Developing Data-Driven Clinical Signatures for People Who Experience Hallucinations

U01MH135901 MPI Dror Ben-Zeev, Trevor Cohen









Hallucination Assessment through Longitudinal Observation (HALO)

U01MH135901 MPI Dror Ben-Zeev, Trevor Cohen













Dror Ben-Zeev PI UW



Trevor Cohen PI UW



Alex Cohen Co-I LSU



Serguei Pakhomov Co-I UM



Oliver Bear Don't Walk Co-I UW



Justin Tauscher Co-I/Project Director UW



Benjamin Buck Co-I UNC



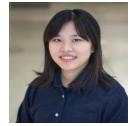
Patrick Heagerty Co-I UW



Alexa Beaulieu Research Manager UW



Anna Larsen Co-I UW



Changye Li Post-Doc UW



Ella DeVries Research Coordinator UW



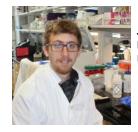
Gillian Sparks Research Coordinator UW



Michael Michalowski Co-I UM



Feng Chen Research Assistant UW



Jacob Solinsky Research Assistant UM



Maya Stemmer ^{Co-l} UW



Patrick Wedgeworth Co-I UW



Weizhe Xu Research Assistant UW



Meliha Yetsigen Co-I UW

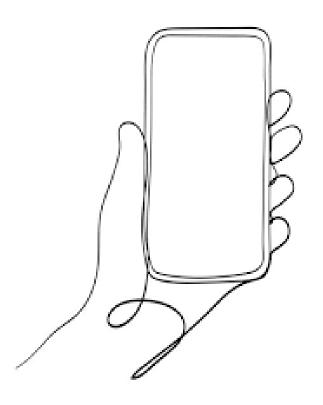








Hallucinations and poor outcomes do not always coincide



Hallucinations

- Prevalent in many mental disorders
- Also occur in 10% of the general population
- Don't always portend serious negative outcomes
- Early intervention can improve outcomes

Smartphones

- Ubiquitous
- Scalable behavioral measurement platforms

Automated speech and language analysis

Substrate for actionable clinical signatures









Scalable predictive models to inform clinical decisions

Our objective is to leverage novel data sets and cutting-edge computational methods to generate clinical signatures that can be used to inform scalable and timely risk detection and clinical decision making.

Specifically, we aim to:

- 1) Derive data-driven clinical signatures from mobile behavioral tasks to predict individual differences in severe negative outcomes among people experiencing hallucinations;
- 2) Identify and mitigate inaccuracies in modelling across groups;
- 3) Examine whether **adding smartphone-captured behavioral data** to information that is typically available in the clinical record **improves model clinical utility**; and
- 4) Produce **machine learning-ready data structures** that adhere to FAIR (Findable, Accessible, Interoperable, Reusable) principles.









Computable phenotypes in the wild

- Prospective Cohort Study
- Online recruitment of 2000
 individuals 18 years or older in the
 USA who experience hallucinations
 for one year of data collection.
- Data collected from the subjects directly via <u>data collection system</u> <u>downloaded on their device</u>.



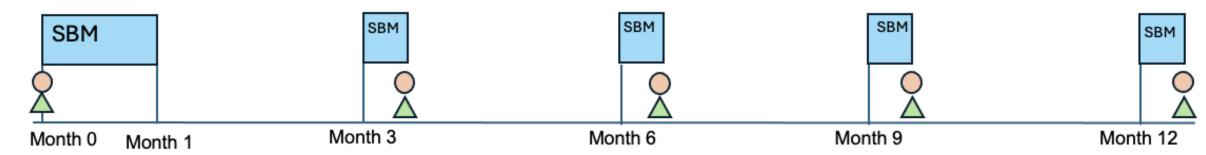






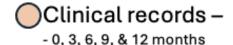


Infrequent outcomes – intermittent extended data capture





- 30 days at baseline (3x per week)
- 7 day "bursts" at 3, 6, 9, & 12 months (3x per week)



△ Clinical outcomes –

Smartphone Behavioral Measurement (SBM)

- Ecological Momentary Assessment (EMA)
- Audio Diaries
- Verbal Recall Task

Clinical Records

- Clinical History
- Psychiatric Symptoms
- Functional Impairment

Clinical Outcomes

- Relevant ED visits
- Hospitalizations
- Suicide attempts / behavior









E.g. "clinical records data"

History: Clinical, service use, demographics

Depression: Patient Health Questionnaire,

9-item Version (PHQ-9)

Anxiety: Generalized Anxiety Disorder

Questionnaire, 7-item version (GAD-7)

