Reinforcement Learning Models of Dynamic Risky Decision Making in Rats

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INTRODUCTION

- Risky choice paradigms present individuals with choices between a single certain outcome (e.g., 2 pellets) and a variable risky outcome (e.g., 1 vs. 5, 0 vs. 4 pellets).
- Variable choice outcomes may be more ecologically valid.[1]
- Different procedures differentially affect how previous outcomes influence subsequent choice,[2,3] which may be due to the relationship between outcome magnitude and the expected value of other outcomes in the environment.[2]
- Hypothesis: Probabilistic presentation of differential risky outcome magnitudes may shift the encoding of risky gains and losses, altering riskiness following these outcomes
- Goals: (1) Determine how risky loss magnitude/probability affect risky choice; (2) Determine if common reinforcement learning (RL) models can account for such effects

METHODS

- 24 experimentally-naïve male Sprague Dawley rats
- Risky (R-0, R-1, R-11) vs. certain choice (C-2, C-4)

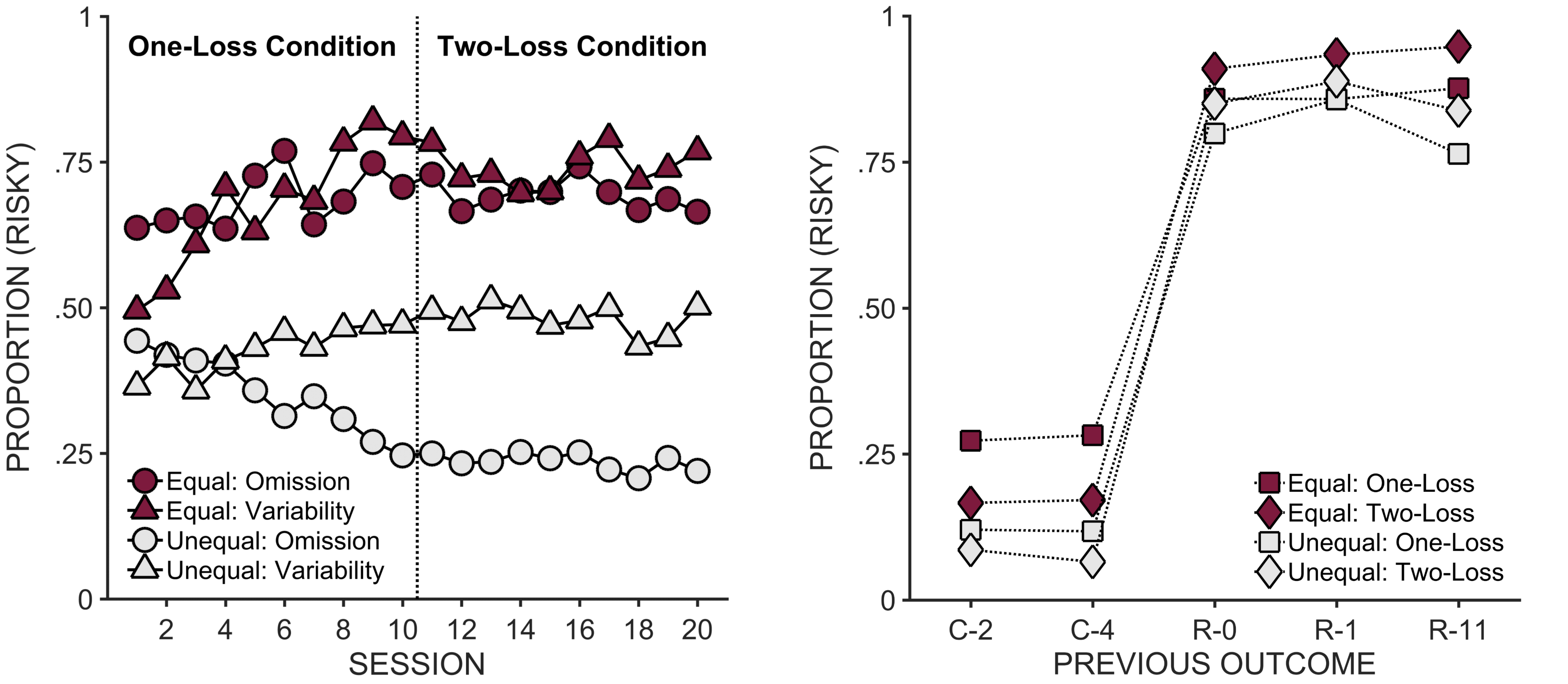
Group	Risk Paradigm	Risky Choice Task Phase	
		One-Loss	Two-Loss
		Outcome (Probability)	Outcome (Probability)
Equal-Risk (n = 12)	Risk-Omission	R-0 (.50) R-11 (.50)	R-0 (.33) R-1 (.33) R-11 (.33)
	Risk-Variability	R-1 (.50) R-11 (.50)	
Unequal-Risk (n = 12)	Risk-Omission	R-0 (.67) R-11 (.33)	
	Risk-Variability	R-1 (.67) R-11 (.33)	

REINFORCEMENT LEARNING (RL)

- Three models: Simple,[4] Asymmetric,[5] Valence-Attentive RL[6]
- Model Selection: Akaike Information Criterion (AIC)

