Investigating individual differences in latent structure learning in a changing environment

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Background

Whether faced with the volatility of the stock market or the availability of goods on grocery store shelves during the pandemic, it is important to learn adaptively in changing environments. Critical to successful adaptive learning is the ability to identify the relevant causal aspects of the environment (known as latent structure) in order to figure out which changes are enduring and which are momentary.

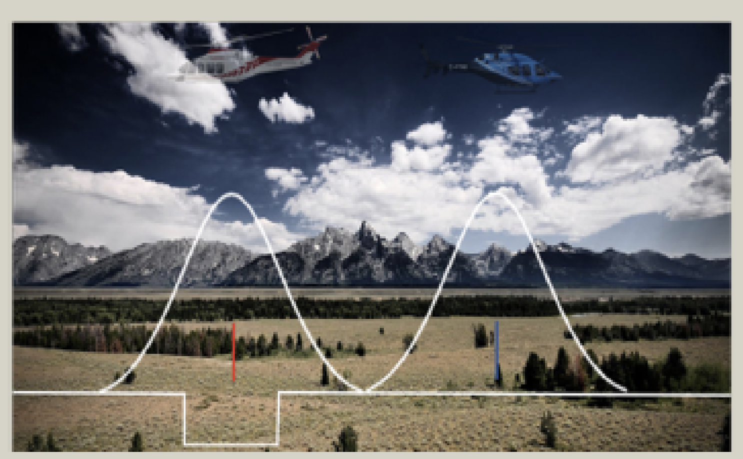
Individuals exhibit great variability in how much they change behavior in response to deviations from expectations, and in how well they recognize latent structure in tasks (Nassar & Trioani, 2020; Collins & Koechlin, 2012; Vaidya et al., 2020).

The characteristics that underlie these individual differences are not well known, but identifying them would be beneficial for policy, business, and health interventions. The objective of this study is to characterize the neural and behavioral architecture of individual differences in latent structure and adaptive learning in a large sample of participants.

Participants and Methods

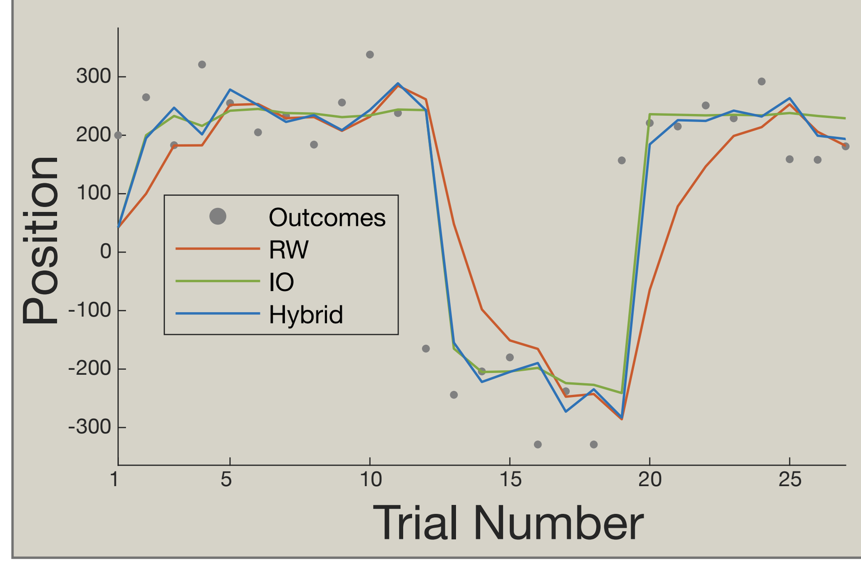
Participants: 294 healthy individuals (ages 17-30, median age = 20), (96 male, 198 female)

Task: Latent-state predictive learning task



Participants are asked to maximize their earnings by finding the hidden helicopter locations (means of two, alternating distributions) using locations of reward outcomes

