



Center for
Precision Psychiatry
MGH Department of Psychiatry

TAPPING INTO COGNITION: CONNECTING BRAIN IMAGING AND DIGITAL BIOMARKERS FOR PRECISION PSYCHIATRY

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DISCLOSURES



Center for
Precision Psychiatry
MGH Department of Psychiatry

I have the following relevant financial relationship with a commercial interest to disclose:

- KeyWise AI (cofounder)
- Embodied Labs (advisory board)
- Blueprint Health (advisory board)
- Otsuka (consultant)



AMERICAN JOURNAL OF INSANITY.

APRIL, 1891.

THE MECHANISM OF INSANITY.*

BY EDWARD COWLES, M. D.,
Superintendent of the McLean Asylum, Somerville, Mass.

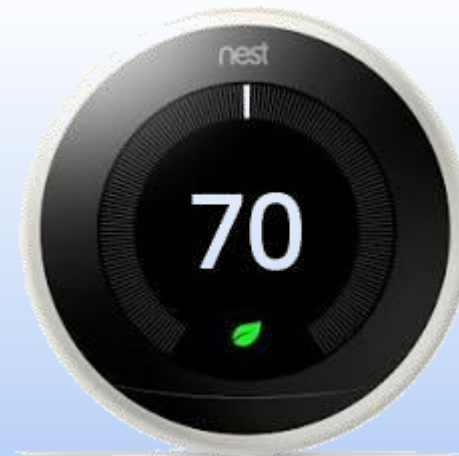
The “empirical valuation” of morbid manifestations of these mental phenomena [retention, reproduction, and association of ideas], that is commonly made by the alienist, has the greater value when, by careful study and comparison with the action of the normal mechanisms...by a like “tireless observation”. Then knowing what to look for, as he who is expert with the microscope, he may report what he sees...with more completeness and precision”

THE LANCET.

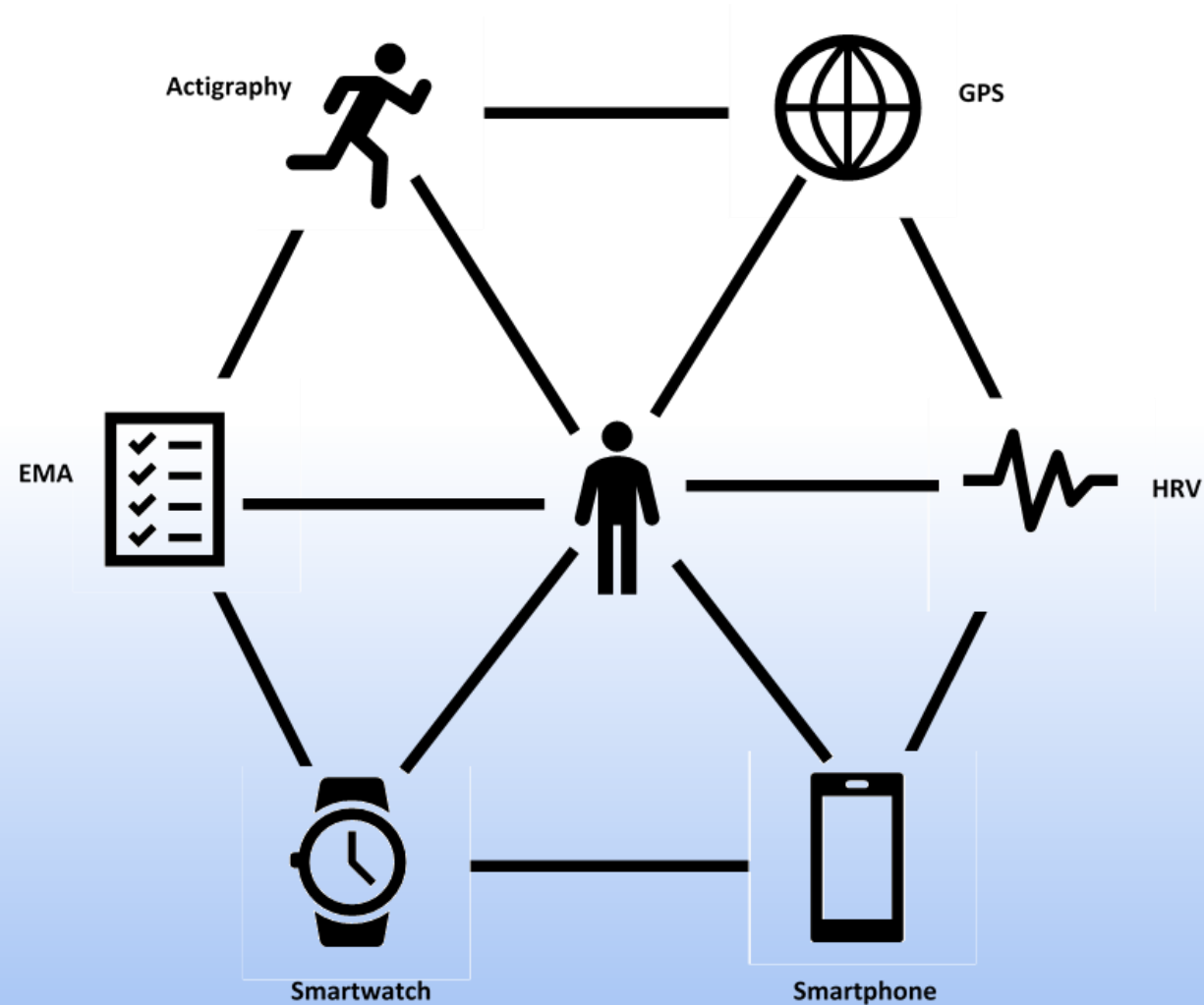
LONDON: SATURDAY, MAY 14, 1859.

When a lunatic is received into an asylum, he is removed by an interval of time, and of locality, from the origin of his disease; he is completely isolated from the sphere, and separated from all the surrounding conditions, in which he passed his life. The necessary clues to trace back the causes of his malady are broken by the reserve of friends, the want of knowledge of others, and by numerous difficulties which, in most cases, reduce the formal statement entered in the asylum case-book to a mere hypothesis, void of precision and of authority.

TOOLS OF “TIRELESS OBSERVATION” IN OUR “SURROUNDING CONDITIONS”



ECOLOGICAL MOMENTARY ASSESSMENT (EMA)/UBIQUITOUS SENSING



PASSIVE MONITORING OF MOOD AND COGNITION: DEEP EMBEDDED REAL-TIME DIGITAL SAMPLING

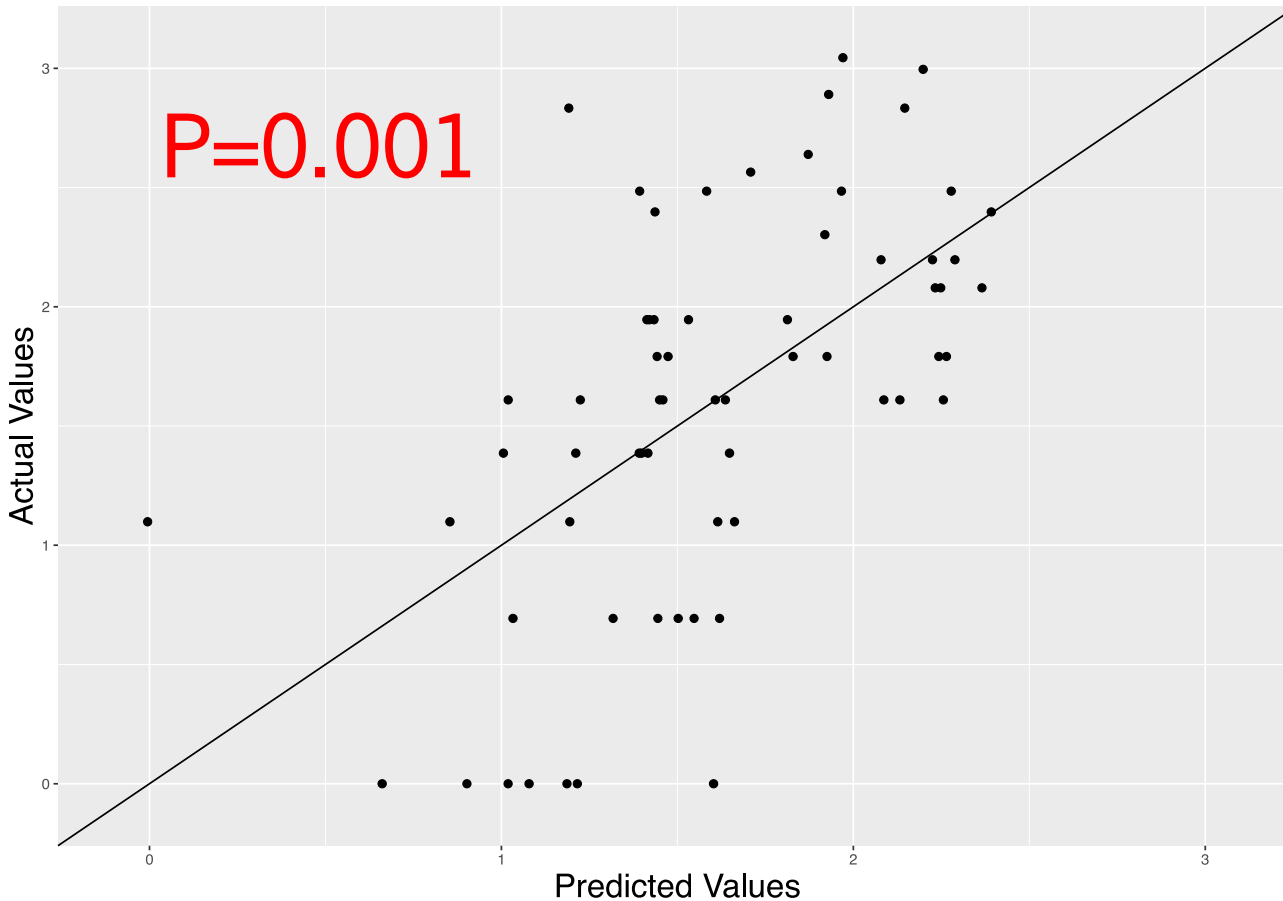


iOS BiAffect Keyboard

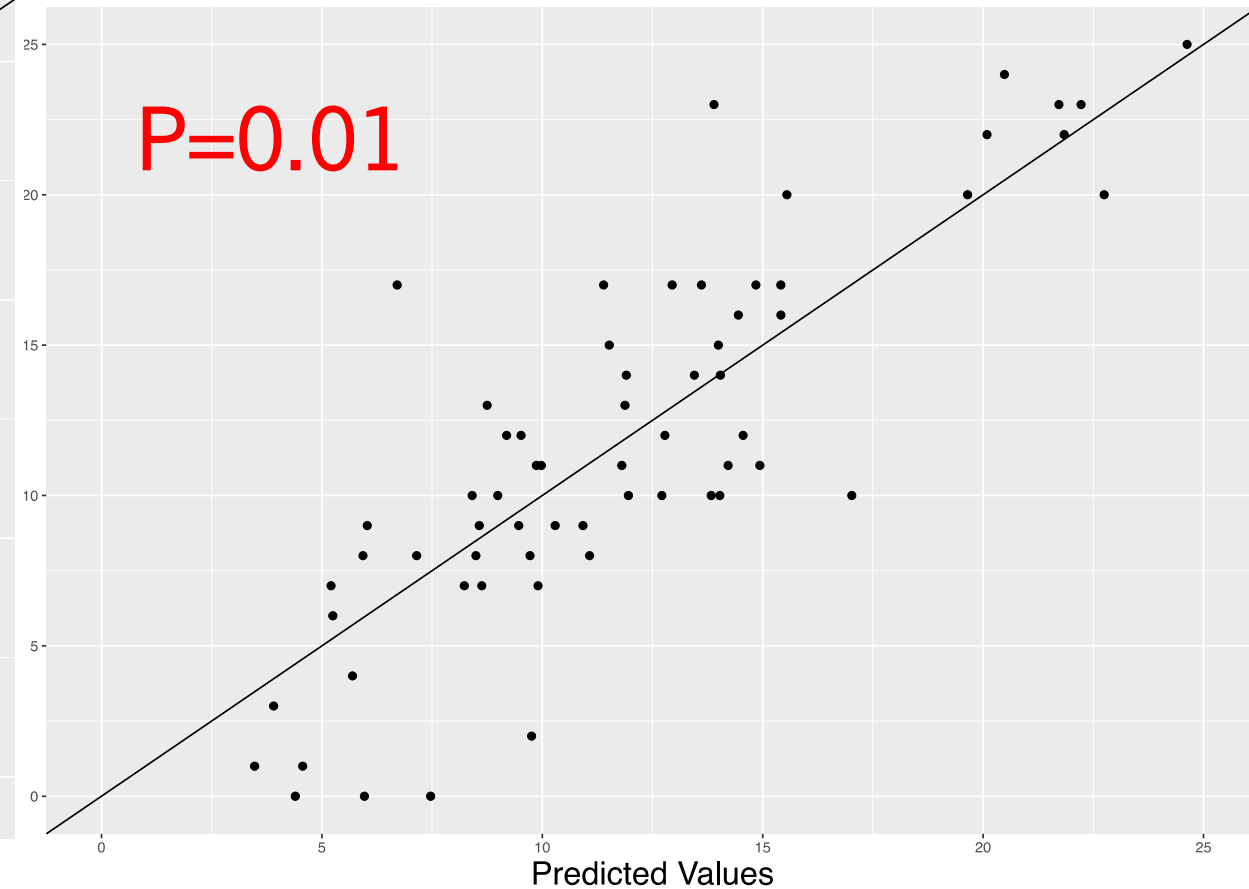
- The core is a custom keyboard that tracks **ALL keystroke metadata in the background**. E.g.,
 - Force of key presses measured by accelerometer
 - Residence time
 - Inter-key time
 - Character count
 - Backspace ratio
 - Auto-correction rate
- Using both keystroke dynamics and iPhone sensor data, BiAffect builds a mathematical model that performs **neuropsychological testing without actually testing**.

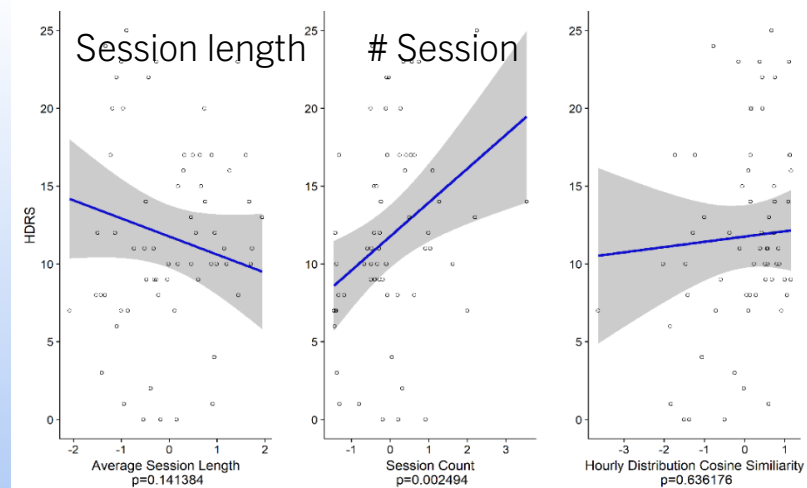
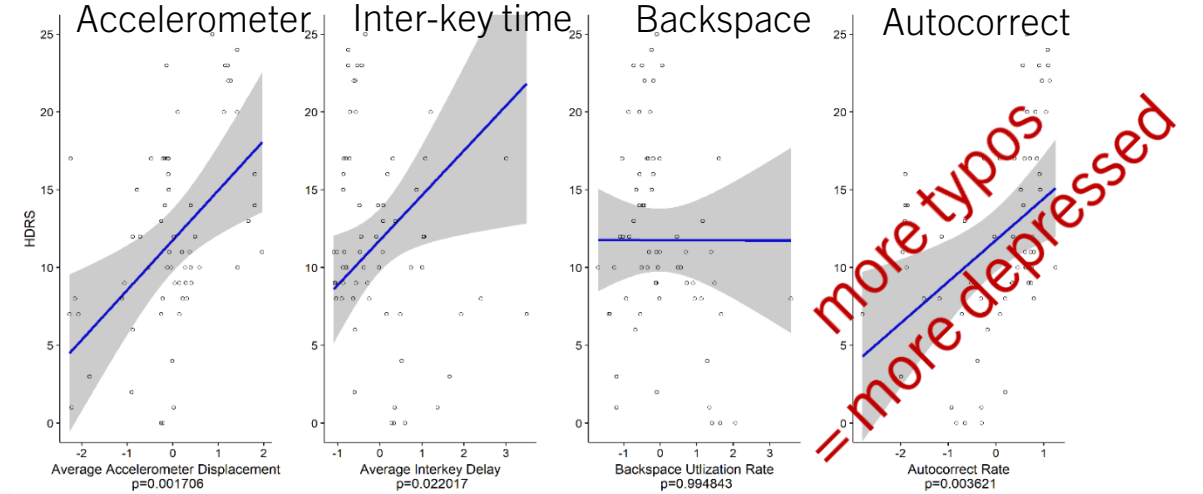
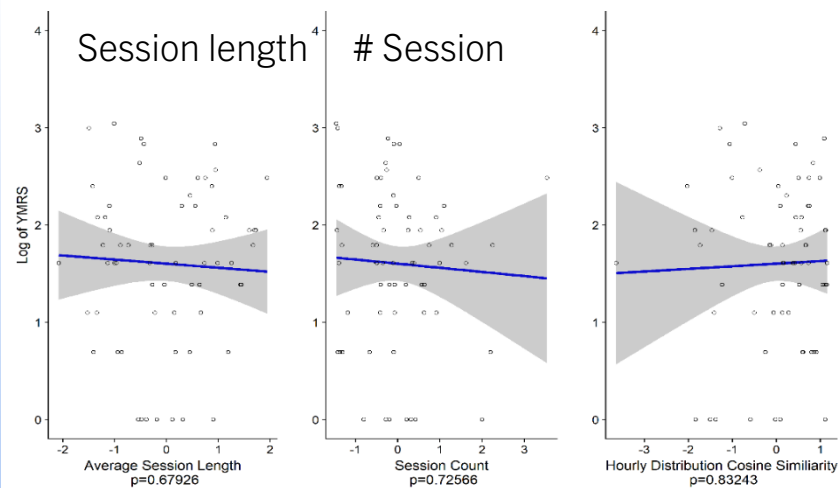
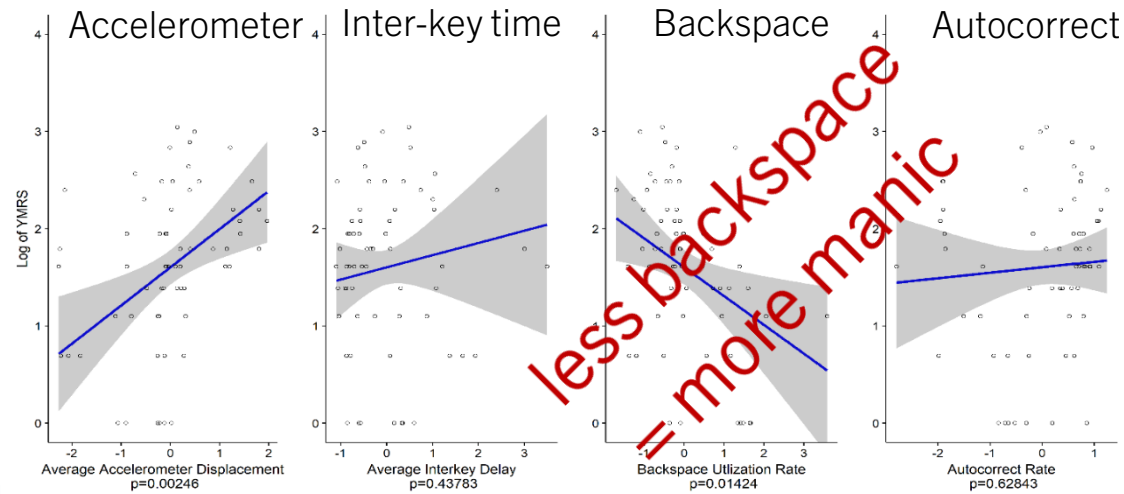