Symptoms (General): DSM-5 Cross-Cutting

Symptom Measure (DSM-5-CCM)

Functional Impairment: WHO Disability

Assessment Schedule (WHODAS)



PSYCHIATRIC SYMPTOMS (DSM5 Cross Cutting Symptom Measure)

	chiatric Symptoms					
	M5 Cross Cutting Symptom Measure	_				
	uring the past two (2) weeks, how much (or how often) have you been b	othe	erec	l by	the	?
	owing problems?"					_
	Not at all, $1 = Less$ than a day or two, $2 = Several days$, $3 = More than$	hal	f th	e da	ys,	4
	early every day			_	_	Т
1	Little interest or pleasure in doing things?	0	1	2	3	ļ
2	Feeling down, depressed, or hopeless?	0	1	2	3	ļ
3	Feeling more irritated, grouchy, or angry than usual?	0	1	2	3	ļ
4	Sleeping less than usual, but still have a lot of energy?	0	1	2	3	ļ
5	Starting lots more projects than usual or doing more risky things than usual?	0	1	2	3	
6	Feeling nervous, anxious, frightened, worried, or on edge?	0	1	2	3	Ī
7	Feeling panic or being frightened?	0	1	2	3	Ī
8	Avoiding situations that make you anxious?	0	1	2	3	İ
9	Unexplained aches and pains (e.g., head, back, joints, abdomen, legs)?	0	1	2	3	
10	Feeling that your illnesses are not being taken seriously enough?	0	1	2	3	I
11	Thoughts of actually hurting yourself?	0	1	2	3	Ī
12	Hearing things other people couldn't hear, such as voices even when no one was around?	0	1	2	3	1
13	Feeling that someone could hear your thoughts, ot that you could hear what another person was thinking?	0	1	2	3	İ
14	Problems with sleep that affected your sleep quality over all?	0	1	2	3	t
15	Problems with memory (e.g., learning new information) or with location (e.g., finding your way home)?	0	1	2	3	ı
16	Unpleasant thoughts, urges, or images that repeatedly enter your mind?	0	1	2	3	Ì
17	Feeling driven to perform certain behaviors or mental acts over and over again?	0	1	2	3	
18	Feeling detached or distant from yourself, your body, your physical surroundings, or your memories?					
19	No knowing who you really are or what you want out of life?	0	1	2	3	ſ
20	Not feeling close to other people or enjoying your relationships with them?	0	1	2	3	Î
21	Drinking at least 4 drinks of any kids of alcohol in a day?	0	1	2	3	İ
22	Smoking cigarettes, a cigar, or using snuff or chewing tobacco?	0	1	2	3	İ
23	Using any of the following medicines ON YOUR OWN, that is, without a doctor's prescription, in greater amounts or longer than prescribed [e.g., painkillers (like Vicodin), stimulants (like Ritalin or Adderall), sedatives or tranquilizers (like sleeping pills or Valium),	0	1	2	3	
	or drugs like marijuana, cocaine or crack, club drugs (like ecstasy),					I