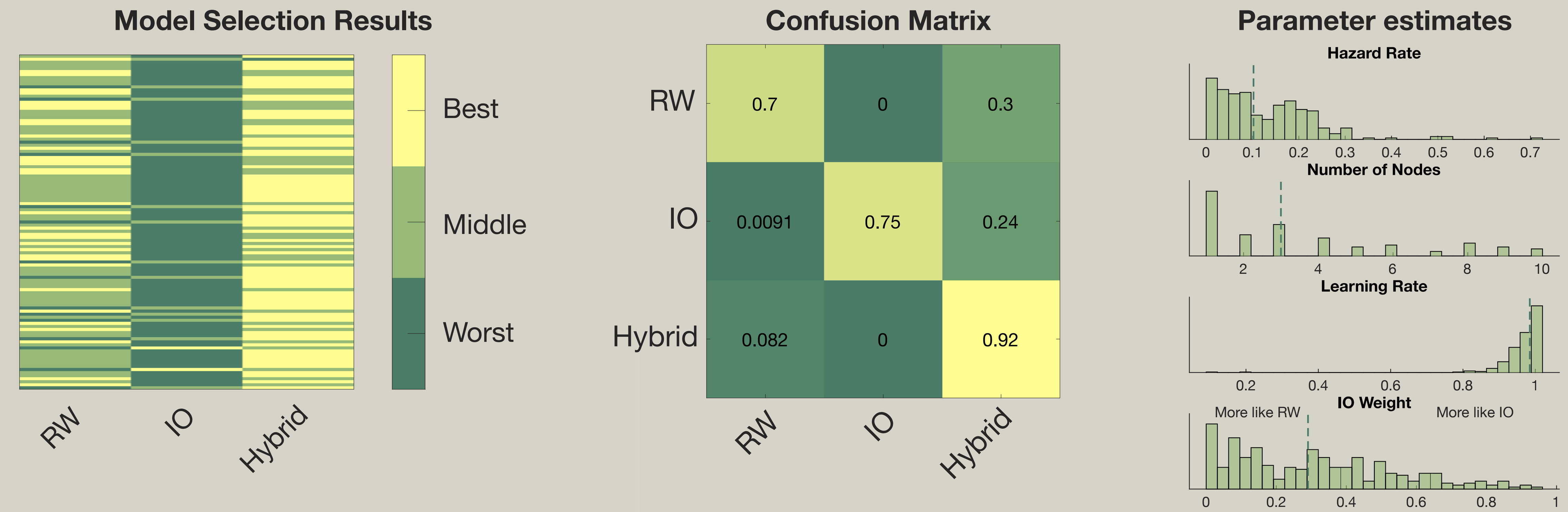
Models: Rescorla-Wagner (RW), ideal observer (IO), and hybrid



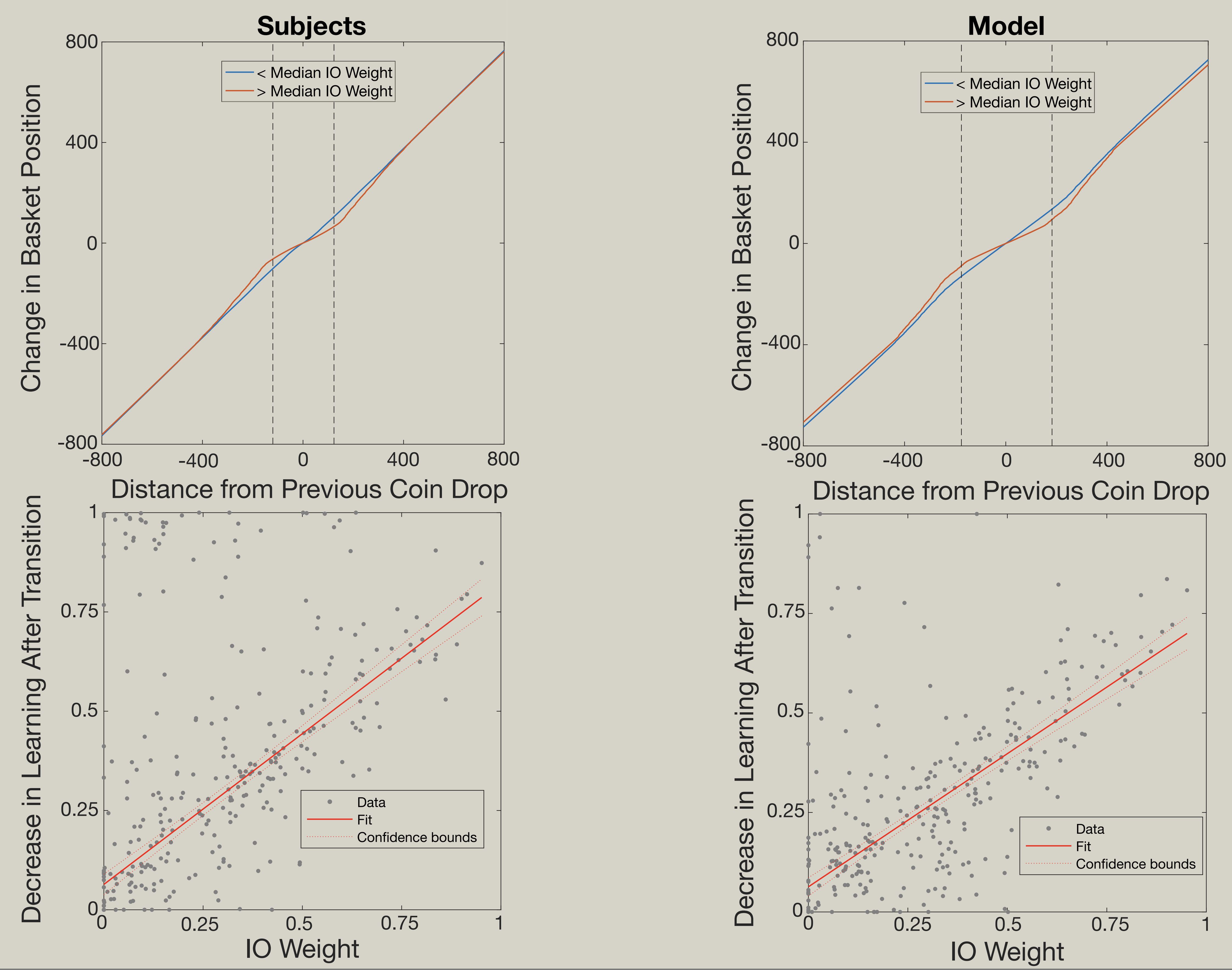
RW: updates proportional to error from previous outcome
IO: Bayesian inference on most likely locations of helicopters under the assumption there are two states
Hybrid: weighted linear combination of predictions from RW and IO models, fits that are more similar to IO model have a greater value for the 'IO weight' parameter

