

Overhang Tower



Resource-Rational Adaptation in Sequential Physical Planning

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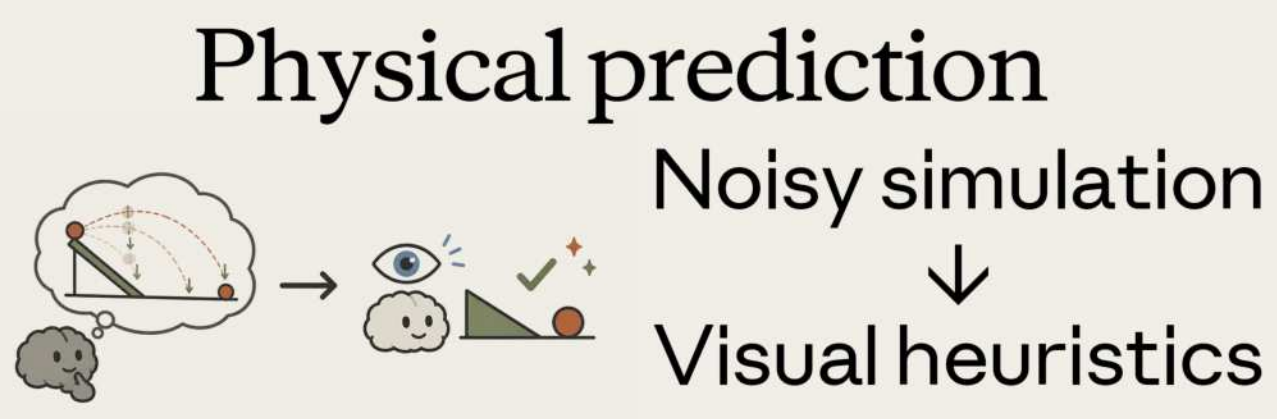
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Intuitive Physics · Resource Rationality

Sequential Planning

01 TL;DR

Rising cognitive demands trigger a **resource-rational** shift in human physical prediction and planning horizons.

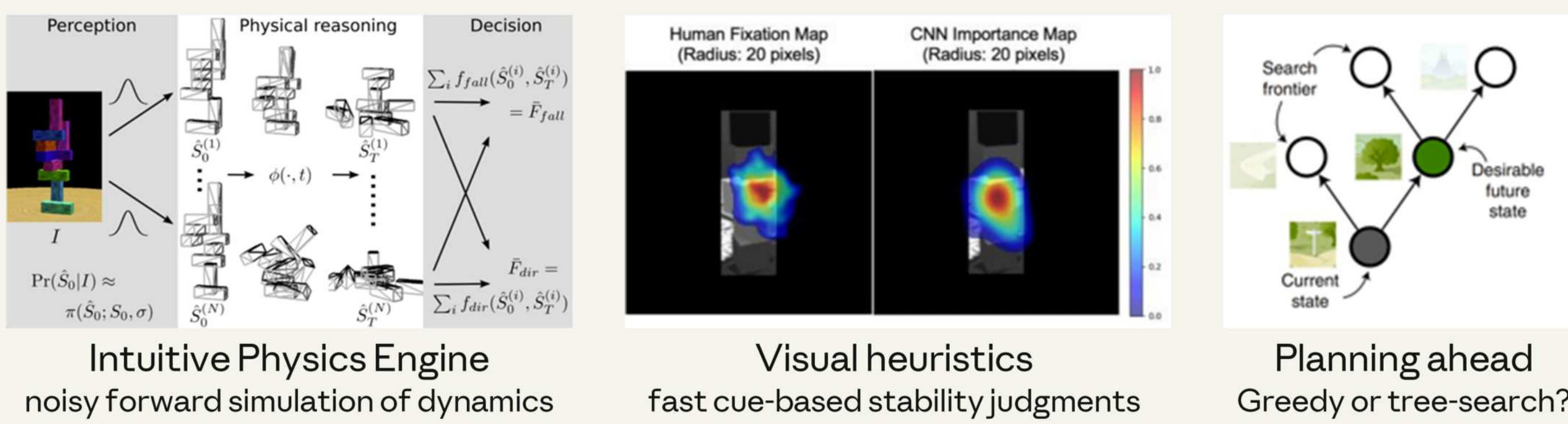


02 Motivation



Everyday physical intelligence is **active and sequential**.

Gap: Prior works mainly focus on passive, single-step judgments or planning with perfect state transitions.



