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Bot or not: How passenger tells apart AI and human drivers in the Turing test of automated driving?

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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

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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 stages for the results in the Turing test

	First road stage: Human driver	First road stage: AI driver	Second road stage: Human driver	Second road stage: AI driver	Third road stage: Human driver	Third road stage: AI driver
1	6	8	6	10	11	6
2	15	9	4	14	13	6
3	10	20	10	24	9	20

First road stage 38.24%

Second road stage 44.12%

Third road stage 47.69%

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

How do human passengers choose?

Passenger

First-order mentalizing
(self-other mentalizing)

Human driver

or

AI driver

Kurt Lewin, (1936)

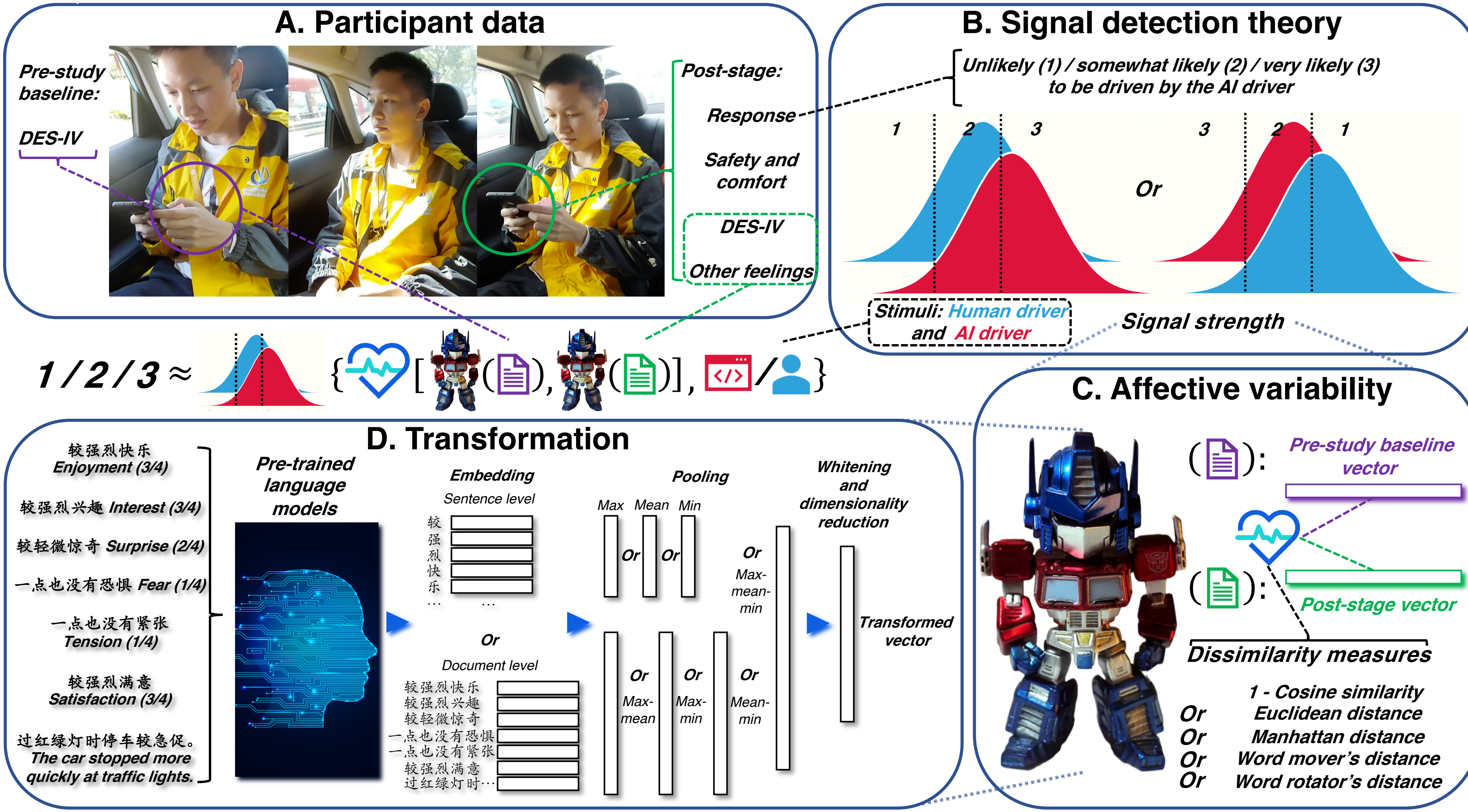
Choice behaviour →

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

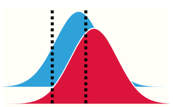
Passenger

Driving environment

How do human passengers choose?