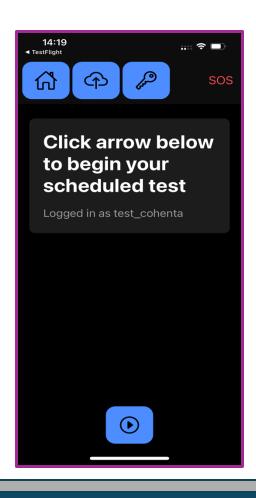




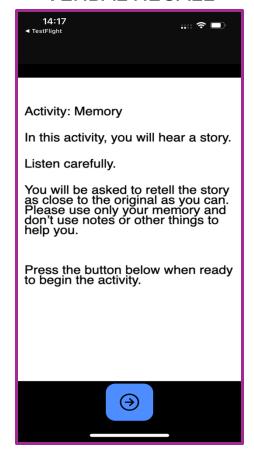




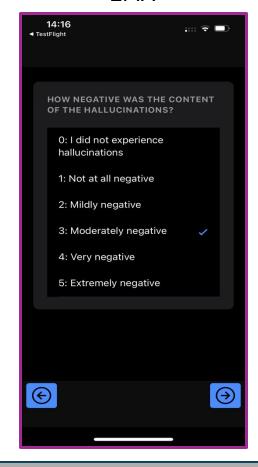
Smartphone-based behavioral measurement



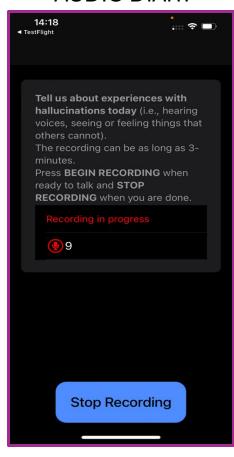
VERBAL RECALL



EMA



AUDIO DIARY



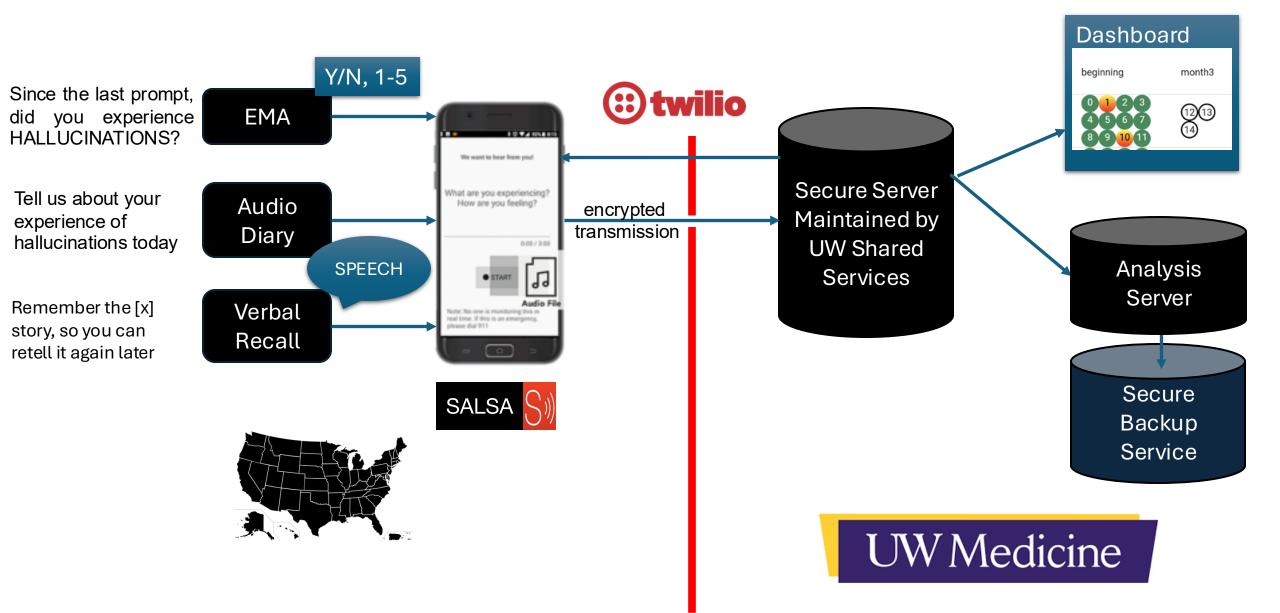






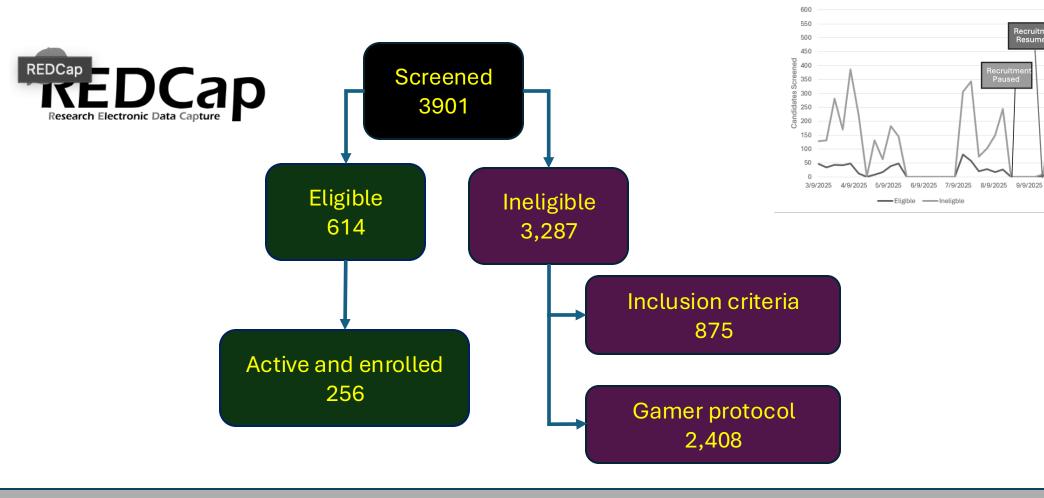


Data collection infrastructure



Data to date









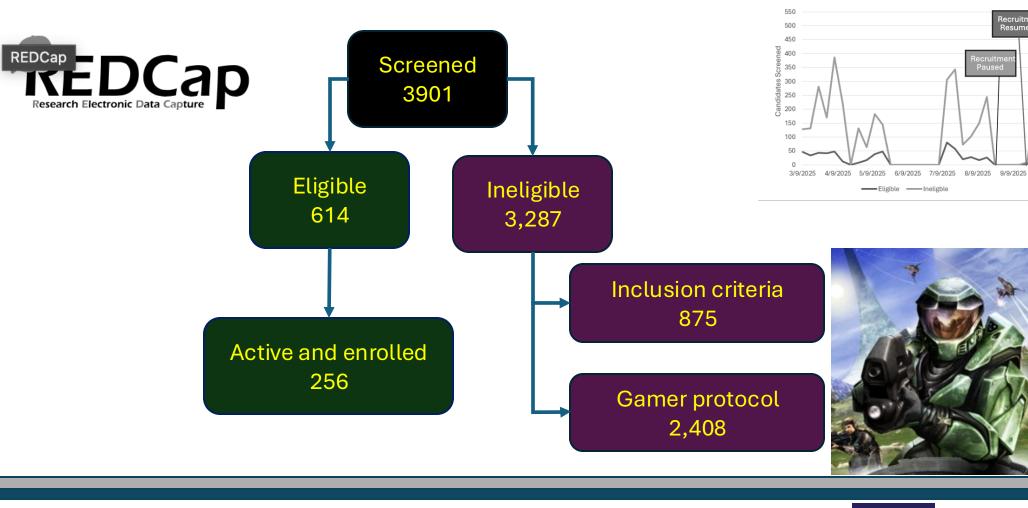




Eligible Ineligible

Data to date









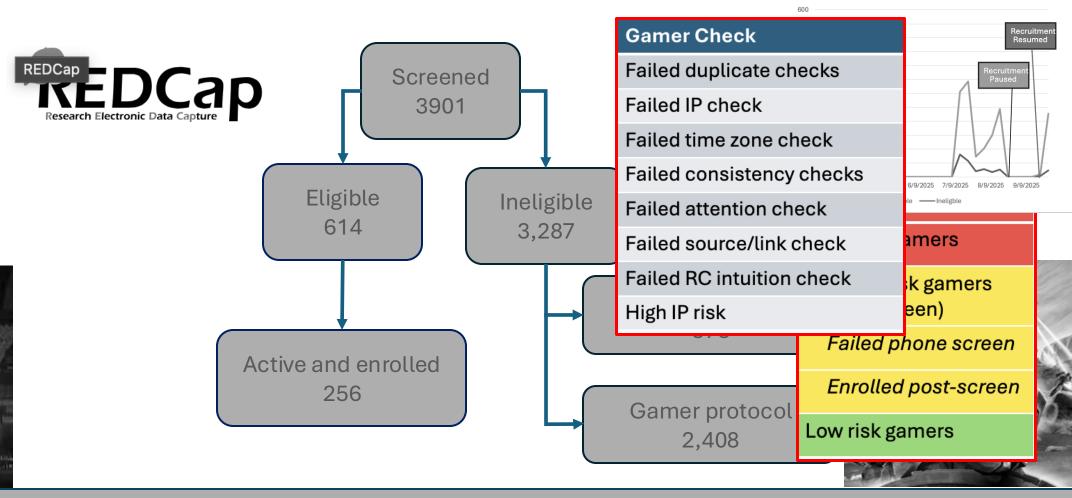




Eligible Ineligible

