

Cognitive modeling of decision making in human drivers

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About me

- MSc in applied mathematics
- PhD on modeling human control behavior
 - Virtual balancing tasks
 - Car following, steering
- Previous postdoc in cognitive psychology
 - Decision making
 - Interplay between motor behavior and cognition
- Postdoc @ Cognitive Robotics (3mE) & AiTech
 - Modeling & managing human-AV interactions
 - Meaningful human control: how to?



Human-AV interaction



Are you going? Or should I go?

What if I point a lot
and flail my arms around?

Wait, maybe you should go.

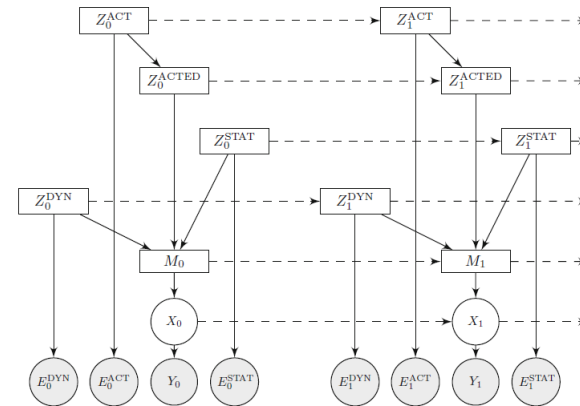
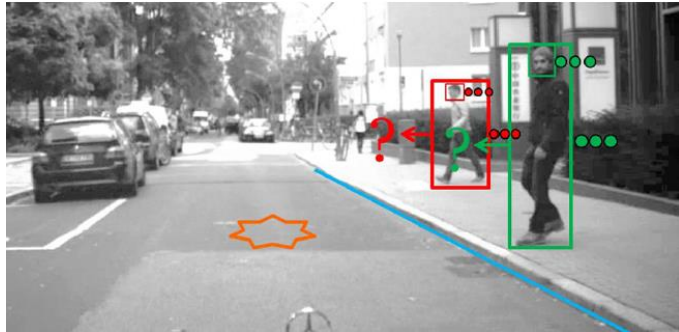
You go first.

This is confusing.

Let's just sit here
and reflect.

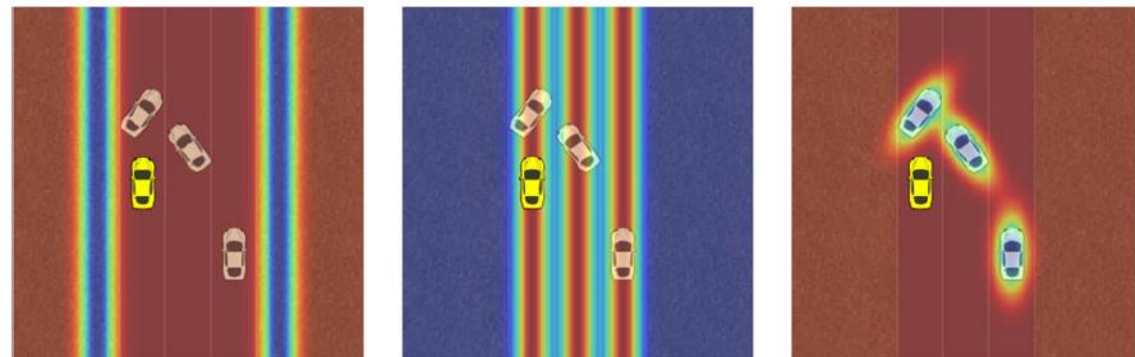
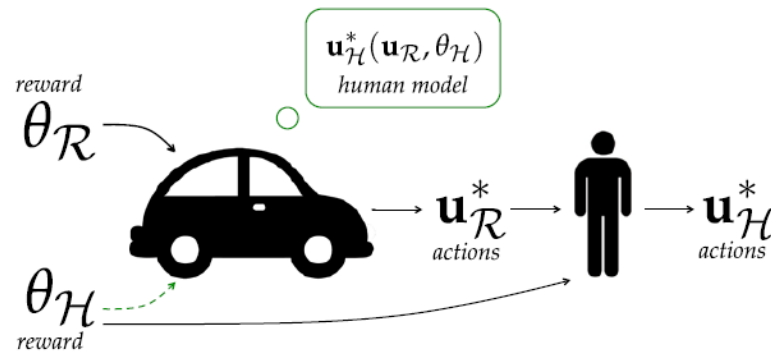
Human-AV interaction: existing approaches

- Intention recognition



Kooij, J. F. P. et al. "Context-Based Path Prediction for Targets with Switching Dynamics." *International Journal of Computer Vision* 127, no. 3 (March 2019): 239–262.

- Game-theoretic motion planning

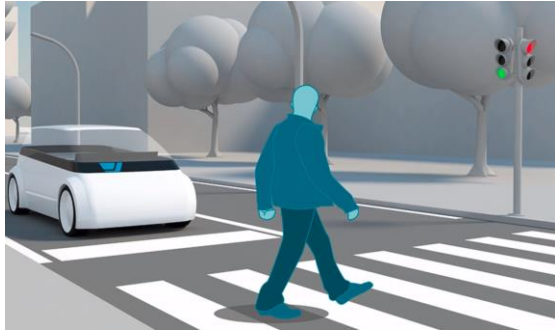


Sadigh, D. et al, "Planning for cars that coordinate with people: Leveraging effects on human actions for planning and active information gathering over human internal state." *Autonomous Robots*, 42(7), 1405–1426. (2018)

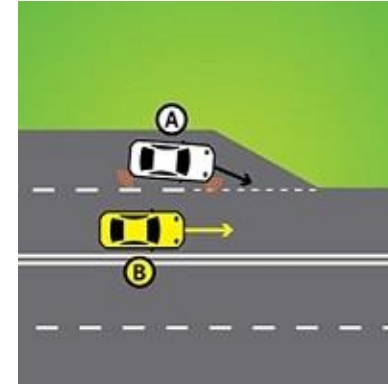
Limitations of current approaches

- Human models are chosen based on computational convenience
- Basic assumptions of these models are not cognitively plausible
 - “humans are moving obstacles”
 - “humans operate like on-off switches”
 - “humans optimize a utility function”
 - “all traffic behavior can be captured by one utility function”
- Models are not validated against the actual driver behaviour
- Alternative way?
 - Utilize the available knowledge about human behavior
 - Check how well the model describes the humans
 - No silver bullet: Focus on context-specific models of stereotypical interactions

