

Toward expert systems in mental health assessment:

A framework for Context-Adaptive Multimodal Informatics (CAMI) to inform discharge planning

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INTRODUCTION

Objective, context adaptive measures of psychiatric disease are necessary to better inform costly, challenging clinical decisions.

Traditional methods of assessing and monitoring mental health and psychological illnesses are currently expensive, predominately subjective, and not always reliable. Clinicians extract information about a patients' mental health from interviews as the basis for record-keeping and decision-making. The major goal in this study is to design a system to extract similar information from video and audio signals by training classifiers to map between behavioral features and psychiatric attributes.

Study Aims

- Acquire a multimodal dataset of 400 inpatients with severe mental illness
- Deepen our understanding of the trajectory leading to hospitalization discharge
- Contribute to the knowledge on how social context impacts patient's behaviors
- Contribute a credible, objective framework for behavioral measurement

PARTICIPANTS AND PROCEDURES

Interviews

- 90 McLean inpatients with diagnoses of schizophrenia, bipolar, and related conditions
- Once a week during inpatient stay, participants completed two semi-structured interviews
 - For each interview pair participants completed both an RA Interview and an MD Interview within 24 hours
 - Interviews were completed in available rooms on five inpatient units (NB1, NB2, AB1-S, AB2-N, AB2-S), and associated offices.
 - Synchronized audio and video data were acquired from 1080p webcams and a cardioid headset microphones
- Participants completed a Post-Hospitalization RA Interview over Zoom 30 days after their discharge from McLean

RA Interview Procedure

Prepare for Recording

Patient Alone Epoch (2 min)

- RA begins recording and steps out of the room
- RA observes the participant discreetly for two minutes

RA Interview (15–30 min)

- RA steps back into the room
- RA assess the participant's symptoms using the RA Interview Checklist designed for use in this study
- RA stops recording and dismisses the participant

RA Scoring

- RA completes PANNS-6, MADRS, YMRS

MD Interview Procedure

Prepare for Recording

Patient Alone Epoch (2 min)

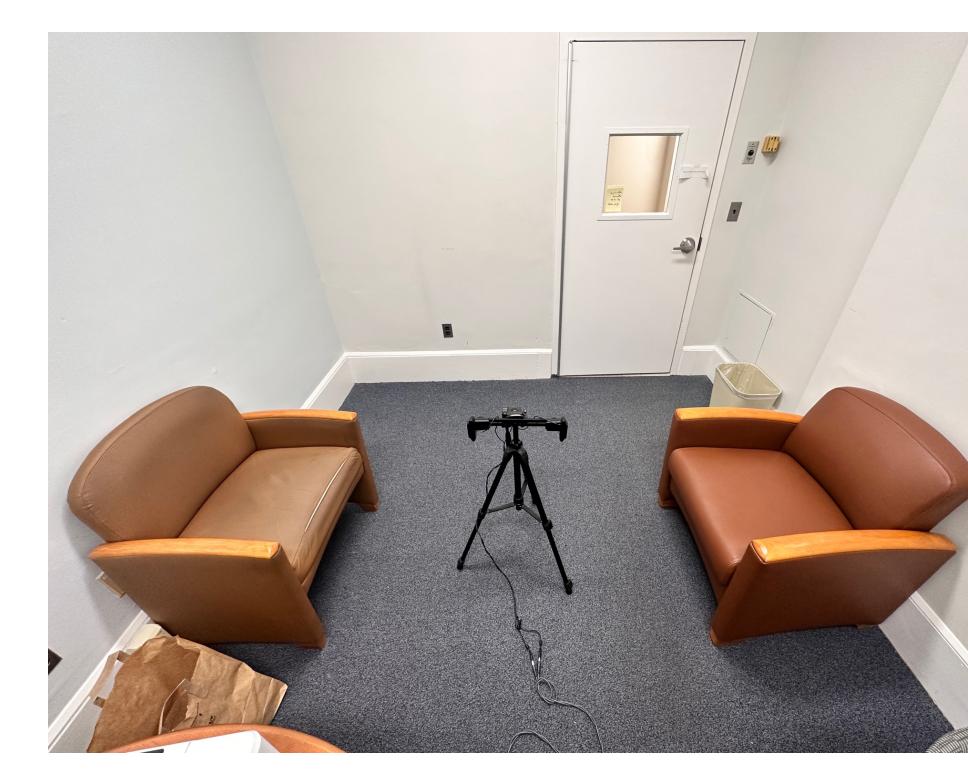
- RA begins recording and steps out of the room
- RA observes the participant discreetly for two minutes