Intuitive Physics Engine
noisy forward simulation of dynamics

Visual heuristics
fast cue-based stability judgments

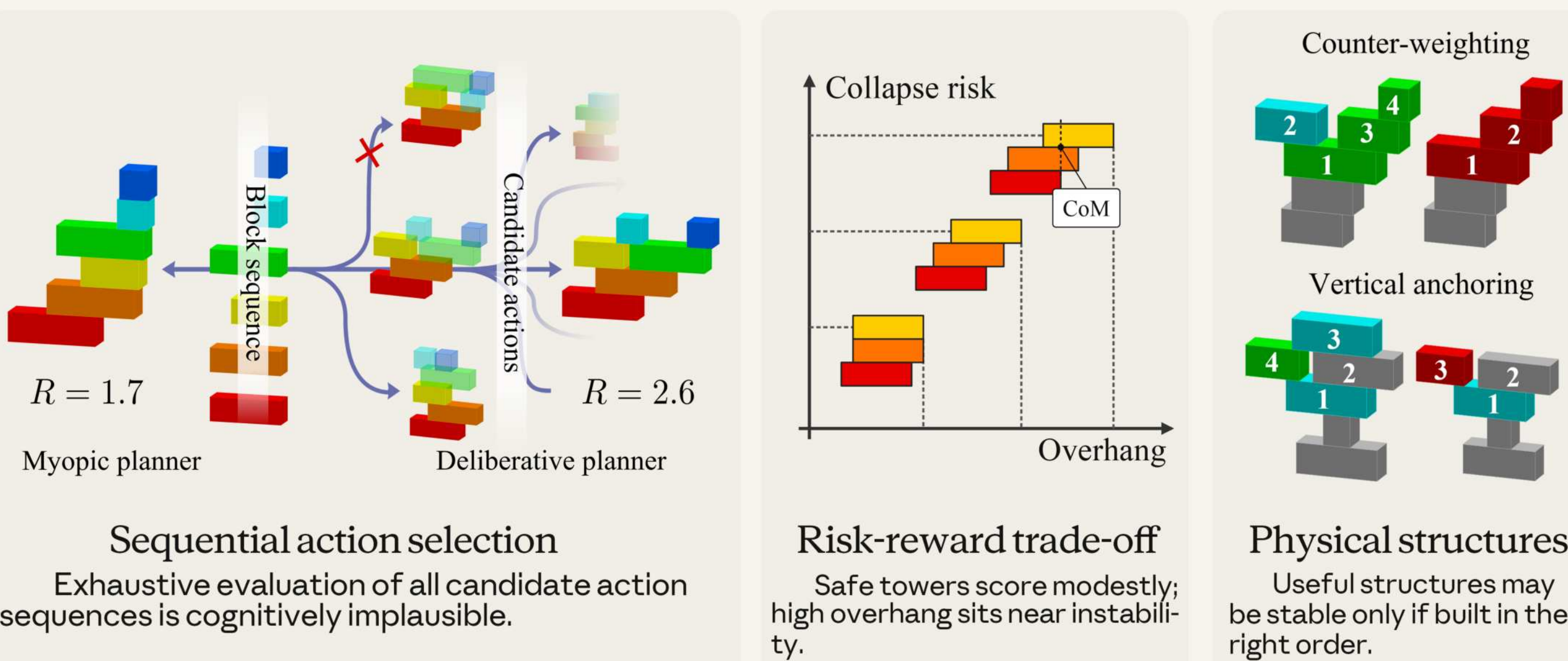
Planning ahead
Greedy or tree-search?

Research question: In multi-step planning, do humans adapt only the search depth, only the prediction mechanism, or both?

03 Overhang Tower Environment

Task goal:

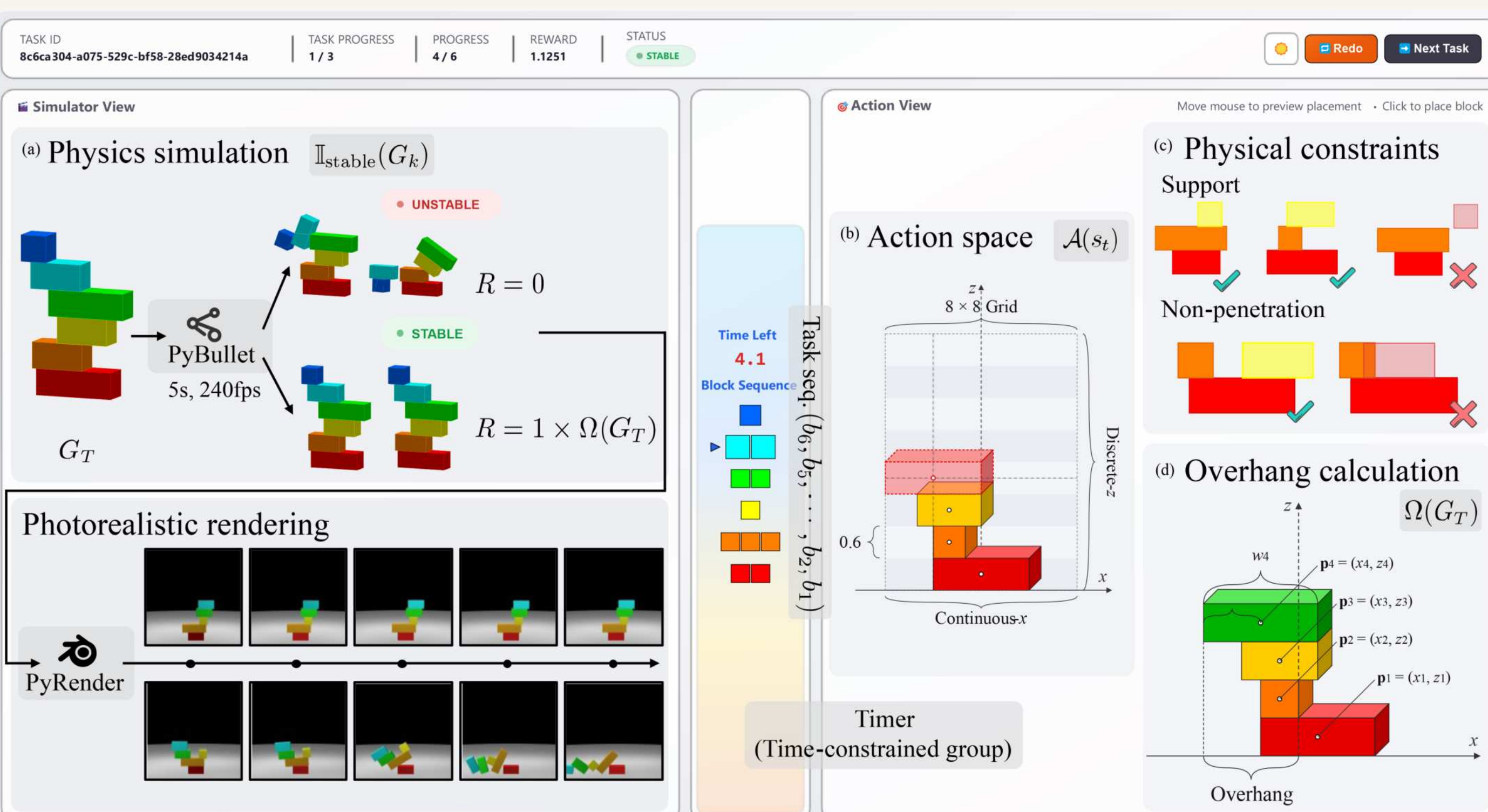
- Given a sequence of 6 blocks in a continuous horizontal space.
- Place the blocks sequentially while maintaining **continuous stability**.
- Optimize **horizontal overhang** for maximum reward



Sequential action selection
Exhaustive evaluation of all candidate action sequences is cognitively implausible.

Risk-reward trade-off
Safe towers score modestly; high overhang sits near instability.

Physical structures
Useful structures may be stable only if built in the right order.



04 Models and Experiments

Participants

82 participants · 20 tasks · 5-second time-constrained group vs. unlimited time group

Computational Models

Intuitive Physics Engine
Noisy forward simulations with Gaussian perturbations
 $\hat{p}_{\text{IPE}}(\text{stable} | s_t, a) = \frac{1}{K} \sum_{i=1}^K \mathbb{I}[\text{Stable}^{(i)}(G_{t+1})]$

Visual-heuristic predictor
An Inception-V4 CNN maps geometry to stability.
 $\hat{p}_{\text{NN}}(\text{stable} | s_t, a) = f_{\theta}(I(G_{t+1}))$

Myopic planning
Evaluates only the immediate next placement.
 $a_t^* = \arg \max_{a \in \mathcal{A}(s_t)} \hat{p}_P(s_t, a) \cdot r(s_t, a)$

