 1), and in parallel, a slowly updating UDP process that biases movements in the direction of immediately preceding movements (Diedrichsen et al., 2010). Critically, our two-process model is much less sensitive to the consistency of the environment than the Bayesian model. Thus, we have designed a set of walking experiments that vary the amount of environmental consistency and assess the state of use-dependent biases during no-feedback trails in order to discriminate between these two competing theories on the underlying constraints of UDP.

**Materials and Methods**

**Behavioral Methods:**

*Participants****:***

Young, healthy individuals between the ages of 18-40 years will be recruited to participate in this study. Potential subjects will be included if they are naive to locomotor learning tasks. Potential subjects will be excluded if they have a history of any neurologic, psychiatric or cognitive conditions; or have any cardiovascular or musculoskeletal problems that limit their walking. This study has been approved by the (university name redacted until approved for publication) institutional review board. We expect to recruit 12-18 individuals for this study. The sample size was chosen to ensure appropriate counterbalancing of practice schedules across participants while also being well-above the threshold for good statistical power relative to documented effect sizes in comparable motor learning studies. (Diedrichsen et al., 2010; Verstynen and Sabes, 2011).

*Data replacement:*

Data will only be replaced under the following conditions:

1) If a participant does not complete the entire learning task for all 3 conditions due to 2) 3) , which will be defined as falling outside of 3 SDs from the mean performance of all other participants in terms of either

*Paradigm:*

Subjects will participate in three sessions of walking spaced 5-10 days apart. During each session they will walk on a dual belt treadmill (with the belts tied throughout the experiment) at their self-selected speed between 1.0-1.2 meters per second. Subjects will wear a ceiling mounted harness which does not provide any body weight support and hold onto a handrail for safety during all walking phases. A computer monitor placed 60 cm in front of the treadmill will provide real-time visual feedback of the subject’s step length (Figure 1A; The Motion Monitor Toolbox, Innovative Sports Training Inc., Chicago, IL, USA). A step length is defined as the sagittal distance between the leading limb’s heel marker and the trailing limb’s heel marker at the moment of the leading limb heel strike.

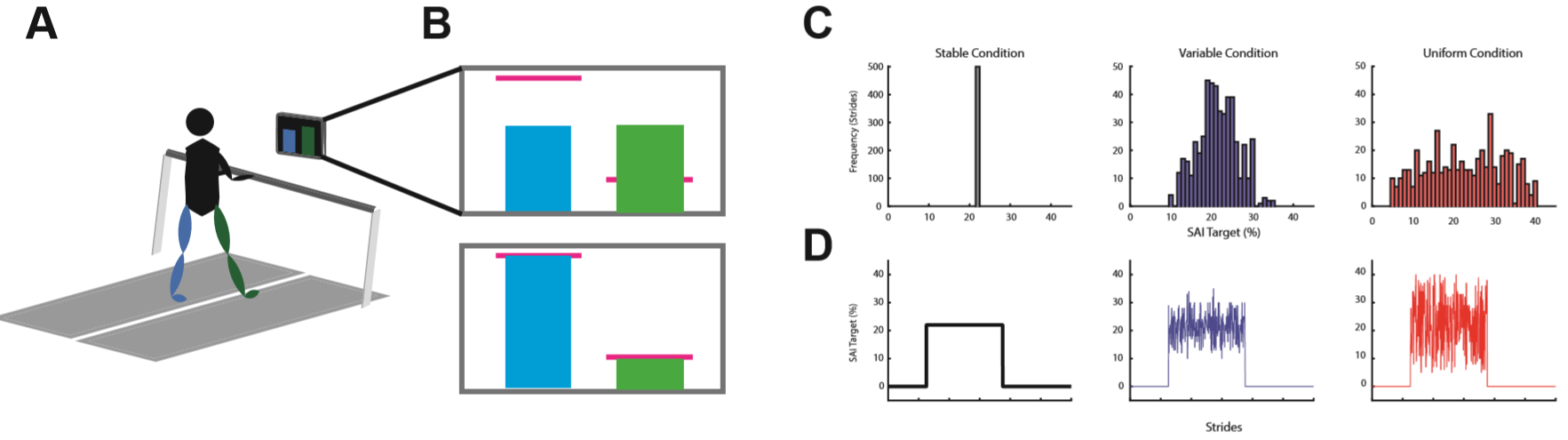
The visual feedback will be in the form of a bar graph with a blue bar representing the left leg’s step length and a green bar representing the right leg’s step length. The bars will be time synchronized with each respective limb’s swing phase, increasing in height until the limb reaches heel strike at which point the bar will hold on the screen until the next swing phase begins. There will also be a pink horizontal target line for each leg which will be derived from each subject’s current baseline step length for each session and serve as the target during that session’s Learning phase (Figure 1B).

