澳門大學
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Towards human-compatible autonomous car: A study of Turing test in automated driving with affective variability modelling

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Background

1, 350, 000*

Automated driving have the potential to increase road safety, as they can react faster than human drivers and are not subject to human errors.

* World Health Organization. (2018). Global status report on road safety 2018.

Background

Despite the potential benefits, there is no large scale deployment of autonomous cars (ACs) yet.

Existing literature has highlighted that the acceptance of the AC will increase if it drives in a human-like manner.

A variety of algorithms concern:

Human-like driving trajectories
Human-like decision-making at intersections
Human-like car following
Human-like braking behaviour
Human-like 'crawling forward' at pedestrian crossings
Human-like 'peeking' when approaching road junctions
Human-like cost function
Human-like driving policies in collision avoidance and merging

Background

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A variety of algorithms concern:

- *Human-like driving trajectories*
- *Human-like decision-making at intersections*
- *Human-like car following*
- *Human-like braking behaviour*
- *Human-like '[illegible]' towards pedestrian crossings*
- *Human-like 'peeking' when approaching road junctions*
- *Human-like cost function*
- *Human-like driving policies in collision avoidance and merging*

Teaching ACs about human-like driving from the algorithmic perspective

Background

Despite the potential benefits, there is no large scale deployment of autonomous cars (ACs) yet.

Existing literature has highlighted that the acceptance of the AC will increase if it drives in a human-like manner.

However, literature presents no human-subject research focusing on passengers in a natural environment that examines whether the AC should behave in a human-like manner.

How to offer naturalistic experiences from a passenger’s seat perspective to measure the people’s acceptance of ACs?

The Turing test of automated driving

Results of the Turing test

Confusion matrix of three road stages for the results in the Turing test

		First stage: Human driver	First stage: AI driver	Second stage: Human driver	Second stage: AI driver	Third stage: Human driver	Third stage: AI driver
Unlikely	**1**	6	8	6	10	11	6
Somewhat likely	**2**	15	9	4	14	13	6
Very likely	**3**	10	20	10	24	9	20

(to be driven by the AI driver)

First stage
38.24%

Second stage
44.12%

Third stage
47.69%

How do human passengers choose in the Turing test of automated driving?

How do human passengers choose?

Passenger

Human driver

or

AI driver

First-order mentalising (self-other mentalising)