How do human passengers choose?

1 / 2 / 3 ≈  {

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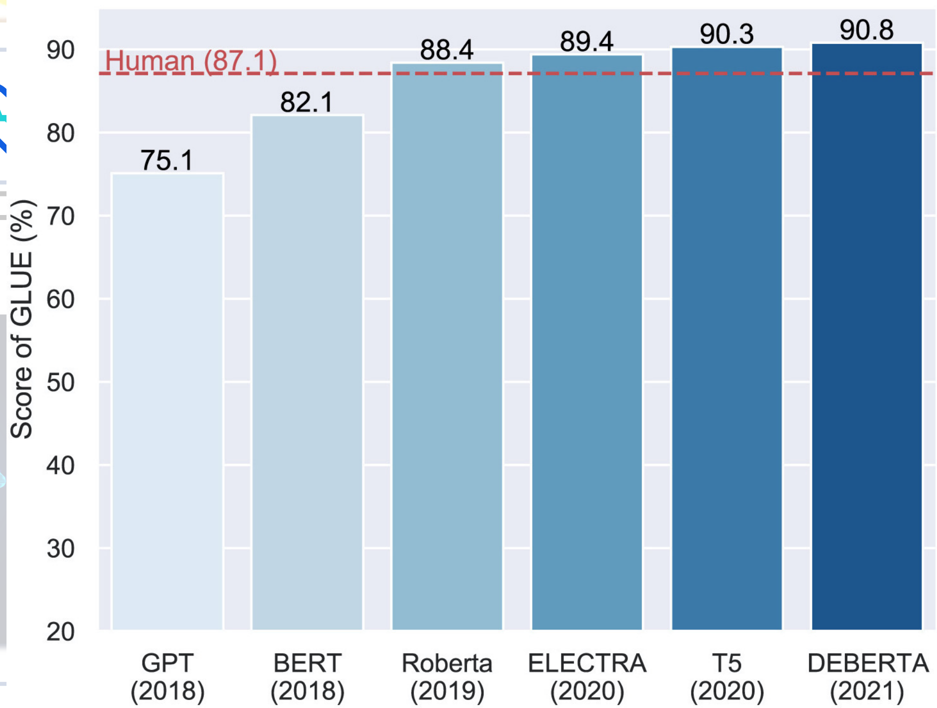
AI Open
Available online 26 August 2021
In Press, Journal Pre-proof

Pre-Trained Models: Past, Present and Future

Xu Han [1]*, Zhengyan Zhang [1,*], Ning Ding [1,*], Yuxian Gu [1,*], Xiao Liu [1,*], Yuqi Huo [2,*], Jiezhong Qiu [1], Liang Zhang [2], Wentao Han [1,†], Minlie Huang [1,†], Qin Jin [2,†], Yanyan Lan [4,†], Yang Liu [1,4,†], Zhiyuan Liu [1,†], Zhiwu Lu [3,†], Xipeng Qiu [5,†], Ruihua Song [3,†], Jie Tang [1,†] ... Jun Zhu [1,†]



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*	ρ
Baselines					
Random	33.27	33.21	33.25	32.27	0.07
Probability	36.14	33.24	33.26	33.00	-0.68
God	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	**56.25*****
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*	*ρ*
Baselines					
Random	33.35	33.37	33.36	32.15	0.15
Probability	37.71	33.55	33.58	33.32	0.25
God	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	36.46**
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.