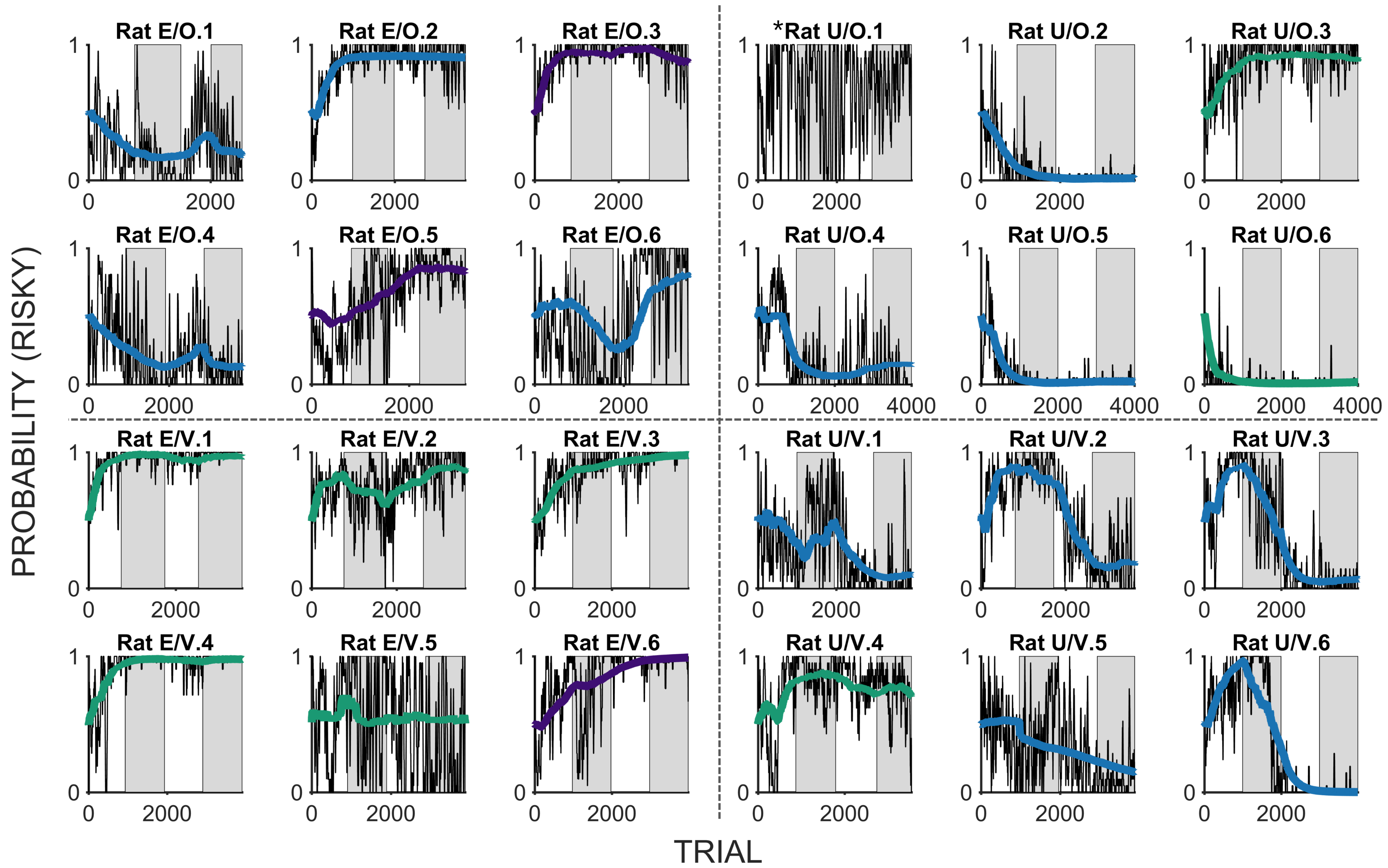
Simple	Asymmetric	Valence-Attentive
Constant value-updating rate for gains and losses	Separate value-updating rates for gains and losses	Differences in attention to gains and losses

RESULTS: GLOBAL AND LOCAL CHOICE BEHAVIOR



- Globally and locally, Group Equal-Risk was riskier than Group Unequal-Risk, even when there were equivalent expected values in the Two-Loss conditions
- The added 2nd loss (Two-Loss) elicited greater post-outcome staying behavior

RESULTS: RL MODELS



- Smoothed data (—) vs. best-fitting model of data
- Overall, Asymmetric RL provided best fit (median ω^2: Asymmetric = .30; Valence-Attentive = .26; Simple = .16)

- **E**: Equal-Risk; **U**: Unequal-Risk; **O**: Risk-Omission First; **V**: Risk-Variability First
- **Asymmetric RL** best fit 12 rats; **Valence-Attentive**, 8; **Simple**, 3; *Rat U/0.1 not fit well by models

DISCUSSION

- Loss frequency has distinct effects on global and local risky choice behavior.
- Asymmetric RL provided best overall account of data out of the models tested.
- The lack of convergence in the model fits suggest that basic RL models may not reflect dynamic decision making mechanisms in this task, warranting further model development and testing (e.g., model-based RL, Bayesian models)

REFERENCES & ACKNOWLEDGMENTS

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