



A naturalistic reinforcement learning paradigm for characterizing real-world risky behavior

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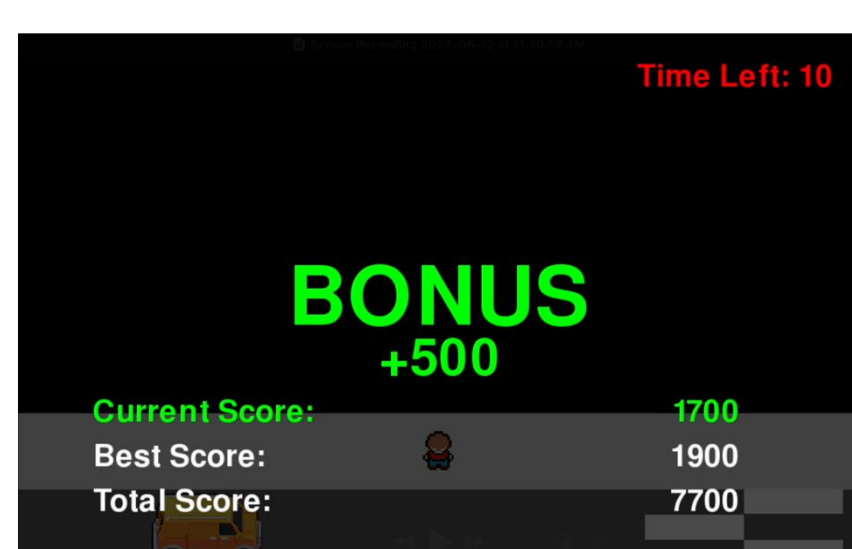
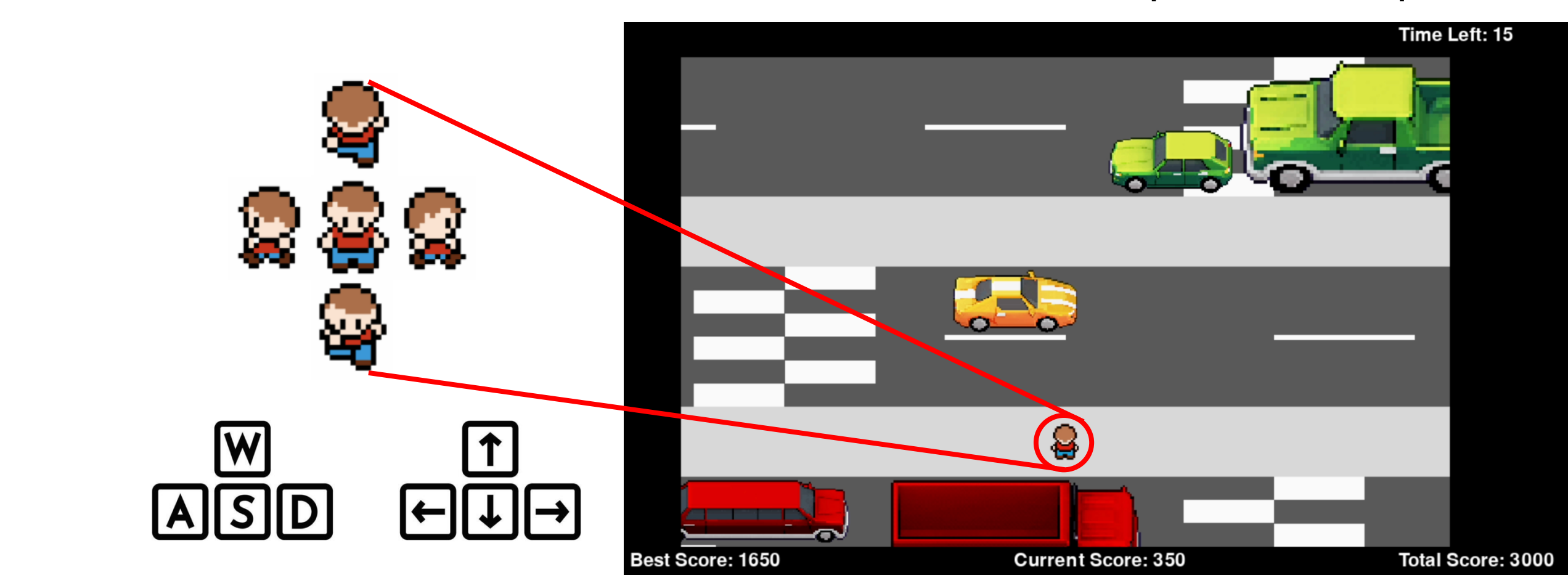
Professional Profile