MD Interview (10–20 minutes)

- MD steps into the room
- MD assess the participant's symptoms
- MD completes their interview and signals to the RA
- RA reenters, stops recording, and dismisses the participant

MD Scoring

- MD completes an assessment based on the Mental Status Examination



Mobile recording setup on an example inpatient unit showing placement of dual-camera tripod for each recording.

Video capture of participant and evaluator using the Open Broadcasting Software (OBS).

Above: Logitech C920 1080p webcam. Below: Sennheiser microphone.

Ecological Momentary Assessment (EMA)

- Willing participants completed Metricwire surveys in the hospital and up to 90 days post-discharge
- Participants received their daily survey at 8:00PM
- Participants rated 15 questions about their experience that day using a 5-point Likert scale
- Inpatients rated an additional five questions regarding their fitness for discharge

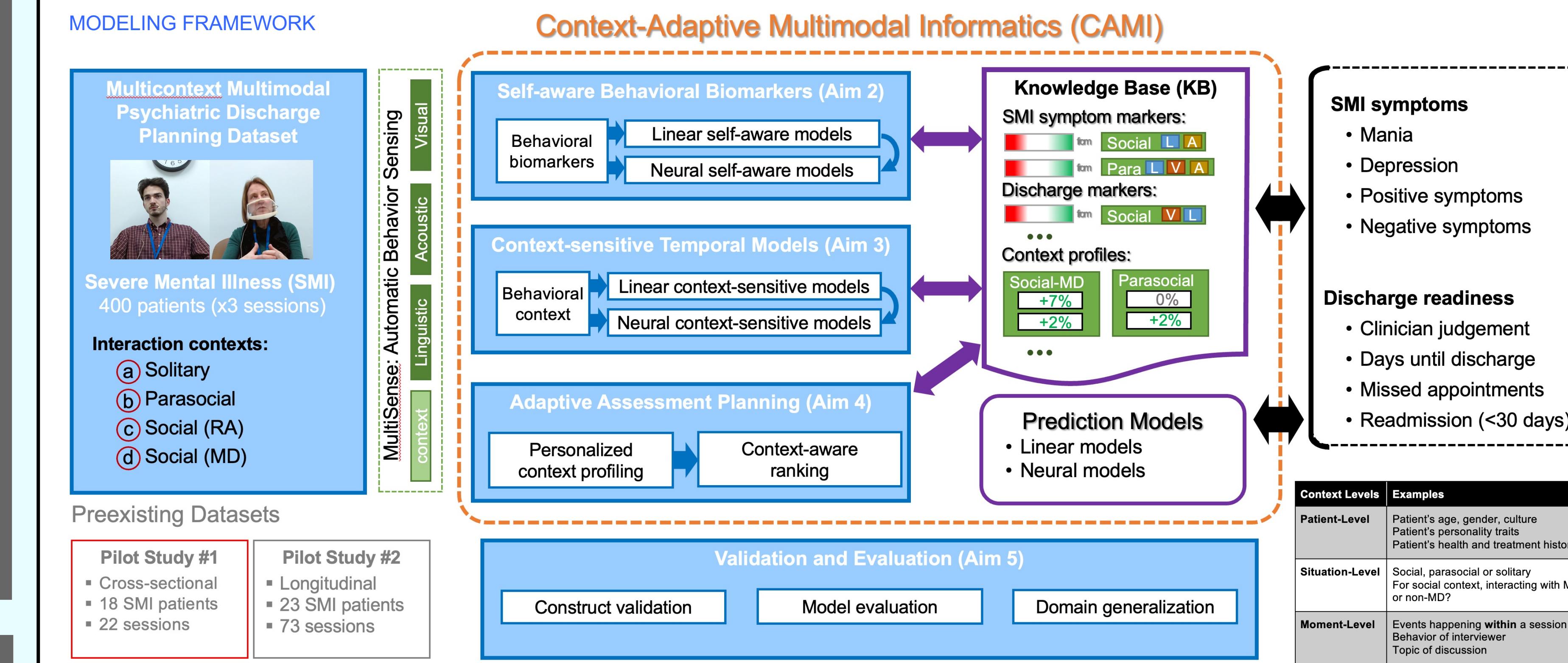
Actigraphy

- Willing participants wore an actigraphy watch for the duration of their inpatient stay
- Actigraphy watches collected continuous triaxial accelerometer data for 30 days
- This data is used to infer sleep and activity
- If participant stay exceeded 30 days, they were given a new watch for the remainder of their stay