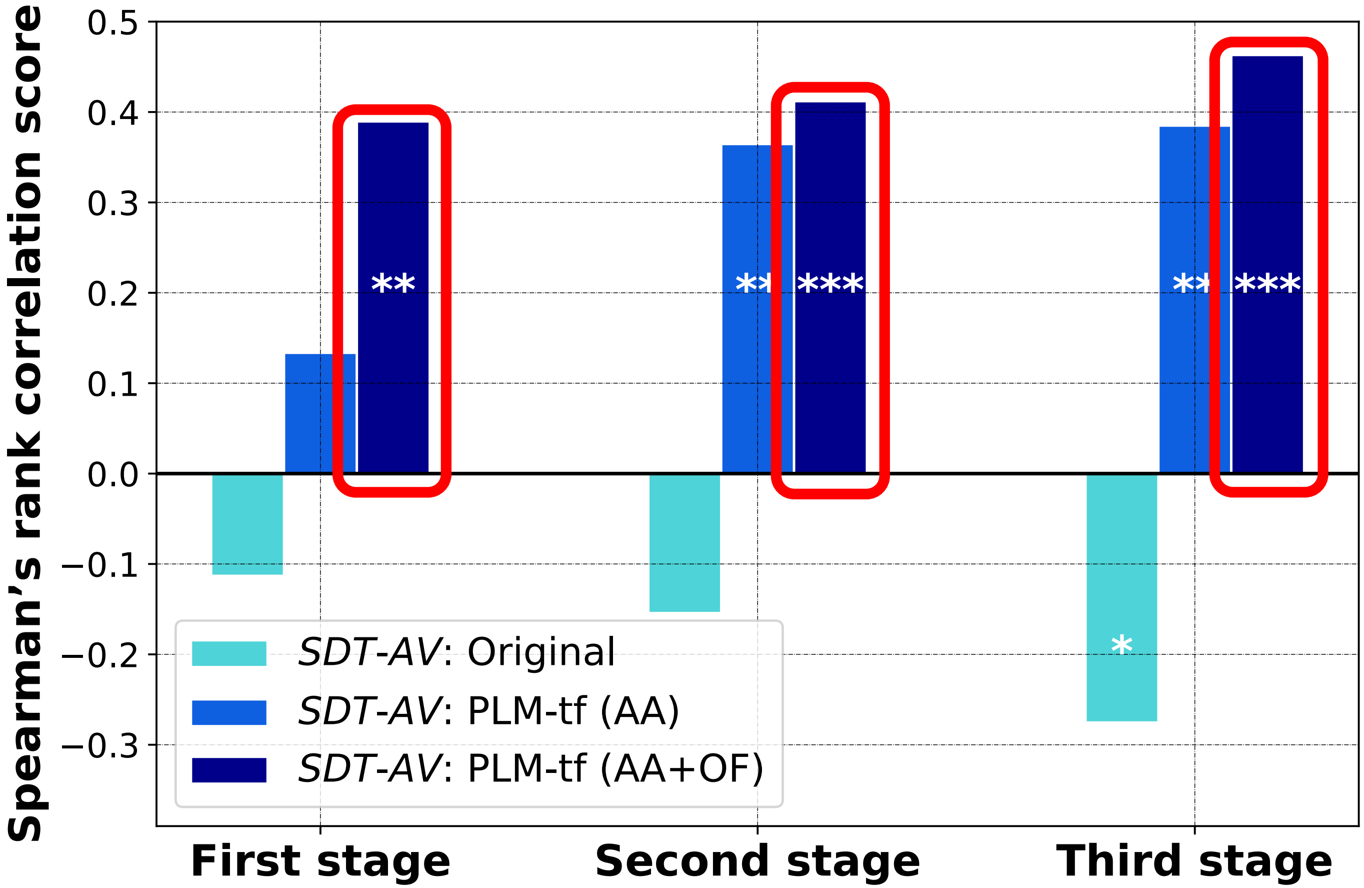
(b) Evaluation results on the second stage.

(c) Evaluation results on the third stage.