Forthcoming attraction













Cohort to (slightly more recent) date

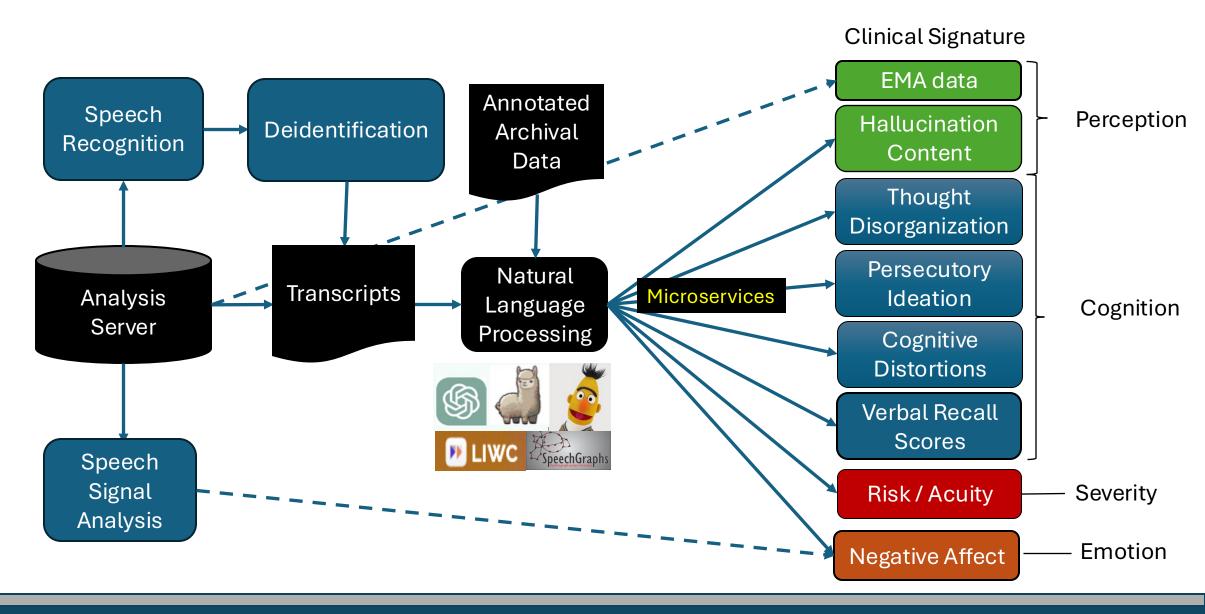
Race	N (%)	29 6 3 4 4 13 8 11 2 2 10 23 6 16 16 16 16 16 16 16 16 16 16 16 16 1	
American Indian/Alaskan Native	11 (3.5%)	$\frac{4}{1} \frac{1}{1} \frac{4}{6} \frac{13}{20}$	
Asian	14 (4.5%)	16 4 14	
Black/African American	104 (33.2%)	What diagnosis (or diagnoses) have you received? (Check all that apply;	
Middle Eastern/North African	6 (1.9%)	Among those who reported "yes" to above question)	
Native Hawaiian/Pacific Islander	5 (1.6%)	Anxiety disorder	94 (56.3%)
White	190 (60.7%)	Obsessive-compulsive disorder	13 (7.8%)
Other	8 (2.6%)	Bipolar disorder	55 (32.9%)
Prefer not to say/not reported	0	Depressive disorder	56 (33.5%)
Ethnicity		Developmental or learning disorder	16 (9.6%)
Hispanic/Latino Origin	50 (15.8%)	Personality disorder (e.g. borderline, paranoid, schizotypal, antisocial)	19 (11.4%)
Not Hispanic/Latino Origin	266 (84.2%)	Schizophrenia spectrum or psychotic disorder	65 (38.9%)
Unknown/Prefer not to say	0	Trauma and stressor related disorder	50 (29.9%)