Young Mania Rating Scale Scores
Actual vs Predicted,



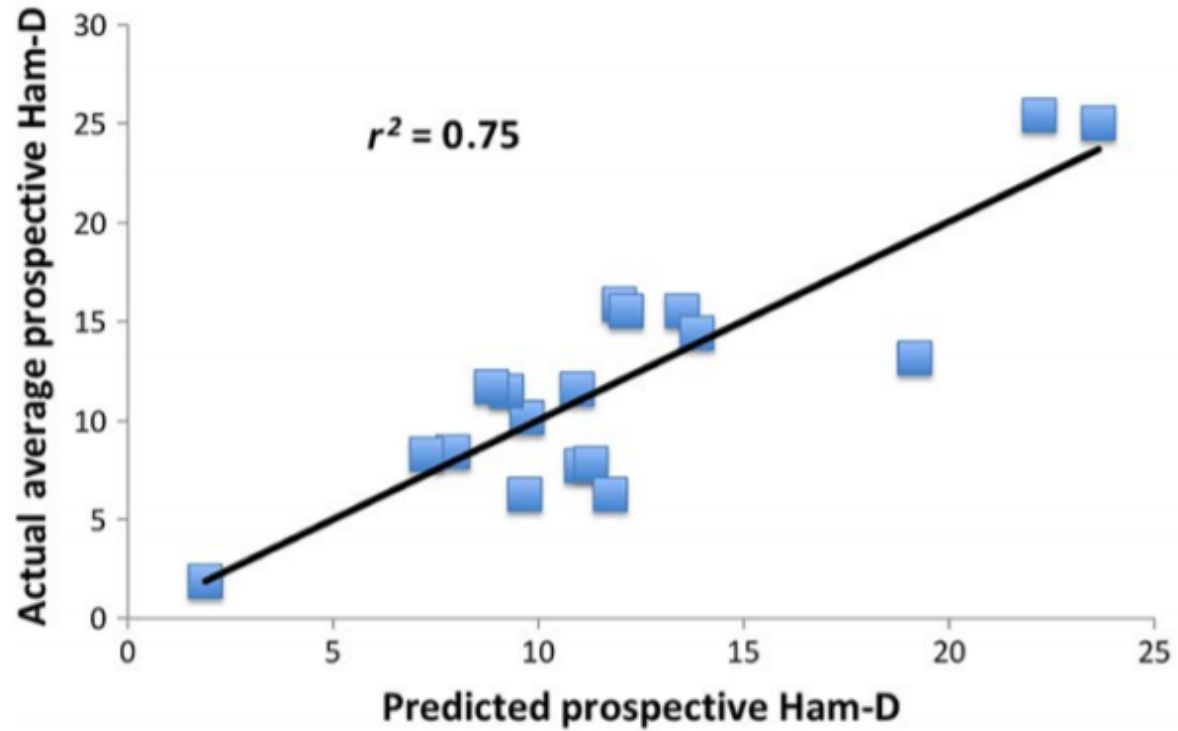
Hamilton Depression Rating Scale Scores
Actual vs Predicted,



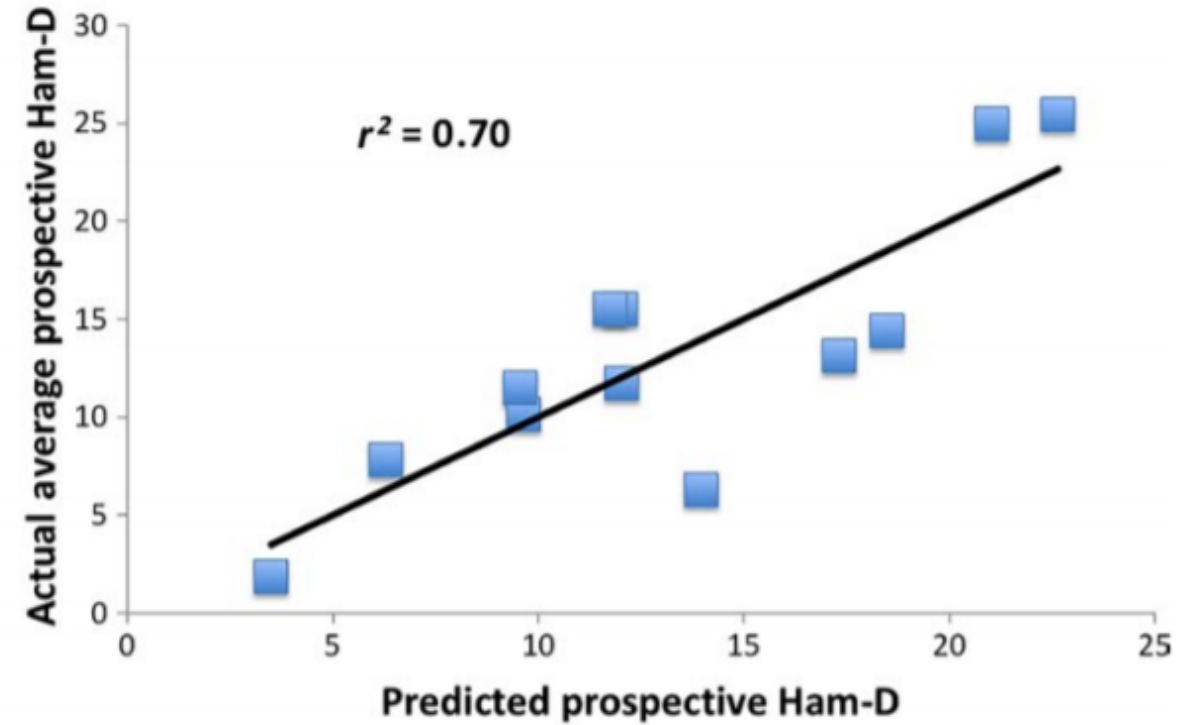


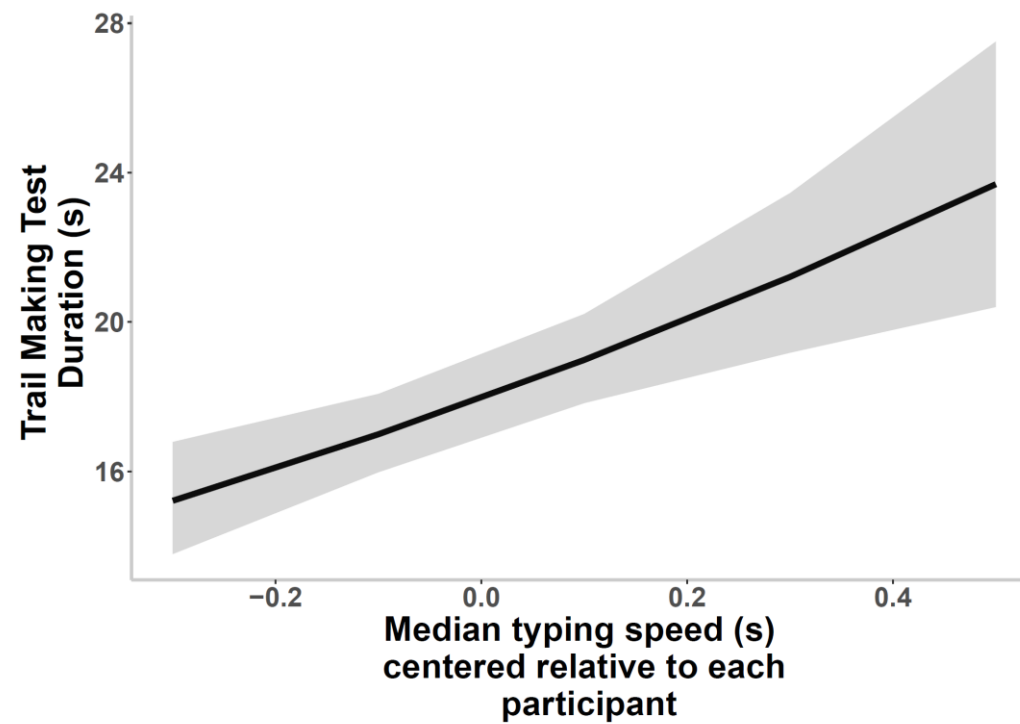
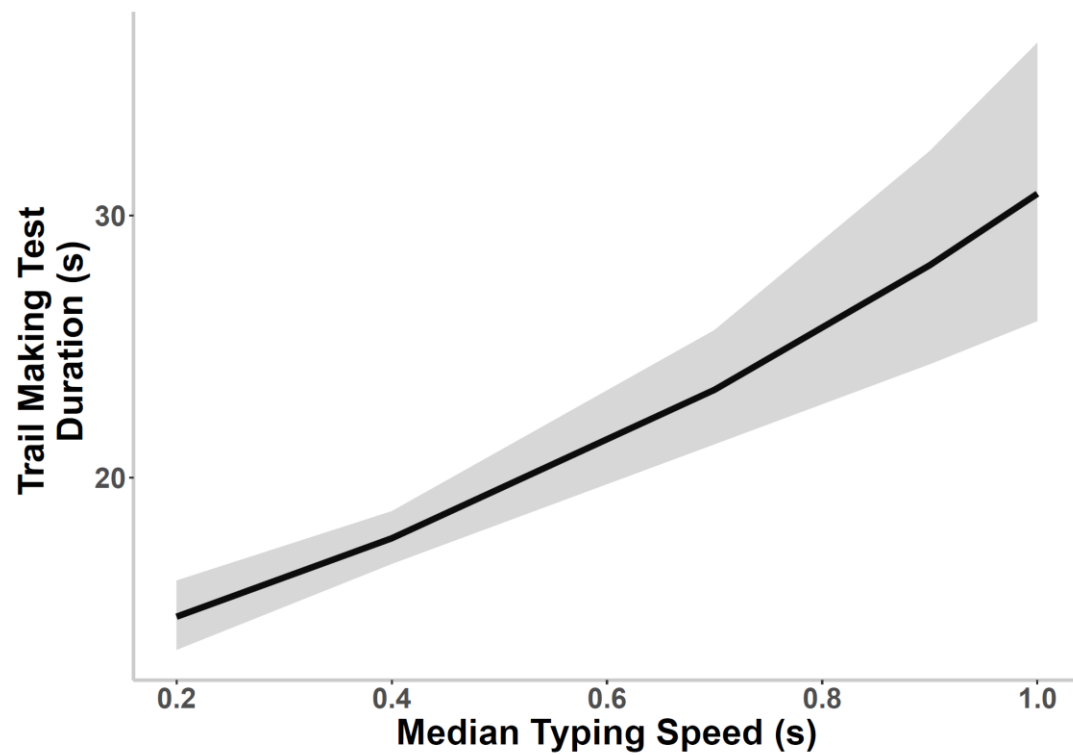


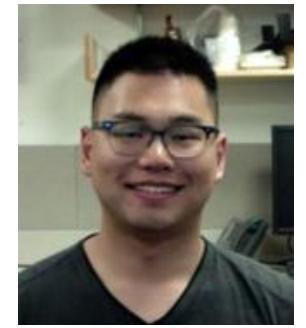
(A) Instability of daily mood
predicting future depression levels



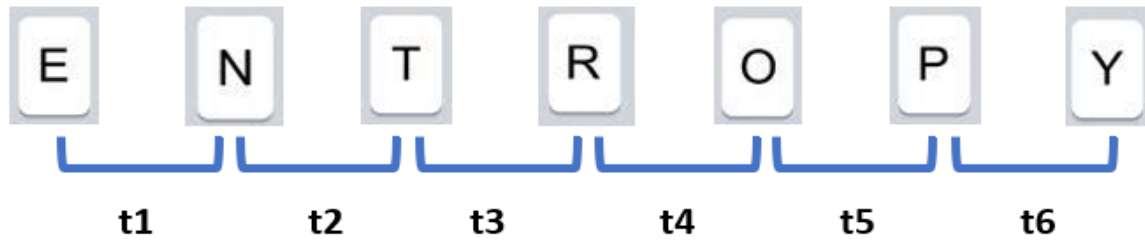
(B) Instability of daily typing speed
predicting future depression levels







TIME-SERIES OF KEYPRESSES

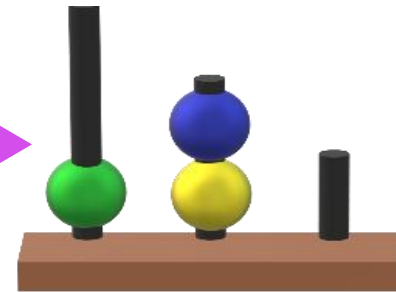
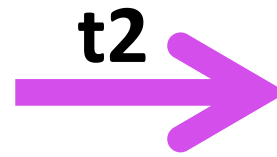
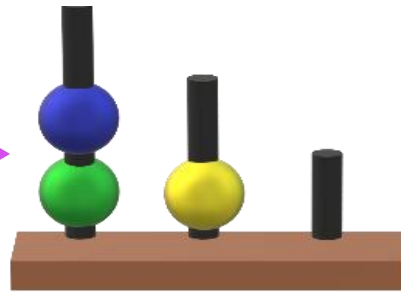
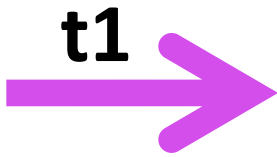
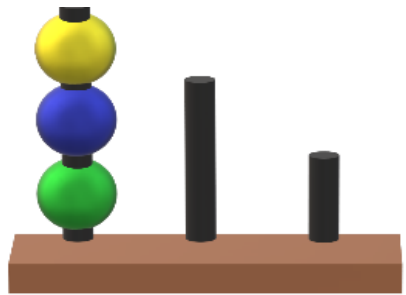


↓ entropy, ↑ regularity time-series

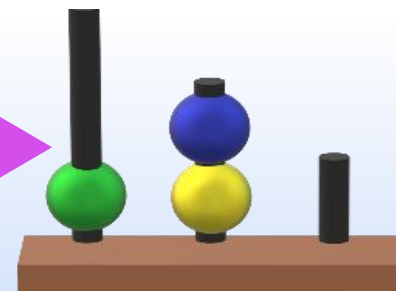
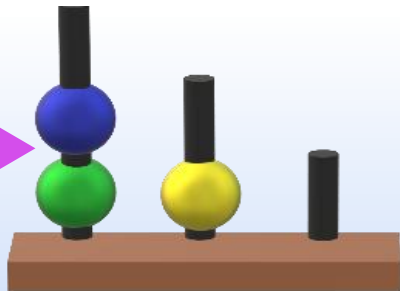
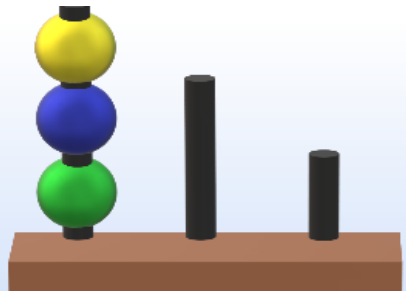


↑ entropy, ↓ regularity time-series

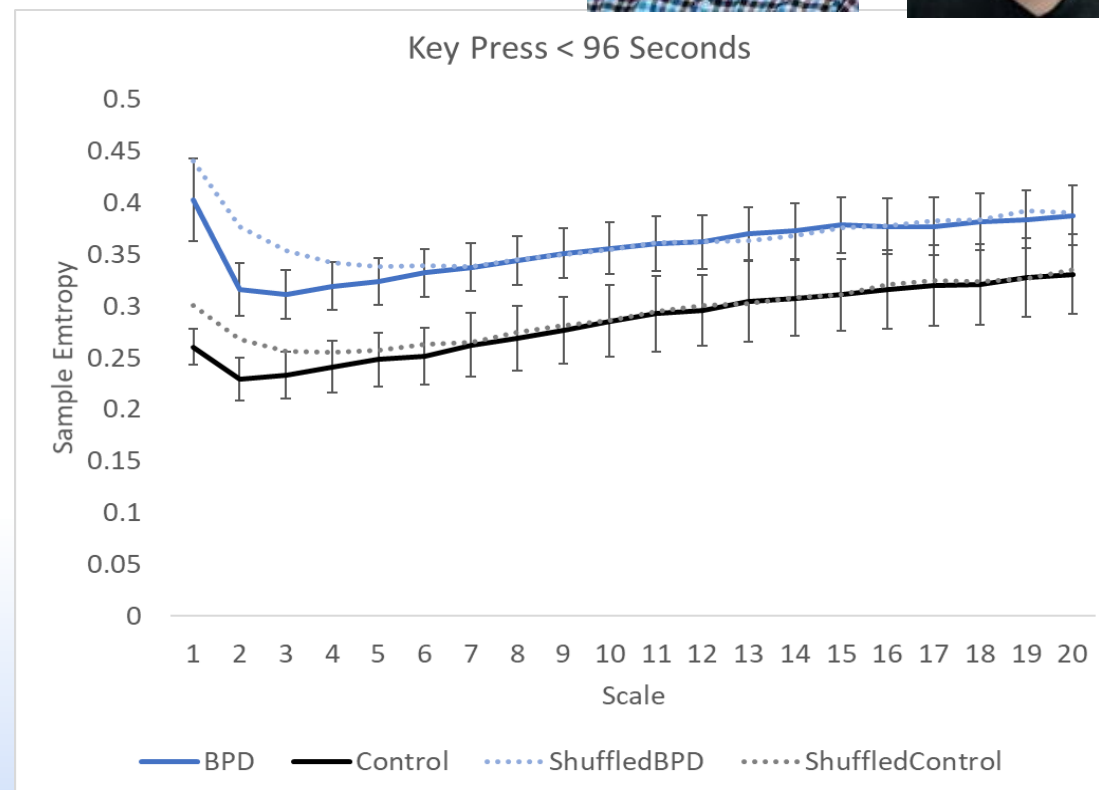
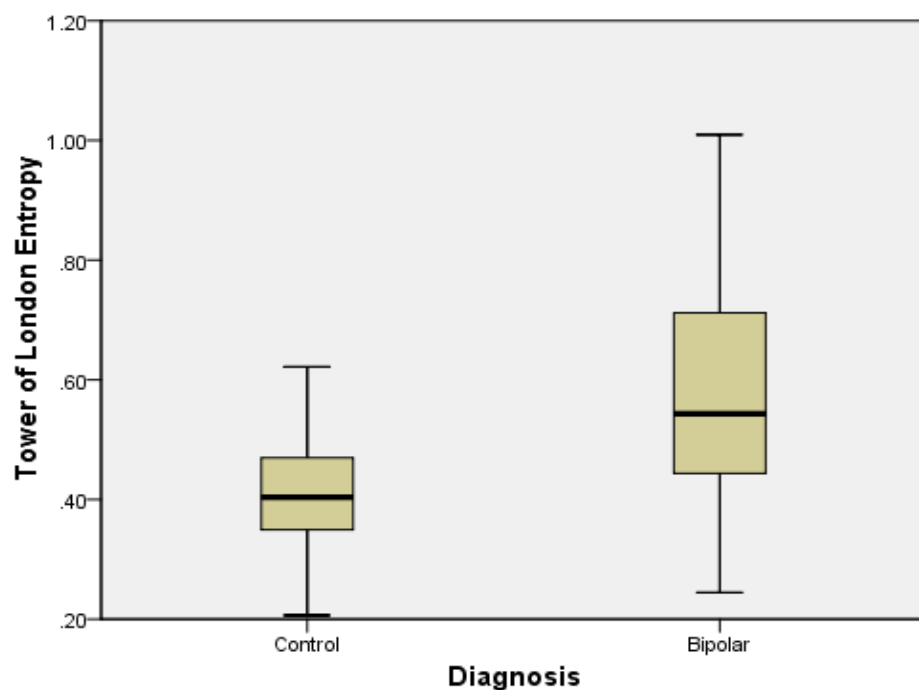
TIME-SERIES OF TOWER OF LONDON MOVES