Introduction

- **Naturalistic reinforcement learning** suggests that real-world behavior emerges from continuous, dynamic, and context-dependent interactions (Wise et al., 2024).
- Recent studies have shown that impulsive behaviors observed during a **real-time driving task** can reflect individual differences in trait-level impulsivity and are linked to reward-related neural responses (Lee et al., 2024a,b).
- **Road-crossing behavior** has also been used as a naturalistic paradigm to assess risk-taking propensity, but prior work has not fully captured the continuous dynamics of real-time decision making (Herrero-Fernández et al., 2016; Rubio et al., 2010).
- To address this gap, we developed the **crosswalk task**, a naturalistic real-time decision-making task designed to capture individual differences in risk-taking.

Crosswalk Task

- **Goal:** cross all the roads and reach the end of the map as fast as possible



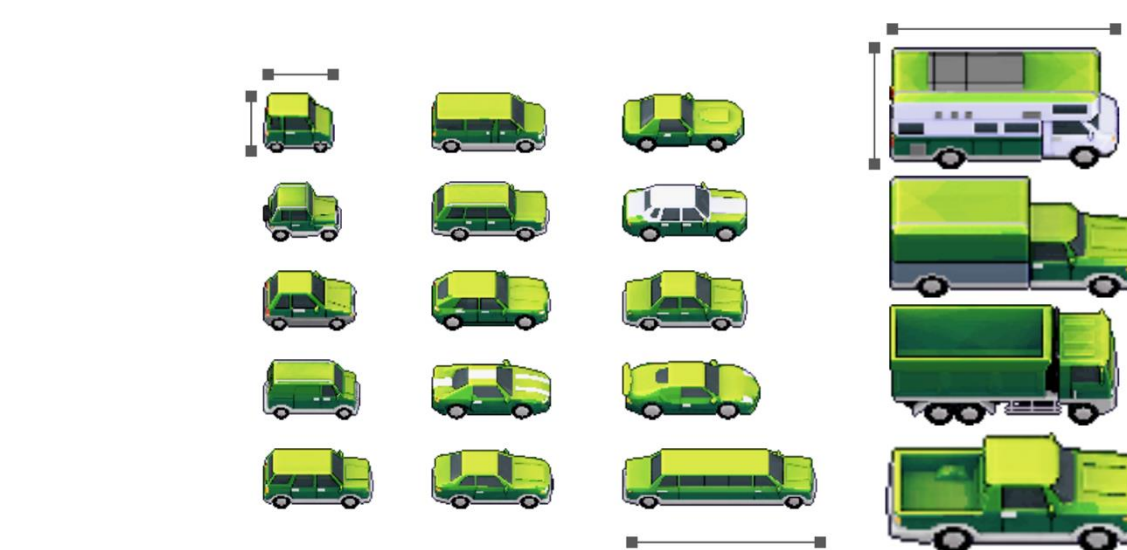
- Road-crossing reward
- Episode completion bonus



