*Model Recovery*

Due to the central importance of model selection in the proposed study, we performed model recovery analysis in order to 1) confirm that the models are distinguishable under ideal circumstances (Hardwick et al., 2019; Wilson and Collins, 2019) and 2) identify the ideal method of model comparison for this situation (between Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC); Wilson and Collins, 2019). We first sequentially simulated data 1000 times per condition with both models using randomized parameter values obtained by fitting data from a similar study (details in Simulations section). We then fit the simulated data with each model, calculating AIC scores for each model fit and directly compared the two values. A confusion matrix summarizes this process, providing the probability that the model which generated the simulated data was better fit by itself or the other model. Ideally, the model that generated simulated data will be better fit by itself than by the other model, resulting in values closer to 1 when comparing the simulations and fits from the same models (lighter colors on main diagonals in Figure 2) and values closer to 0 when comparing simulations and fits from opposing models (duller colors on off-diagonals in Figure 2). In Figure 2, we show one confusion matrix for each condition and a combined confusion matrix which reveals that the models are distinguishable under these ideal circumstances when using AIC as an objective model comparison criteria. We performed the same procedure for BIC, however this analysis revealed reduced model discriminability (i.e., smaller range between on- and off-diagonal values in the confusion matrix). Therefore, this analysis demonstrates that the two models are distinguishable under these constraints and that AIC is better-matched for the current experiment.

*Simulations:*

We simulated both models to demonstrate how each accounts for the consistency of practiced target step lengths. The Strategy plus Use-Dependent model is robust to environmental consistency in cases, as here, where there is a large asymmetry in one direction. The model assumes use-dependent learning is slower to learn and washout than cognitive strategies; therefore, as long as the practiced asymmetry is much larger than the current state of use-dependent learning, the consistency of target step lengths has minimal impact on its output. The Adaptive Bayesian model stands in direct contrast to this framework. In this model, the MAP estimate, and thus the observed use-dependent bias during Washout, is sensitive to environmental consistency: The more consistent (i.e. less variable) the schedule of target step lengths, the more biased towards the prior (i.e., away from the likelihood) the MAP becomes; conversely, the more variable the schedule, the less weight is given to the prior and the more the MAP is pulled towards the likelihood (i.e., the actual target location).

Preliminary model parameters were obtained by fitting the models to walking data (n=16 participants) from [withheld due to double-blinding], which used a protocol most similar to the Constant condition that we currently propose. (R-squared values: Adaptive Bayesian model = 0.895 ± 0.019; Strategy plus Use-Dependent = 0.870 ± 0.021 [mean ± SEM]). We then simulated our proposed experiment 1000 times with the mean learning function from each bootstrapped sample of the individual parameter fits. Figure 3 details the simulated data from these parameters for each condition. The panels in Figure 3A show each model simulation for the entire experiment. Across all 3 conditions, the models diverge in their predictions regarding use-dependent biases during the Washout phase.

We plotted use-dependent biases during both Initial Bias and Early Washout (Figure 3B and C). Overall, the Strategy plus Use-Dependent model predicts more consistent use-dependent biases across conditions for both Initial Bias and Early Washout. However, the Adaptive Bayesian model demonstrates consistently decreasing bias when the conditions become less stable during the Learning phase. For our third point of direct comparison between model predictions, we also analyzed the washout rates for each model (Figure 3D). The Strategy plus Use-Dependent model predicts a consistent washout rate across conditions, whereas the Adaptative Bayesian model predicts slower washout as the conditions during Learning increase in variability. Based on these simulations, if the Strategy plus Use-Dependent model is a more accurate model, we will observe similar use-dependent biases between conditions; however, if the Adaptive Bayes model is more accurate, we should observe different use-dependent biases between conditions.

*Pilot Data:*

To assess the feasibility of our behavioral methods, and specifically, to determine if individuals are able to follow frequently changing step length targets, we collected pilot data from 3 individuals for the High Variability condition, with 2/3 of these individual also completing the Constant condition (see Figure 4). The pilot results show that participants were able to follow the feedback during the High Variability condition with a mean absolute distance of 4.2 cm from the targets (Figure 4A). Furthermore, we correlated step length targets with actual step lengths for each subject during the Learning phase: mean R-value = 0.59 and 0.78 for the right and left step lengths, respectively (p < 0.0001 for all). We also calculated the Initial Bias and Early Washout for those participants who completed both the Constant and High Variability conditions (Figure 4B & C). The pilot results are also consistent with our assumption that, during the Learning phase, SAI means will be similar across conditions (Learning SAI mean), but SAI standard deviation (Learning SAI σ) will be different (Figure 4D). These pilot data will not be included in the final analysis.