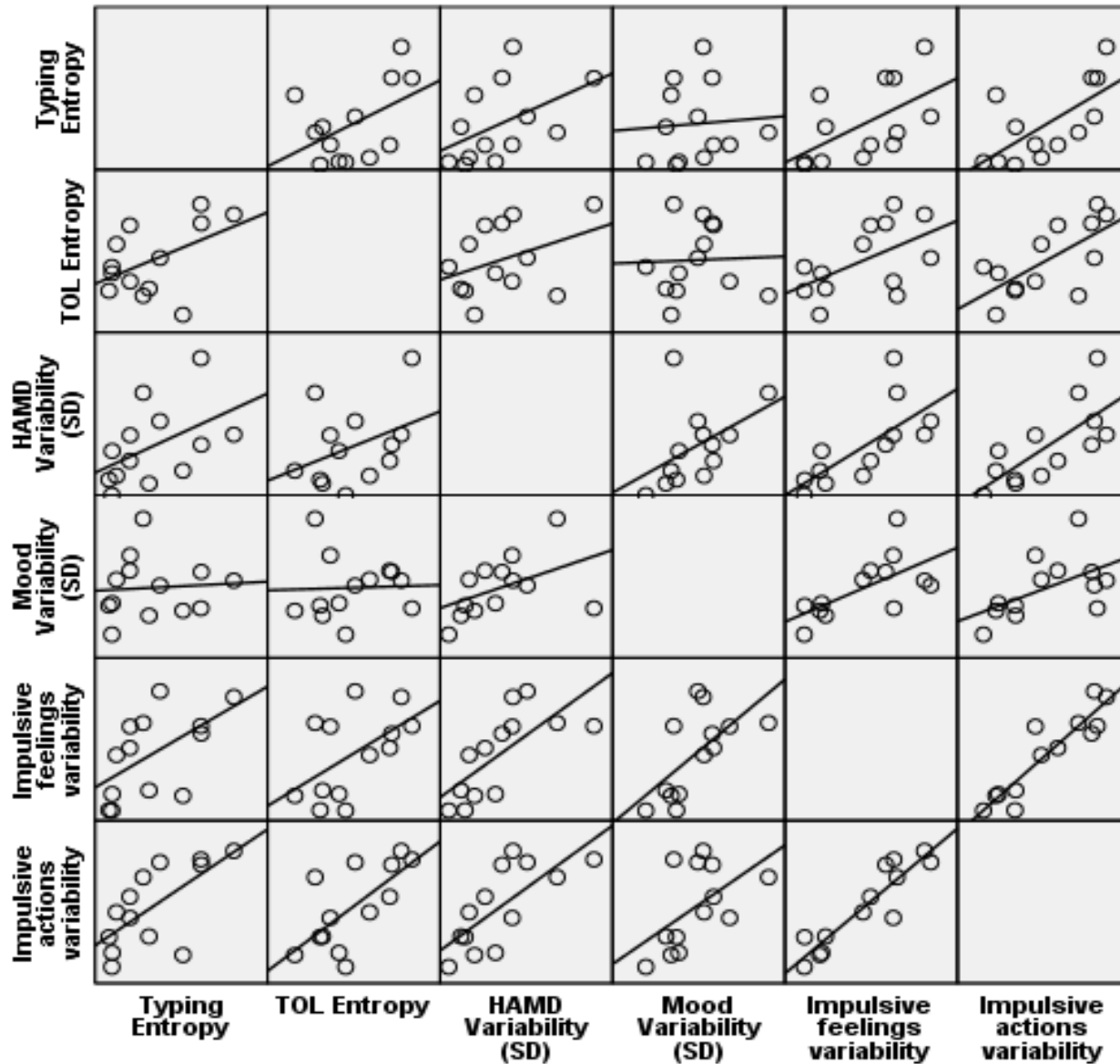
↓ entropy, ↑ regularity time-series



↑ entropy, ↓ regularity time-series



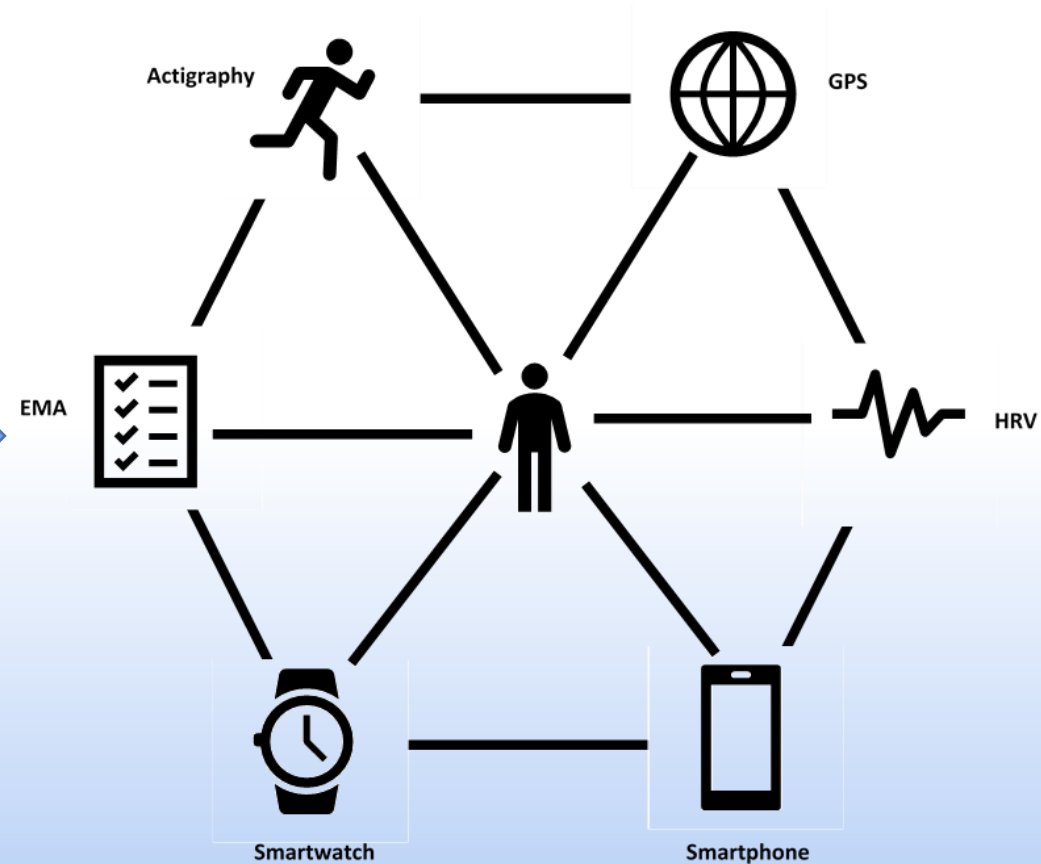
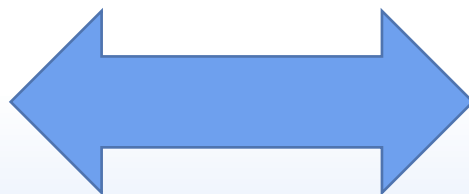
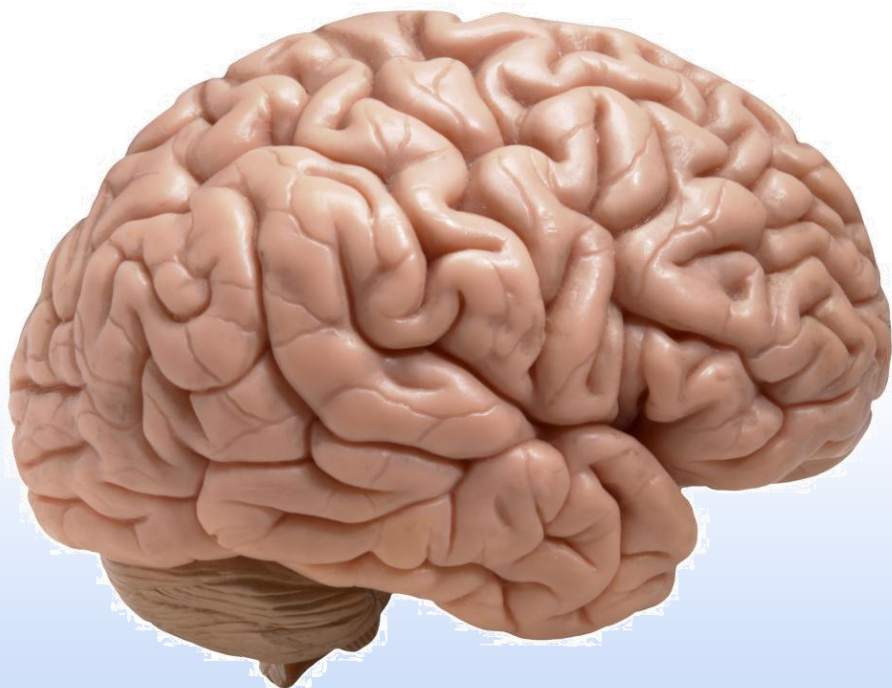
Participants with bipolar disorder demonstrate significantly increased entropy/decreased regularity in move times for the Tower of London task and in typing ($p < .05$)



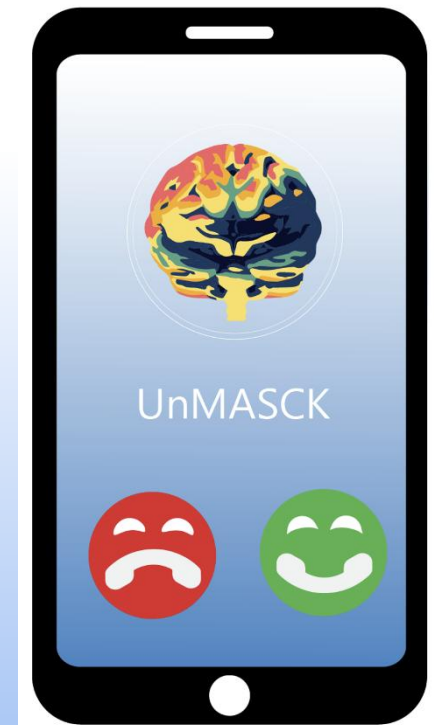
In participants with bipolar disorder, **typing entropy** was significantly correlated:

- TOL entropy ($r=.53, p=.03$)
- HAMD variability ($r=.5, p=.03$)
- Variability in impulsive actions ($r=.55, p=.04$)
- Variability in impulsive feelings ($r=.63, p=.02$).

LINKING NEURAL AND DIGITAL SIGNATURES OF AFFECTIVE DISORDERS



UNOBTRUSIVE MONITORING OF AFFECTIVE SYMPTOMS AND COGNITION USING KEYBOARD DYNAMICS (UNMASCK)



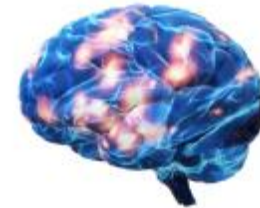


UNMASCK - APPROACH

- **Specific Aim 1.** To evaluate whether keyboard dynamics prospectively predict brain network correlates of cognitive dysfunction in 132 participants (100 with mood disorders, 32 controls) using multimodal neuroimaging (diffusion imaging, task-based and resting functional imaging)
- **Specific Aim 2.** To evaluate whether keyboard dynamics prospectively predict changes in clinical mood symptoms in 132 participants (100 with mood disorders, 32 controls) (increased depressive and/or manic symptoms)
- **Exploratory Aim.** To examine whether the relationship between keyboard dynamics and clinical mood symptoms is mediated in a mechanistic way by alterations in brain network properties.



UNMASCK - APPROACH



Baseline Assessment (T0)	2 weeks of BiAffect	1st Scan 2nd Assessment (T1)	2 weeks of BiAffect	2nd Scan 3rd Assessment (T2)
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BIAFFECT METRIC

CONNECTOMIC CORRELATE

COGNITIVE DOMAIN/CONSTRUCT

Typing speed

Structural brain network Efficiency
Interhemispheric Efficiency

Processing speed

Instability in typing
speed

Reduced nodal efficiency in ventrolateral prefrontal
cortex/altered modularity

Response inhibition

Backspace

Reduced nodal efficiency in anterior cingulate
cortex

Performance monitoring

Autocorrect

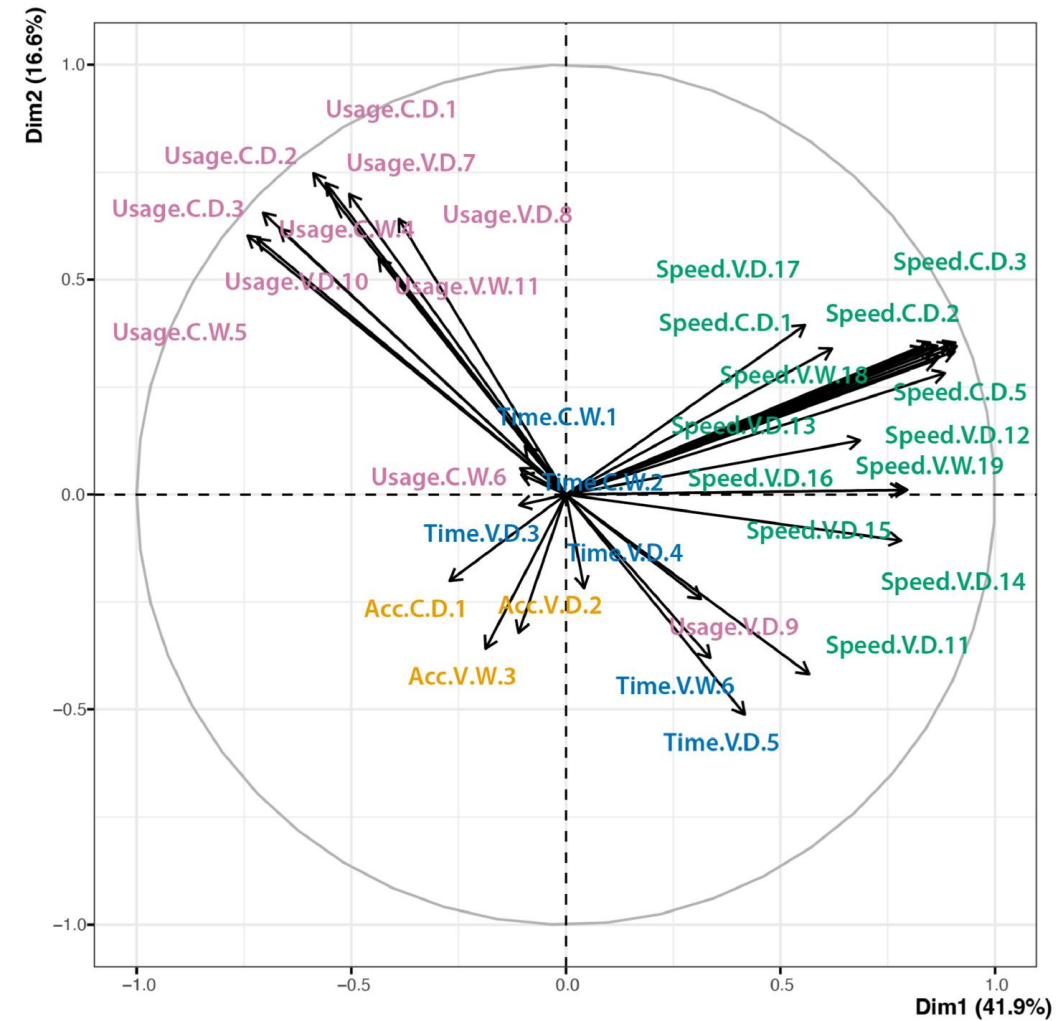
Reduced nodal efficiency in salience networks

Attention

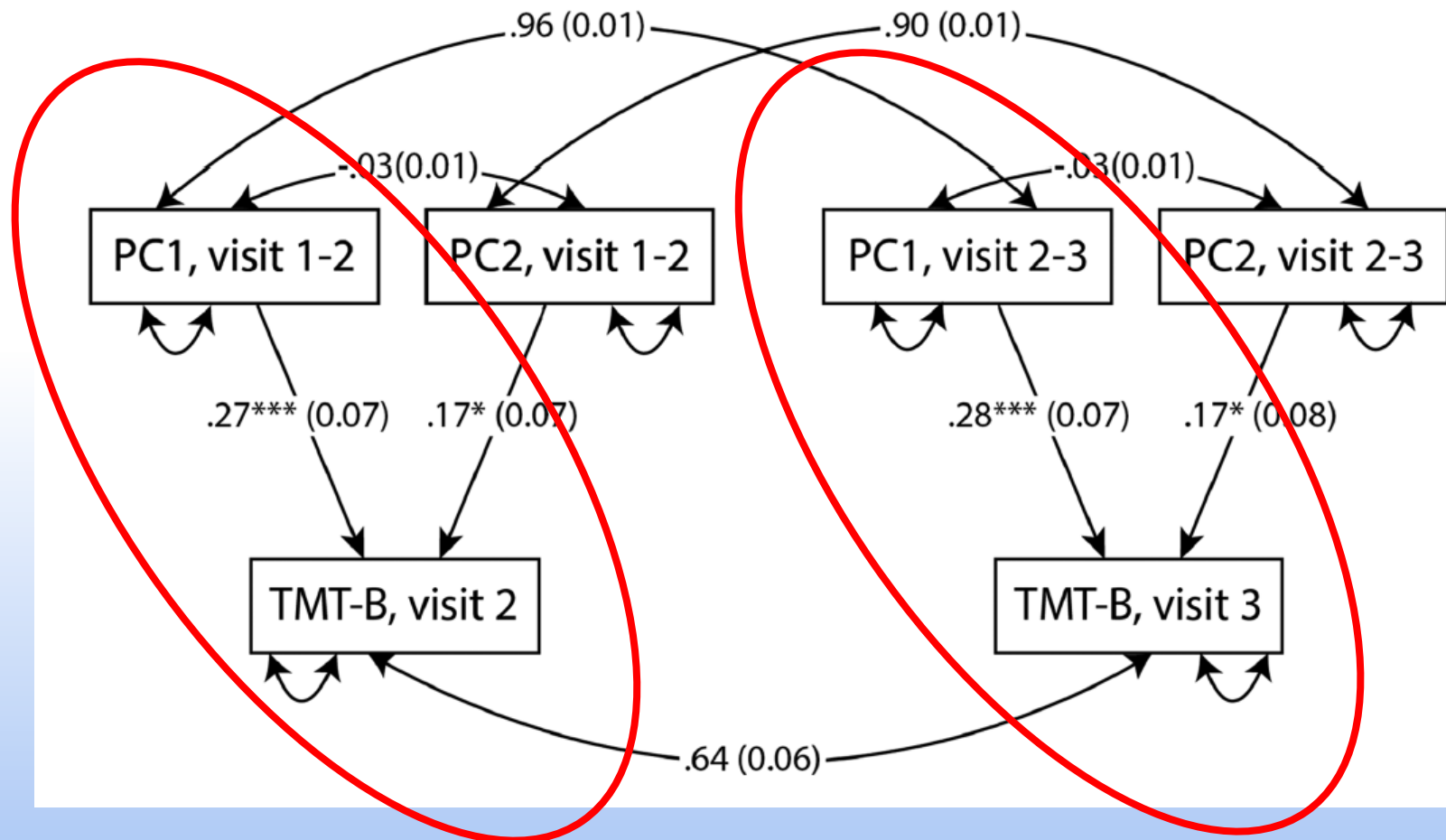
WHAT TYPING FEATURES MAP ONTO COGNITION?