GENEActiv Watch

MODELING FRAMEWORK



Overview of the modeling framework. This proposal introduces a new computational framework, which we term **Context-Adaptive Multimodal Informatics**, that is specifically designed to study contextualized behavioral biomarkers related to discharge-readiness and severe mental illness (SMI) symptoms. This proposal further identifies five fundamental research goals and presents our plan to attain them:

Aim 1. Multicontext multimodal psychiatric discharge planning dataset. We will follow 400 individuals with SMI over the course of psychiatric hospitalization and follow up with them one-month after discharge. In the hospital setting, we will collect rich, longitudinal information about their symptoms, discharge-readiness, and multimodal (i.e., acoustic, visual, and language) measurements of their behavior during four task conditions designed to create different social contexts.

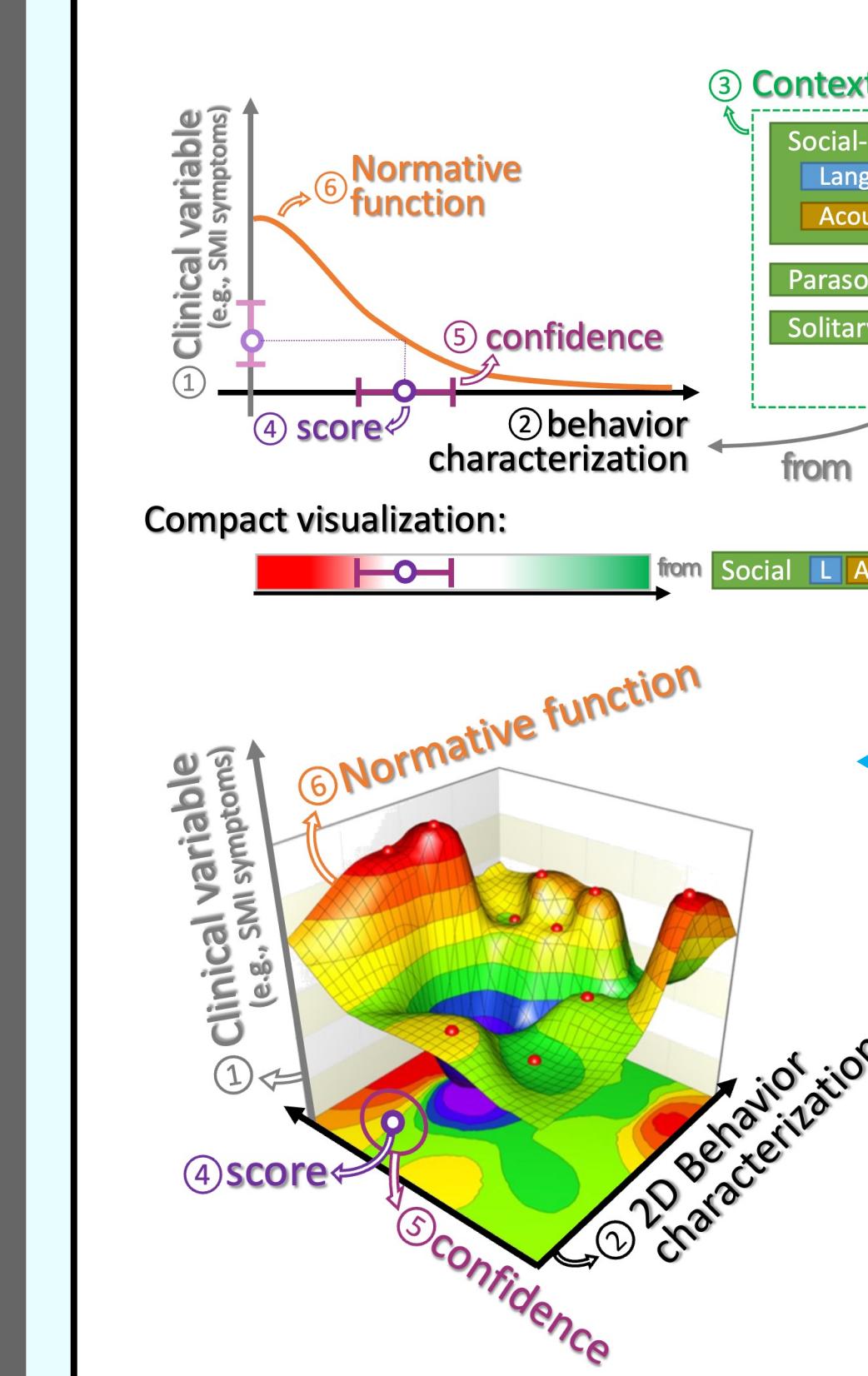
Aim 2. Self-aware multimodal behavioral biomarkers. We will develop new self-aware models that are interpretable and able to quantify their own uncertainty. This research aim will combine the interpretability of linear models and the predictive power of neural architectures.