Models	*ACC*	*P*	*R*	*F1*	ρ
Baselines					
Random	33.40	33.34	33.39	32.66	-0.58
Probability	35.14	33.13	33.16	32.87	-0.15
God	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	38.50**
PLM-tf (AA+OF)	**55.38**	**51.81**	**51.56**	**51.67**	**46.31*****

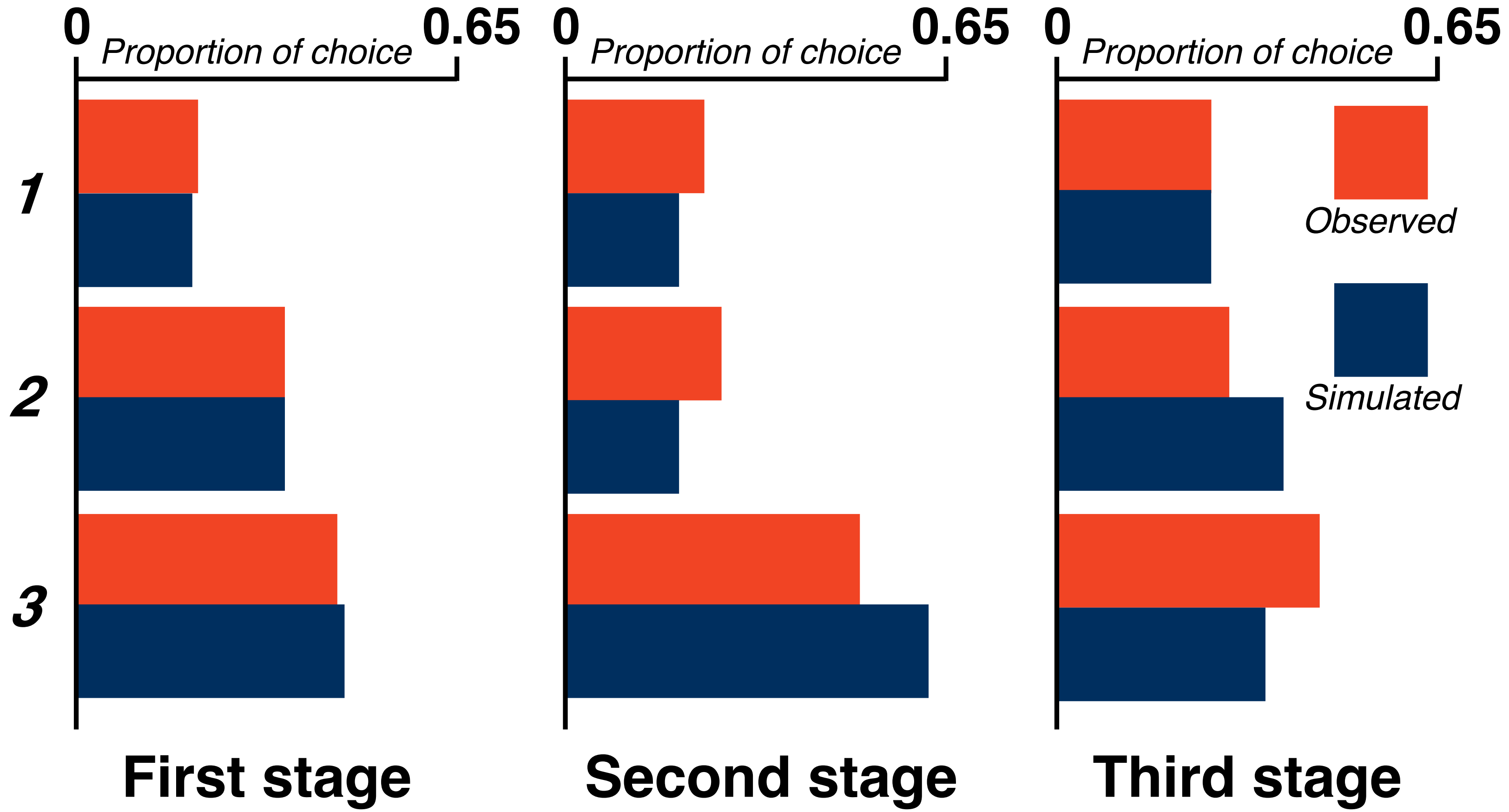
Correlations between choice of preference and affective variability

Comparison of the Spearman's rank correlation score between the gold labels and the magnitude of affective variability