PRINCIPLE COMPONENT ANALYSIS OF TYPING FEATURES

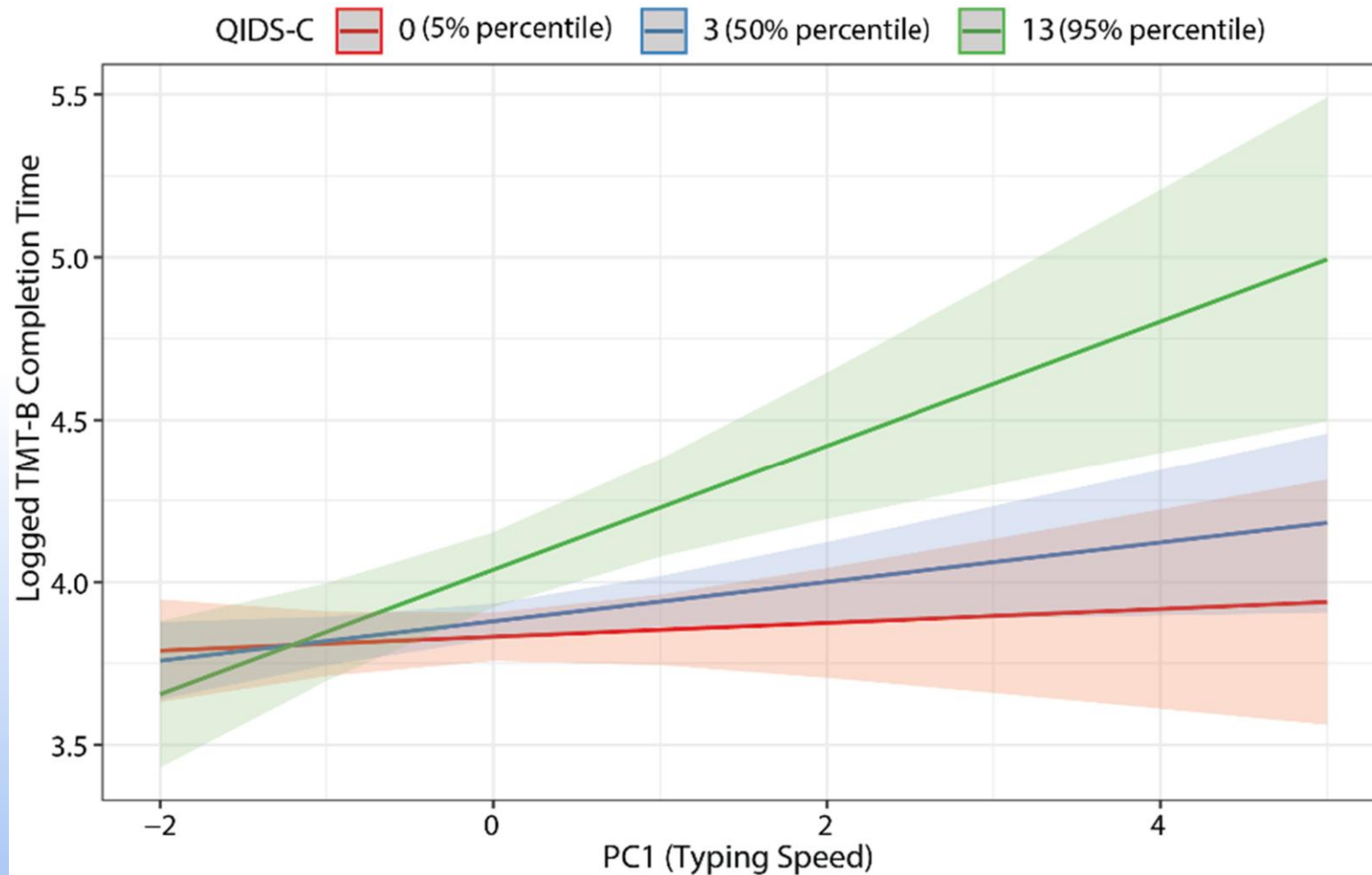
- PC1 – Typing Speed
- PC2 – Typing Volume



TYPING SPEED PREDICTS TMT-B PERFORMANCE



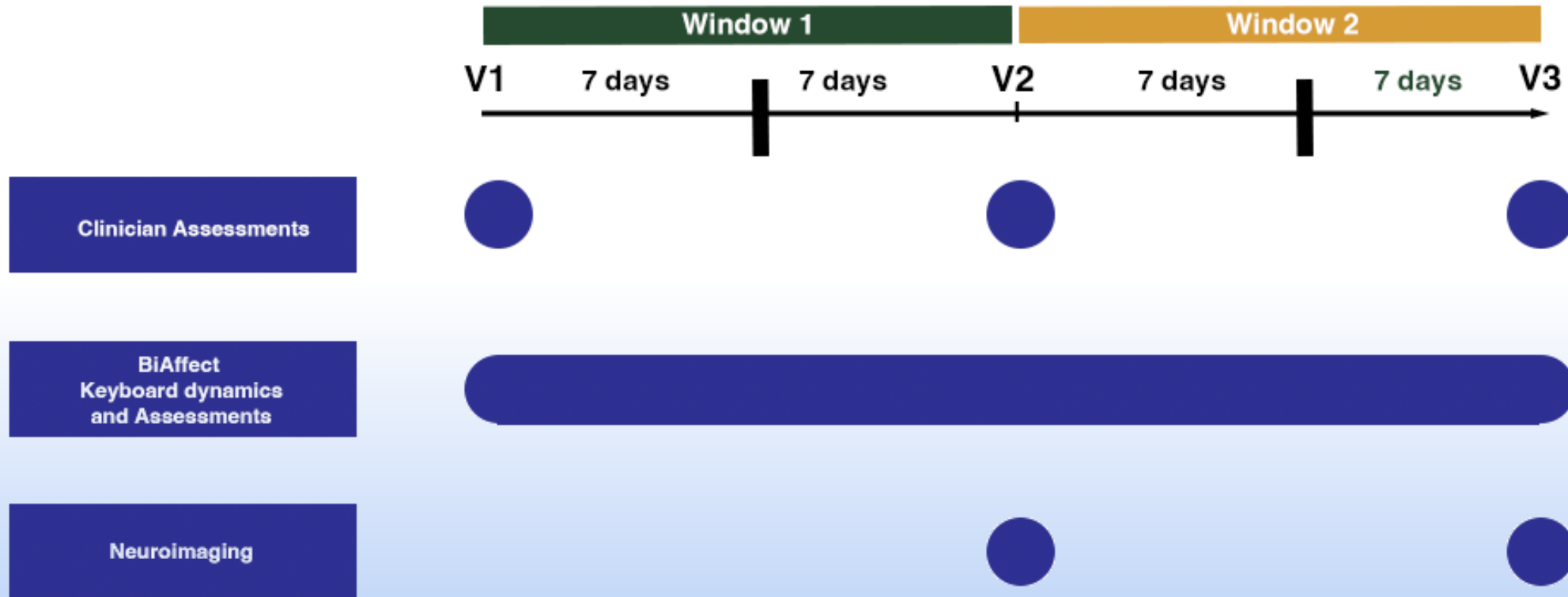
DEPRESSION MODERATES THE RELATIONSHIP BETWEEN TYPING SPEED AND PROCESSING SPEED



S U M M A R Y

- Typing features such as typing speed and typing volume predict processing speed
- The relationship between typing speed and processing speed is strongest for participants with more depressive symptoms

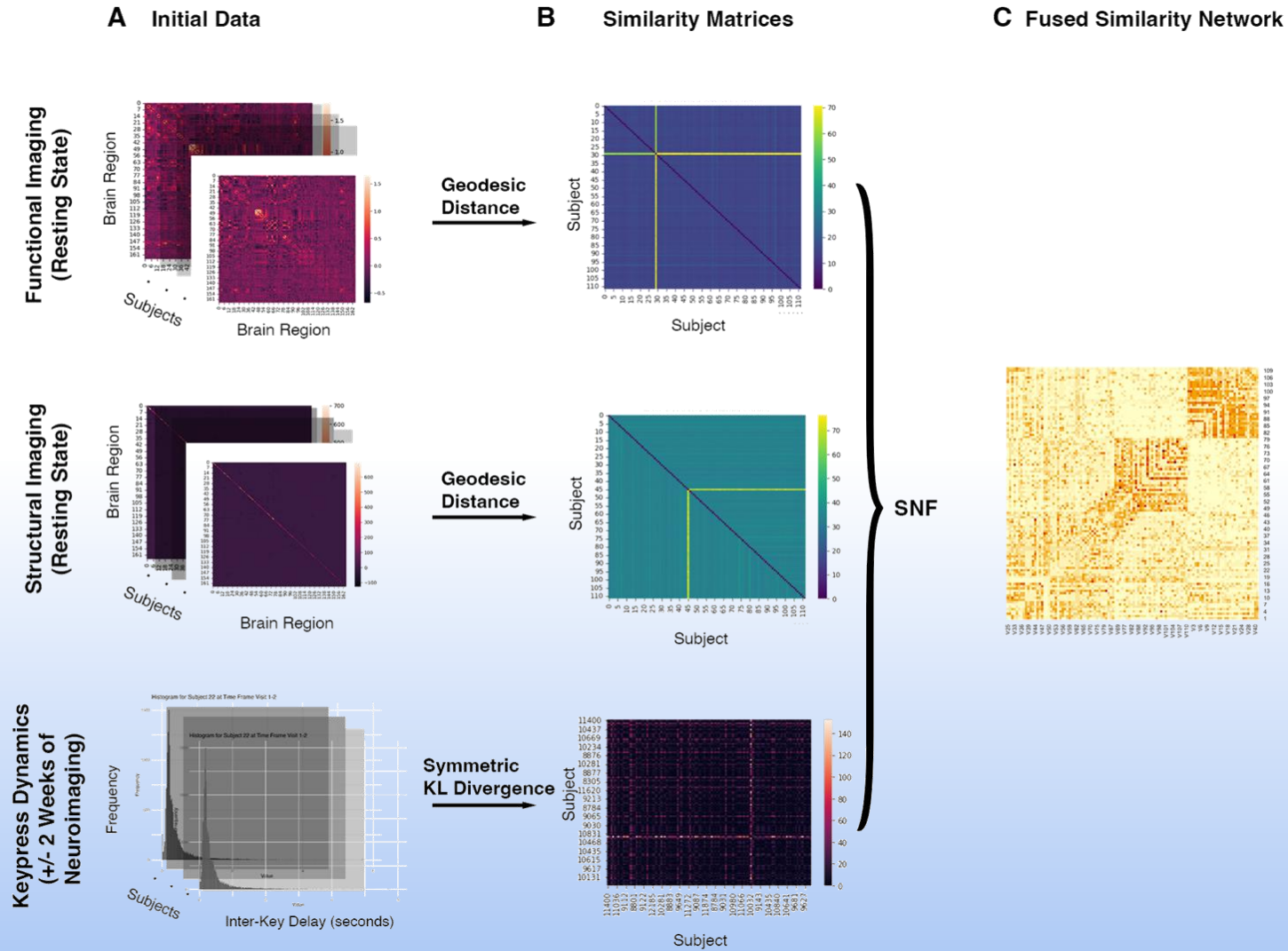
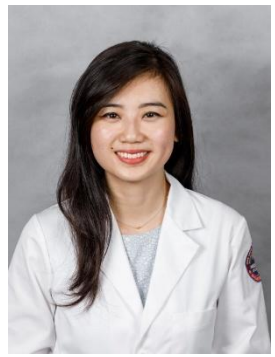
UNMASK STUDY TIMELINE OVERVIEW:

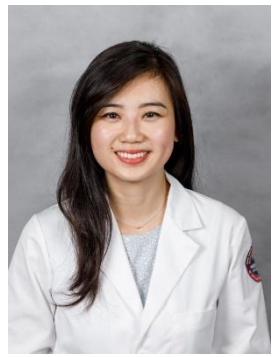


WHICH BRAIN NETWORKS ARE ASSOCIATED WITH TYPING FEATURES AND COGNITION?

Identify altered brain networks via digital phenotypes by extracting features from multimodal data sets (i.e., structural and functional neuroimaging and longitudinal keypress data) that can be associated with predicting differences in cognitive performance.

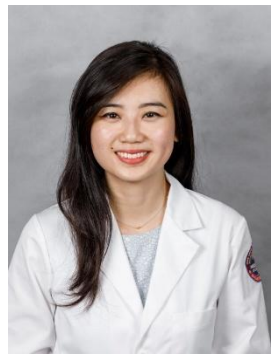
SIMILARITY NETWORK FUSION





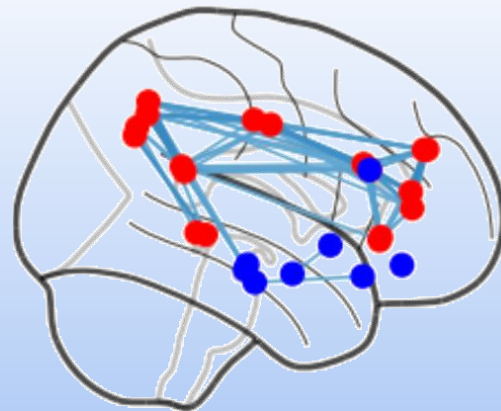
CLUSTER ANALYSIS RESULTS

- Inputs:
 - 1) Functional Neuroimaging Data
 - 2) Structural Neuroimaging Data
 - 3) Smartphone Keyboard Typing Data
- SNF clustered participants by similarity from all three inputs
- SNF → 3 clusters
- Examined cluster differences to use in a data driven approach for regression models



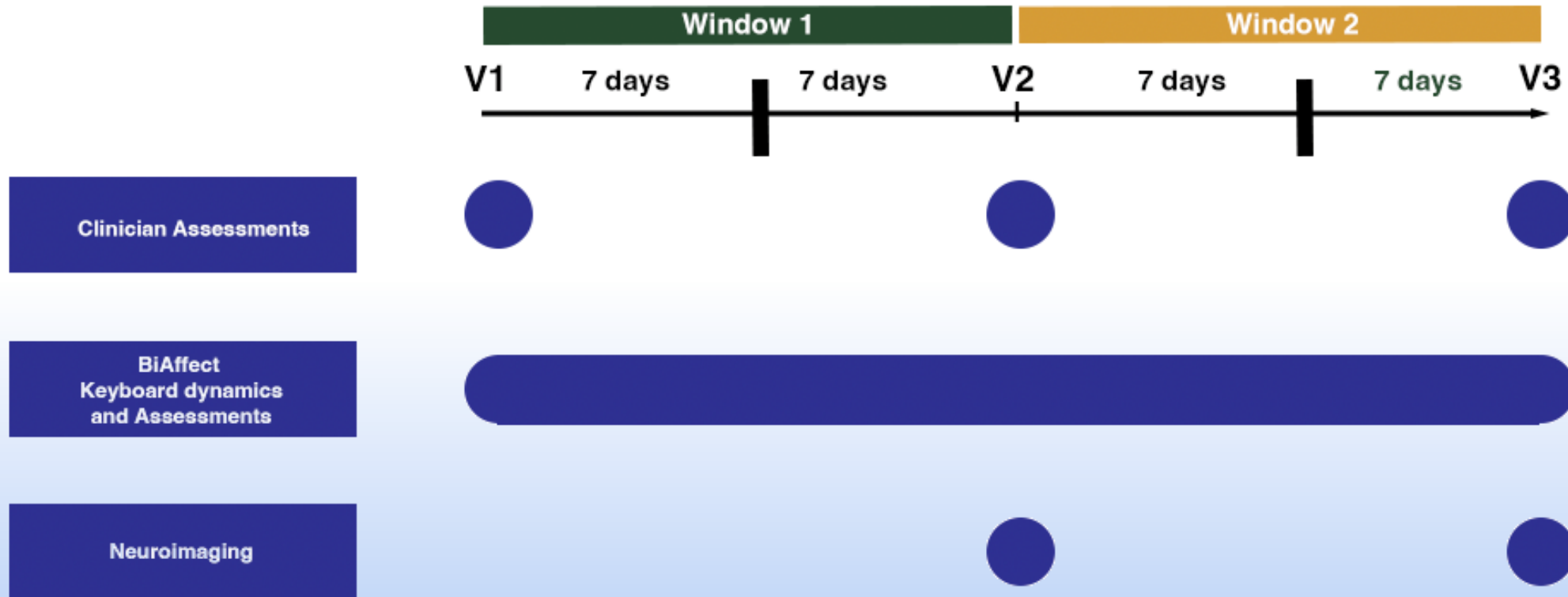
CLUSTER DIFFERENCES

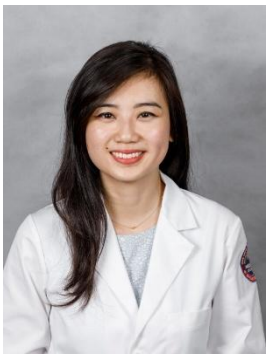
- Age
- Gender
- Typing Speed
- Cognitive Function
- Between-network Functional Connectivity (centered on salience network)