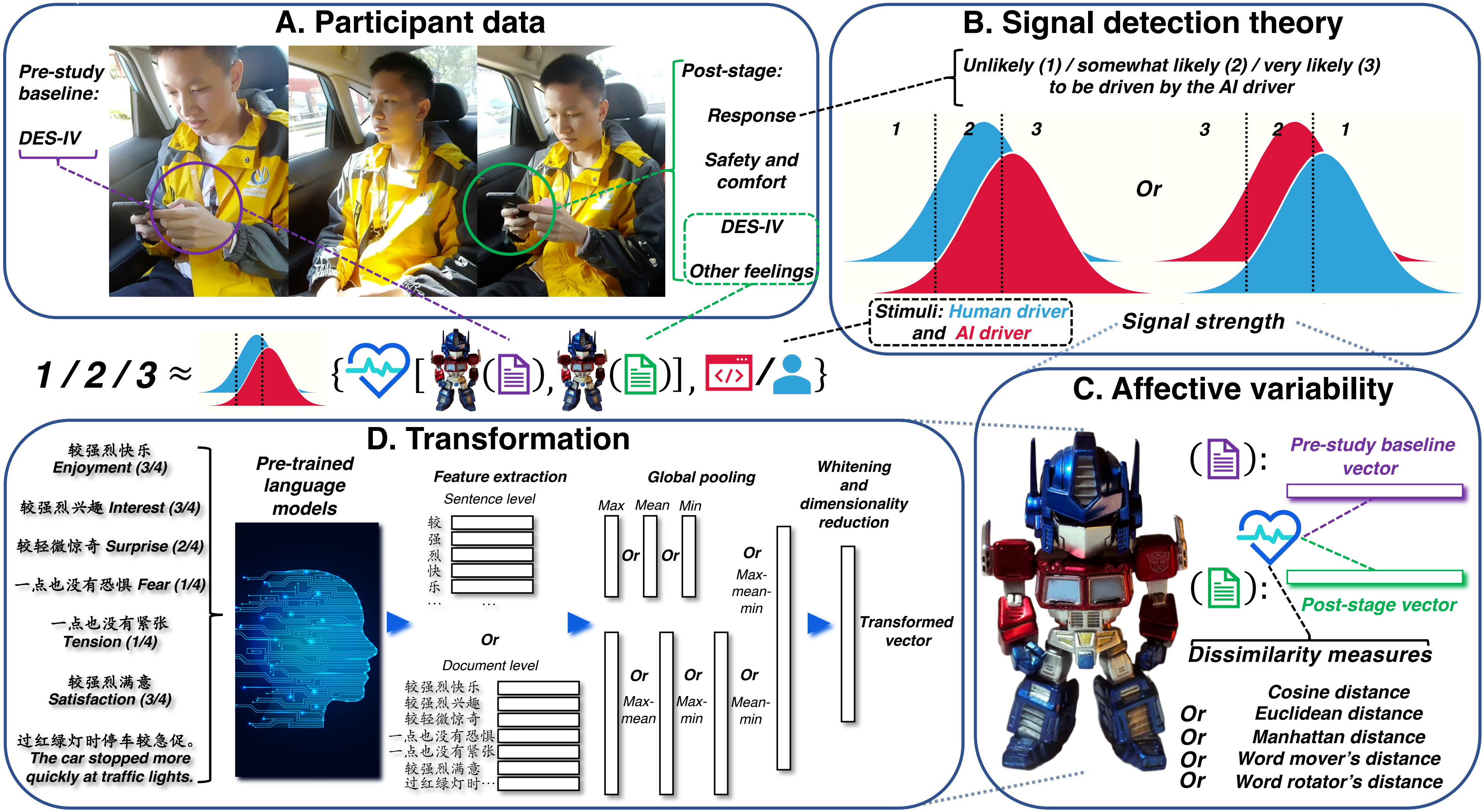
Choice behaviour →

$$B = f(P, E)$$

Passenger **Driving environment**

Kurt Lewin, (1936)

How do human passengers choose?



Results of the computational models

Comparison on the Outer Loop Cross-Validation of Nested-LOOCV with Baselines

(a) Evaluation results on the first stage.

Models	*ACC*	*P*	*R*	*F1*	*rho*
Baselines					
Random	33.27	33.21	33.25	32.27	0.07
Probability	36.14	33.24	33.26	33.00	-0.68
Golden	38.24	24.47	36.51	28.79	14.91
SDT-AV					
Original	33.82	27.36	28.21	27.09	16.31
PLM-tf (AA)	51.47	50.71	**51.11**	50.30	38.75**
PLM-tf (AA+OF)	**54.41**	**50.94**	50.08	**50.37**	**38.96****

Results of the computational models

Comparison on the Outer Loop Cross-Validation of Nested-LOOCV with Baselines

(a) Evaluation results on the first stage.

(b) Evaluation results on the second stage.

Models	*ACC*	*P*	*R*	*F1*	*rho*
Baselines					
Random	33.35	33.37	33.36	32.15	0.15
Probability	37.71	33.55	33.58	33.32	0.25
Golden	44.12	26.67	36.03	30.62	3.94
SDT-AV					
Original	45.59	41.20	37.19	36.92	15.43
PLM-tf (AA)	57.35	56.65	53.80	54.59	29.70*
PLM-tf (AA+OF)	**63.24**	**59.74**	**56.62**	**57.48**	**41.20*** **

Results of the computational models

Comparison on the Outer Loop Cross-Validation of Nested-LOOCV with Baselines

(a) Evaluation results on the first stage.