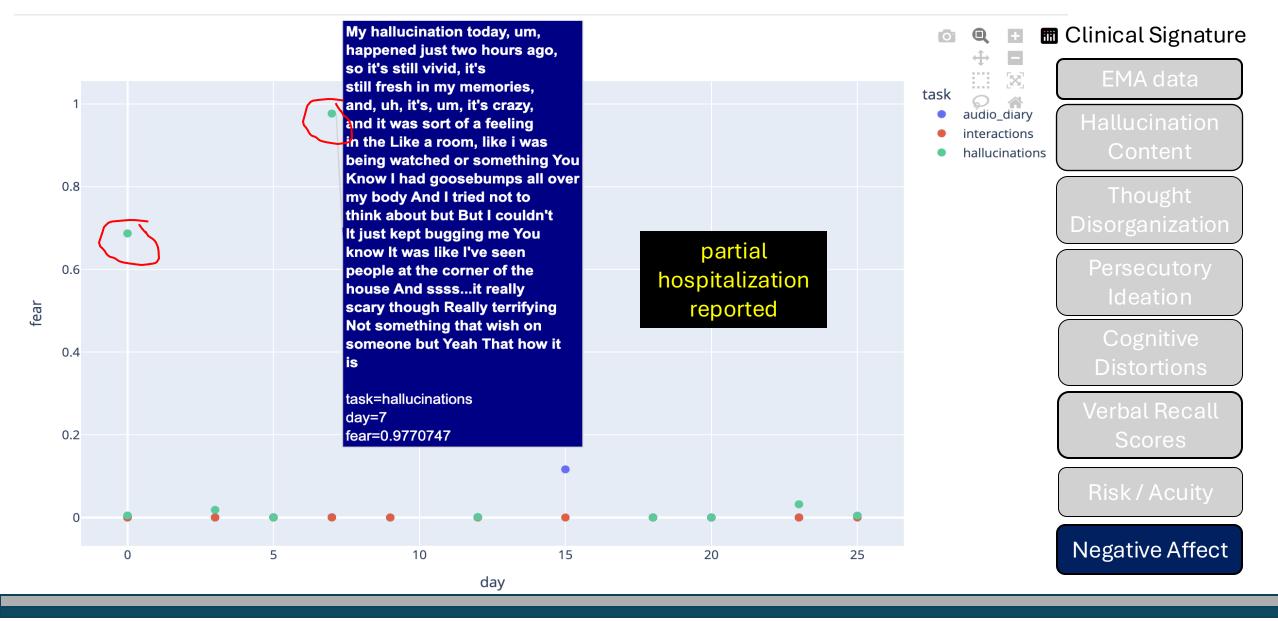










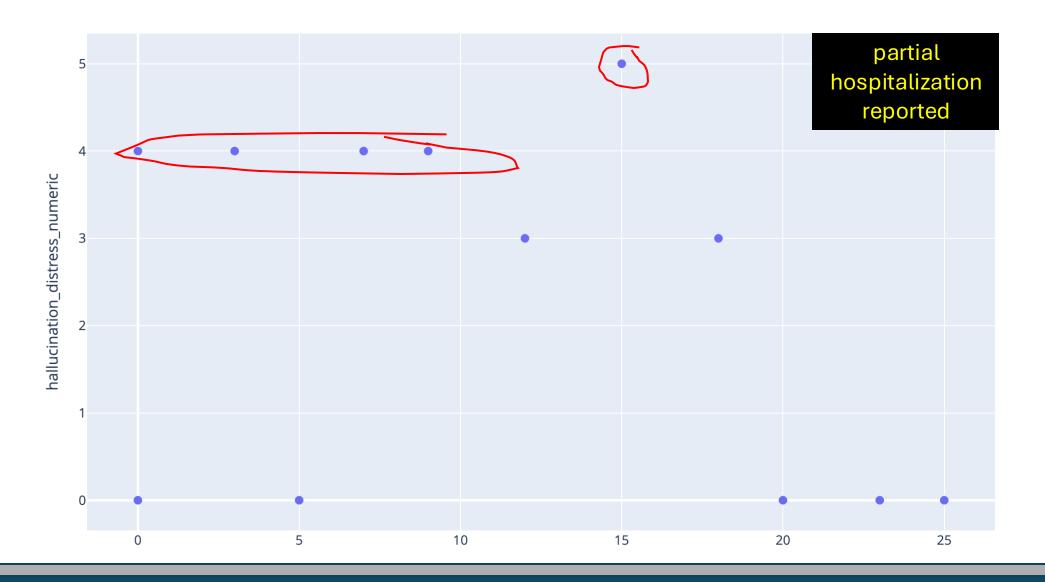












Clinical Signature

EMA data

Hallucination Content

Thought Disorganizatior

Persecutory Ideation

Cognitive Distortions

Verbal Recall Scores

Risk / Acuity

Negative Affect







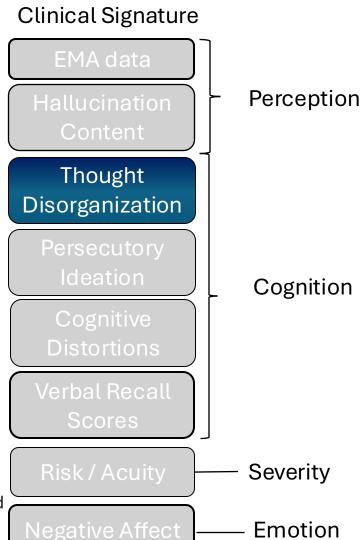




Excerpt From: The Center Cannot Hold: My Journey through Madness By Elyn R. Saks

Elvevåg B, Foltz PW, Weinberger DR, Goldberg TE. Quantifying incoherence in speech: an automated methodology and novel application to schizophrenia. Schizophrenia research. 2007 Jul 1;93(1-3):304-16.

Bedi G, Carrillo F, Cecchi GA, Slezak DF, Sigman M, Mota NB, Ribeiro S, Javitt DC, Copelli M, Corcoran CM. Automated analysis of free speech predicts psychosis onset in high-risk youths. npj Schizophrenia. 2015 Aug 26;1(1):1-7..