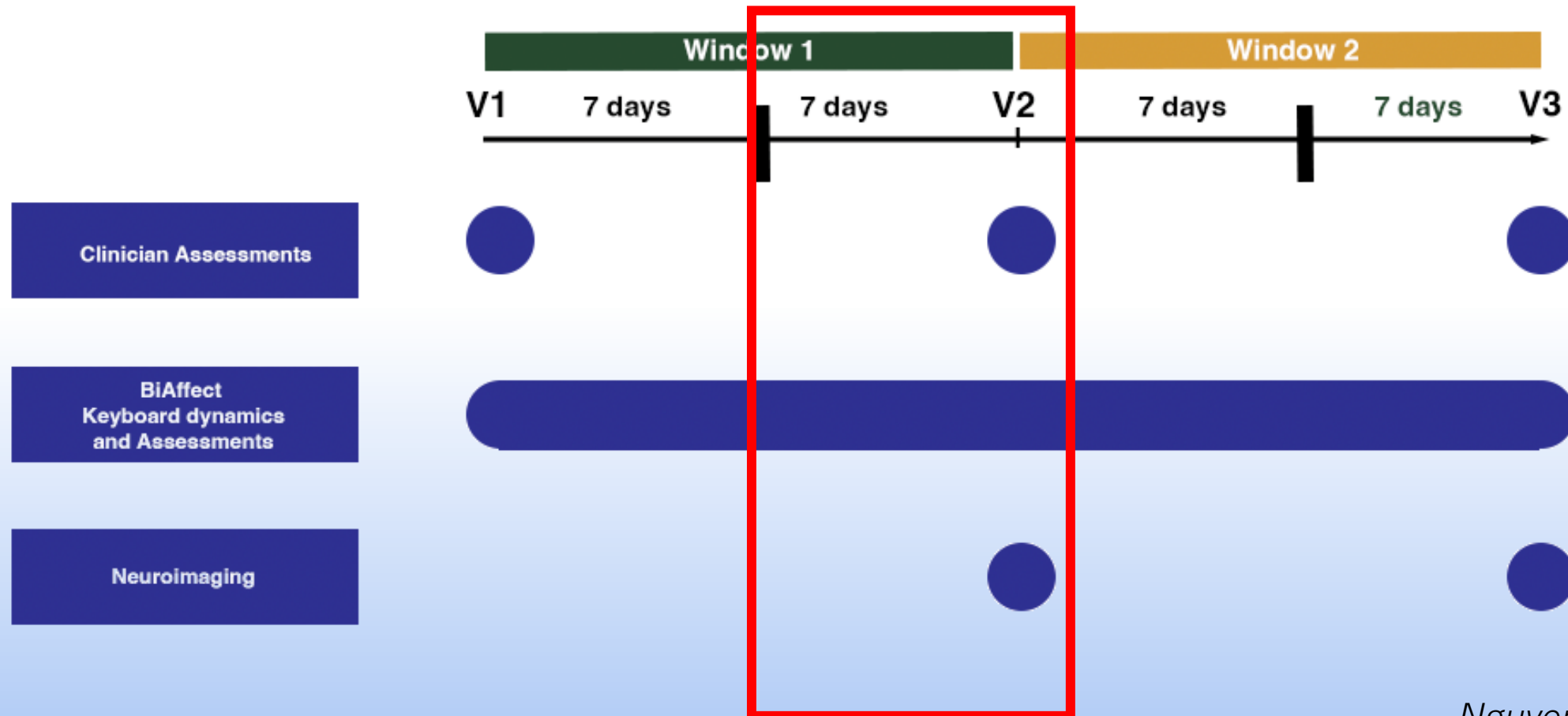
**HOW DO THESE FEATURES RELATE TO EACH
OTHER?**

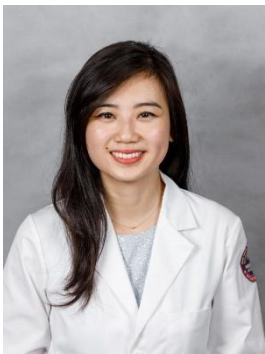
UNMASK STUDY TIMELINE OVERVIEW:





TYPING SPEED PREDICTS BRAIN CONNECTIVITY

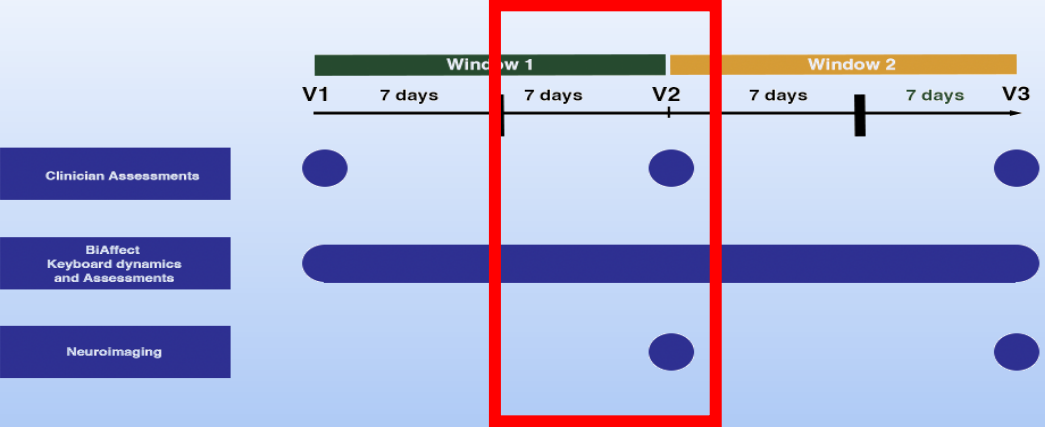
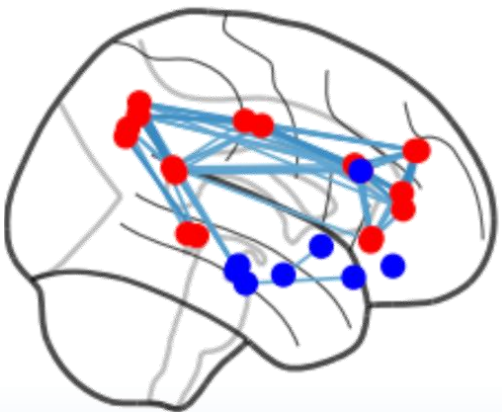




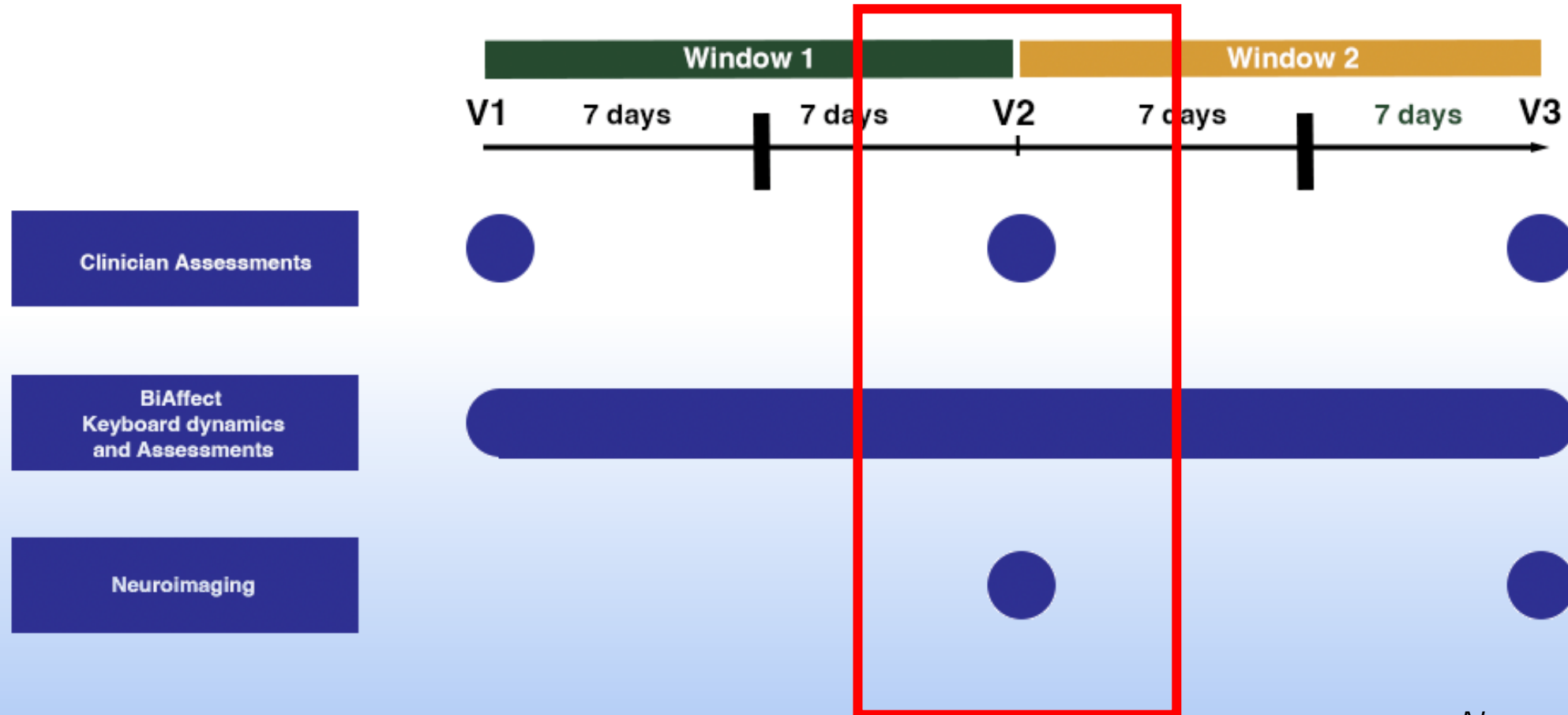
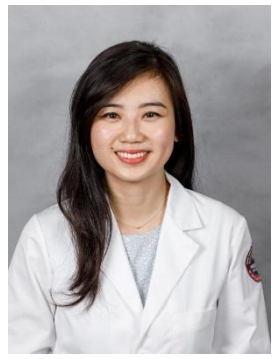
TYPING SPEED PREDICTS BRAIN CONNECTIVITY

1 Week Before V2 median IKD

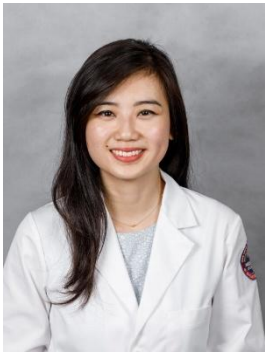
Predictors	log(IKD)				log(IKD)				log(IKD)			
	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p
(Intercept)	-1.52	0.81	<0.001	<0.001	-1.48	0.87	<0.001	<0.001	-1.47	0.88	<0.001	<0.001
SN to DMN	-0.06	-0.09	0.009	0.008	-0.05	-0.07	0.025	0.023	-0.06	-0.09	0.026	0.025
age					0.12	0.17	<0.001	<0.001	0.12	0.17	<0.001	<0.001
gender [Female]					-0.09	-0.13	0.029	0.028	-0.10	-0.14	0.020	0.018
age × SN to DMN									0.02	0.03	0.408	0.343
gender [Female] × SN to DMN									0.04	0.05	0.366	0.388



TYPING SPEED IS ASSOCIATED WITH BRAIN CONNECTIVITY

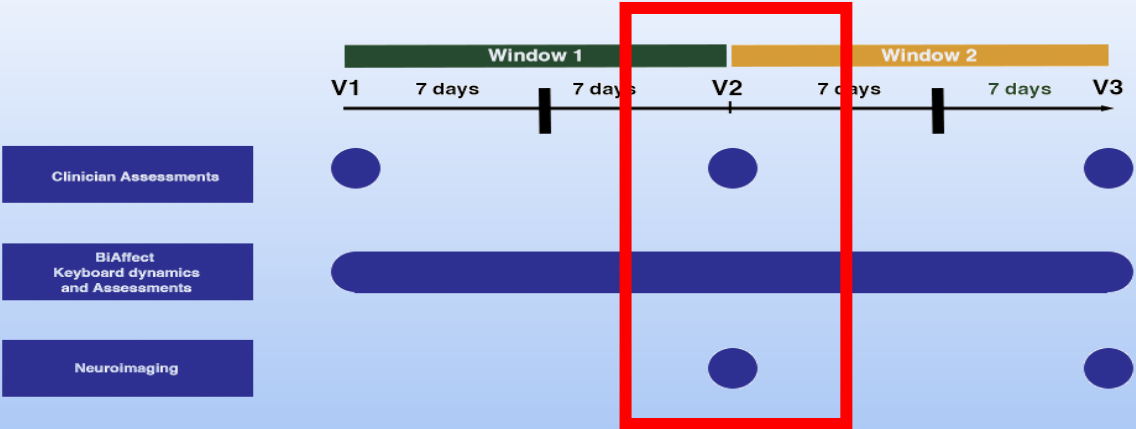
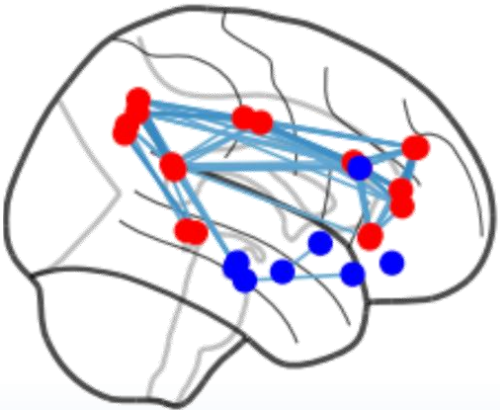


TYPING SPEED IS ASSOCIATED WITH BRAIN CONNECTIVITY

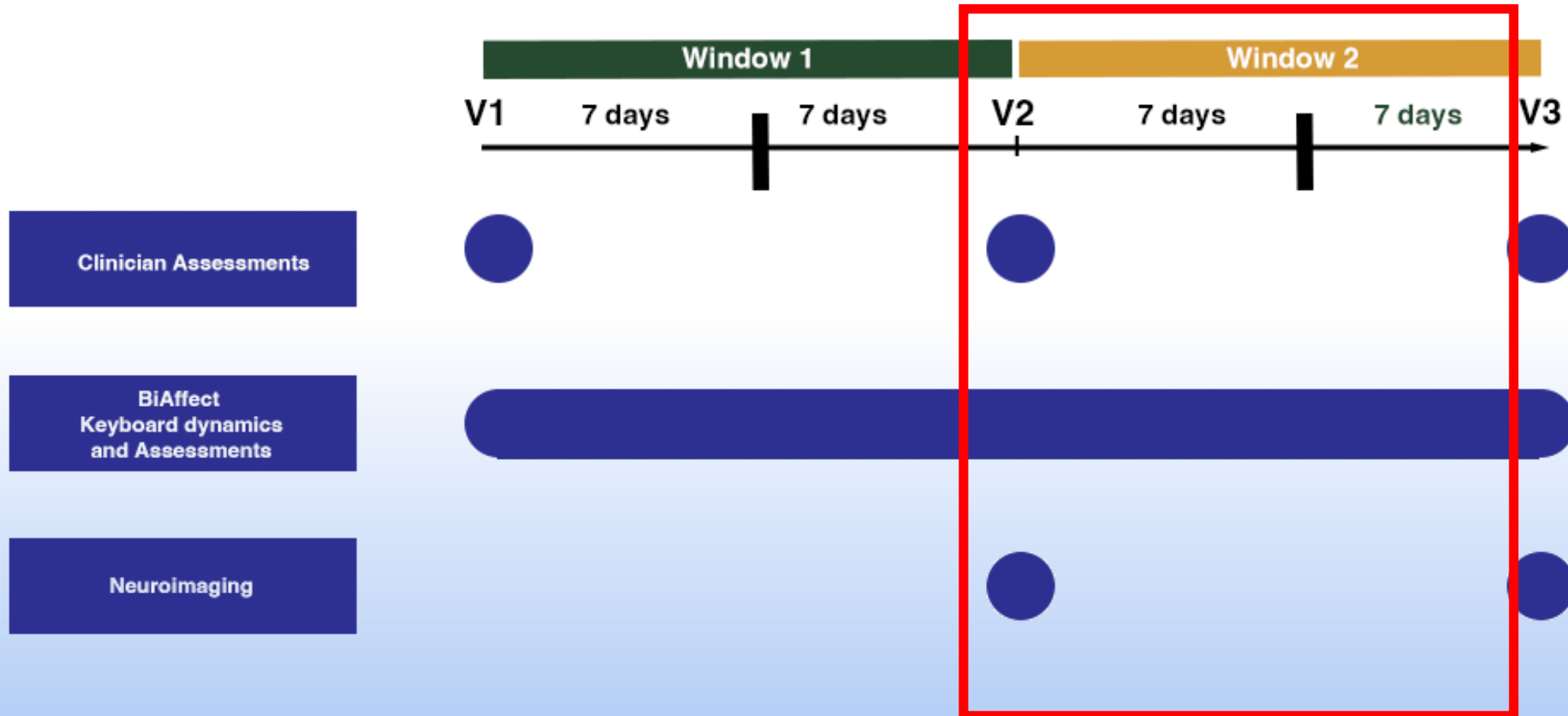
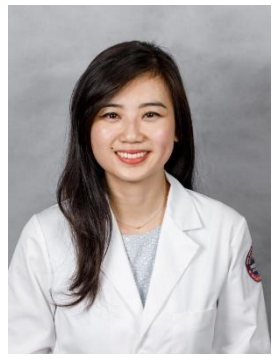


Week of V2 median IKD

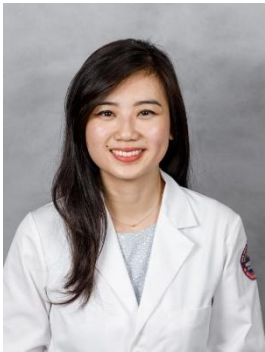
Predictors	log(IKD)				log(IKD)				log(IKD)			
	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p
(Intercept)	-1.52	0.78	<0.001	<0.001	-1.49	0.83	<0.001	<0.001	-1.48	0.84	<0.001	<0.001
SN to DMN	-0.06	-0.09	0.012	0.010	-0.05	-0.07	0.035	0.029	-0.06	-0.08	0.051	0.045
age					0.12	0.17	<0.001	<0.001	0.12	0.17	<0.001	<0.001
gender [Female]					-0.07	-0.10	0.095	0.090	-0.08	-0.11	0.076	0.068
age × SN to DMN									0.02	0.03	0.514	0.425
gender [Female] × SN to DMN									0.03	0.04	0.520	0.533



BRAIN CONNECTIVITY PREDICTS TYPING SPEED

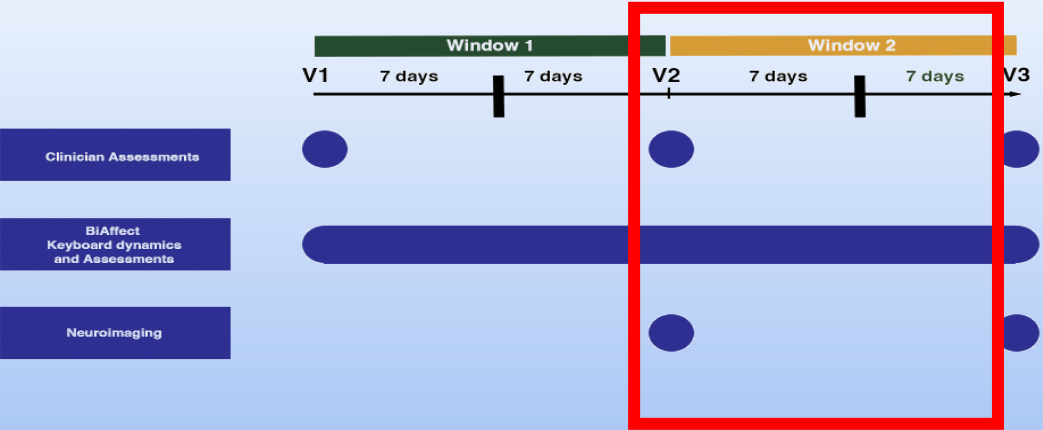
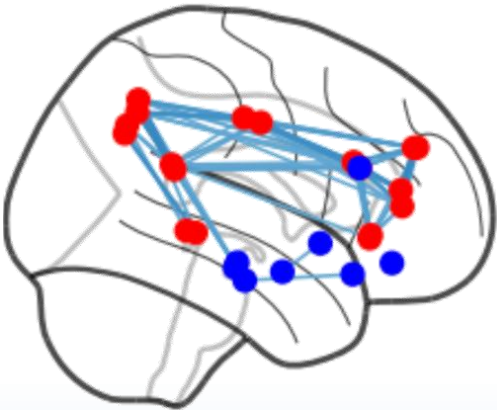