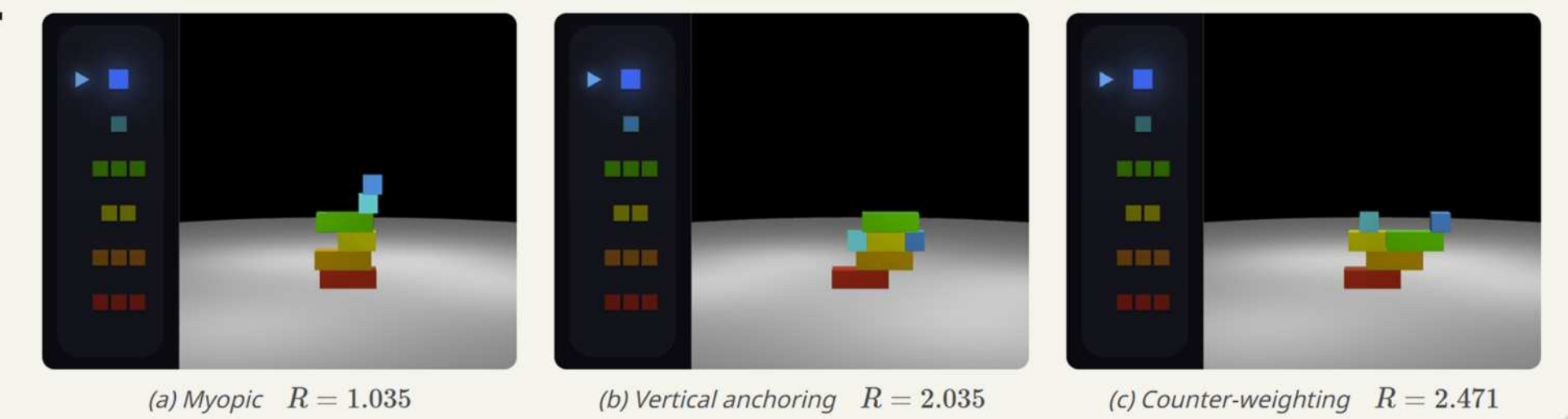
Deliberative lookahead
Tree-based sequence search.
 $U(\pi | s_t) = \left(\prod_{k=t}^{t+D-1} \hat{p}_P(s_k, a_k) \right) \cdot V(s_{t+D})$

Evaluation

Physical prediction test: Human choices serve as positive samples of perceived plausibility to compare log-likelihoods across models.

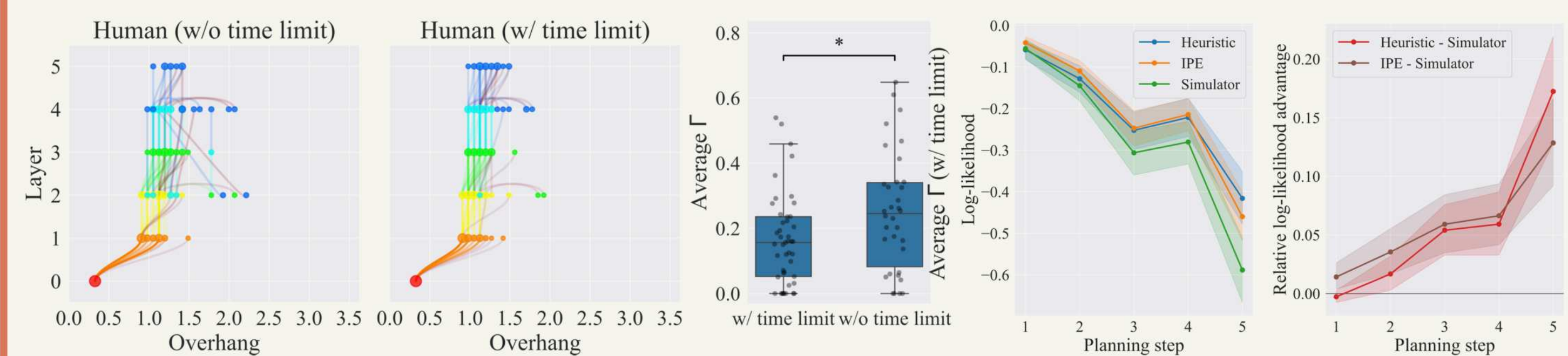
Order dependency: $\Gamma_{G_T} = 1 - \frac{|\{\pi \in \Pi(G_T) | \text{Stable}(\pi)\}|}{|\Pi(G_T)|}$

High Γ implies fewer stable building sequences, requiring deliberative planning to manage strict physical dependencies.