Contents lists available at ScienceDirect

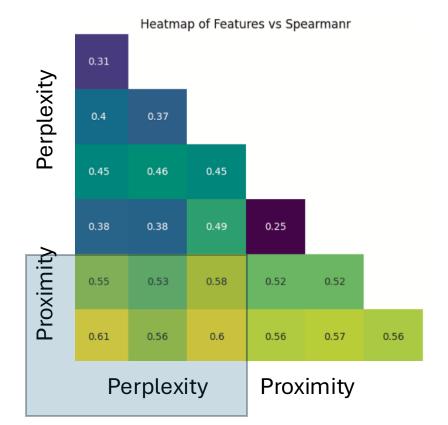
Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Original Research

Perplexity and proximity: Large language model perplexity complements semantic distance metrics for the detection of incoherent speech

Weizhe Xu^{a,*}, Serguei Pakhomov^b, Patrick Heagerty^c, Eric Horvitz^d, Ellen R. Bradley^e, Josh Woolley^e, Andrew Campbell^f, Alex Cohen^g, Dror Ben-Zeev^h, Trevor Cohen^{a,h}





Bigger But Not Better: Small Neural Language Models Outperform Large Language Models in Detection of Thought Disorder

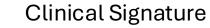
Changye Li^{1*} Weizhe Xu^{1*} Serguei Pakhomov²

Ellen Bradley³ Dror Ben-Zeev¹ Trevor Cohen¹

	Sliding windows							
Model	8	16	32	64	128			
70m	0.265	0.482***	0.338**	0.356**	0.344**			
160m	0.414***	0.433***	0.316*	0.354***	0.325**			
410m	0.385*	0.433***	0.316*	0.354**	0.325**			
1b	0.415***	0.352**	0.380**	0.410***	0.313*			
1.4b	0.458***	0.370***	0.382**	0.418***	0.326**			
2.8b	0.425***	0.385**	0.369**	0.428***	0.348***			
6.9b	0.478***	0.352**	0.394**	0.414***	0.368**			
12b	0.441***	0.313*	0.404**	0.412***	0.357*			
LLaMA	_	_	-	0.249	_			

^{***}p < 0.01, **p < 0.05, *p < 0.1





EMA data

Hallucination Content

Thought Disorganization

Persecutory Ideation

Cognitive Distortions

Verbal Recall
Scores

Risk / Acuity

Negative Affect









Why so perplexed?

Our objective is to leverage novel data sets and cutting-edge computational methods to generate clinical signatures that can be used to inform scalable and timely risk detection and clinical decision making.

Specifically, we aim to:

- 1) Derive data-driven clinical signatures from mobile behavioral tasks to predict individual differences in severe negative outcomes among people experiencing hallucinations;
- 2) Identify and mitigate inaccuracies in modelling across groups;
- 3) Examine whether adding smartphone-captured behavioral data to information that is typically available in the clinical record improves model clinical utility; and
- 4) Produce machine learning-ready data structures that adhere to FAIR (Findable, Accessible, Interoperable, Reusable) principles.

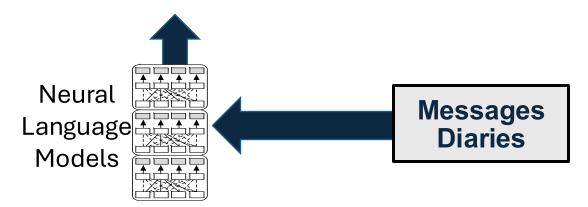






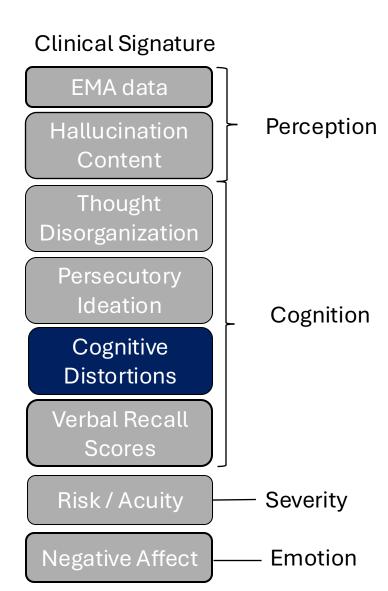


Distortion	SHAP Explainer				
	Good morning how are you? I couldn't fall asleep last night until 1am. And this				
mental filter	morning when I got up I got very dizzy almost like I was going to pass out. I passed				
mental men	out once when I was 11. I remember how I felt right before and that is how I felt this				
	morning. It was very disconcerting, so I don't think I'm doing to do much today.				
jumping to conclusions	Maybe they really don't like me.				
anto atua ulai-iu a	Feeling unsure of myself right now. Desperate. Idk if I can handle my money or tackle				
catastrophizing	my goals of saving for a rainy day.				