BRAIN CONNECTIVITY PREDICTS TYPING SPEED



2 weeks after V2 median IKD

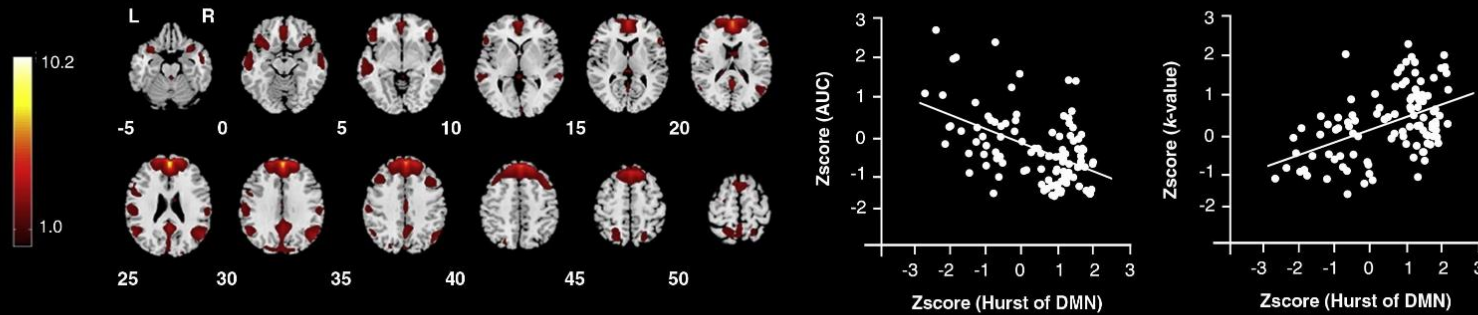
Predictors	log(IKD)				log(IKD)				log(IKD)			
	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p	Estimates	std. Beta	p	std. p
(Intercept)	-1.53	0.77	<0.001	<0.001	-1.50	0.82	<0.001	<0.001	-1.50	0.82	<0.001	<0.001
SN to DMN	-0.08	-0.11	0.002	0.002	-0.06	-0.09	0.006	0.005	-0.08	-0.11	0.008	0.008
age					0.13	0.19	<0.001	<0.001	0.13	0.19	<0.001	<0.001
gender [Female]					-0.07	-0.10	0.107	0.099	-0.07	-0.11	0.095	0.081
age × SN to DMN									0.01	0.02	0.782	0.619
gender [Female] × SN to DMN									0.04	0.06	0.326	0.348



S U M M A R Y

- Similarity Network Fusion can be used to model joint properties of neuroimaging and digital biomarkers to inform relevant clusters of participants that can identify linked features.
- The salience network may play a key role in linking typing dynamics to cognitive dysfunction in the context of mood disorders

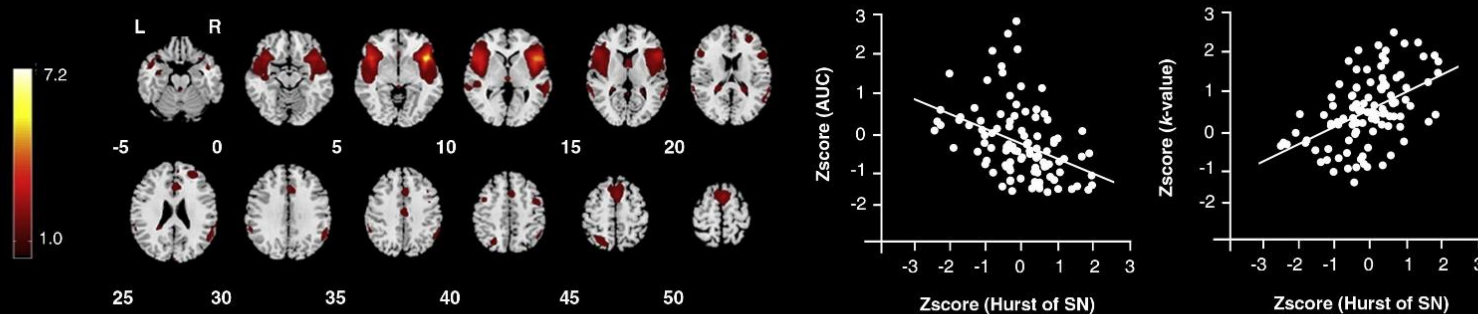
A Spatial patterns of DMN and association of corresponding Hurst on delay discounting with AUC and k -value



Network dynamics of SN and DMN associated with delayed discounting

(“Give me \$5 now, instead of \$50 in a week”)

B Spatial patterns of SN and association of corresponding Hurst on delay discounting with AUC and k -value







Major Depressive Disorder



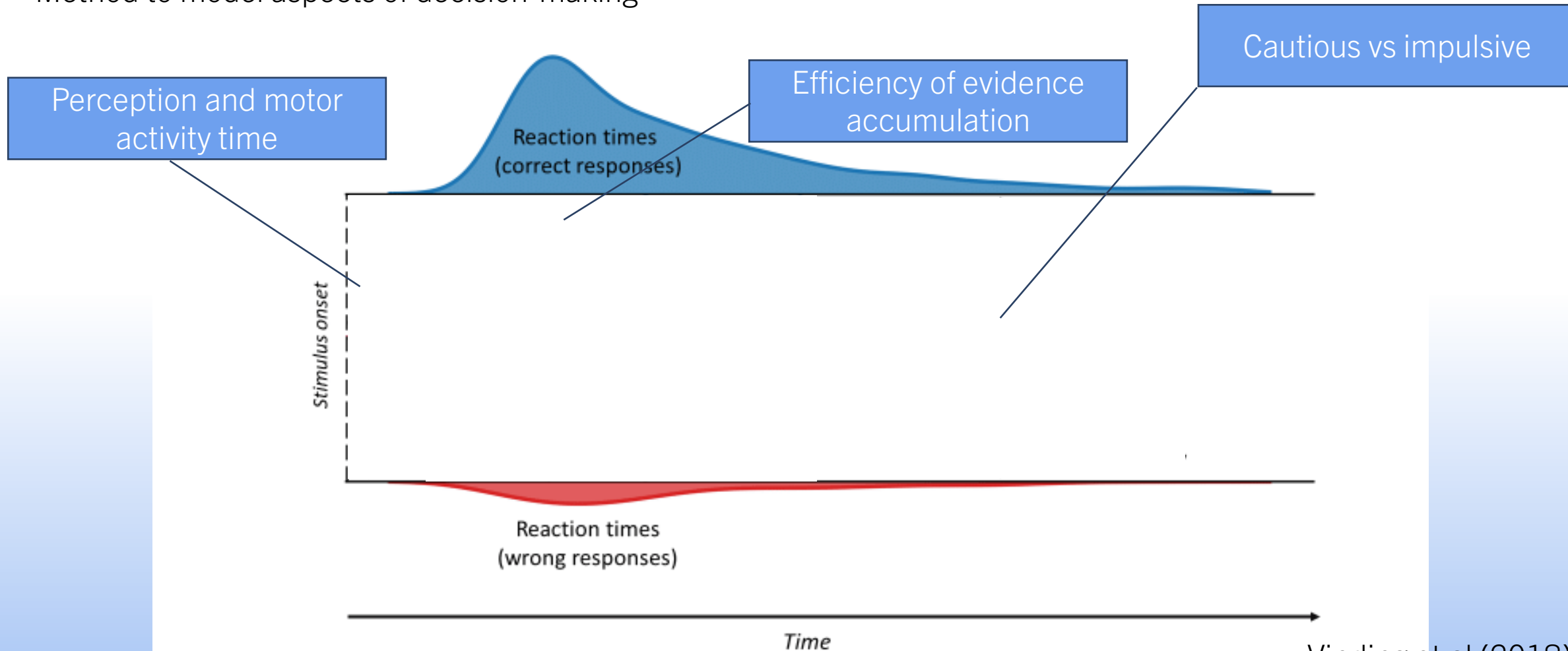
Alcohol Use Disorder

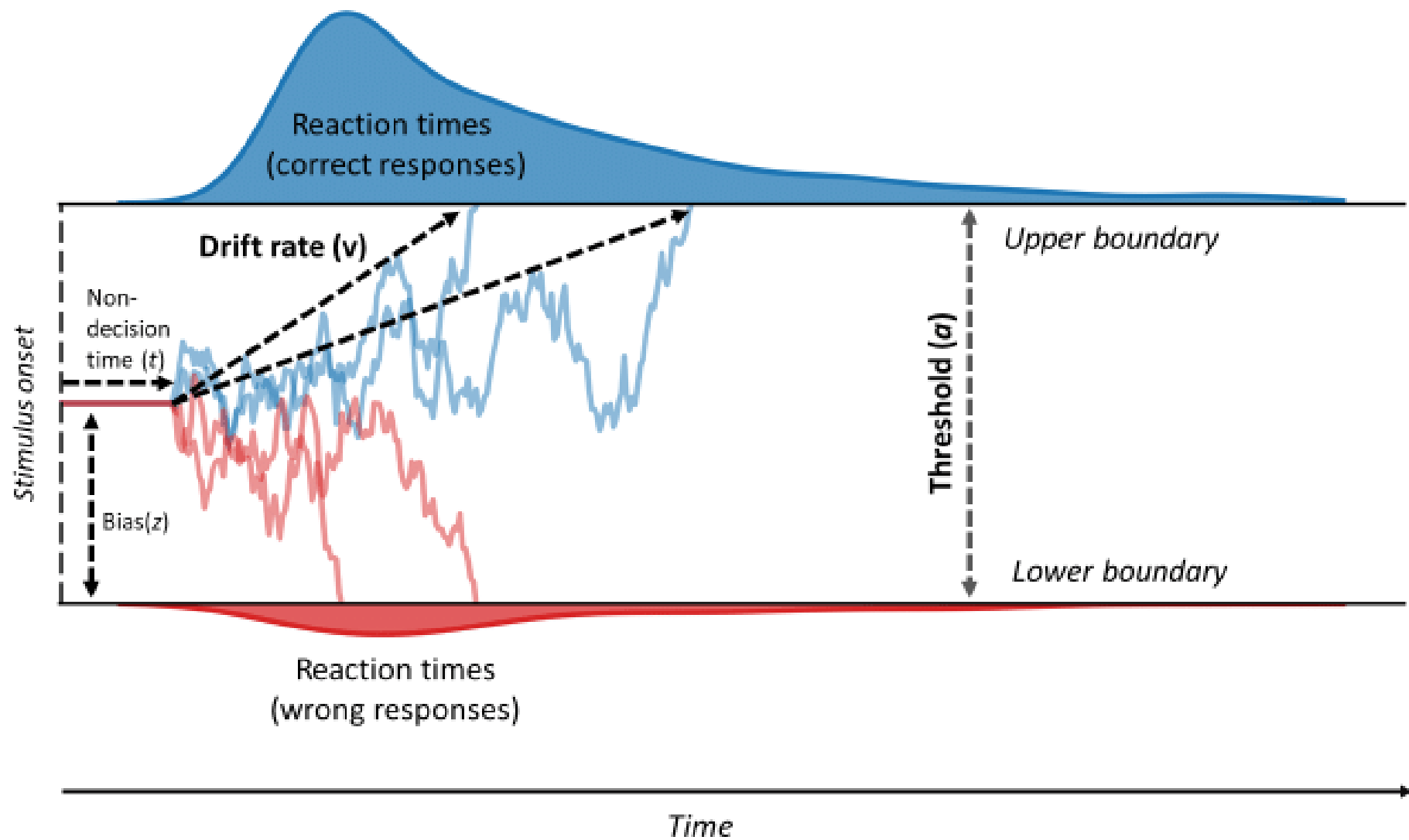


Bipolar Disorder

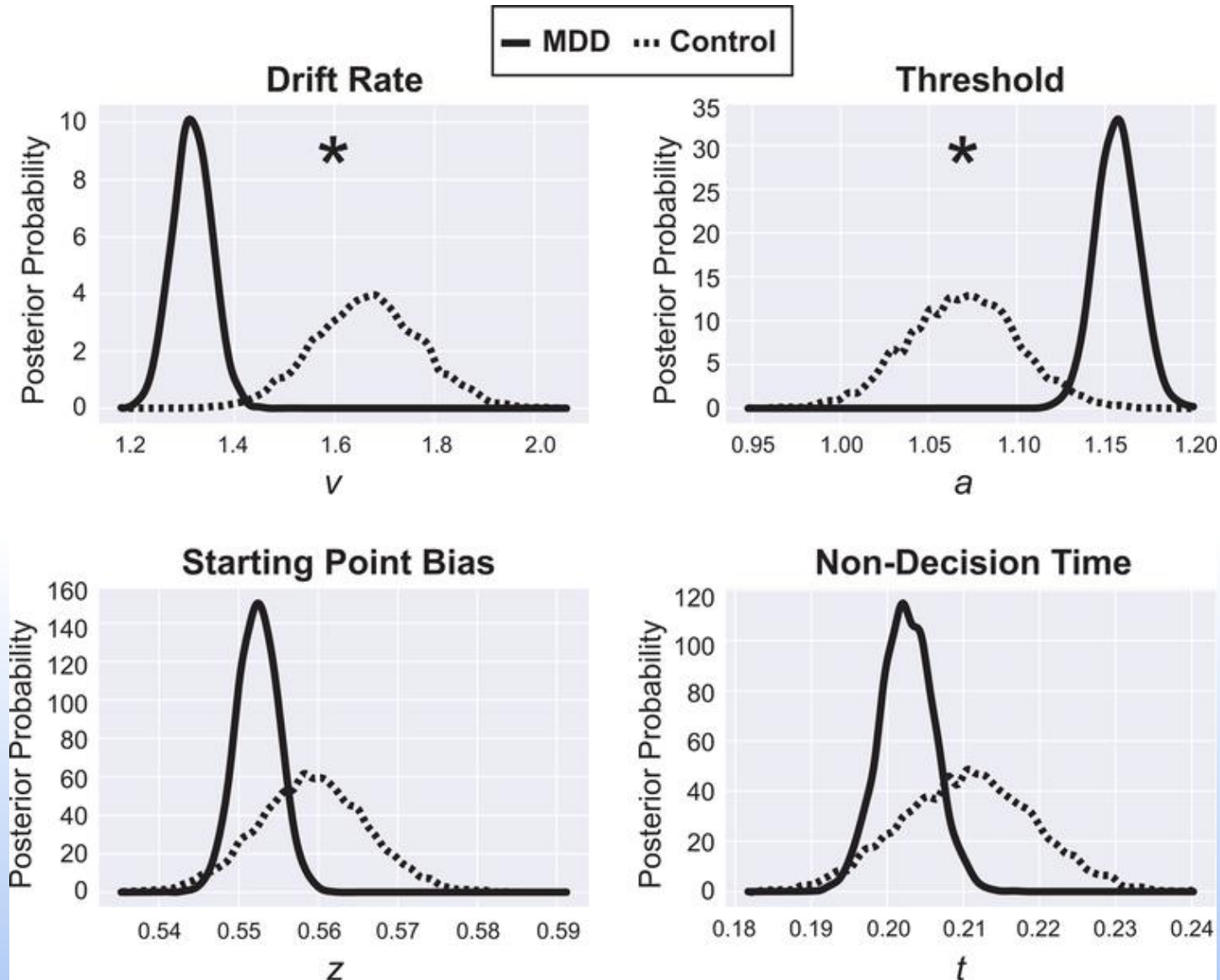
HIERARCHICAL DRIFT DIFFUSION MODEL (HDDM)