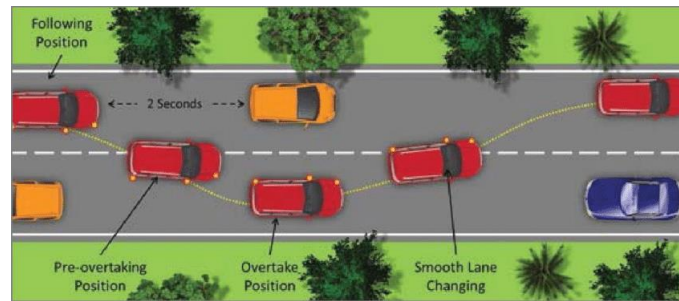
Stereotypical human-AV interactions



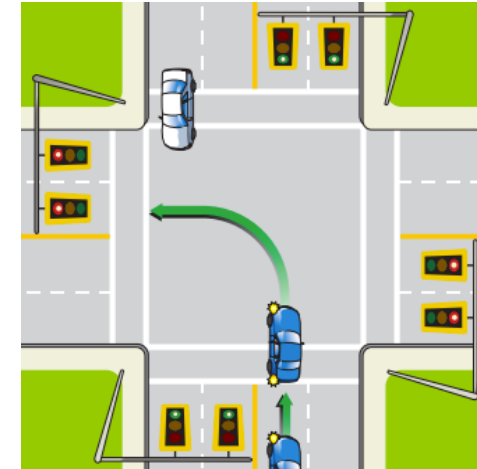
Pedestrian crossing



Lane merging



Overtaking

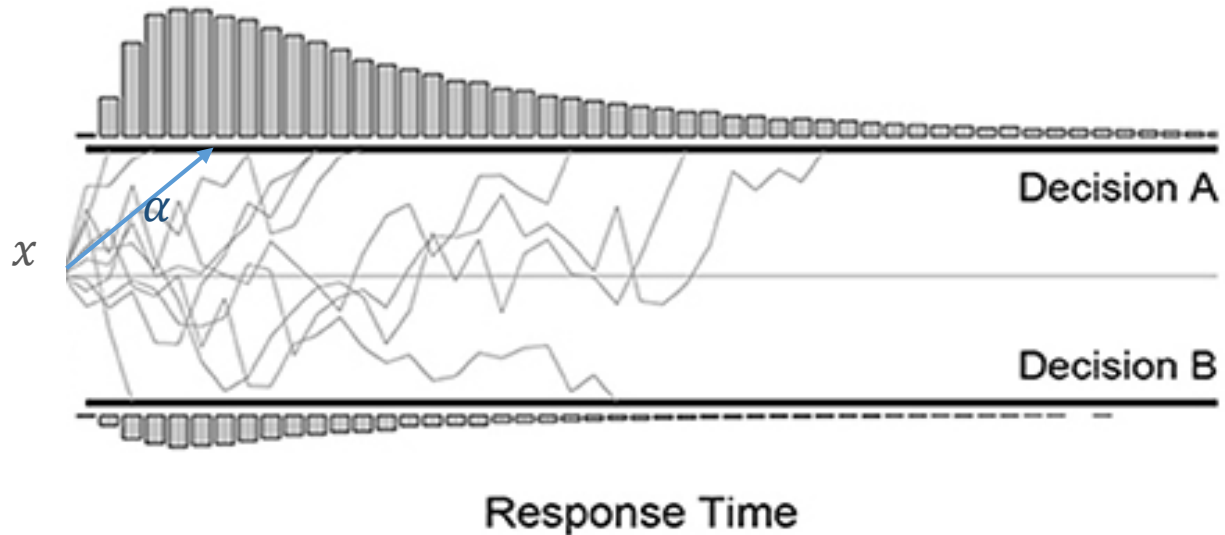


Left turn across path

- In all these interactions, a human faces a binary decision-making task
- What do we know about human decision-making?

Decision making: Evidence accumulation model

$$dx = \alpha dt + dW$$



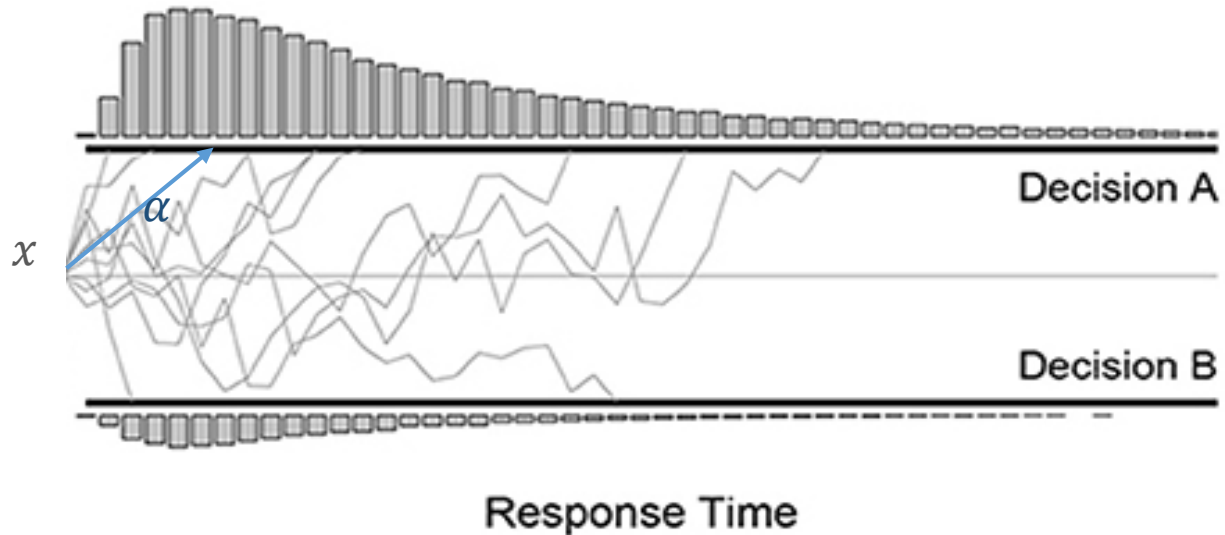
A comparison of two tomato products. On the left is "AH Romatomaten" (750 g) priced at 2.09. On the right is "AH Nederlandse trostomaten" (5 stuks) priced at 1.99. A large yellow "VS" symbol is placed between the two products. Both products have a blue plus sign icon below them, suggesting they can be added to a cart.

Product	Price	Weight/Quantity
AH Romatomaten	2.09	750 g
AH Nederlandse trostomaten	1.99	5 stuks

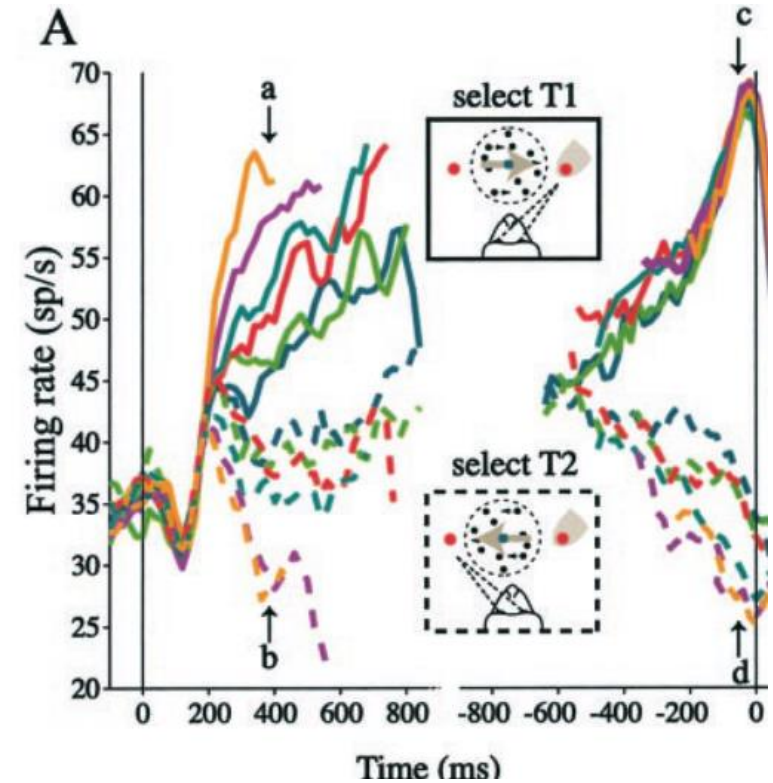
Ratcliff, R. (1978). A theory of memory retrieval. *Psychological review*, 85(2), 59.

Decision making: Evidence accumulation model

$$dx = \alpha dt + dW$$



Ratcliff, R. (1978). A theory of memory retrieval. *Psychological review*, 85(2), 59.



Roitman, J. D., & Shadlen, M. N. (2002). Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *Journal of neuroscience*, 22(21), 9475-9489.

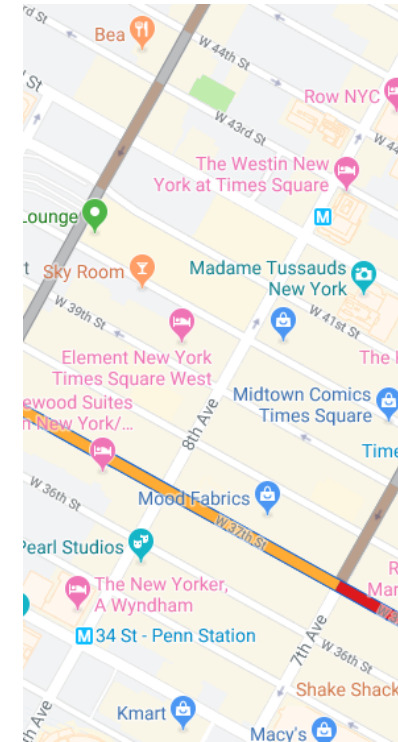
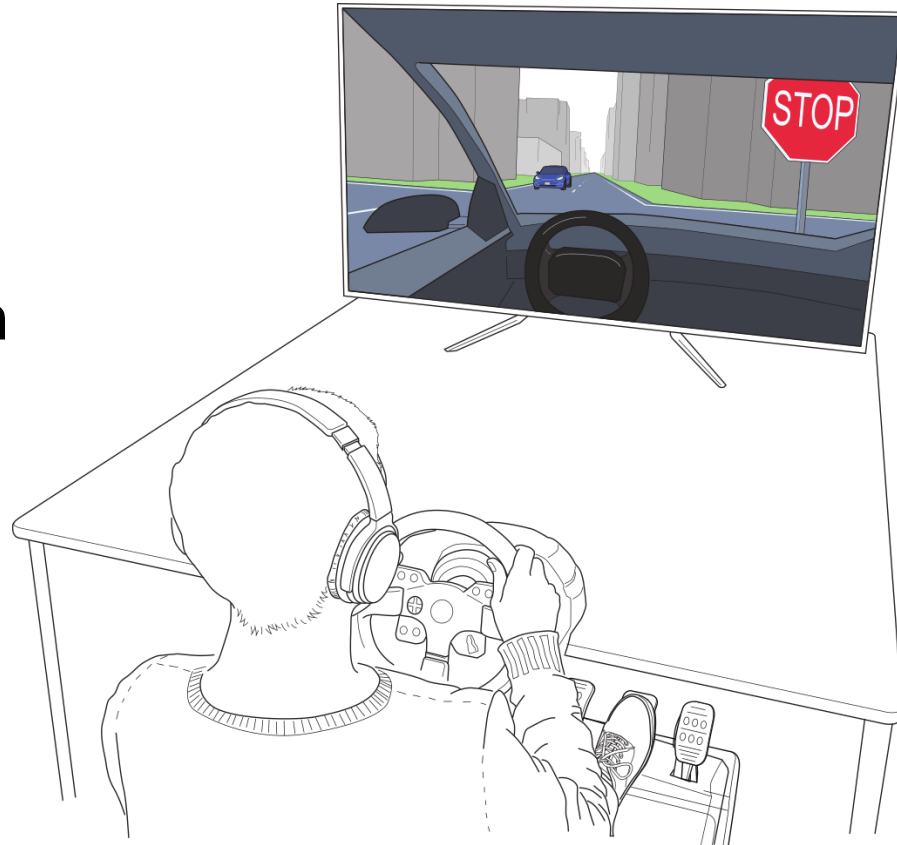
- Can evidence accumulation explain decisions in traffic?