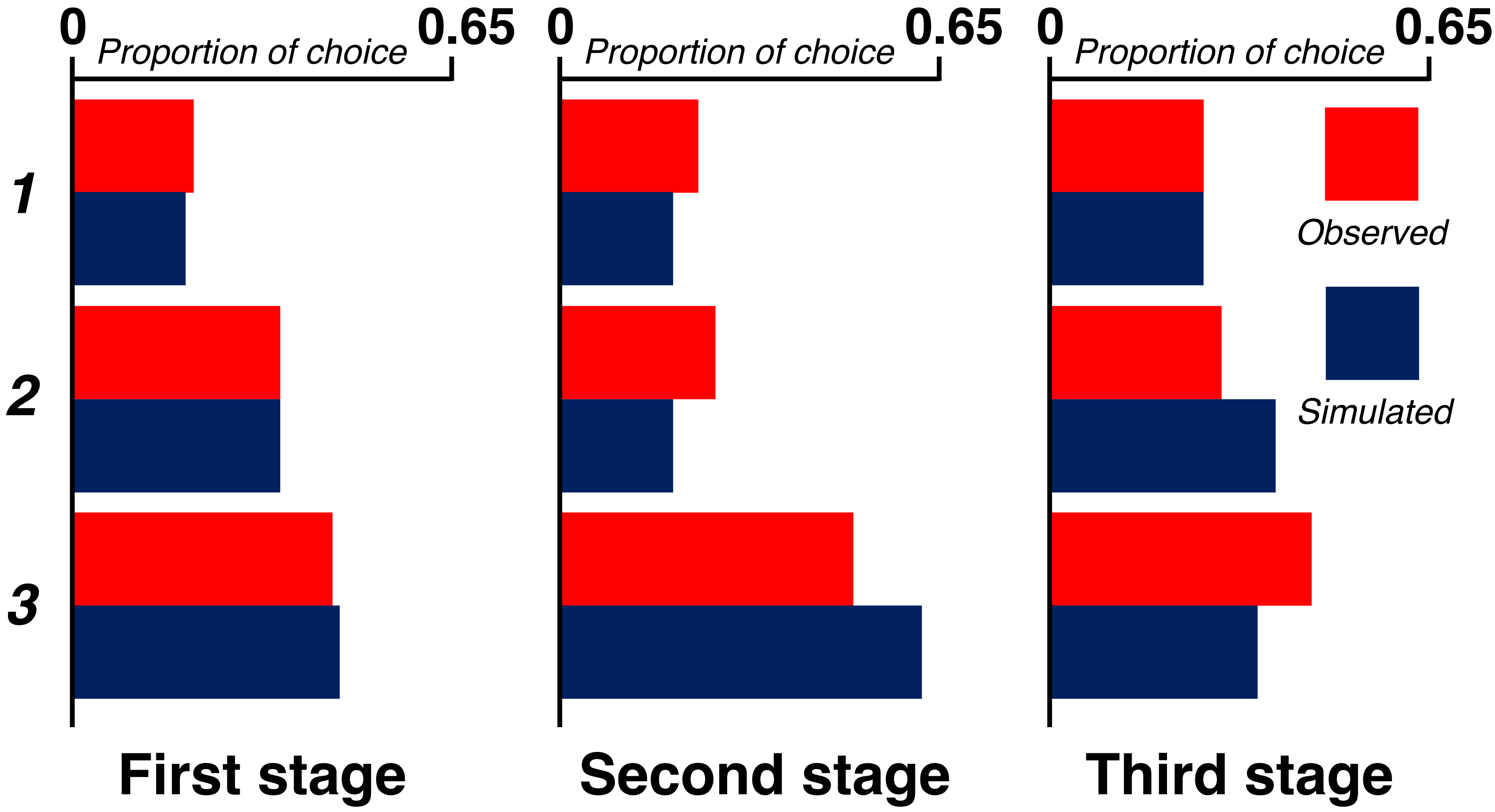
(b) Evaluation results on the second stage.

(c) Evaluation results on the third stage.

Models	*ACC*	*P*	*R*	*F1*	*rho*
Baselines					
Random	33.40	33.34	33.39	32.66	-0.58
Probability	35.14	33.13	33.16	32.87	-0.15
Golden	47.69	31.94	44.56	36.52	31.68*
SDT-AV					
Original	53.85	48.84	45.62	45.42	27.54*
PLM-tf (AA)	52.31	49.65	49.81	49.67	37.90**
PLM-tf (AA+OF)	**55.38**	**51.81**	**51.56**	**51.67**	**46.31*****