Aim 3. Context-sensitive temporal models. We define a framework to study the impact of context and modalities when assessing behavioral biomarkers and create linear and neural models that model the influence of contextual features at the level of patients, situations, and moments. We also build temporal information into these models to account for the trajectory of variables over time.

Aim 4. Adaptive assessment planning. The knowledge learned in Aims 2 and 3 is integrated in this new vision for decision support technologies that can inform clinicians of the relative importance of all context and modality options for a specific patient and given a specific clinical objective. This adaptive assessment planning framework creates a personalized patient analysis and then provides recommendations (i.e., context and modality rankings) for the next assessment session.

Aim 5. Validation of knowledge and models. We will rigorously assess our construct operationalizations, behavioral measurements, and predictive models to optimize and quantify the extent to which they are trustworthy and the situations and populations to which they generalize. We will share our knowledge and methods both within and outside the areas of psychiatry and computer science.

DEFINING "NORMATIVE" FUNCTION IN CONTEXT AT THE GROUP AND INDIVIDUAL LEVEL

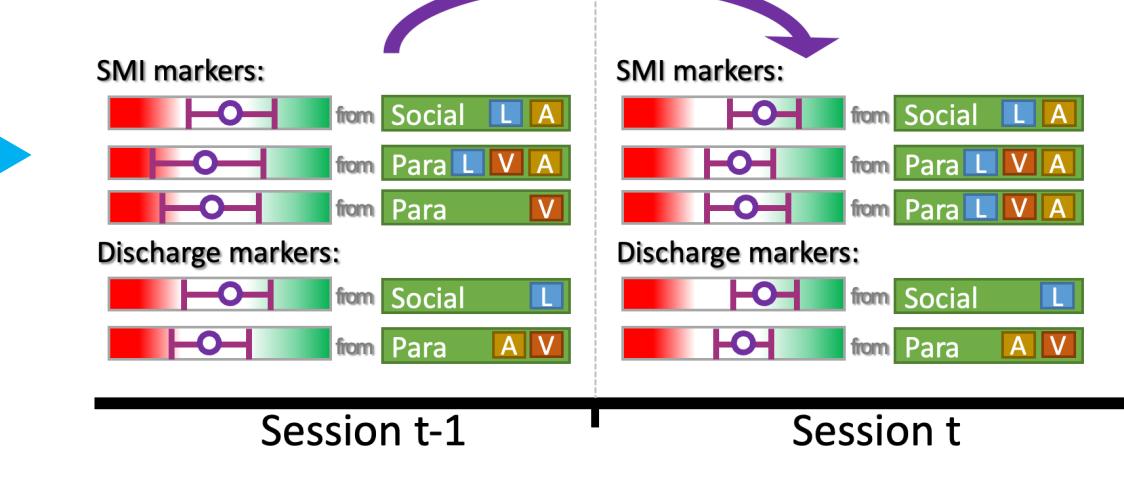
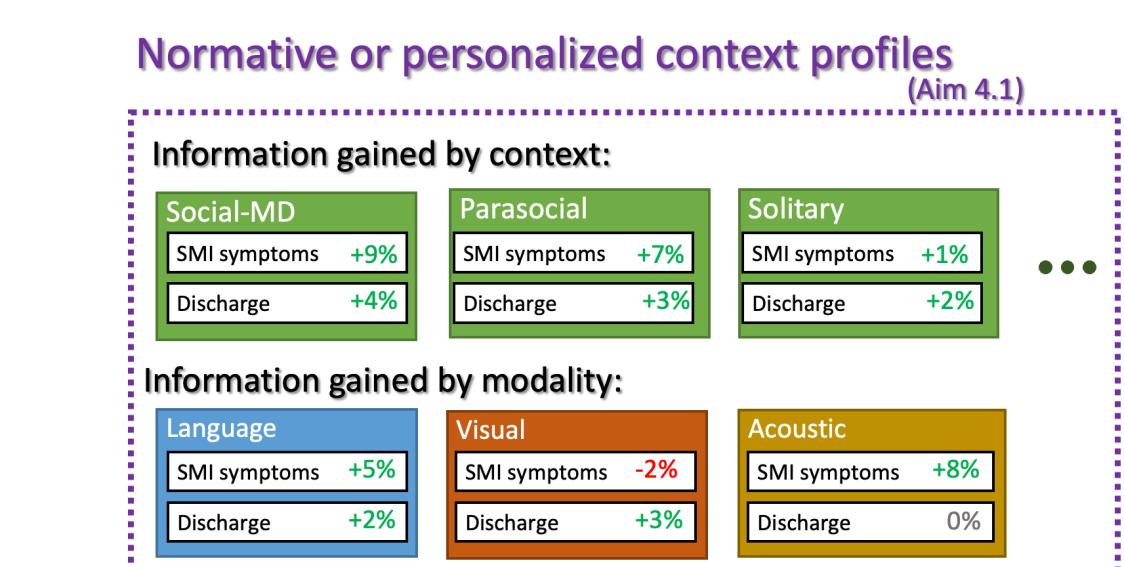


In our proposed framework, a biomarker is always defined with respect to a particular clinical variable ①, such as a medical condition, symptom, or outcome measure to estimate the probability that the patient has the condition or a specific symptom severity. A biomarker is "behavioral" if this estimation is based on some characterization of the patient's observable behavior ②. We can also represent the sources of the behavior characterization, such as the context and modalities it was observed in ③. For each individual patient, we need to assign a score to each patient's behavior ④, as well as the amount of confidence or uncertainty we have in each score ⑤. The final step is to convert the behavioral score to an estimate of the clinical variable. This conversion is formalized in a normative function which maps values of the behavior characterization to values of the clinical variable ⑥, which is derived/learned from normative data and expected to vary across combinations of behavior characterizations, clinical variables, populations, and contexts.