Each of the three sessions of walking will involve the same learning schedule. Subjects will first be told to “look forward and walk normally” on the treadmill during the Baseline phase for 250 strides. One stride is defined as one left heel strike to the subsequent left heel strike. No visual feedback will be presented on the monitor during the Baseline phase. In order for participants to understand how changing each step length changes the height of the bars on the screen, during day one only, they will undergo a short (25 strides) Orientation phase –– following Baseline in which they will practice changing their step length while watching the feedback on the screen. . During the Learning phase subjects will be asked to hit the pink horizontal target lines exactly with each leg for 500 strides. During this phase both target lines will be changed, leading the subjects to take a longer step with the left leg and a shorter step with the right leg. These changes in step length will be quantified with a step asymmetry index (SAI), our primary outcome measure:

Write Equation here or provide pointer to Analysis section.

Thus, SAI represents the difference between the two step lengths normalized by the stride length. We express this measure as a percentage where 0% is perfect symmetry and SAIs further away from 0% are greater asymmetry. During the final Washout phase, the feedback will be removed from the screen and subjects will be asked to “look forward and walk normally” for 750 strides (see Supplemental Material for the full instruction script).

**Figure 1**



*Conditions:*

We will perform a fully counterbalanced, within subjects design with three different conditions, one for each walking session. The primary manipulation will be the consistency of targets during the Learning phase. Going from most to least consistent condition: 1) In the Stable condition, the target positions will be set to 22% SAI throughout the Learning phase; 2) In the Variable condition, target SAI will be drawn from a normal distribution with a mean of 22% and standard deviation of 5%; and 3) In the Uniform condition, the targets will be drawn from a uniform distribution with a range of 5%-39% SAI (Figure 1C & D). Based on our pilot testing, changing the target on a stride-by-stride basis made the task impractically difficult, thus, for both the Variable and Uniform conditions, targets will change every 1-5 strides, with equal probability.

*Data collection:*

Kinetic data will be collected at a frequency of 1000 Hz from the dual belt treadmill instrumented with two force plates, one under each belt (Bertec, Columbus, OH, USA). Kinetic data will be collected at a frequency of 100 Hz using a Vicon MX40 motion capture system with 8 cameras and Nexus software (Vicon Motion Systems, Inc., London, UK). We will use a custom marker set with 7 retroreflective markers, one for each heel, lateral malleolus, and 5th metatarsal head. The seventh marker will be placed on the left 1st metatarsal head. Kinematic data will be time-synchronized with kinetic data in Nexus.

*Proposed analysis pipeline:*

First, any gaps in the kinematic data will be filled using a Woltering filter for small gaps (1-4 frames) and Pattern Fill for larger gaps (>4 frames) in Nexus. The remainder of the data analysis will be performed with custom-written MATLAB scripts (Mathworks, Natick, MA, USA). The code/software described in the paper is freely available online at [URL redacted for double-blind review]. The code is available as Extended Data. Kinematic and kinetic data will be low pass filtered at 10 Hz using a 4th order Butterworth filter. Kinetic data will be used to detect heel strike events when the force plate reads greater that 20 N and toe off events when the force plate reads less than 20 N. Erroneous force plate events will be removed and replaced with kinematic events. For heel strikes this is the most anterior position of the heel marker in the sagittal plane, for toe offs this is the most posterior position of the 5th metatarsal head in the sagittal plane. Step lengths will be calculated as the sagittal difference between the leading and trailing heel markers at the moment of leading heel strike. Step lengths will be used to calculate our primary outcome, step asymmetry index (SAI), which is expressed by this equation:

We will remove any SAI baseline bias for each subject for each respective training session: the mean of the last 50 strides of baseline will be subtracted from all strides for that respective session. The baseline corrected measure will be used for the remainder of our analysis.

To assess how well subjects performed on the learning task, we will calculate SAI accuracy as the absolute difference between the target SAI and the actual SAI during the Learning phase. We expect that the SAI behavior during the learning phase will follow the targets reasonably well. Mean differences for the learning phase will be used as a general measure of accuracy to test how well subjects were able to perform the task. If a subject’s accuracy falls outside 3 standard deviations of all behavior this subject will be replaced.