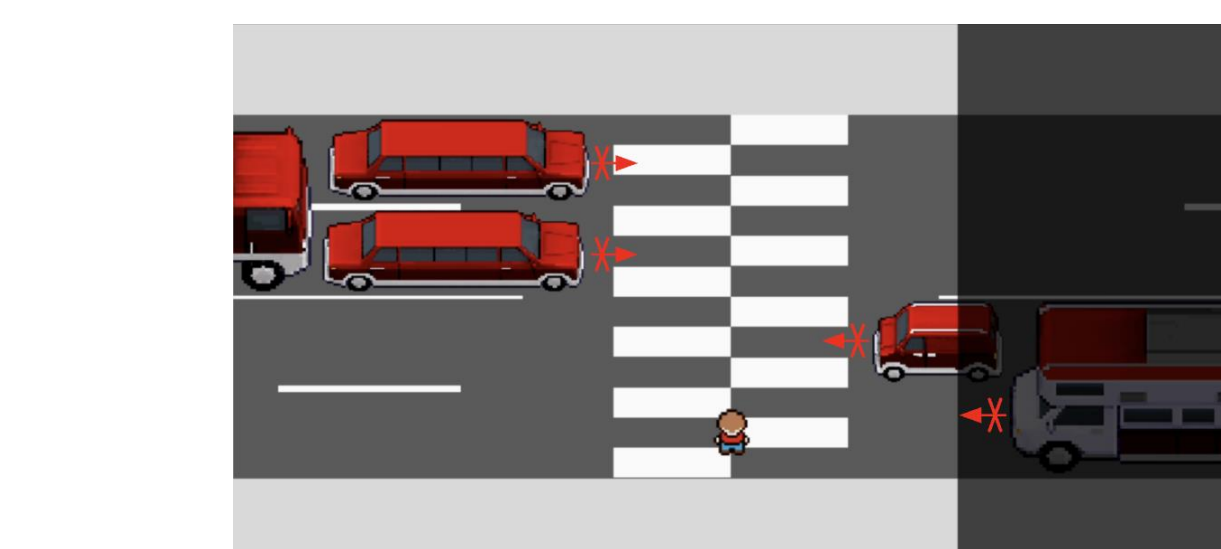
- Collision penalty based on car color
- One car color per road