Experimental study

Gap acceptance in left turns across path

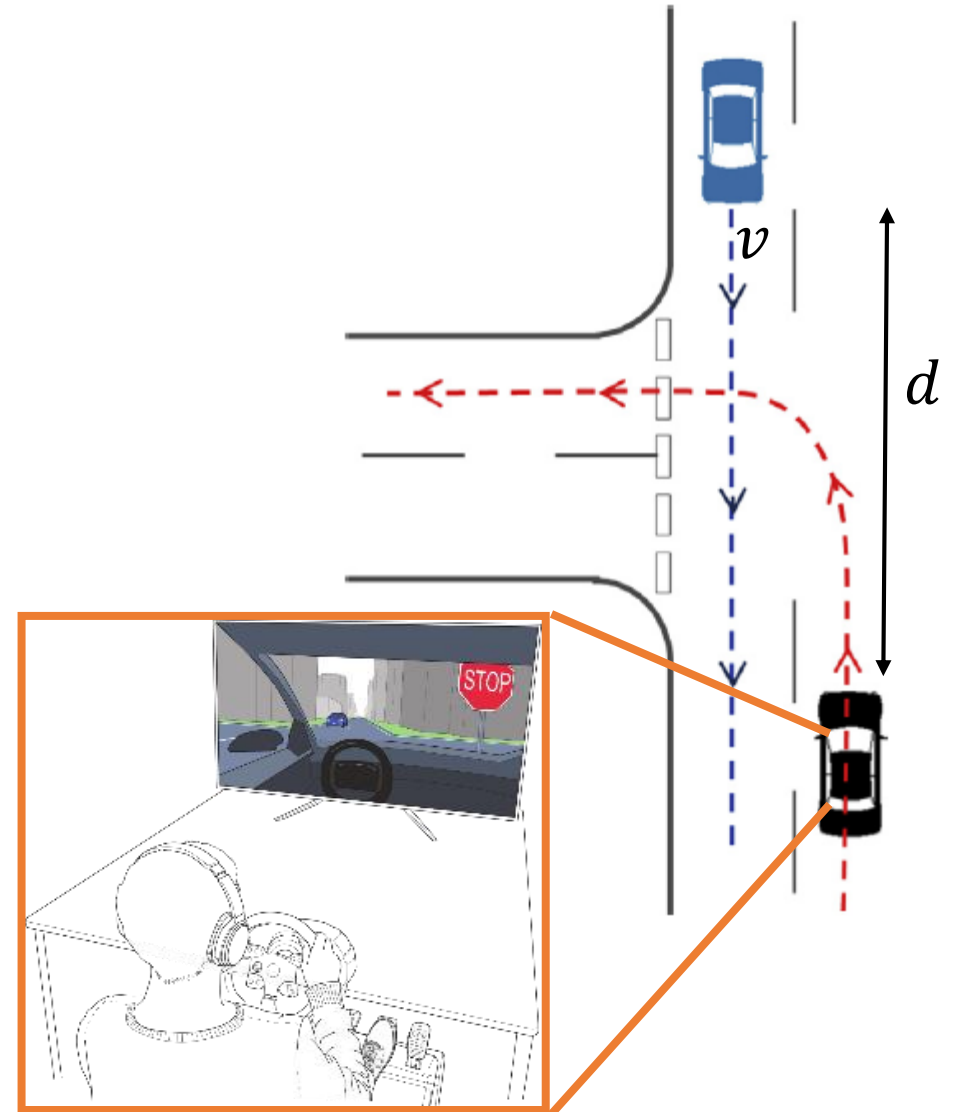
Experimental setup

- Virtual driving simulator
- 7 participants
- Two sessions, about 60 min each
- Each session: four routes 10 min each
- Auditory navigation cues
- Each route: 15 left turns, 5 right turns, 5 go straight

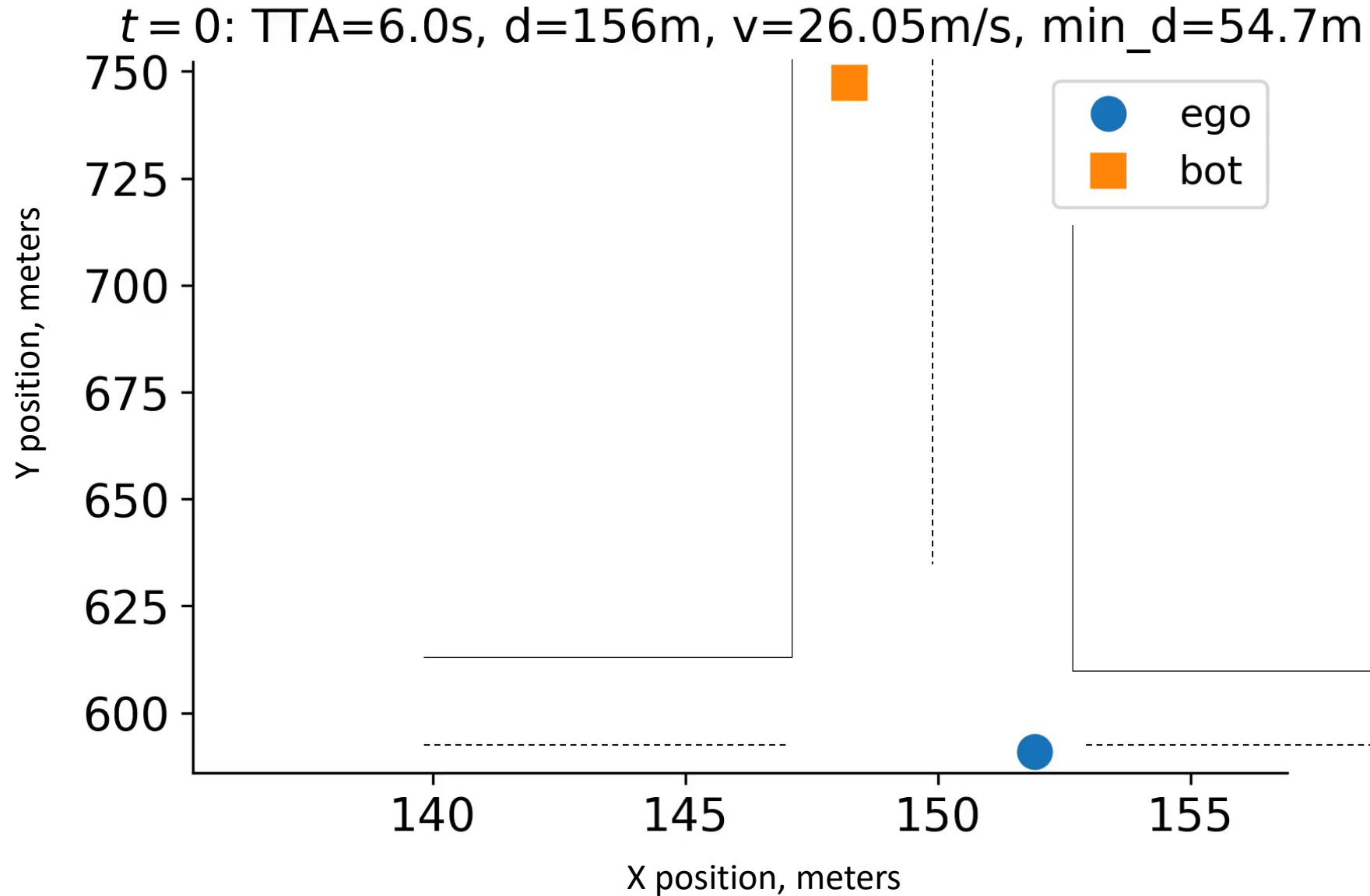


Left turns

- The driver is instructed to stop at the intersection before making a left turn
- When the driver stops, the oncoming car appears
- Oncoming car starts at
 - distance (d) = {90,120,150}s
 - fixed speed v chosen such that
 - time-to-arrival (TTA) = {4,5,6}s
- Distance and TTA conditions are independent variables