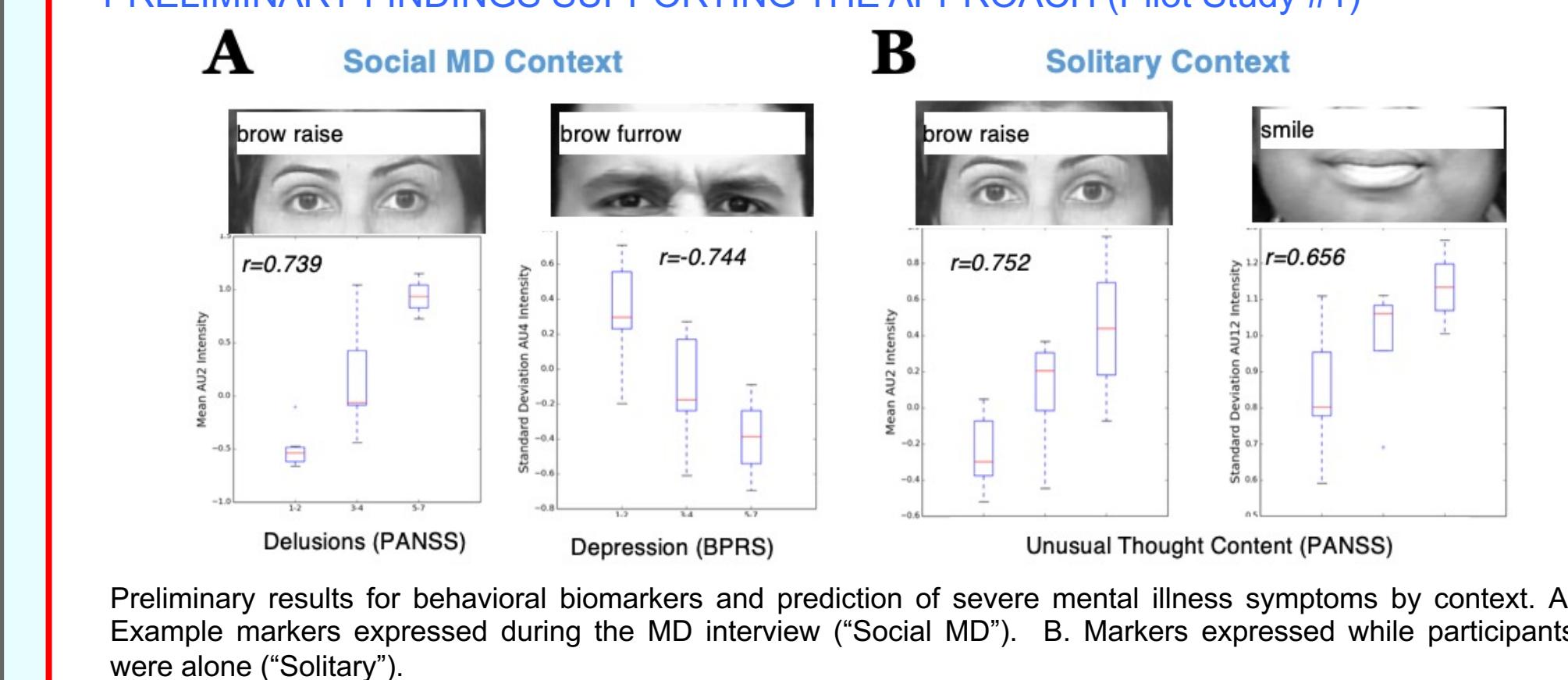
While some normative functions are expected to be linear or monotonic, we can also readily extend our proposed framework to accommodate complex, high-dimensional representations where each score becomes a vector of numbers assigned to each patient and which locates the patient within the space (or hyperspace) defined by the behavior characterization dimensions. The normative function then becomes a surface (or hypersurface) defining the relationship between the behavior characterization dimensions and the clinical variable. Rather than there being risky values of a single behavior characterization dimension, there would then be risky regions of the behavior characterization space (or hyperspace).

The goal of Aim 4 is to quantify the information gained from each context and modality so that we can determine the optimal environment to measure the behavioral biomarkers discovered in Aims 2 and 3.

We will perform this information gain analysis in two stages: (1) We will perform a normative analysis over a large group of patients, which will produce a normative context profile. This normative profile will give very useful information on the trends present in this patient group with regards of the impact of the context and modalities when measuring biomarkers. (2) Next, the normative profile will be adapted to a specific patient, creating a personalized context profile. This personalized profile will be updated sequentially as new sessions come in for the specific patient. The figure above illustrates an example of a context profile estimated between two adjacent sessions.