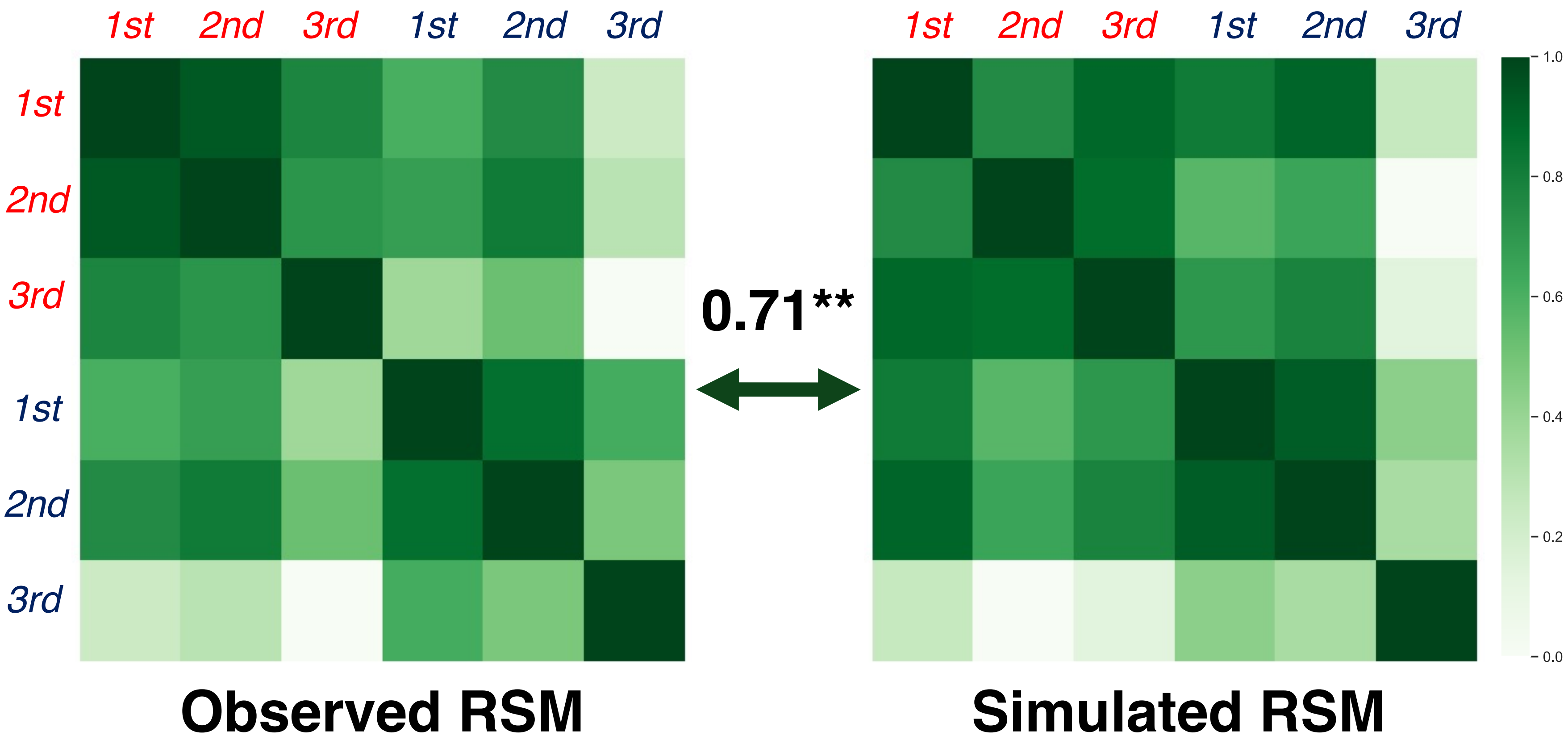
Results of the computational models

Comparison of the proportion of choices between model simulations (blue) and empirically observed choices (red)