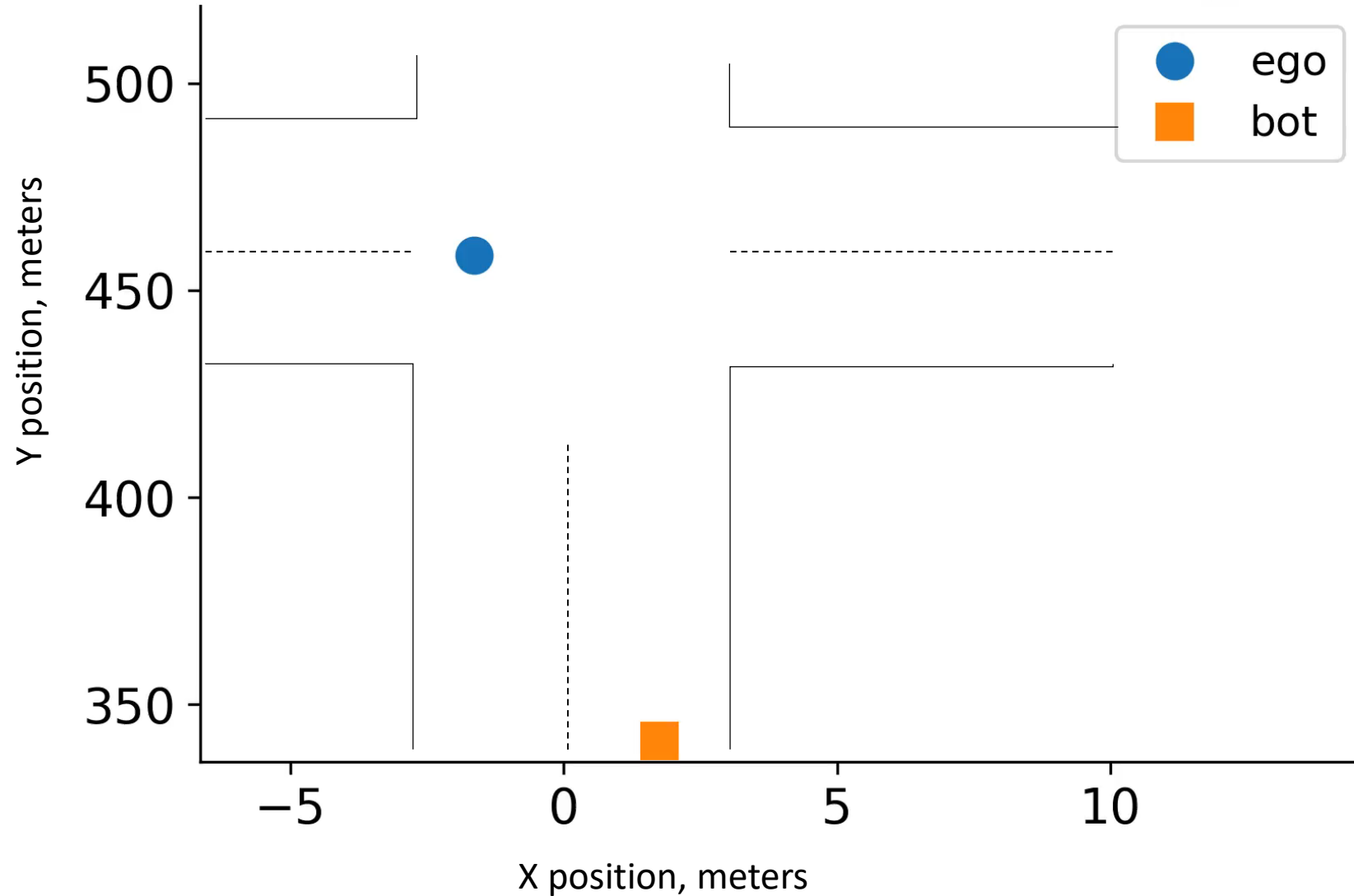


Turn trajectory



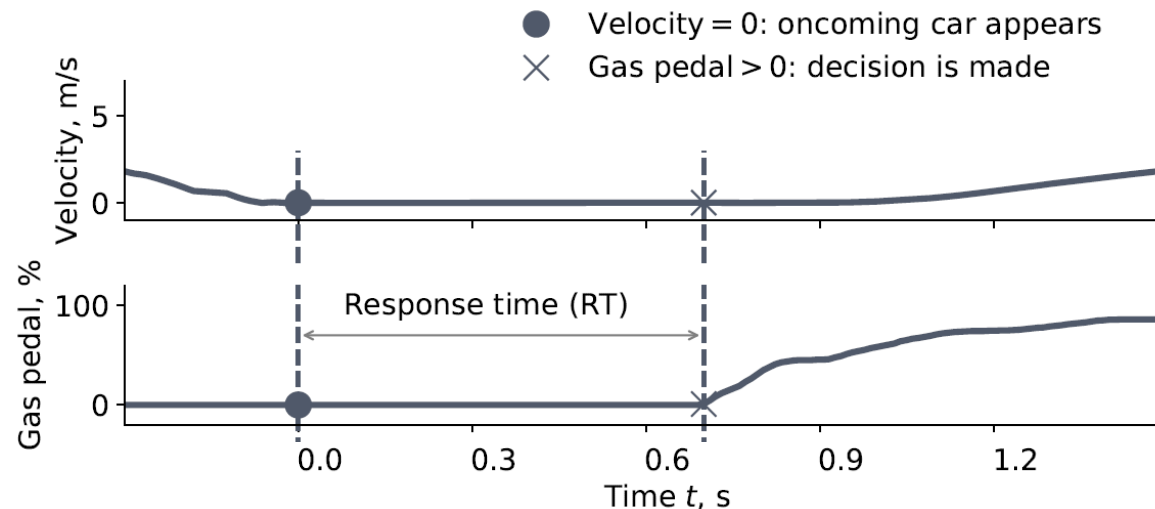
Wait trajectory

$t = 0$: TTA=6.0s, $d=117\text{m}$, $v=19.58\text{m/s}$, $\text{min}_d=3.3\text{m}$



Dependent variables

- Decision (turn/wait)
 - Hypothesis: probability of turning will increase with TTA and distance
- Response time (turn decisions only)