To determine how well the overall distribution of SAI targets during learning matched the distribution of SAI behavior during learning we will determine the mean and standard deviation of the entire Learning phase for both for these measures. We expect that mean SAI behavior during the entire learning phase *will not* be different between the conditions. Furthermore, we expect that the standard deviation of SAI behavior during the entire learning phase *will* be different between conditions. We will test these differences with a repeated measures analysis of variance and post-hoc pairwise comparisons if necessary. If we are incorrect in these assumptions, we will still be able to compare aftereffects at Initial Washout as a ratio of the total amount of SAI during the learning phase.

Our primary dependent variable of use-dependent bias will be calculated as the mean SAI during the first 10 strides of the Washout phase (Initial Washout). As the primary behavioral comparison, we will analyze the measure of use-dependent bias across conditions using a repeated measures analysis of variance and post-hoc pairwise comparisons if necessary. To further assess any differences during the Washout phase, we will analyze SAI differences between conditions across the entire Washout phase using a cluster permutation analysis. We will also analyze the rate of washout using a regression analysis (Kitago et al., 2013) and compare these rates with a repeated measures analysis of variance with post-hoc pairwise comparisons if necessary.

We will report exact p values for all statistical tests. We will report for each test: t-statistic values for t-tests and F-statistic values for repeated measures analysis of variances. Standardized effect sizes will be reported as ƞp2 for repeated measures analysis of variance, and as Cohen’s d for t-tests. To express uncertainty in our data we plan on reporting means and 95% confidence intervals using a bootstrap approach for all data. When plotting subject data at specific timepoints, we will plot means, 95% confidence intervals and individual data. We will check assumptions of normality of residuals for linear models and of the actual SAI data for t-tests with the Shapiro-Wilks test of normality. We assume that the data we collect will be normally distributed, but if we are wrong, we plan on using non-parametric testing.

**Modeling**

We have adapted two computational models of use-dependent learning which make dissociable predictions regarding the effect practice consistency has on use-dependent bias. One is a Bayesian model (Verstynen and Sabes, 2011) the other is a two-process model (Diedrichsen et al., 2010).

*Adaptive Bayesian Model:*

We first consider a Bayesian model which predicts the appropriate step length through weighted combination of expected target locations based on prior history with current sensory estimates of target location. The sensory estimate may become biased based on prior experience. The more consistent (i.e. less variable) the prior experience, the more certain it becomes as more weight is given to prior experience. Therefore, subsequent world state estimates become more biased toward a more consistent prior. If the prior experiences are inconsistent (i.e. more variable), there is a reduced weight on prior experiences. Thus, subsequent world states are less biased toward the inconsistent prior. The Bayesian estimation framework predicts a dependence on consistency of practice in the use-dependent process.

In the context of the current study, this model combines the prior expectation of the step asymmetry target with the current sensory estimate of target position to equal the posterior probability distribution. The model assumes that the motor output is a direct readout of the maximum a posteriori (MAP) estimate (, as in Verstynen and Sabes (2011)::

And . We assume that the likelihood is centered around the actual target on each stride, , . The likelihood’s standard deviation ( is a free parameter representing the amount of sensory uncertainty regarding target location. The adaptive nature of the model is encapsulated by the stride-by-stride updating of the prior probability’s parameters (, σ2 prior)are :

Where is a free parameter representing the learning rate and constrained to be between 0 and 1.

, and were initialized to 0. and

*Two-process model:*

In contrast, use-dependent plasticity can be conceptualized as a stride-by-stride update which becomes more biased in the direction of the motor output (Diedrichsen et al., 2010). In this model, the motor output, in this case SAI, is being modeled. This process can occur simultaneously with other processes which are error based and more directly influence the motor output. In the current study, this error-based process is strategic aiming (French et al., 2018). In the two-process framework the use-dependent process is a low-level bias which only changes based on only the direction, not the consistency, of the motor output. Therefore, two-process model predicts that the use-dependent aftereffect does not depend on the consistency of prior movements. This model’s behavioral output is SAI () on each stride. Each stride’s SAI is the sum of the strategic process () and the use-dependent process ():

The strategic process corrects errors () between the motor output () and the target ():