Results of the computational models

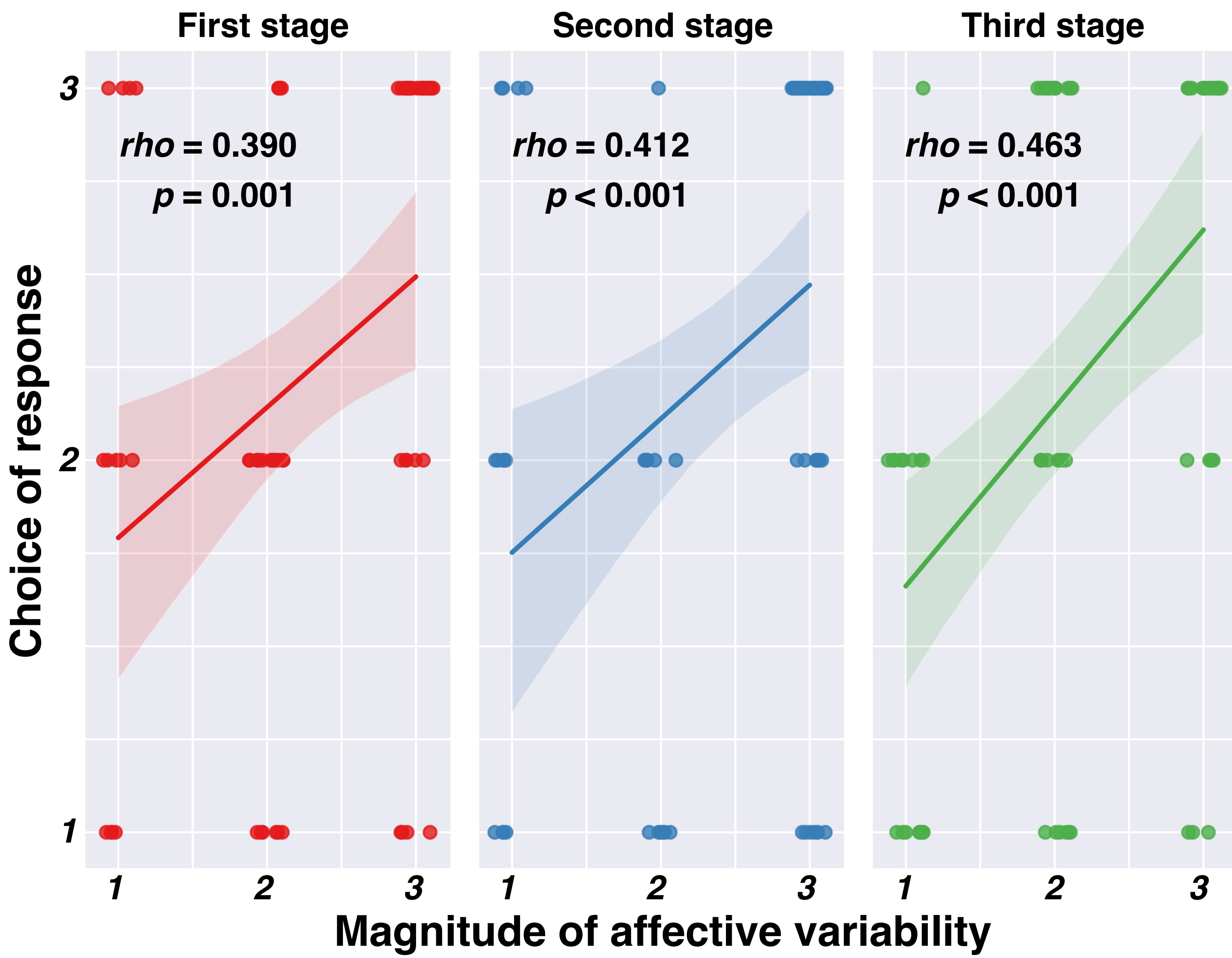
Representational similarity between the representational similarity matrix (RSM) of empirically observed choices (left) and model simulations (right) averaged over all participants.



Correlations between choice of response and affective variability

The Spearman's rank correlation score between

the gold labels and the magnitude of affective variability (AV)



Ordinal logistic regression analysis of model simulations

(a) Results of OLR predicting simulated labels on the first stage.

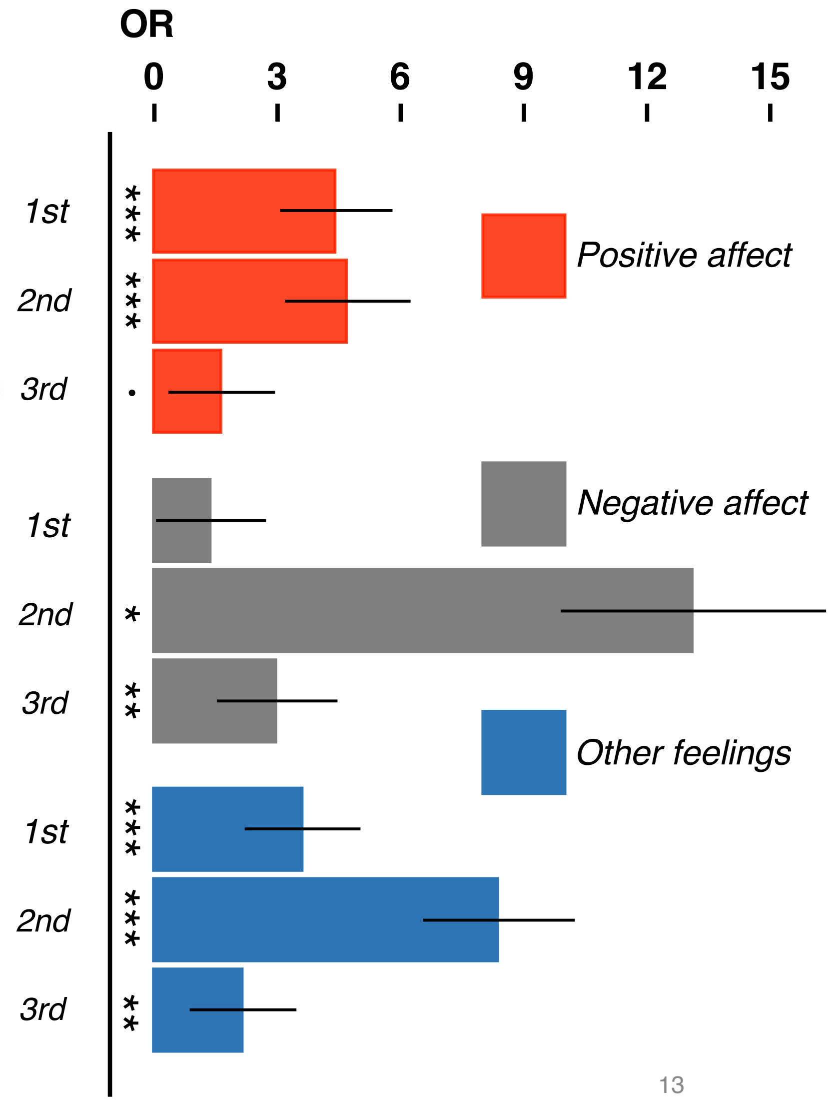
Coeff.	β (SE)	t Value	OR (95% CI)	p Value
I (1|2)	**-2.31 (0.47)**	**-4.92**		**<.0001*** **
I (2|3)	0.40 (0.31)	1.26		.208
PA	**1.49 (0.32)**	**4.66**	**4.42 (2.47-8.72)**	**<.0001*** **
NA	0.31 (0.29)	1.08	1.37 (0.78-2.47)	.28
OF	**1.29 (0.34)**	**3.74**	**3.62 (1.93-7.54)**	**<.001*** **