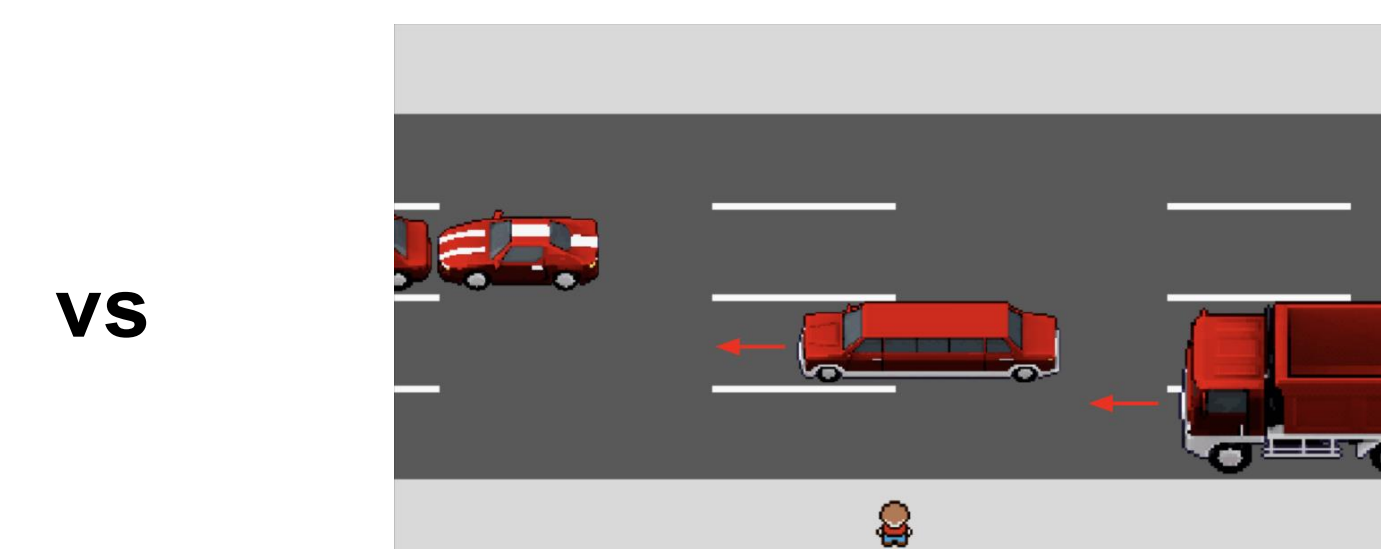
- Episode time limit: 30 seconds



- Size variation => varying crossing difficulty



Crosswalk Activation: risk-averse strategy



Jaywalking: risk-taking strategy

Results

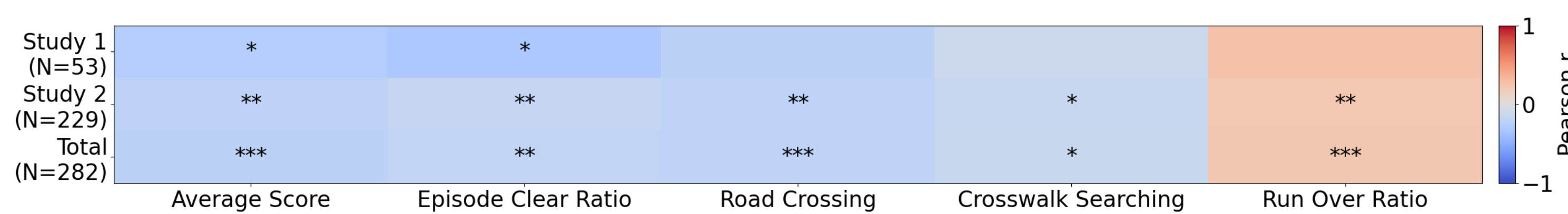
Identifying Indicators of Risk-Taking