When the visual feedback (VF) and thus no target is present on screen, a proportion () of this error is corrected on each stride and is added to a proportion () of the prior strategy. If a target is not present and no visual feedback is seen by the subject, the strategy is set to 0:

Where is the error correction rate and is the strategic retention rate. We assume that strategy is set to 0 during the Baseline and Washout phases because there is no visual no target on the screen. We also ask subjects to walk normally during this phase which we assume effectively eliminates any strategic component of learning. This leaves only the use-dependent process to be observed during the Washout phase. The use-dependent process () learns a proportion of the current behavior () and retains a proportion of the current use-dependent process:

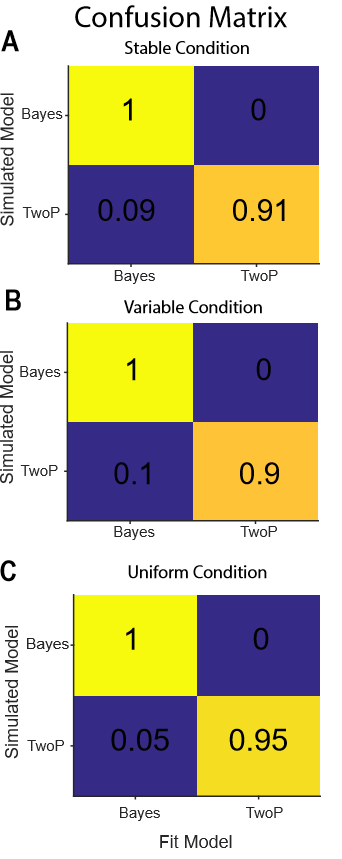
Where is the use dependent retention rate and is the use-dependent learning rate. We constrained all parameters between 0 and 1. All parameters were initialized to 0. Since we assume that the use-dependent process learns slowly and decays slowly, while the strategic process learns quickly, we constrain to be the lowest parameter in relation to the others.

We determined that both models demonstrate good parameter recovery (Supplemental Figure 1A and B). To recover parameters, we simulated both models using uniformly chosen parameters within the constraints provided above. The only exception is for the F parameter of the two-process model. This parameter was initialized between 0 and 0.2 as initialized values above this value create instability in model fits. Next the simulated models are fit with MATLAB’s fmincon function using a sum of squares objective function. Both the simulated and fit parameters are recorded and plotted against each other. These plots are provided in Supplemental Figure 1A and B with both models demonstrate consistency in the simulated and recovered parameters. This process also revealed that the recovered parameters are not correlated (Supplemental Figure 1C).

*Model Comparison:*

First, we sought to determine if the models are distinguishable and determine an adequate method of comparing them. We performed model recovery analysis by comparing fits for each model after simulating both models with randomized parameters. The model which generated the simulation should demonstrate better fits when using that same model. We fit the simulated data with the same fitting procedure as above. This procedure was performed 100 times and revealed that each model is more likely to have better fit statistics for the data generated by itself. Furthermore, Akaike Information Criterion (AIC) is an adequate method to distinguish between the two models (Figure 2).