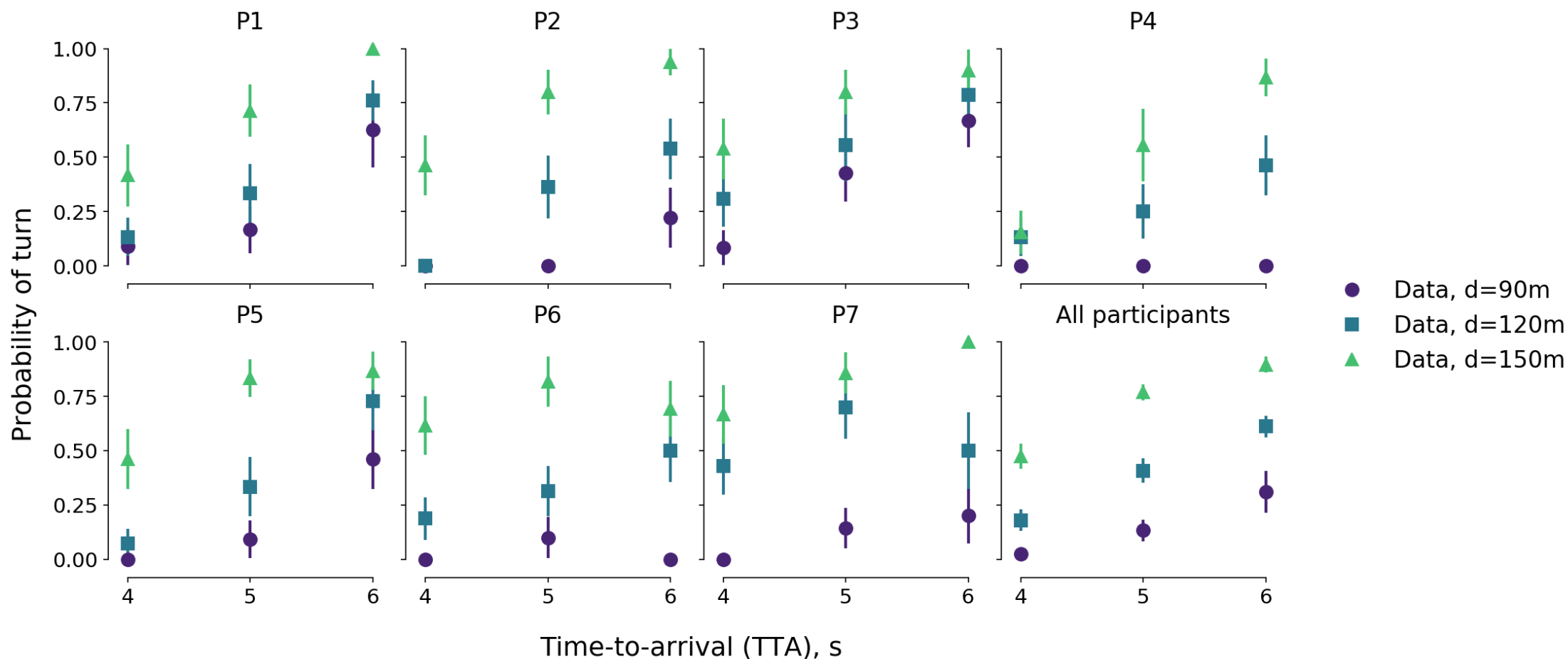


- Hypothesis: RT will decrease with time and distance gaps
 - For large gaps, evidence in favour of turning is very strong → fast response
 - For small gaps, relative evidence favours waiting → takes more time to arrive to “turn” decision

Results

decision \sim TTA + distance + (d|subject)

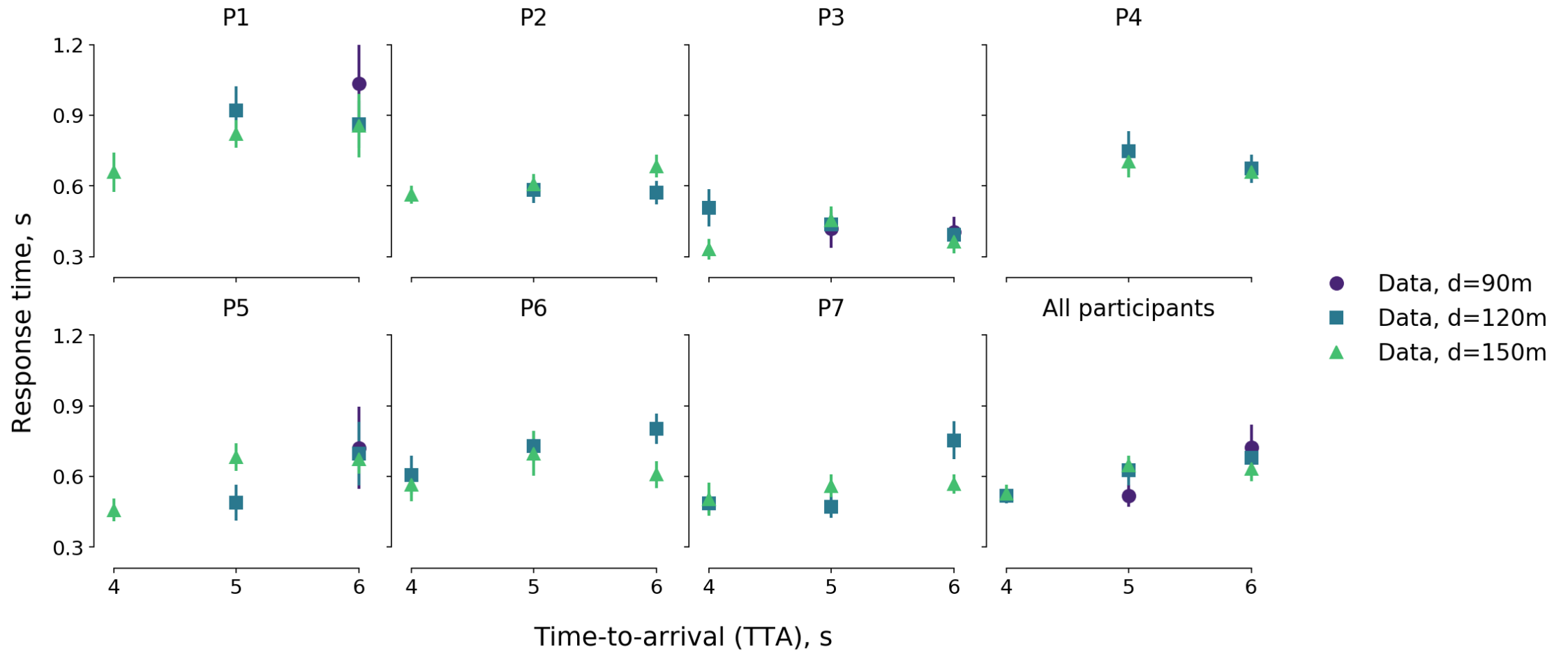
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.5	0.24	-2	0.042
TTA	0.96	0.098	9.8	1.2×10^{-22}
distance	1.4	0.17	8.2	1.7×10^{-16}



Results

RT ~ TTA + distance + (I|subject)

	Estimate	Std. Error	df	t value	Pr(> t)
Intercept	-0.72	0.033	6.8	-22	1.4×10^{-7}
TTA	0.028	0.0089	3.4×10^2	3.2	0.0017
distance	-0.0052	0.01	3.4×10^2	-0.52	0.6



Interim conclusions

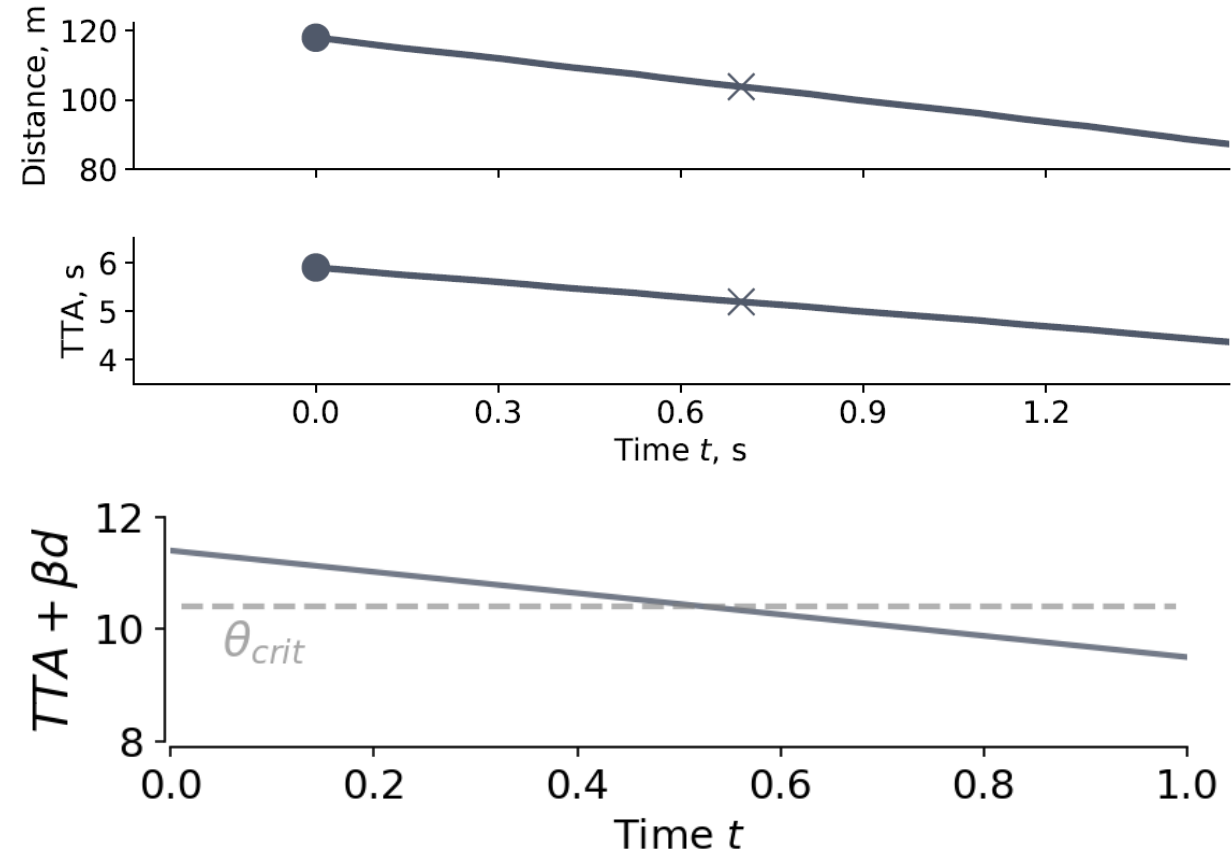
- Probability of turning increases with distance and time gap
- Response time increases with time gap
- Substantial individual differences in effect magnitudes
- What *processes* lead to the observed behavior?