- Goal: Identify crosswalk task features correlated with DOSPERT

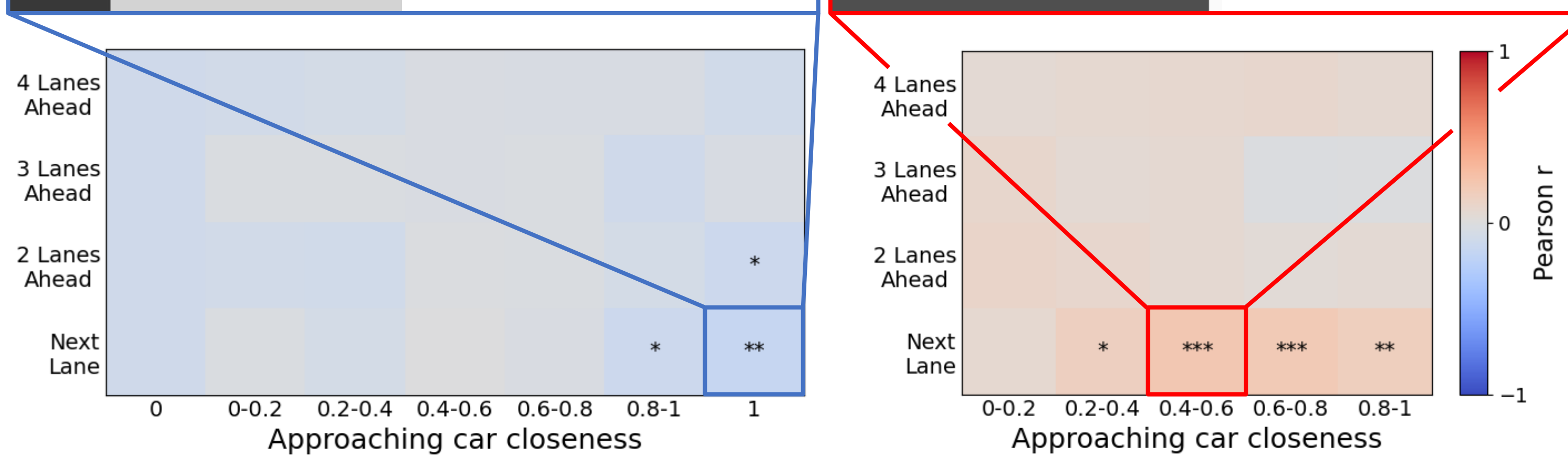
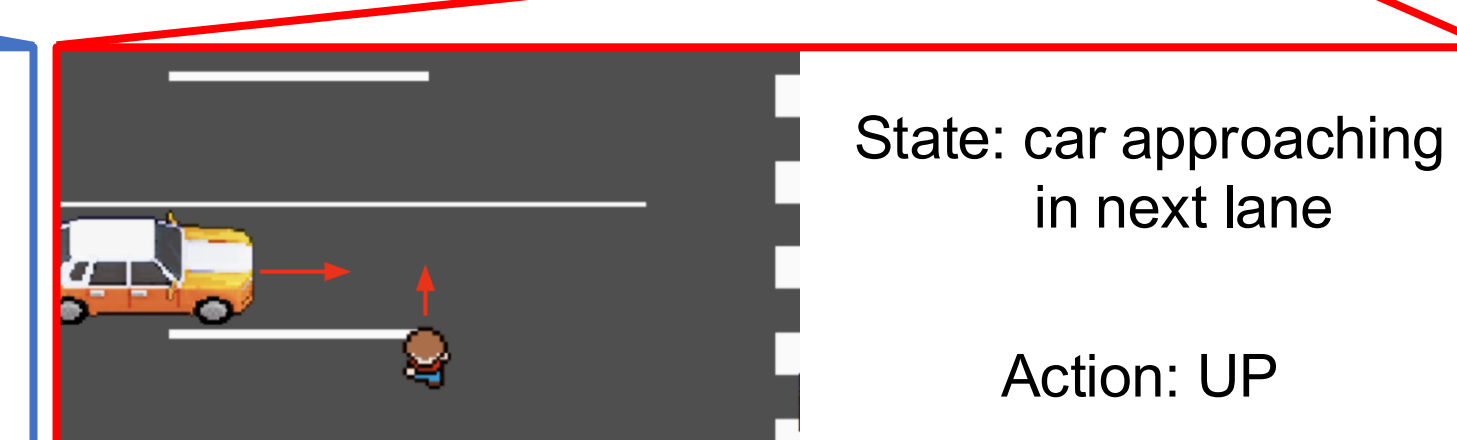
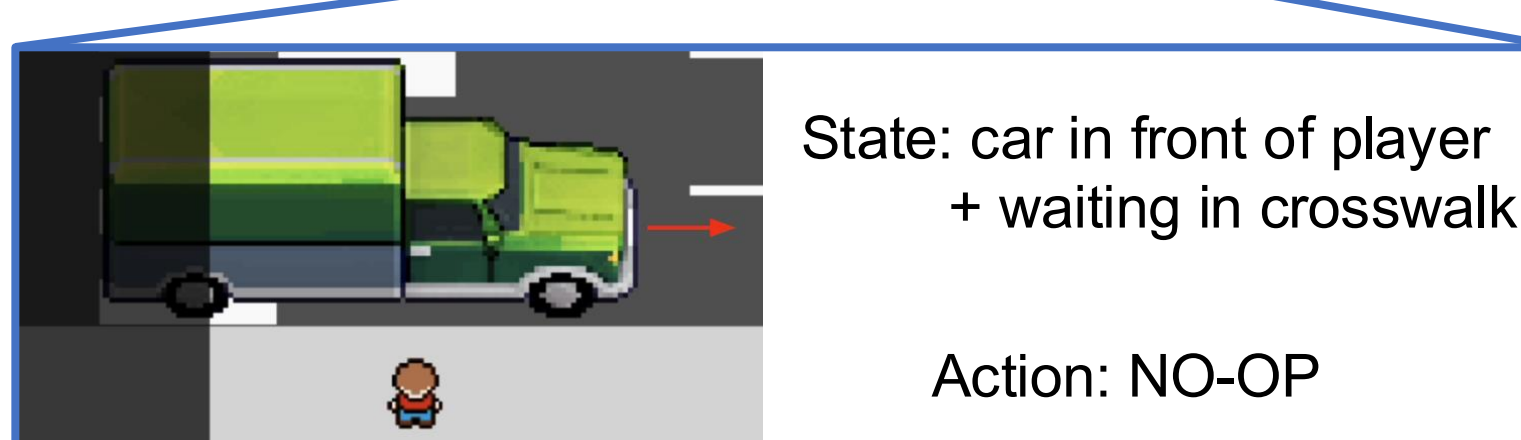
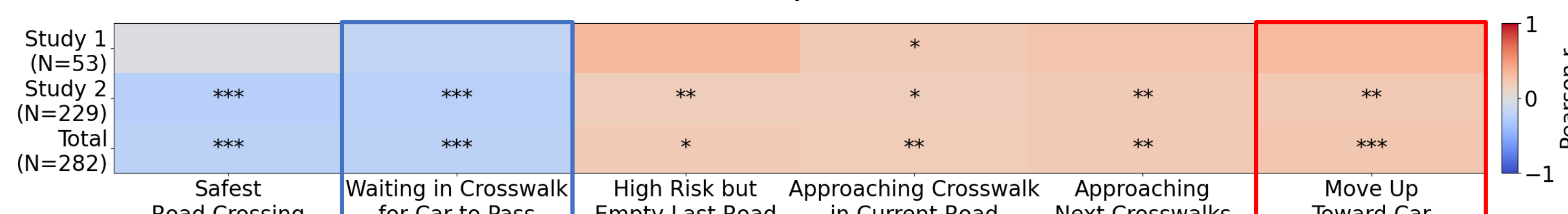
- **Behavioral features:** task-level summary statistics