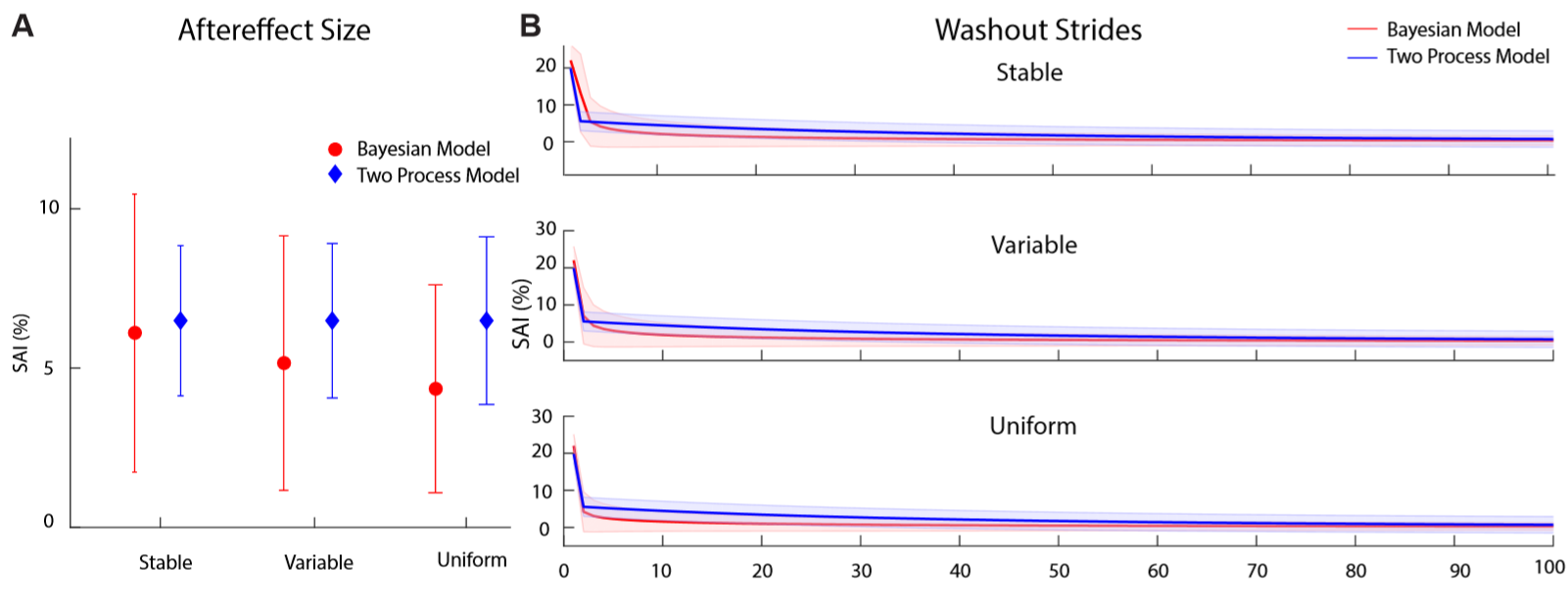
**Figure 2**

After data are collected, we will fit both models to individual subject data for each condition to obtain parameter values using the fitting method as above. We will assess the face validity of each model’s range of parameter values for the fitted models. We will further simulate each model with the fitted parameters as a posterior predictive check. We will then analyze these simulations in the same way we will analyze the empirical data. We will also use our selected objective model comparison method, AIC, to compare the model fits. Using the objective criteria, AIC, we will determine the number of subjects for all conditions best fit by each model.

*Simulations:*

To obtain parameters for model simulation, we fit the models to previously collected walking data. We used 10,000 bootstrapped samples and fit each sample to the models using MATLAB’s fmincon function (Supplemental Figure 2). We simulated 1000 experiments with 18 subjects in each of the Stable, Variable and Uniform conditions. To obtain a range of possible outcomes, we simulated over a range of possible parameters based on the fits from the prior data. Each simulated experiment sampled parameters from a normal distribution with a mean and standard deviation equal to that of the parameter fits from prior data. Figure 3A details the predicted aftereffects between the two models across the conditions. The two-process model predicts the conditions will demonstrate similar aftereffects regardless of the condition while the Bayesian model predicts that aftereffects will be reduced with less certainty in the learning targets. Figure 3B depicts simulated SAI behavior for the first 100 strides of the Washout phase for each condition. The models also predict differences in the rate of washout for each condition with the Bayesian model predicting changes in rate across conditions while the two-process model predicts no change in the rate of washout across the different conditions.

**Figure 3**



**Timeline for completion:**

We have received IRB approval from our university for this project. All labs have been shut down due to the COVID-19 pandemic. Data collections are ready to be initiated as soon as human research resumes at the university. Labs are currently mandated to be shut down until May 15th at the earliest. If we allow 4 months for data collection, analysis, and writing this leaves us with a proposed resubmission data of September 15th. Since we are uncertain if the May 15th date will be extended, we offer a proposed resubmission window from September 15th to February 15th, 2021.

**Figures:**

* Figure 1: experimental paradigm
  + Figure 1A: experiment set up (include step length)
  + Figure 1B: visual feedback
  + Figure 1C: Target distributions (histogram)
  + Figure 1D: Stride by stride learning targets
* Figure 2: Confusion Matrices
  + Figure 2A: Stable condition confusion matrix
  + Figure 2B: Variable condition confusion matrix
  + Figure 2C: Uniform condition confusion matrix
* Figure 3: Model simulations
  + Figure 3A: Aftereffects
  + Figure 3B: Washout simulations

**Supplemental material:**

* Instruction script
* Parameter recovery (S1)
  + Correlations between recovered parameters
* Fits and parameter values for prior data (S2)

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