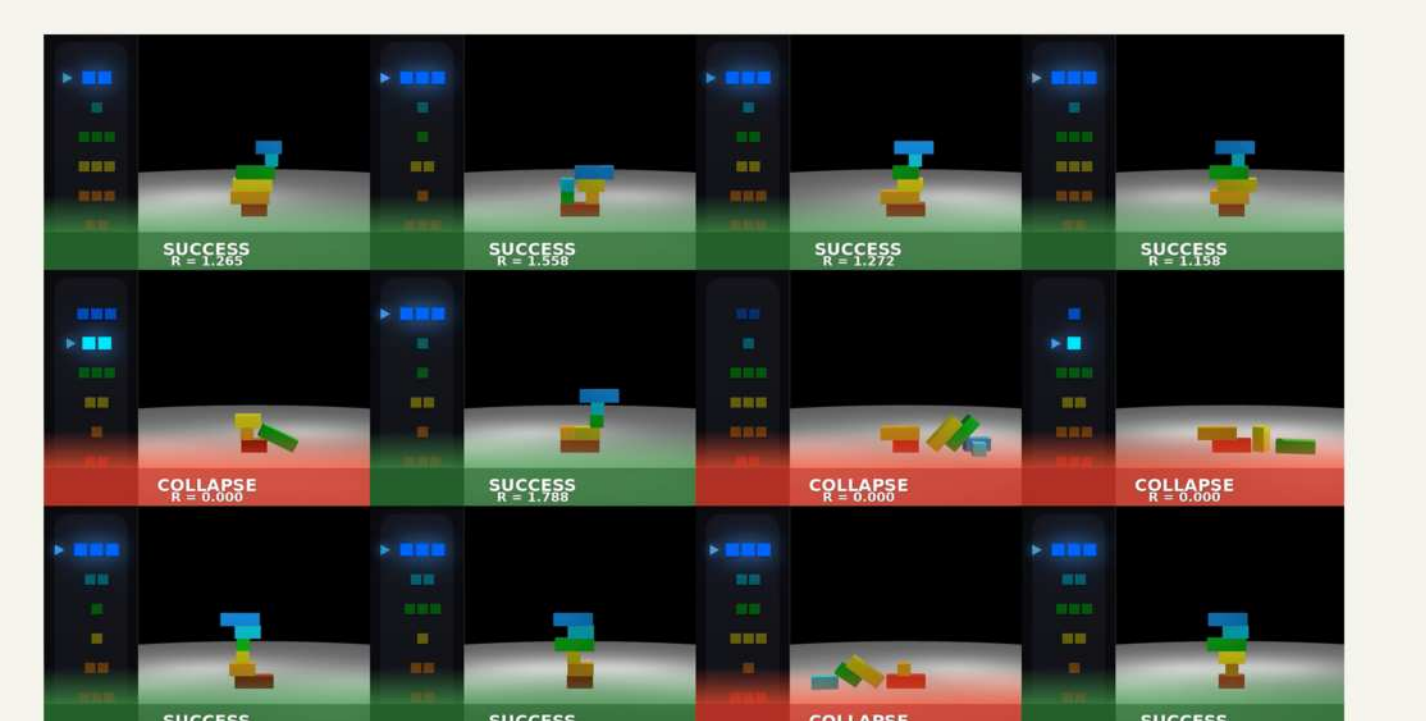
05 Results

Metric	5s time limit	No time limit	p-value
Total reward	18.25 ± 0.57	19.57 ± 0.56	.107
Stable rate	0.702 ± 0.025	0.678 ± 0.021	.482
Average overhang	1.321 ± 0.023	1.460 ± 0.029	<.001
Decision time (s)	2.47 ± 0.07	7.27 ± 0.88	<.001



- Stability stayed similar across conditions, suggesting **safety-preserving adaptation** towards vertical stacking.
- Time-constrained group reveals clear **risk-reward trade-off**.
- Order dependency and model fits suggest deeper lookahead given unlimited time, plus a **simulation-to-heuristic shift** as complexity grew.

Model	Reward
Human (w/ time limit)	0.913 ± 0.03
Human (w/o time limit)	0.979 ± 0.03
Myopic	0.52 ± 0.12
Lookahead (D = 2)	0.912 ± 0.10
Lookahead (D = 3)	1.180 ± 0.24



Takeaways

- Cognitive pressure **reshapes strategy**, rather than simply degrading physical performance.
- Humans seamlessly modulate computational cost for efficiency, guided by **task demands and cognitive budget**.
- Prediction and planning **co-adapt**: Sequential physical planning reflects a **resource-rational dual transition** across reasoning and action.

06 Contact