- e.g., run-over ratio = car collisions / total episodes;

road-crossing success ratio = successful crossings / encountered roads

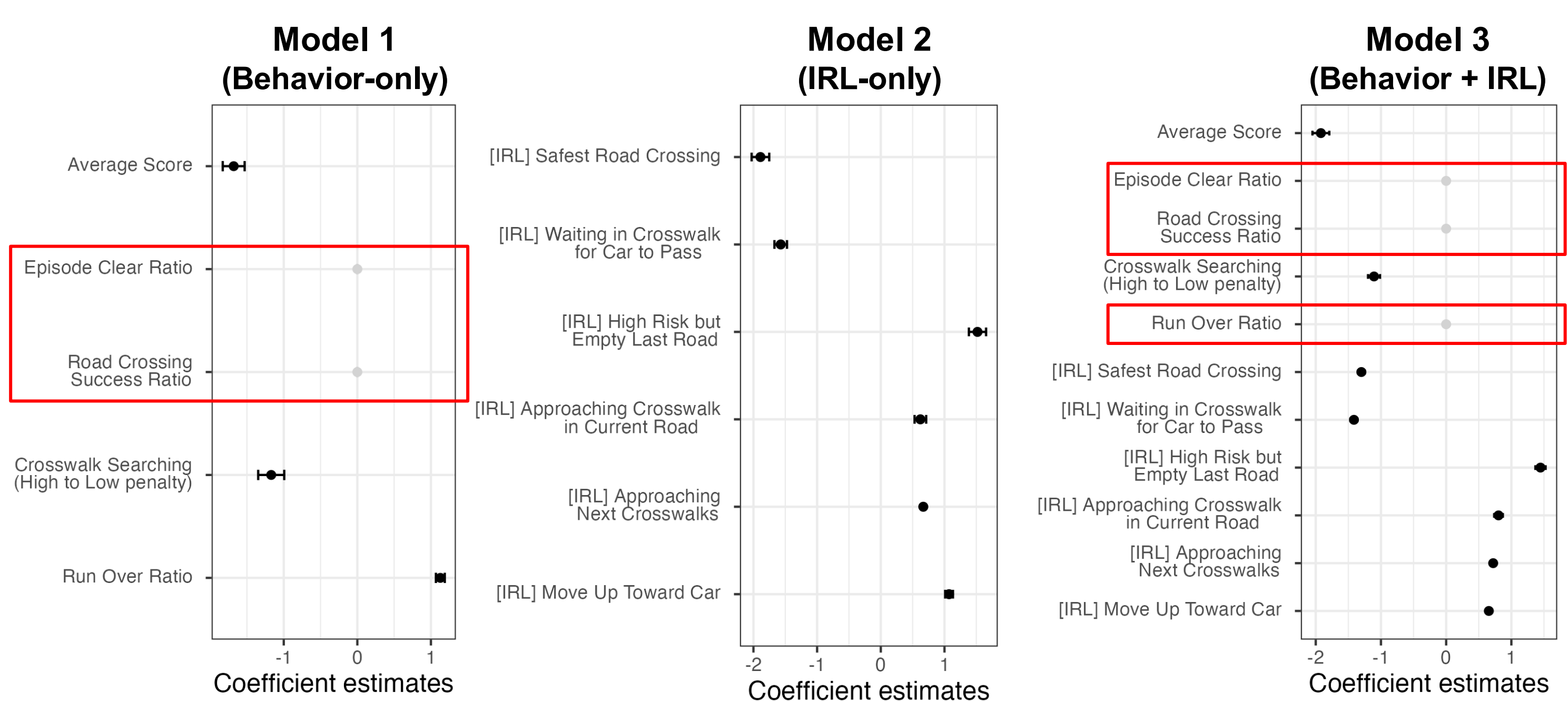


- **IRL features:** IRL reward estimates for specific state-action conditions



*Car closeness: 0 = no visible car in the lane; 1 = car in front of the player

Elastic Net Model Comparison



	Model 1	Model 2	Model 3
Feature Selection	Behavioral: 3/5	IRL: 6/6	IRL: 6/6 Behavioral: 2/5
Pearson r (Train)	0.2632	0.3640	0.4153
Pearson r (Test)	0.2237	0.3067	0.3345