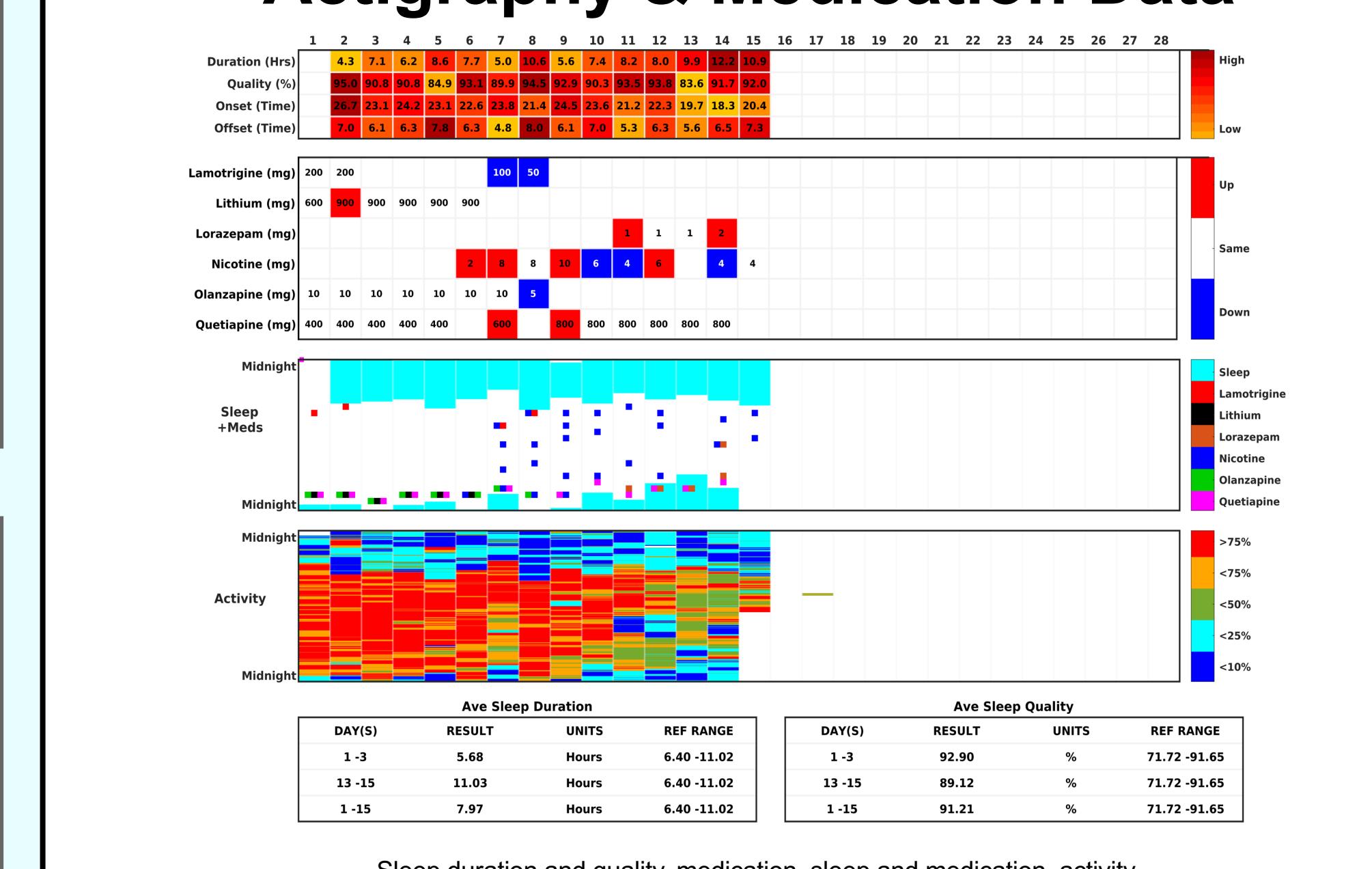


PRELIMINARY FINDINGS SUPPORTING THE APPROACH (Pilot Study #1)



Preliminary results for behavioral biomarkers and prediction of severe mental illness symptoms by context. A. Example markers expressed during the MD interview ("Social MD"). B. Markers expressed while participants