(b) Results of OLR predicting simulated labels on the second stage.

Coeff.	β (SE)	t Value	OR (95% CI)	p Value
I (1|2)	**-3.85 (0.85)**	**-4.55**		**<.0001*** **
I (2|3)	**-1.72 (0.65)**	**-2.67**		**.008** **
PA	**1.55 (0.42)**	**3.65**	**4.70 (2.23-12.11)**	**<.001*** **
NA	**2.57 (1.17)**	**2.19**	**13.11 (2.10-226.37)**	**.028***
OF	**2.12 (0.61)**	**3.47**	**8.37 (3.04-35.96)**	**<.001*** **

(c) Results of OLR predicting simulated labels on the third stage.

Coeff.	β (SE)	t Value	OR (95% CI)	p Value
I (1|2)	**-1.35 (0.33)**	**-4.04**		**<.0001*** **
I (2|3)	**0.80 (0.30)**	**2.63**		**.009** **
PA	0.49 (0.26)	1.86	1.63 (0.98-2.78)	.062
NA	**1.09 (0.38)**	**2.83**	**2.97 (1.56-7.14)**	**.005** **
OF	**0.77 (0.26)**	**2.93**	**2.15 (1.31-3.69)**	**.003** **



Summary

We conducted a Turing test of automated driving based on 69 passengers' feedback in a real scenario, and test results showed that SAE Level 4 ACs could pass the Turing test when cheating human passengers with more than 50% error judgements.

On this basis, we proposed a computational model combining SDT with AV (transformed by PLM) to predict the passenger's choice behaviour in the Turing test. This is, to the best of our knowledge, the first computational model which provides a mechanistic understanding underlying passengers' mentalising process.

Experimental results and further analysis showed that the greater AV that passengers had, the more likely they identified the driver as the AI algorithm. These findings provide insights into the future automated driving that we should incorporate and improve the affective stability of passengers inside of ACs.

Acknowledgement

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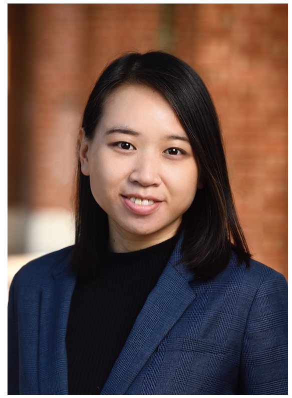
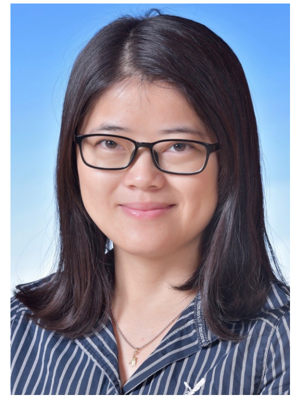


Anqi Liu



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Thanks for your attendance!