- Method to model aspects of decision-making



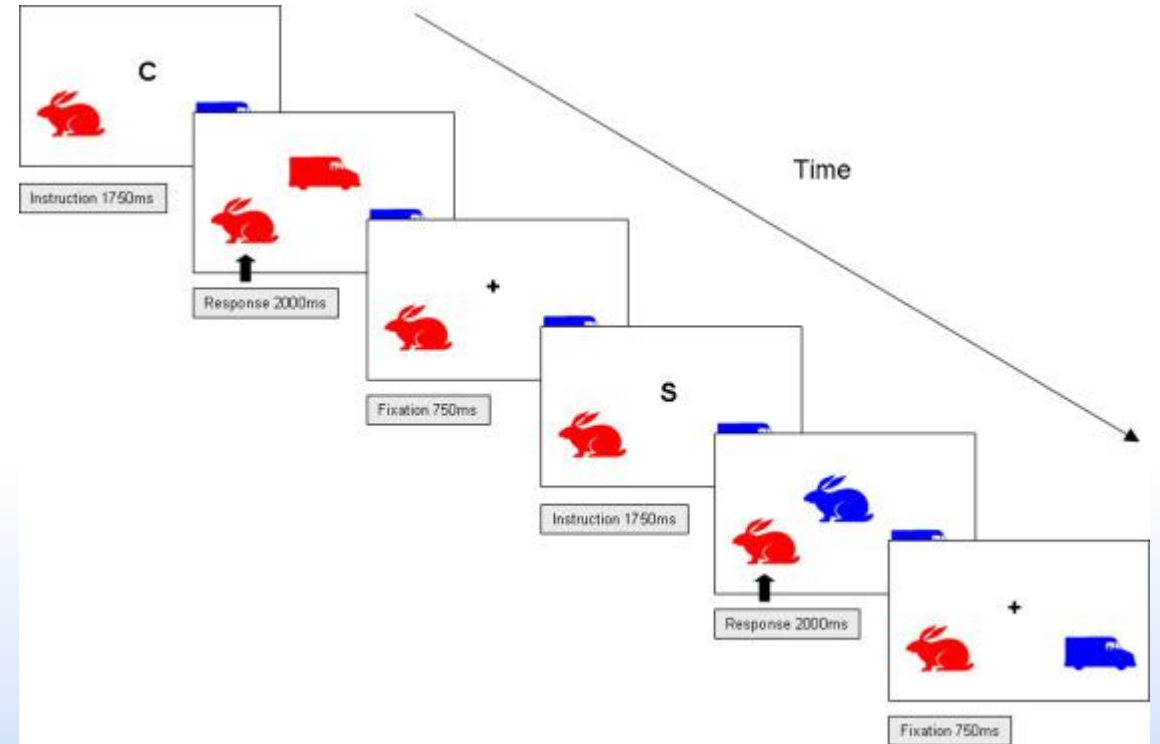


DISSECTING THE IMPACT OF DEPRESSION ON DECISION-MAKING

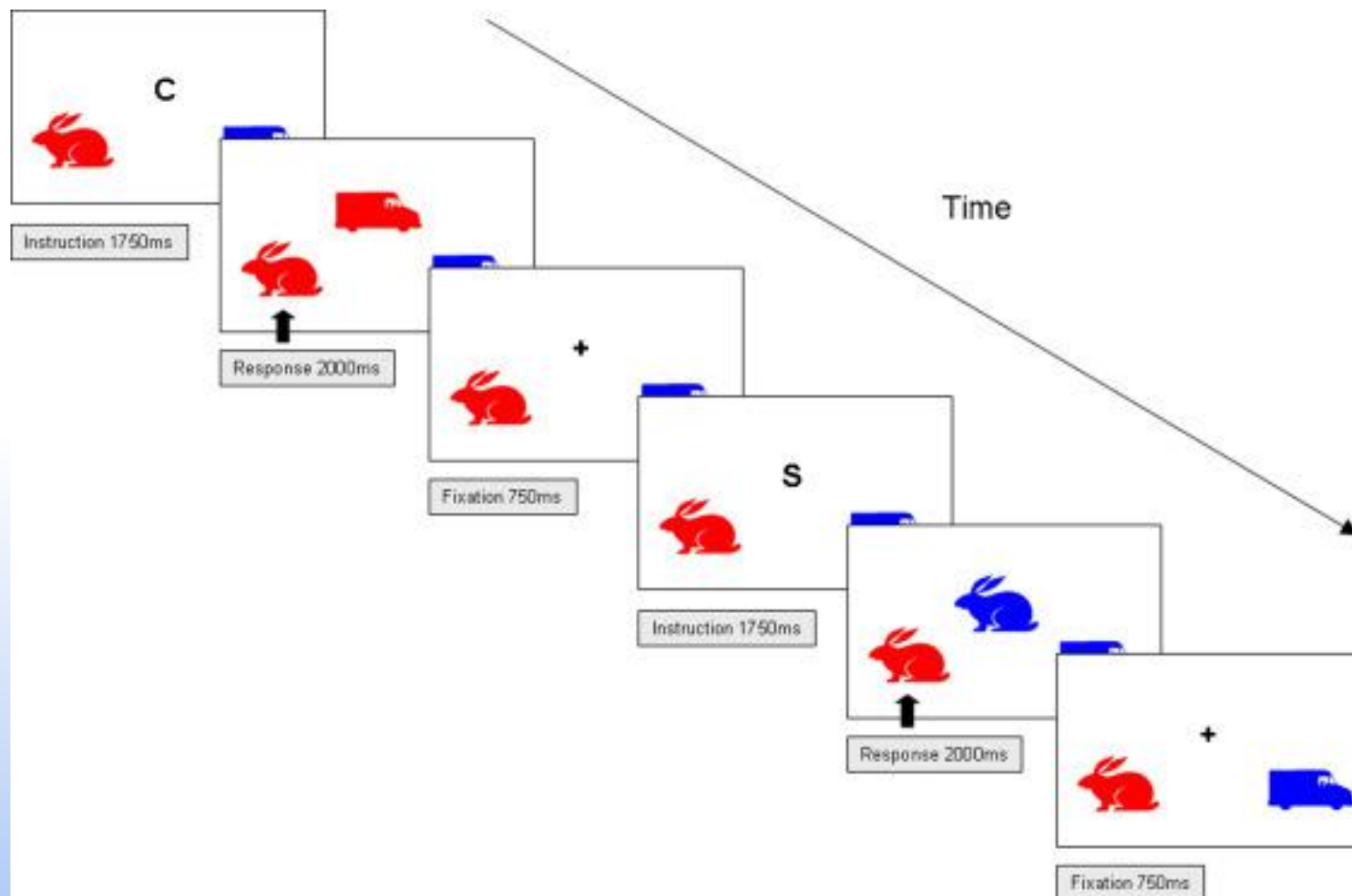


UNMASCK STUDY

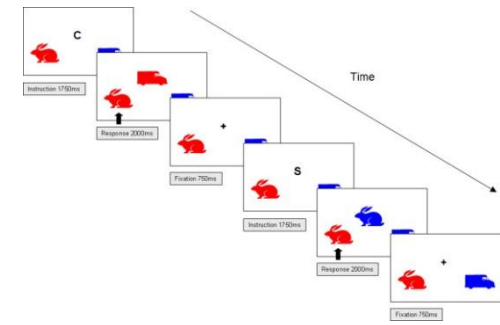
- Neuropsychological assessment
Dimensional Change Card Sort



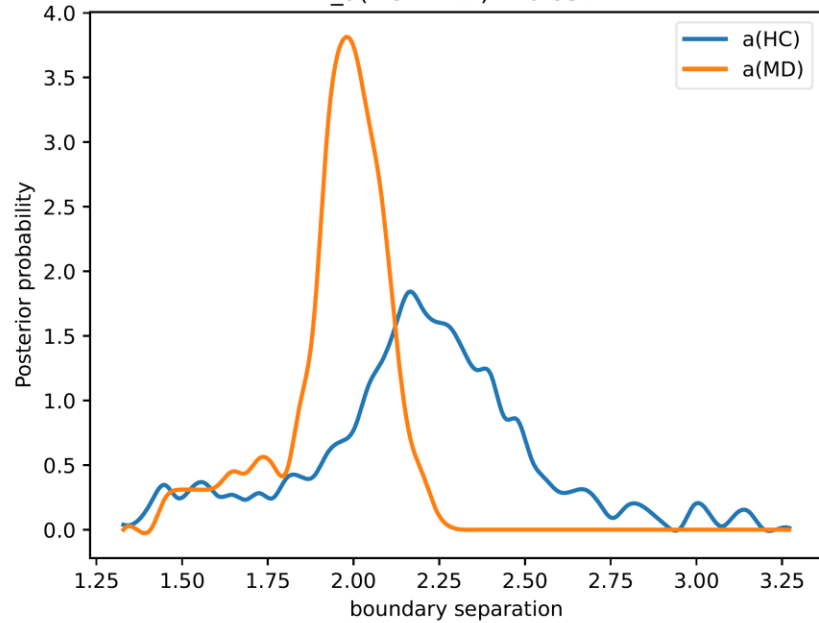
DIMENSIONAL CHANGE CARD SORT TASK (DCCS)



VISIT 1 RESULTS

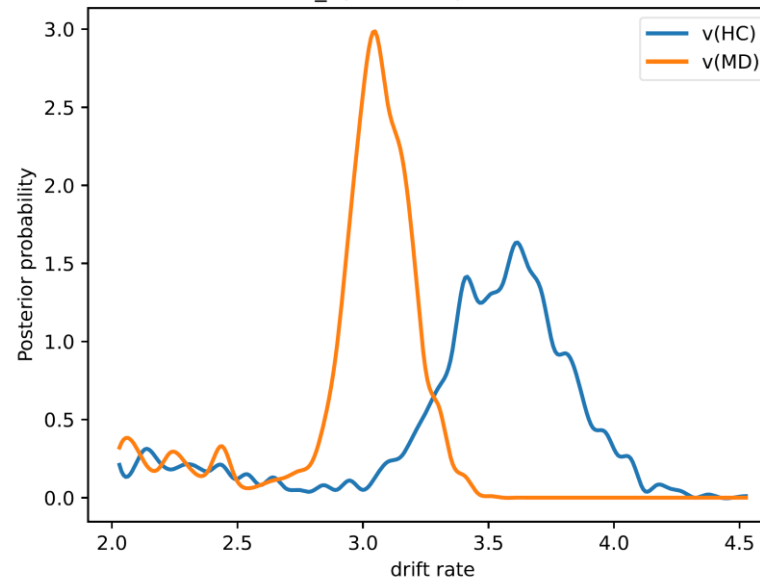


Posterior of boundary separation group data DCCS Visit 1 data:
 $P_{a(HC > MD)} = 0.857$



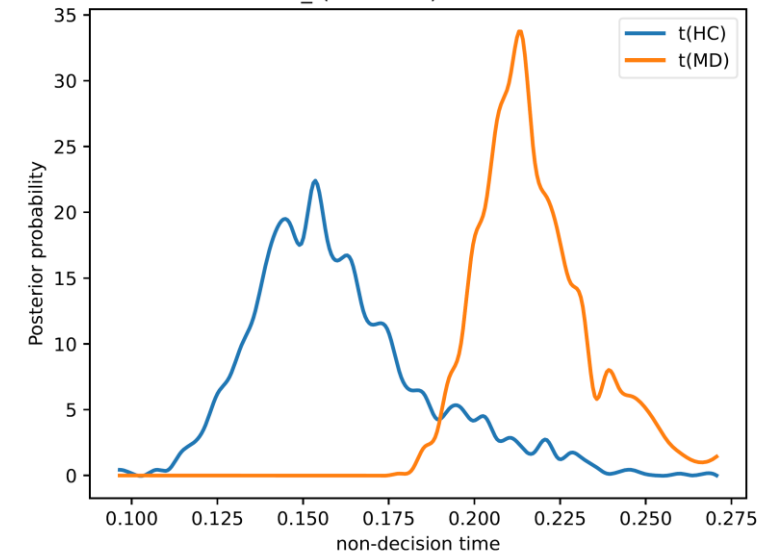
MD have smaller boundary separation compared to HC

Posterior of drift rate group data DCCS Visit 1 data
 $P_{v(HC > MD)} = 0.982$



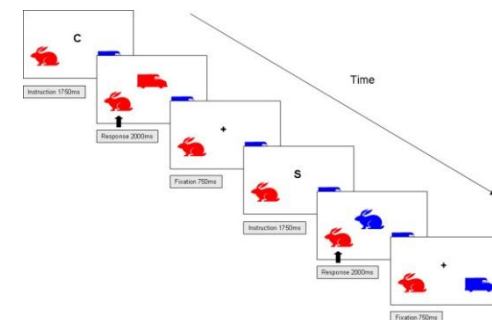
MD have slower drift rates compared to HC

Posterior of non-decision time group data DCCS Visit 1 data
 $P_{t(HC > MD)} = 0.0025$

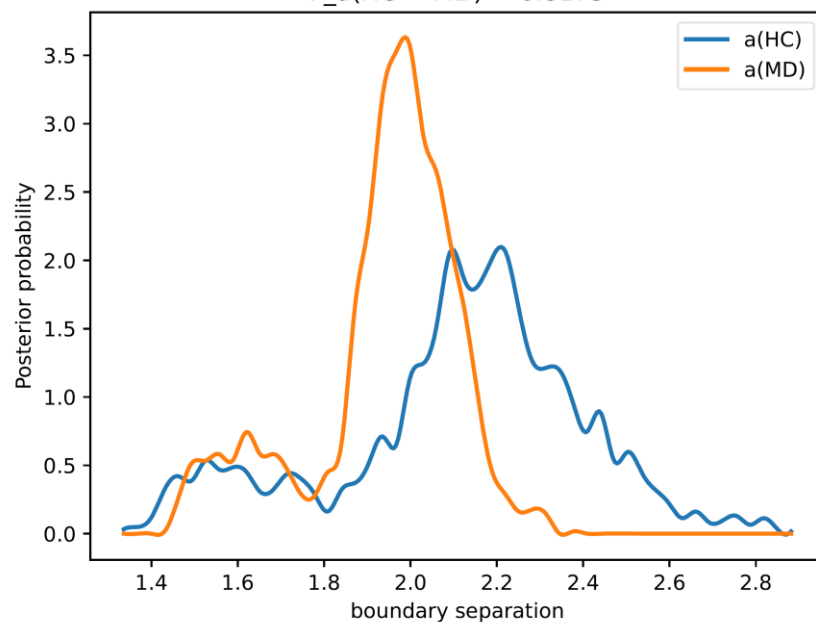


MD have slower non-decision times compared to HC

VISIT 2 RESULTS

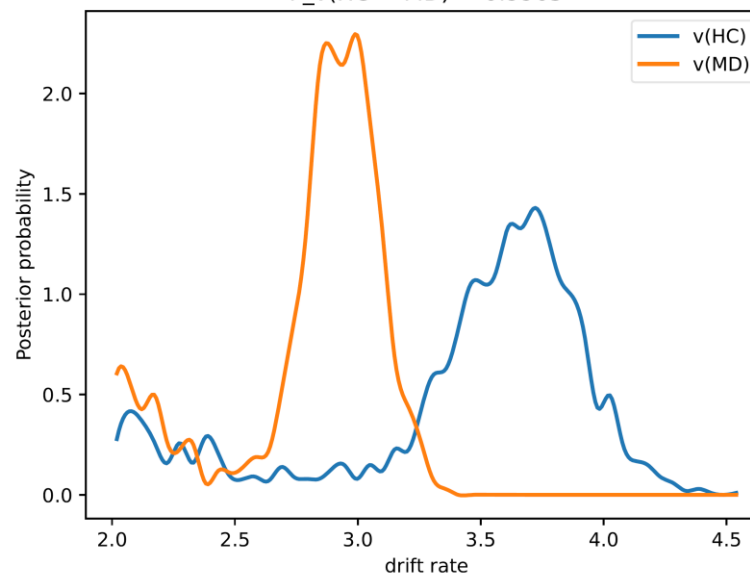


Posterior of boundary separation group data DCCS Visit 2 data
 $P_a(\text{HC} > \text{MD}) = 0.8175$



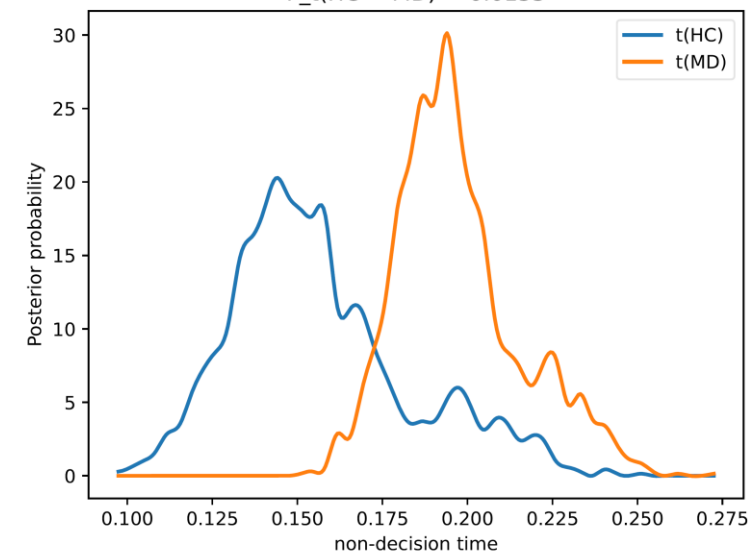
MD have smaller boundary separation compared to HC

Posterior of drift rate group data DCCS Visit 2 data
 $P_v(\text{HC} > \text{MD}) = 0.9905$



MD have slower drift rates compared to HC

Posterior of non-decision time group data DCCS Visit 2 data
 $P_t(\text{HC} > \text{MD}) = 0.0155$



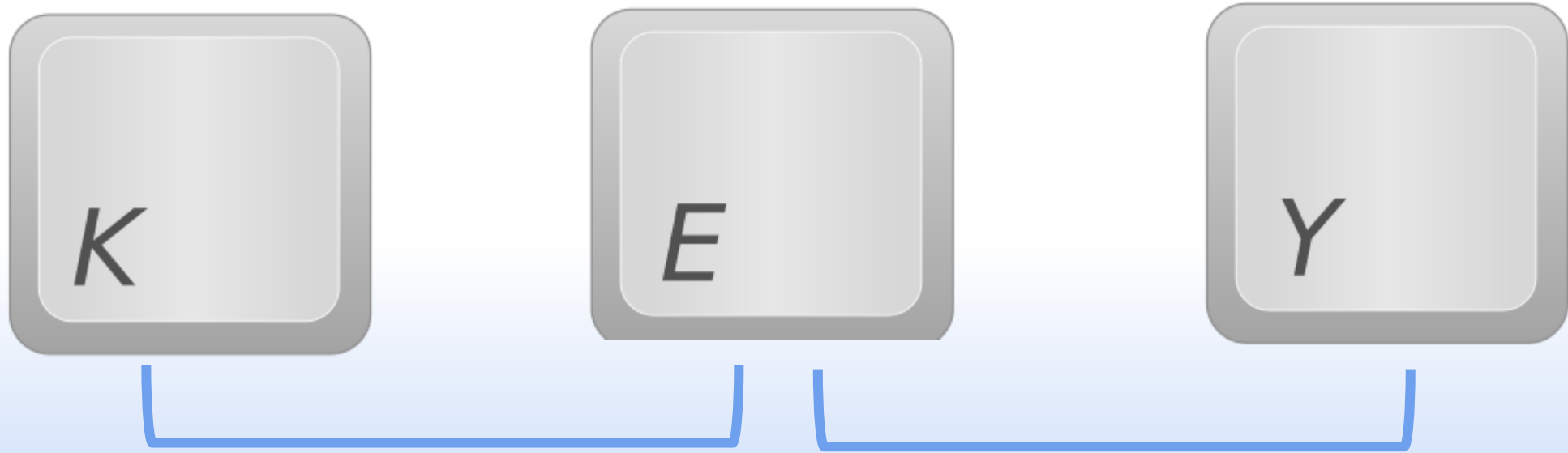
MD have slower non-decision times compared to HC

BIAFFECT TYPING DATA



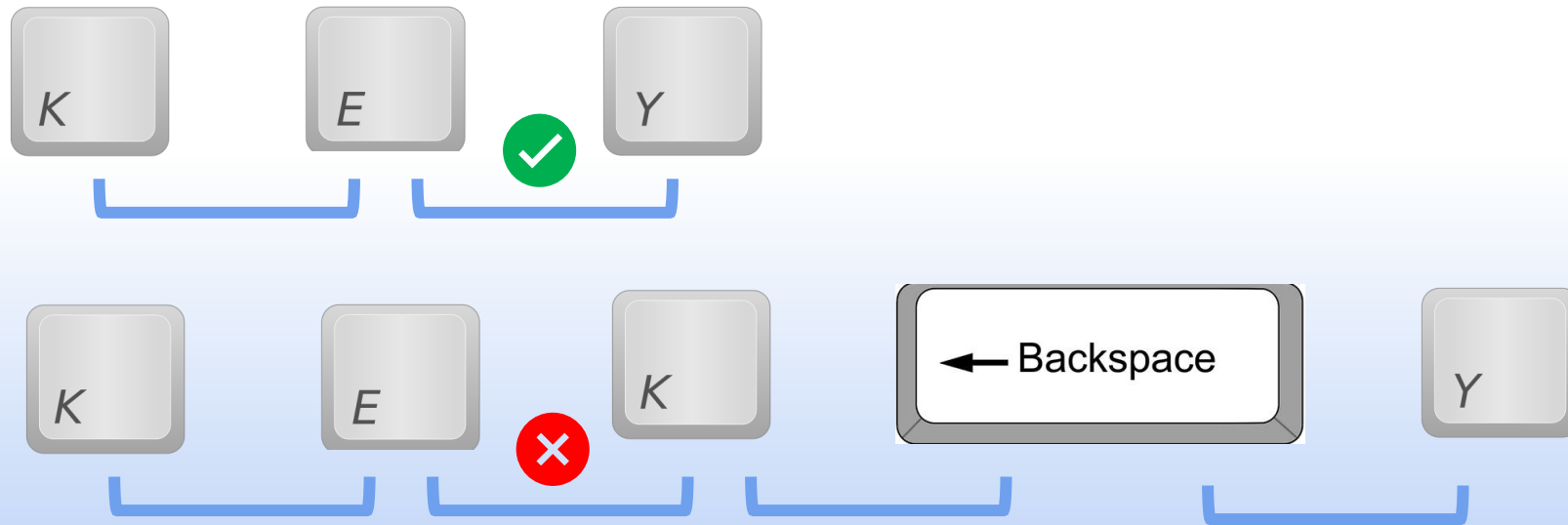
HOW CAN WE COMPARE THIS TO TYPING DATA?