Cognitive process model

Mechanism 1: dynamic accumulation of perceptual information

- Previous studies suggest both distance and time gap affect the decision
- Perceptual information (combination of TTA and distance) is accumulated over time...

- ... and is subject to noise
$$dx = \alpha((TTA + \beta d) - \theta_{crit})dt + dW$$
 $\alpha, \beta, \theta_{crit}$: free parameters

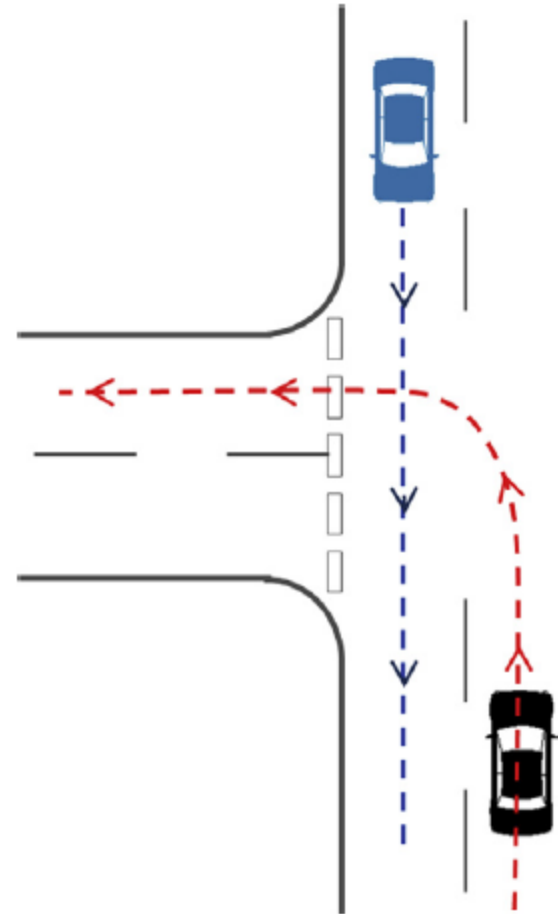


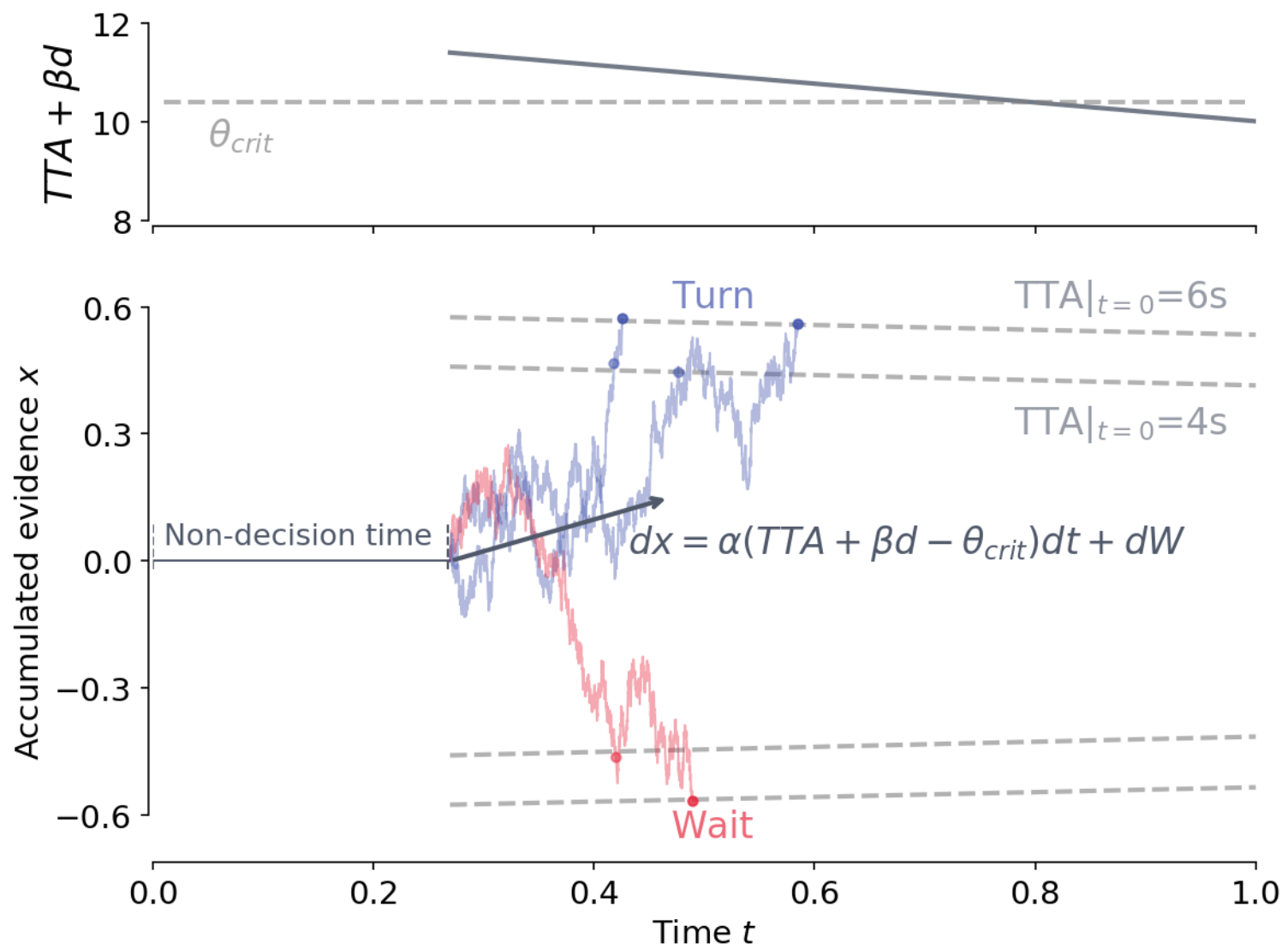
Mechanism 2: collapsing decision boundary

- Response is constrained by the environment
 - At small gaps, the driver has to accumulate the evidence faster, or there will be no time left to complete the maneuver
- Task constraints (oncoming car) induce urgency signal
- Decision boundaries collapsing with closing gap