- IRL features were **more likely to be selected** than behavioral features.
- Models with IRL features showed **better predictive performance** than Model 1 => **IRL features** provided more consistent and informative predictors of risk-taking

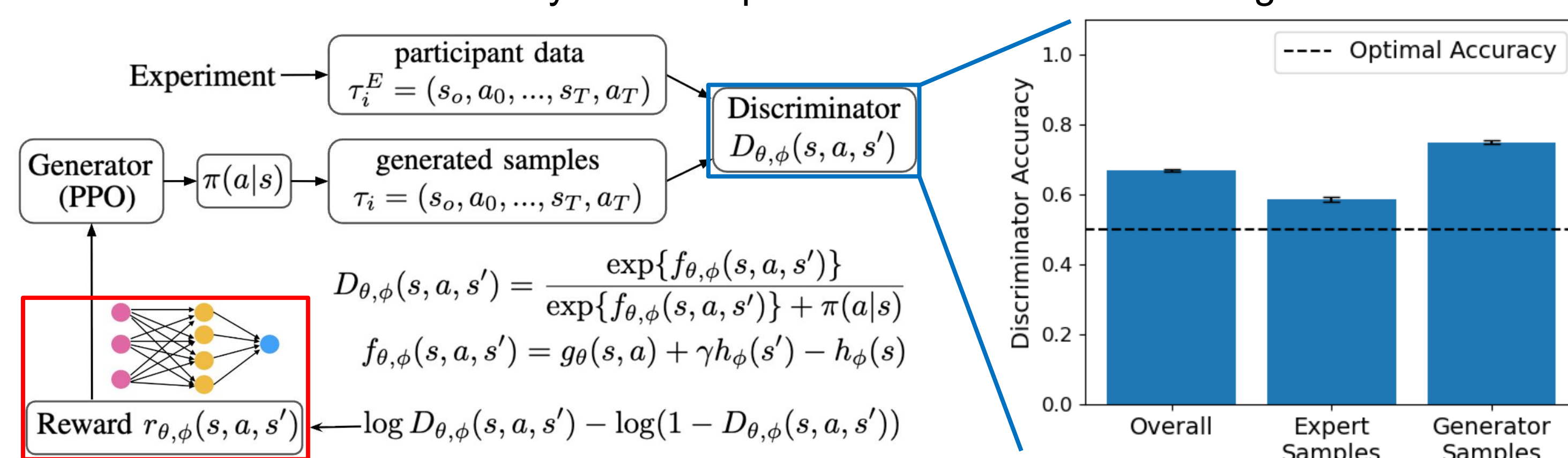
Methods

Data Collection

	Study 1 (N = 55)	Study 2 (N = 254)
Participants	Korean adults	U.S. adults
Sex	23 males / 32 females	107 males / 140 females
Age (M±SD)	25.2 ± 5.2	37.4 ± 11.0
Experiment Setting	In-person (SNU lab)	Online (Prolific)
Collection Period	2025.10.03 – 2025.12.05	2026.03.23 – 2026.04.07

Adversarial Inverse Reinforcement Learning

- One AIRL model trained per participant (N = 309)
 - **Reward networks** used to compute state-action rewards ("IRL rewards")
- => **IRL rewards** used to identify context-specific indicators of risk-taking



Elastic Net Regression

- Goal: **predict DOSPERT*** total scores using **crosswalk task features**
- Model: Elastic Net ($\alpha = 0.5$) for **feature selection and prediction**
- Evaluation: 80/20 train-test split + 5-fold cross-validation

*DOSPERT: 30-item self-reported risk-taking measure

Conclusion

- A **real-time task** designed to capture both risk-taking and risk-averse behaviors can yield **features** associated with self-reported risk propensity.
- **IRL-derived context-specific indicators** can better capture individual differences in risk-taking behavior than aggregate task-level summaries.
- These findings highlight the crosswalk task's potential as a meaningful behavioral paradigm for studying real-time risk-taking in future neuroimaging studies.

References

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