Tauscher JS et al. Automated Flagging of Cognitive Biases in the Spoken Language of People Hallucination Experiences. Journal of Technology in Behavioral Science. 2025 Sep 11:1-0./

Tauscher JS et al. Automated detection of cognitive distortions in text exchanges between clinicians and people with serious mental illness. Psychiatric services. 2023. https://pubmed.ncbi.nlm.nih.gov/36164769/

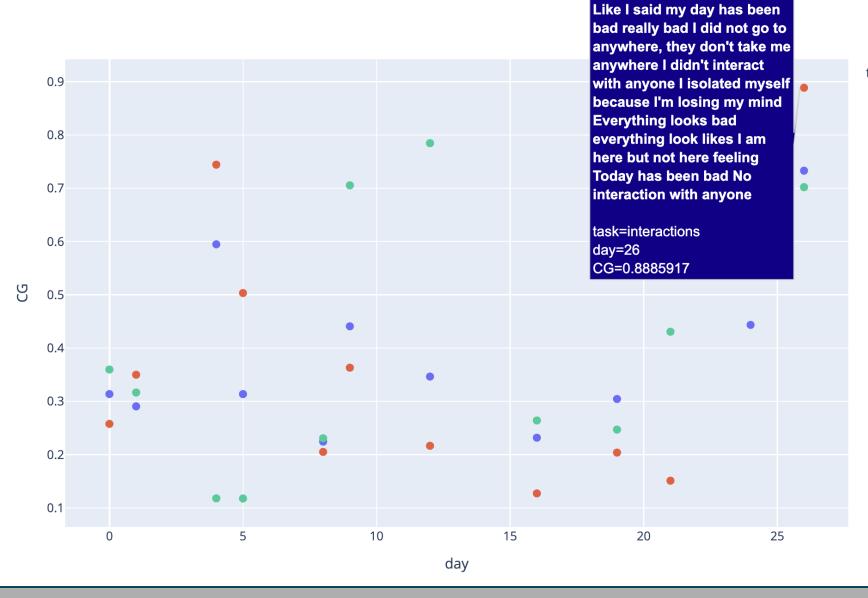


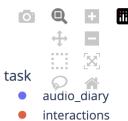












hallucinations

Clinical Signature

EMA data

Hallucination Content

Thought Disorganization

Persecutory Ideation

Cognitive Distortions

Verbal Recall Scores

Risk / Acuity

Negative Affect



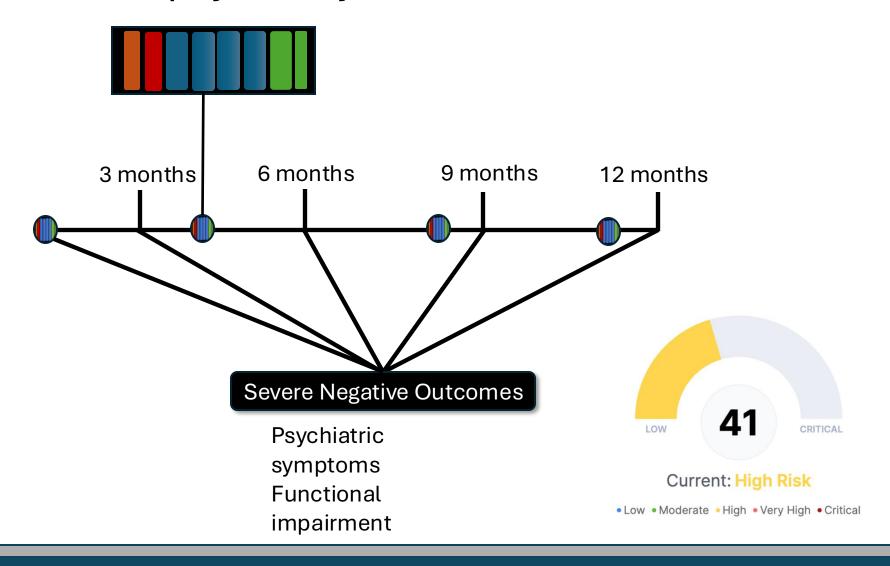






Computational psychiatry in the wild?

Clinical Signature EMA data Hallucination Content Thought Disorganization Persecutory Ideation Cognitive Distortions Verbal Recall Scores Risk / Acuity Negative Affect











Acknowledgements

- Now:
 - NIMH, NLM, IMPACT-MH, Garvey Institute for Brain Health Solutions
- Then:
 - NIMH, NLM, NIA, NIH Common Fund
 - Garvey Institute for Brain Health Solutions