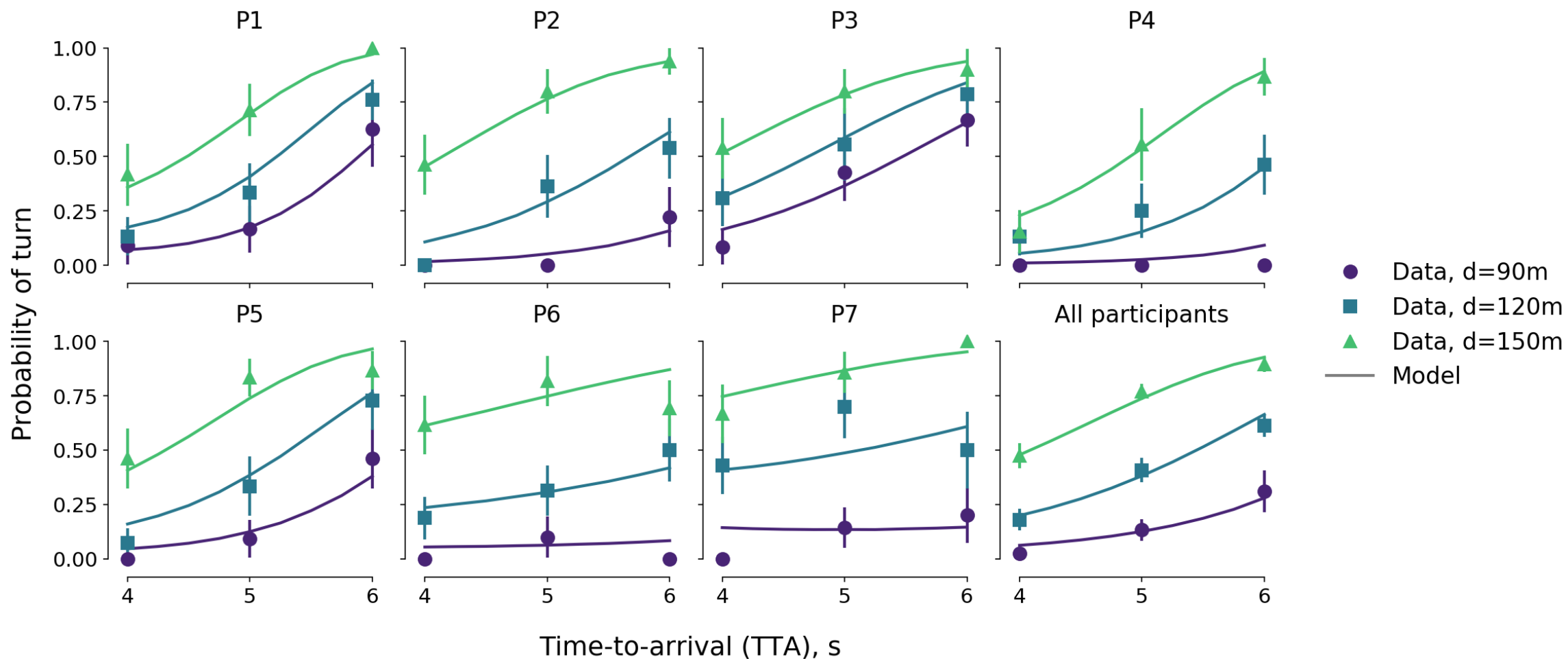
$$b(t) = \pm b_0 f(TTA)$$

where f decreases with TTA

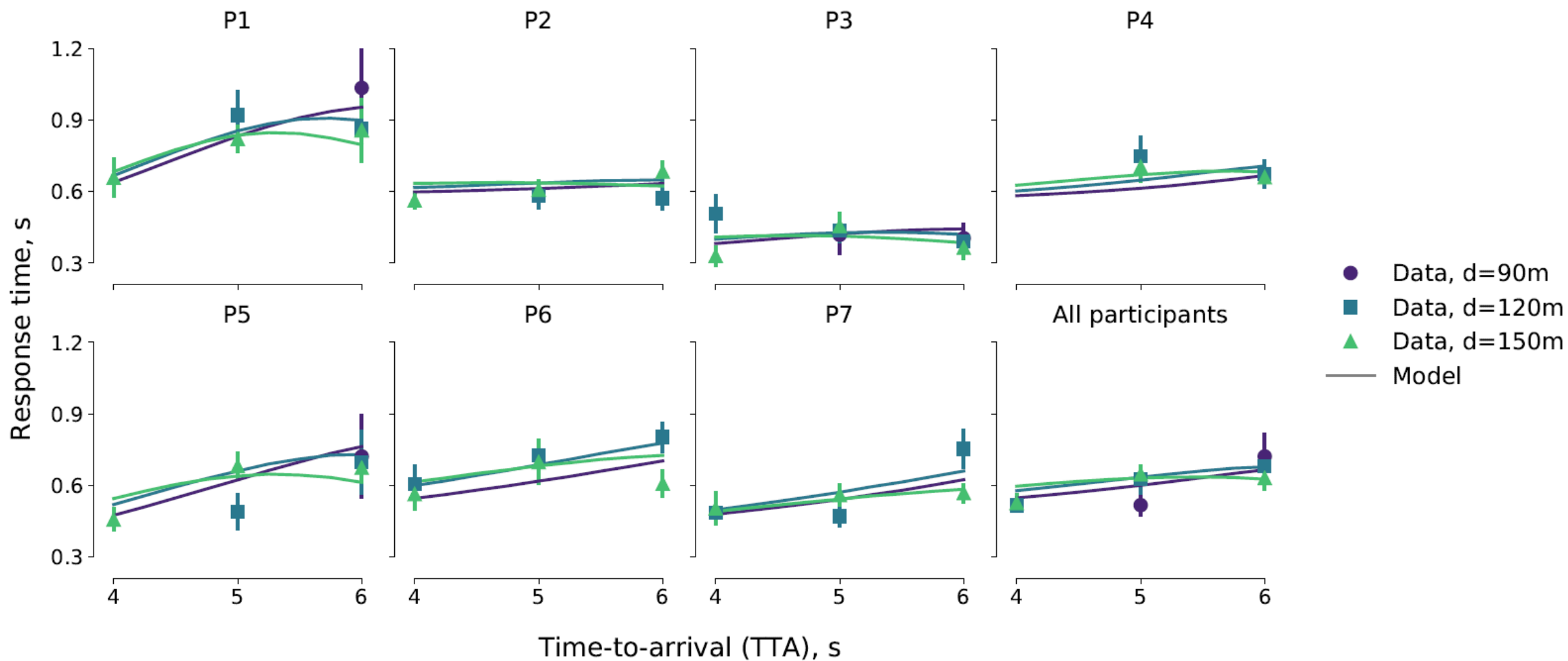




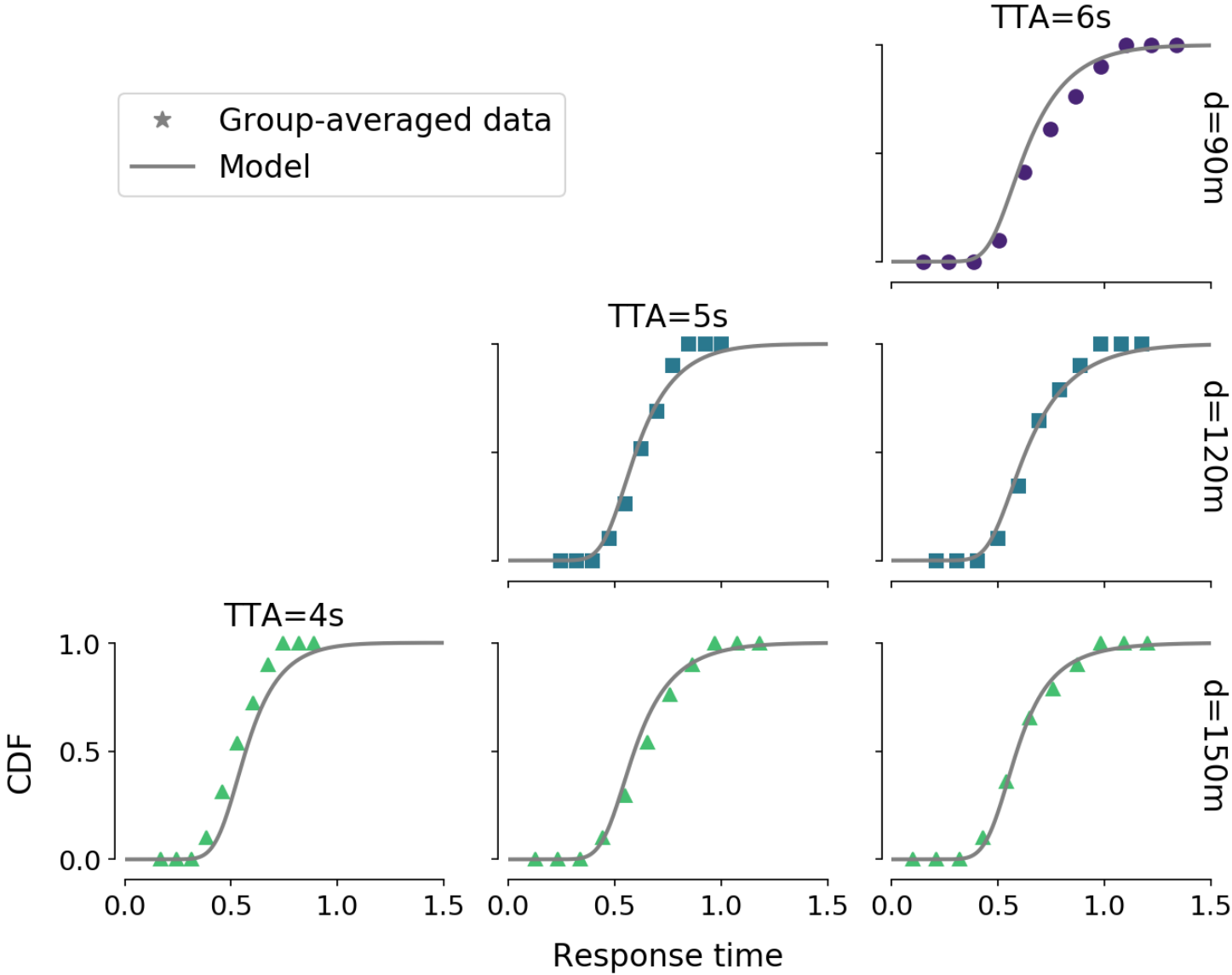
Model results



Model results



Full RT distributions



Model cross-validation

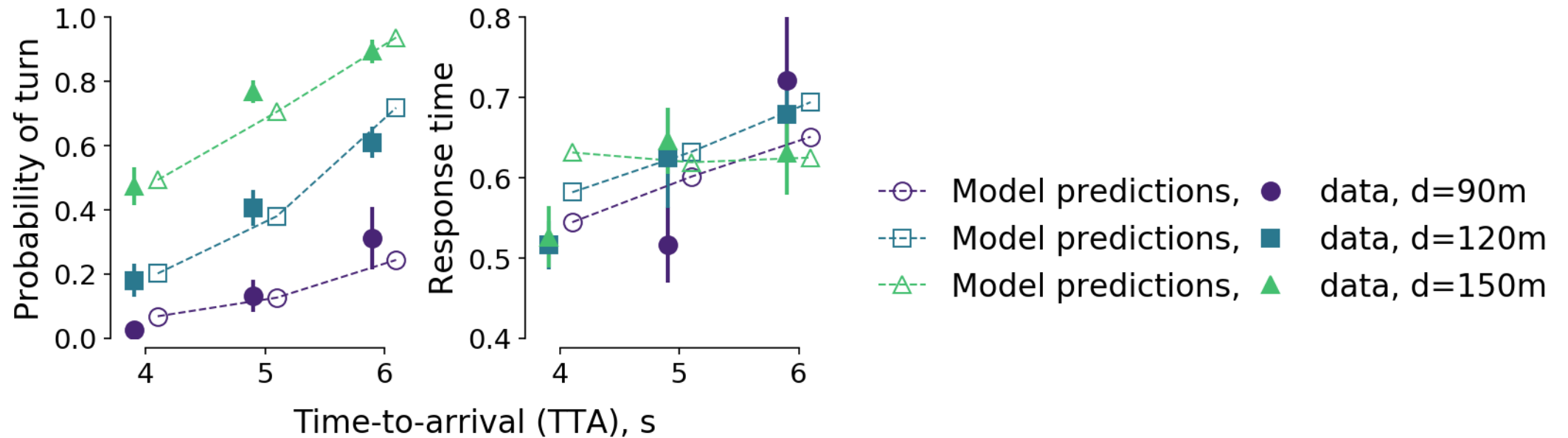
	TTA=4	TTA=5	TTA=6
d=90	•	•	•
d=120	•	•	•
d=150	•	•	•

Fit using all data (9 conditions)

	TTA=4	TTA=5	TTA=6
d=90	•	•	•
d=120	•	•	•
d=150	•	•	•

Hold-one-condition-out: fit using all data except the condition to be predicted

Model cross-validation



Summary

- Decisions and response times in left-turn gap acceptance decision can be explained by
 - Accumulation of dynamically varying evidence
 - ... constrained by closing window of opportunity to turn
- Proof-of-concept of how cognitive process models can help to understand and predict human road user behavior

Discussion

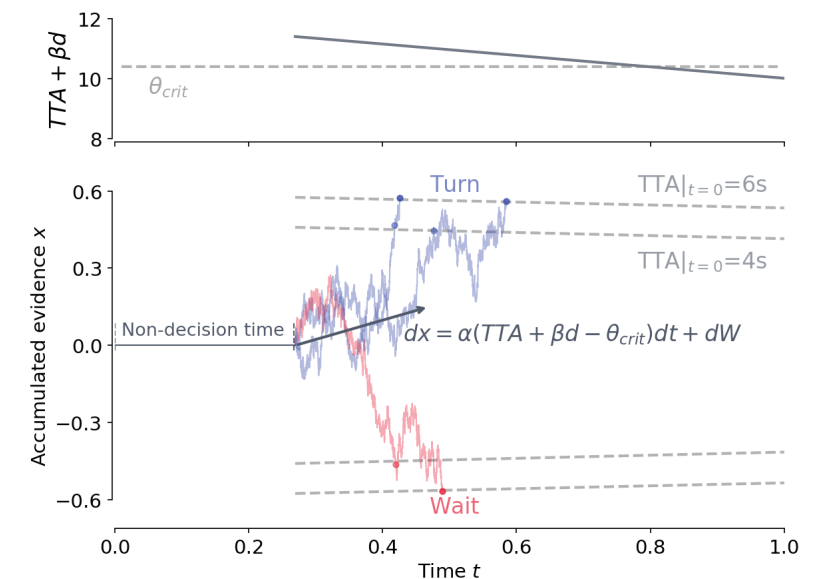
Discrete choice vs process models

- Numerous *discrete choice* models of gap acceptance
 - Effect of kinematic variables (distance, velocity, time gap)
 - Sociodemographic effects (age, sex, driving experience)
 - Sequential effects (waiting time)
- *Discrete choice* models vs *cognitive process* models
 - What (which gaps are accepted, and under which conditions) vs How? (cognitive mechanism, i.e. how the information is processed over time)
 - Static vs dynamic
 - Simplicity vs fidelity
- For human-robot interaction, dynamic, high-fidelity models are needed in order to be able to predict how humans react to different control policies