The hybrid IO/RW model best explains subject behavior

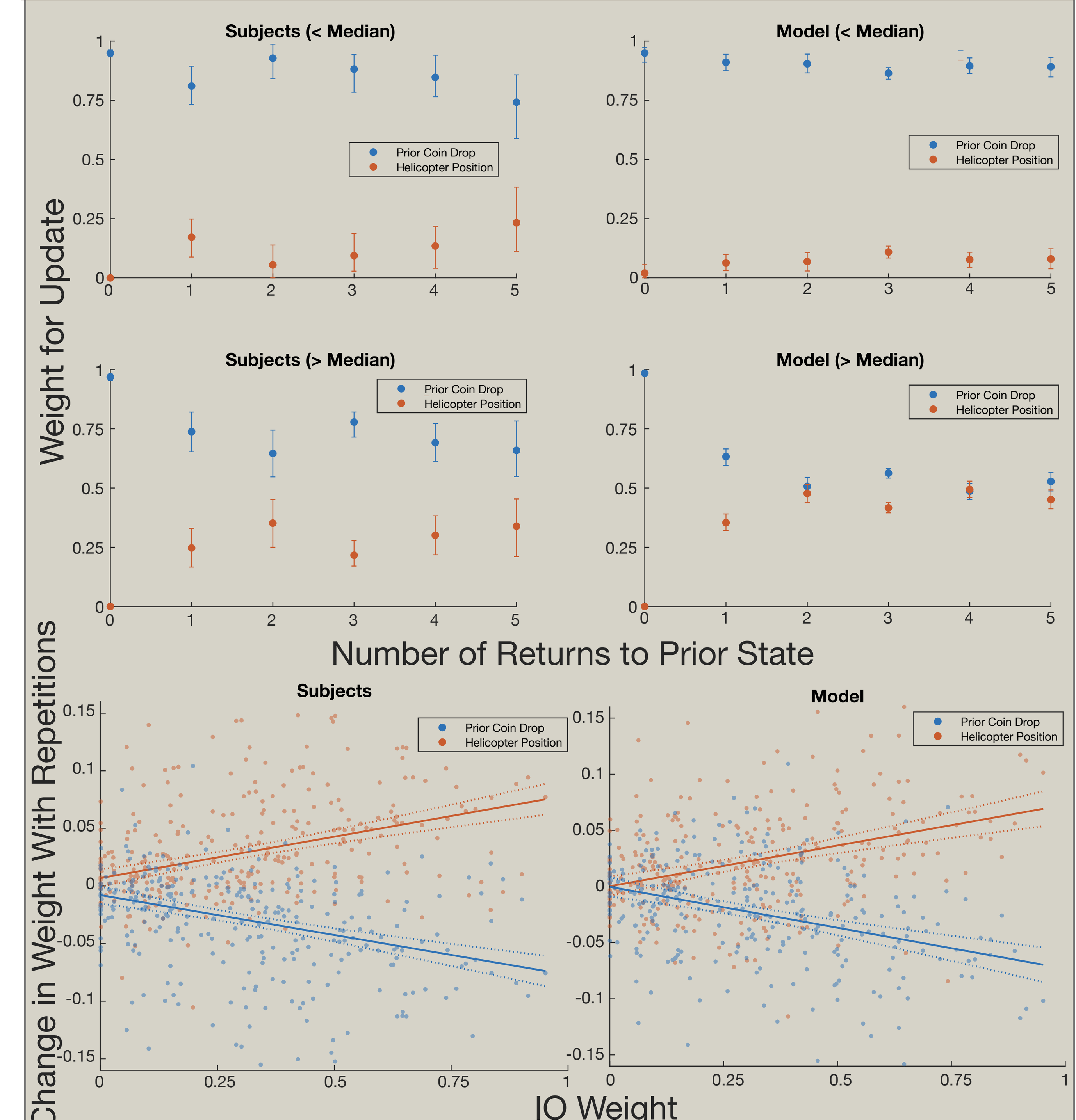
Most subjects are best fit by the hybrid model



The hybrid model captures differences in learning after state transitions



Subjects with high weights for the IO model rely more on the helicopter position during updates



Discussion

A weighted, linear combination of an RW model and IO model is best able to account for the large variability in subject behavior

Subjects fit by models with greater IO weights show reduced learning after changes in state

Subjects fit by models with greater IO weights have updates at transitions that are more influenced by the true position of the helicopter with time at both the group and subject levels

Some of the observed effects are exaggerated in models; in the future we plan to investigate additional models that create a new latent state at transitions as opposed to reusing past states

References

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