- Typing speed measured by inter-key delay ~ reaction time



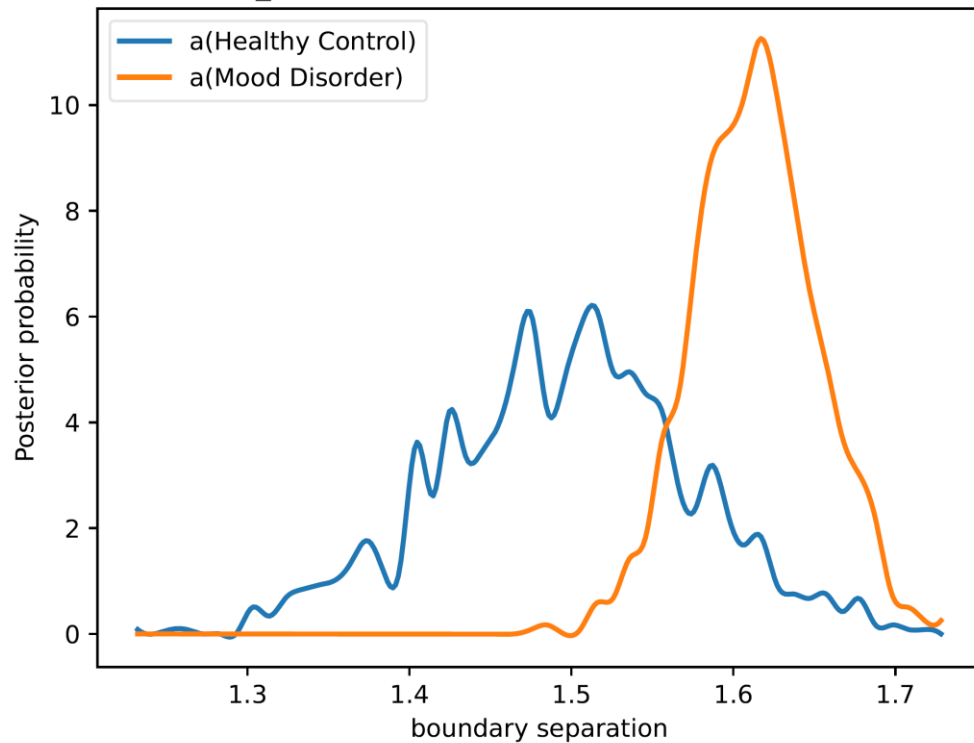
HOW CAN WE COMPARE THIS TO TYPING DATA?

- Intended keypress – “correct RT”
- Typo - “incorrect RT”



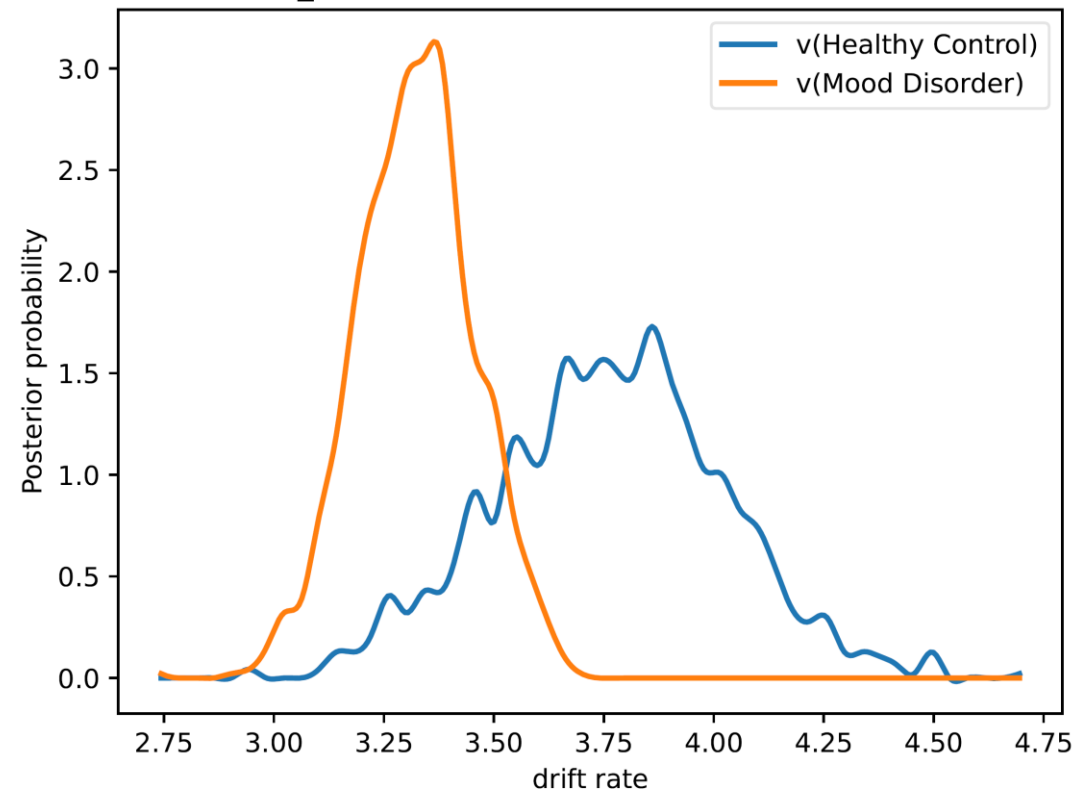
WINDOW 1 RESULTS

Posterior of boundary separation group data window 1 data
 $P_a(\text{HC} > \text{MD}) = 0.07833333333333334$



MD have wider boundary separations compared to HC

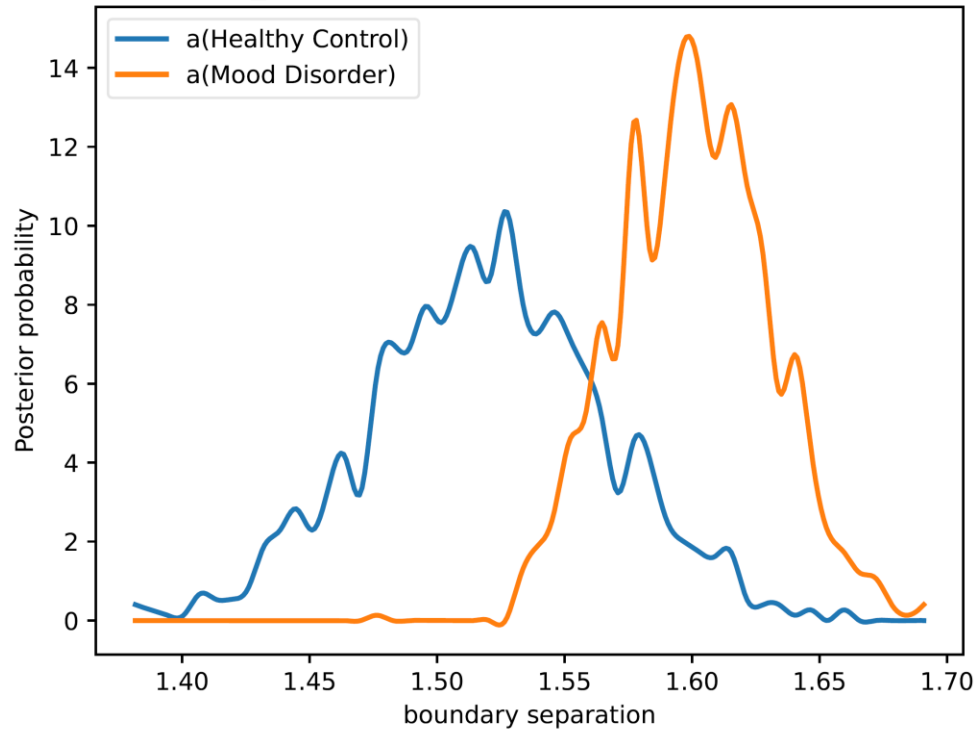
Posterior of drift rate group data window 1 data
 $P_v(\text{HC} > \text{MD}) = 0.9391666666666667$



MD have slower drift rates compared to HC

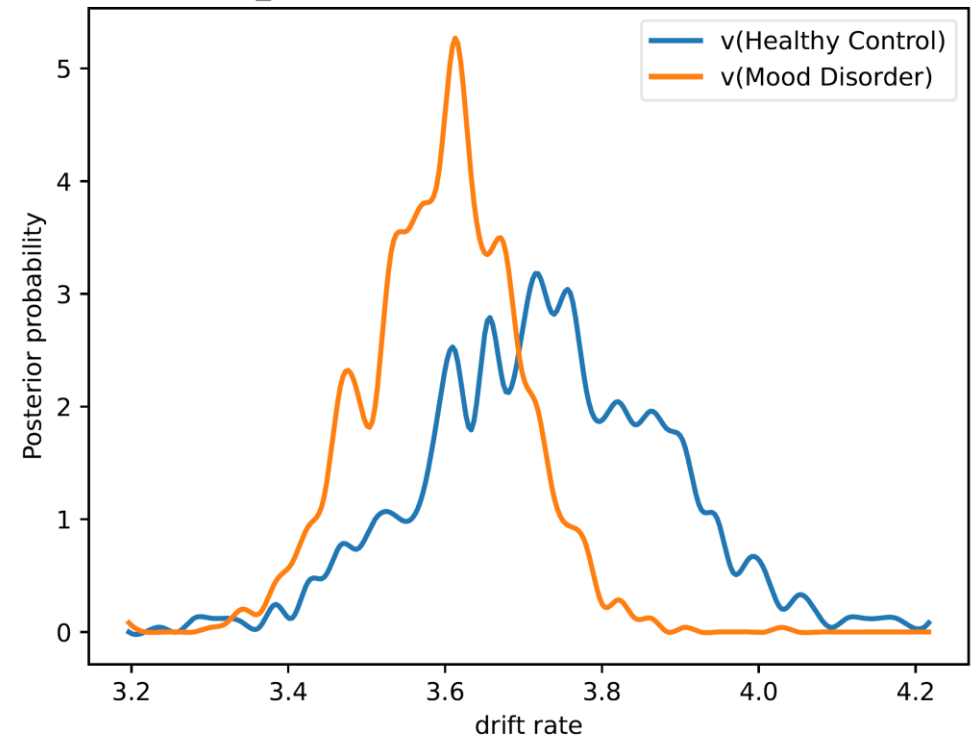
WINDOW 2 RESULTS

Posterior of boundary separation group data window 2 data
 $P_{a(HC > MD)} = 0.06416666666666666$



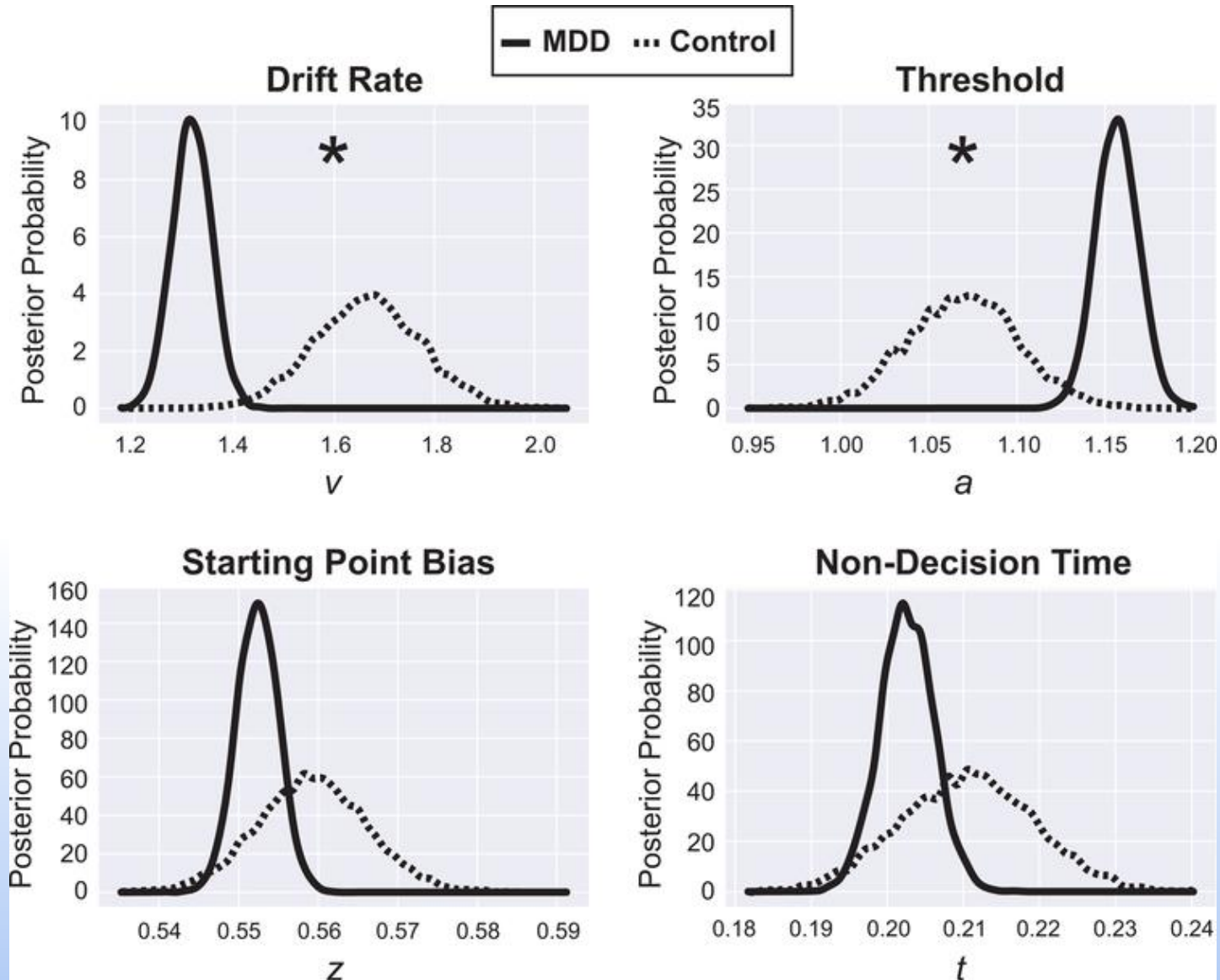
MD have wider boundary separations compared to HC

Posterior of drift rate group data window 2 data
 $P_{v(HC > MD)} = 0.7833333333333333$

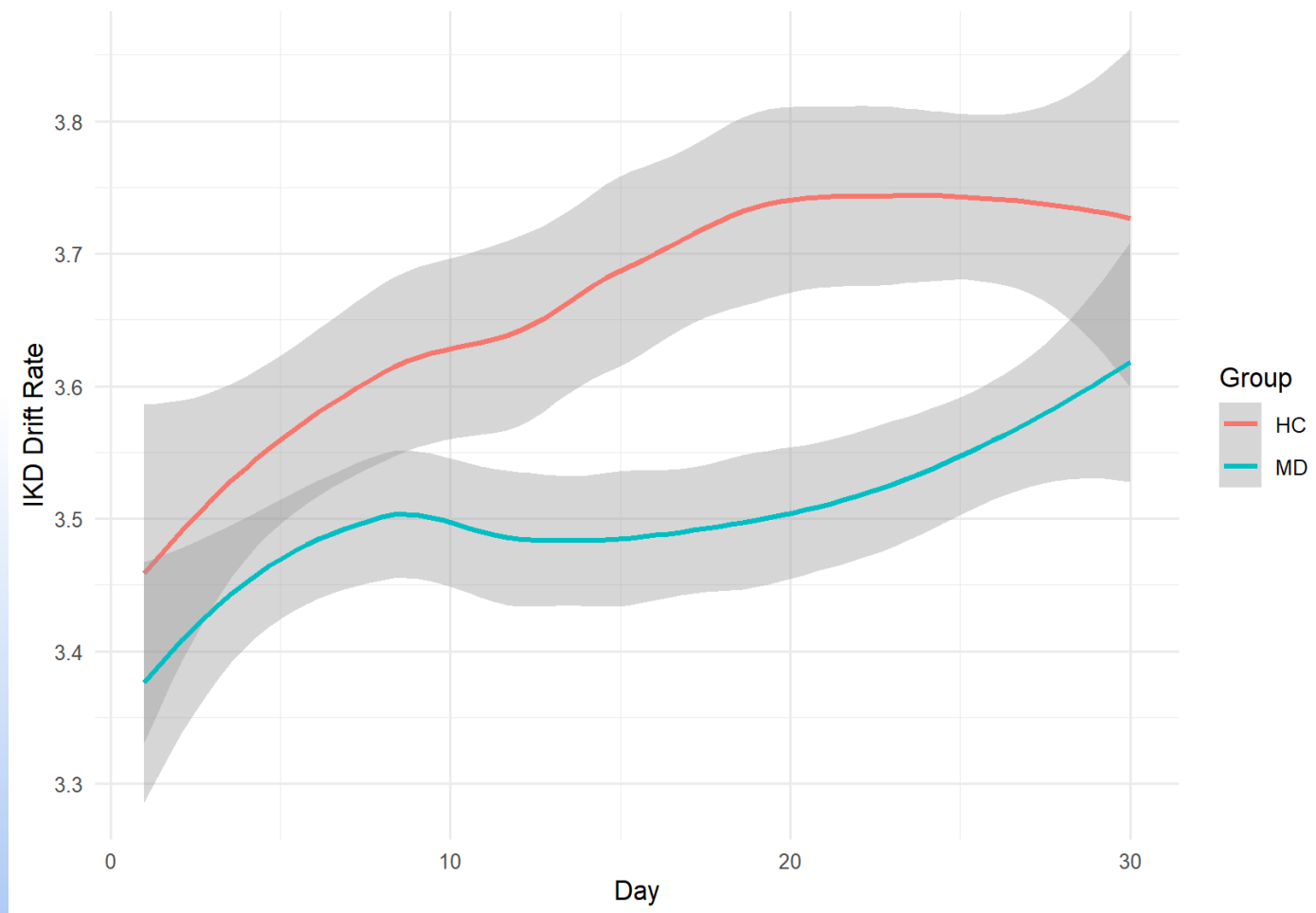


MD have slower drift rates compared to HC

DISSECTING THE IMPACT OF DEPRESSION ON DECISION-MAKING



DAILY DRIFT RATE



S U M M A R Y

- Aspects of decision-making derived from standard neuropsychological tests may be captured by passive, unobtrusively obtained naturalistic smartphone data
- Dense temporal sampling of keyboard data have the potential to be a daily measure of decision-making capacity

CONCLUSIONS

- Using passive sensing to track cognition has the potential to enhance precision in diagnosis and symptom tracking
- This may be particularly relevant for emerging subtypes of psychiatric disorders (i.e. cognitive biotypes of MDD)

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