$$G_{n,i}^{cr} = 34.01 - 0.30 \cdot SS + 5.15 \cdot FG + 0.42 \cdot FS - 0.14 \cdot OS - 2.35 \cdot RG - 7.00 \cdot Age_1 - 4.95 \cdot Age_2 - 2.84 \cdot G + 0.23 \cdot P + 1.05 \cdot Km - 7.5 \cdot E - 5 \cdot CD$$

$$P_{n,i}(\text{accept gap}) = \frac{1}{1 + \exp[-0.22 \cdot (G_{n,i} - G_{n,i}^{cr})]}$$

Farah et al. (2009). A passing gap acceptance model for two-lane rural highways. *Transportmetrica*, 5(3), 159–172.

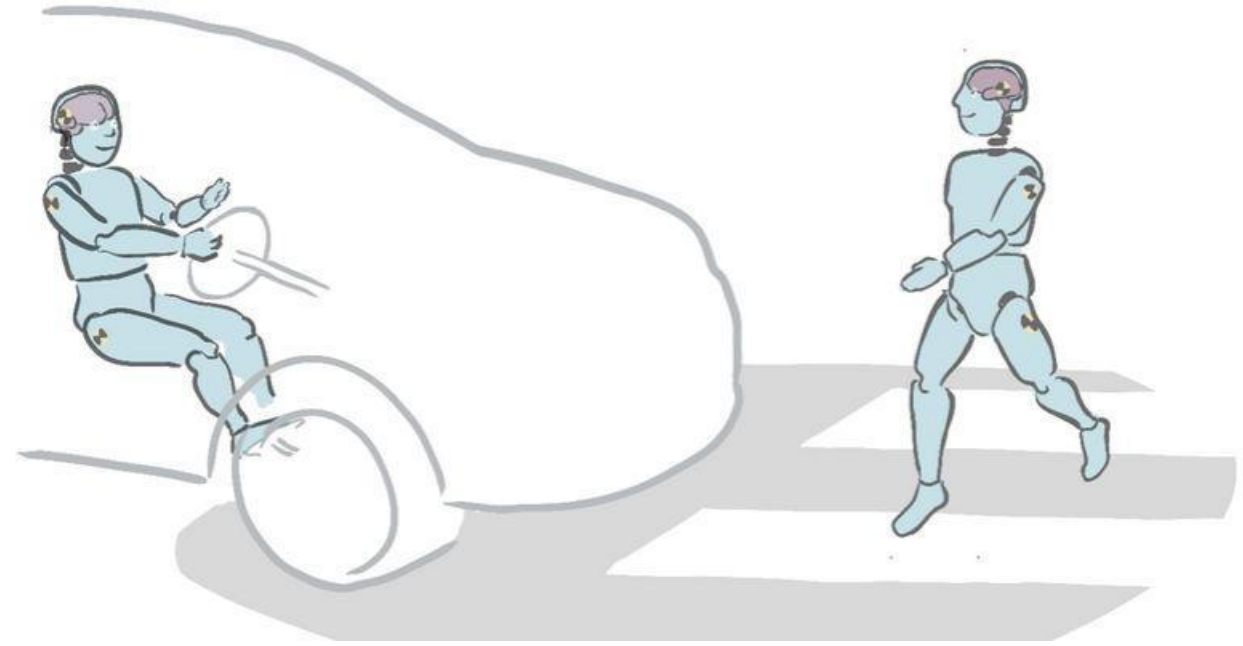


Cognitive models for virtual AV testing



COMMOTIONS: Computational Models of Traffic Interactions for Testing of Automated Vehicles (£1.4M)

PI: Gustav Markkula
University of Leeds



Next steps

- Finer-grained modeling
 - Response times for “wait” decisions
 - Incorporating acceleration/deceleration
 - Changes-of-mind
- Developing cognitive models for other interactions
 - Attention / situation awareness
- Integrating dynamic model predictions in motion planning

Meaningful human control over automated systems

- Increased autonomy of AI → Need to ensure human responsibility
- MHC as tracing and tracking (Santoni de Sio & van den Hoven, 2018)
 - Tracing: humans remain morally responsible for AI's actions
 - Tracking: AI is responsive to relevant human reasons (i.e. "control" signals)
- Hot take: In high-stakes, time-critical human-AI interactions, in order for AI to correctly interpret human actions (and identify the reasons behind them), it should have an adequate mental model of human

Collaborators



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Preprint

SHOULD I STAY OR SHOULD I GO? EVIDENCE ACCUMULATION
DRIVES DECISION MAKING IN HUMAN DRIVERS

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