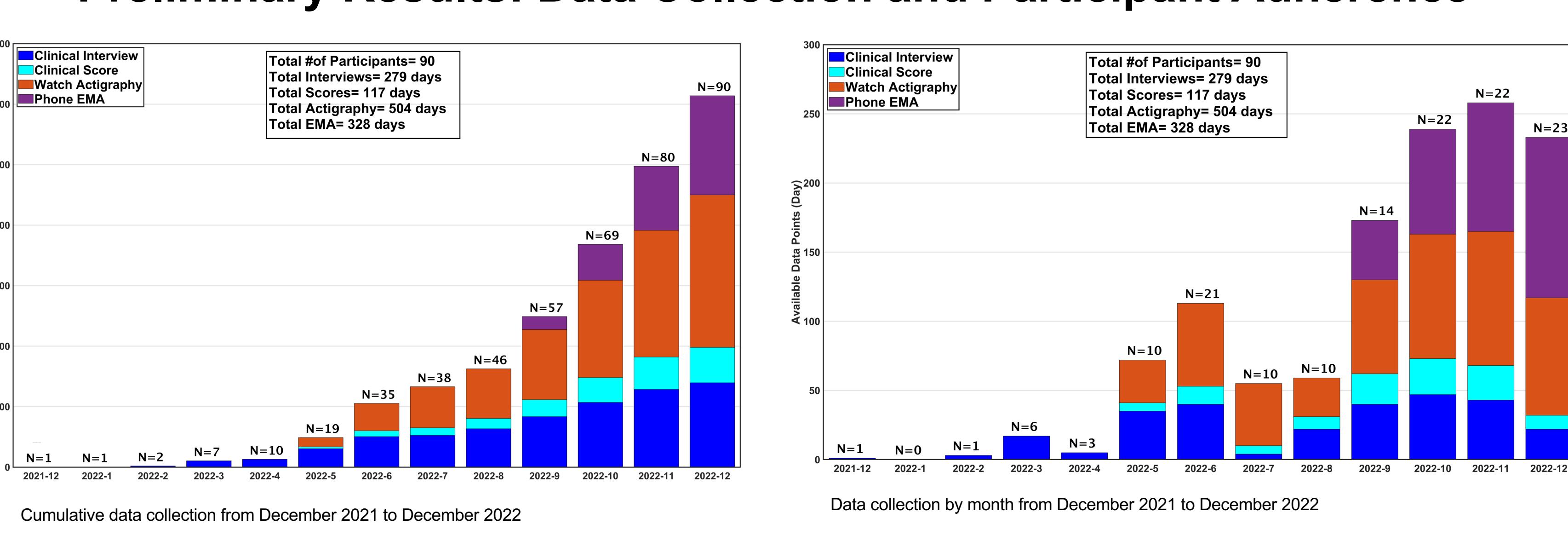
Actigraphy & Medication Data



Discussion

- Preliminary findings suggest that behavioral biomarkers and prediction of severe mental illness symptoms vary by context
- Our data collection and analysis frameworks are mature and allow us to assess participants in a variety of contexts
- Compliance shows that capturing inpatient AV data is feasible
- To improve data fidelity and outpatient compliance, we are fine-tuning our procedures
 - Improving compensation schedules
 - Streamlining interview scripts and checklists
 - Standardizing interview room setup across all locations

Preliminary Results: Data Collection and Participant Adherence



- Data Collected December of 2021 – December 2022
 - Completed 244 inpatient interviews
 - Captured 357 days of actigraphy data
 - Received 233 daily EMAs
- Compliance
 - 83 / 90 have completed at least one MD or RA interview
 - 69 / 90 have completed at least one MD and RA interview
 - 10 / 90 have completed their 30 day follow up interview post discharge

References

- Girard JM, Vail AK, Liebenthal E, Brown K, Kilicikci CM, Pennant L, Liebson E, Öngür D, Morency LP, Baker JT. Computational analysis of spoken language in acute psychosis and mania. *Schizophr Res.* 2022 Jul;245:97-115. doi: 10.1016/j.schres.2021.06.040. Epub 2021 Aug 26. PMID: 34456131; PMCID: PMC8881587.
- Liebenthal E, Ennis M, Rahimi-Eichi H, Lin E, Chung Y, Baker JT. Linguistic and non-linguistic markers of disorganization in psychotic illness. *Schizophr Res.* 2022 Dec 21:S0920-9964(22)00450-9. doi: 10.1016/j.schres.2022.12.003. Epub ahead of print. PMID: 36564239.