Ordinal logistic regression analysis of model simulations

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



Ordinal logistic regression analysis of model simulations

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

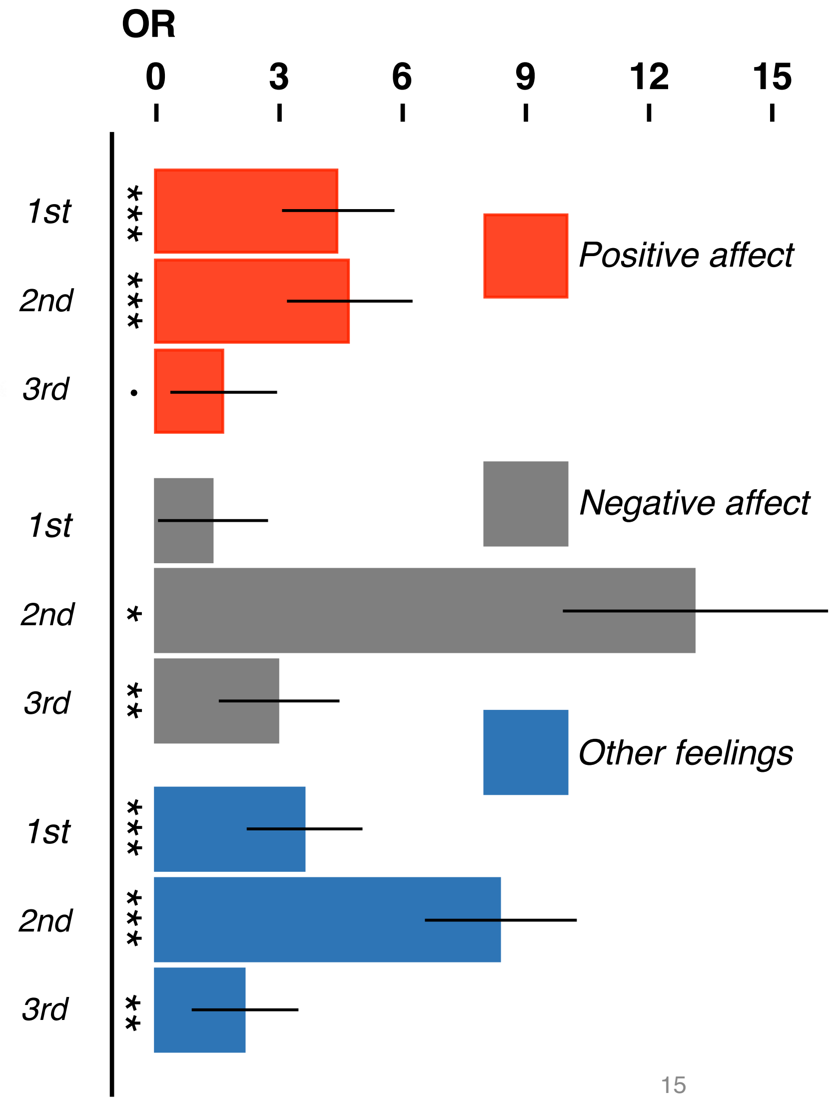
Coeff.	β (SE)	t Value	OR (95% CI)	p Value
I (1|2)	**-2.31 (0.47)**	**-4.92**		**<.0001*****
I (2|3)	0.40 (0.31)	1.26		.208
PA	**1.49 (0.32)**	**4.66**	**4.42 (2.47-8.72)**	**<.0001*****
NA	0.31 (0.29)	1.08	1.37 (0.78-2.47)	.28
OF	**1.29 (0.34)**	**3.74**	**3.62 (1.93-7.54)**	**<.001*****

(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 conduct a Turing test of automated driving based on 69 passengers' feedback in a real scenario, and test results show that SAE Level 4 ACs could pass the Turing test with accuracy no more than 50%.

On this basis, we propose a model combining SDT with AV (transformed by PLMs) 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' mentalizing process.

Extensive experimental results and further analysis show that the the greater AV that passengers have, the more likely they identify the driver as the AI algorithm. These findings suggest that future automated driving should improve the affective stability of passengers.

Thanks for your attendance!