Enhancing User Models with Digital Biomarkers for Adaptive Decision Support Systems

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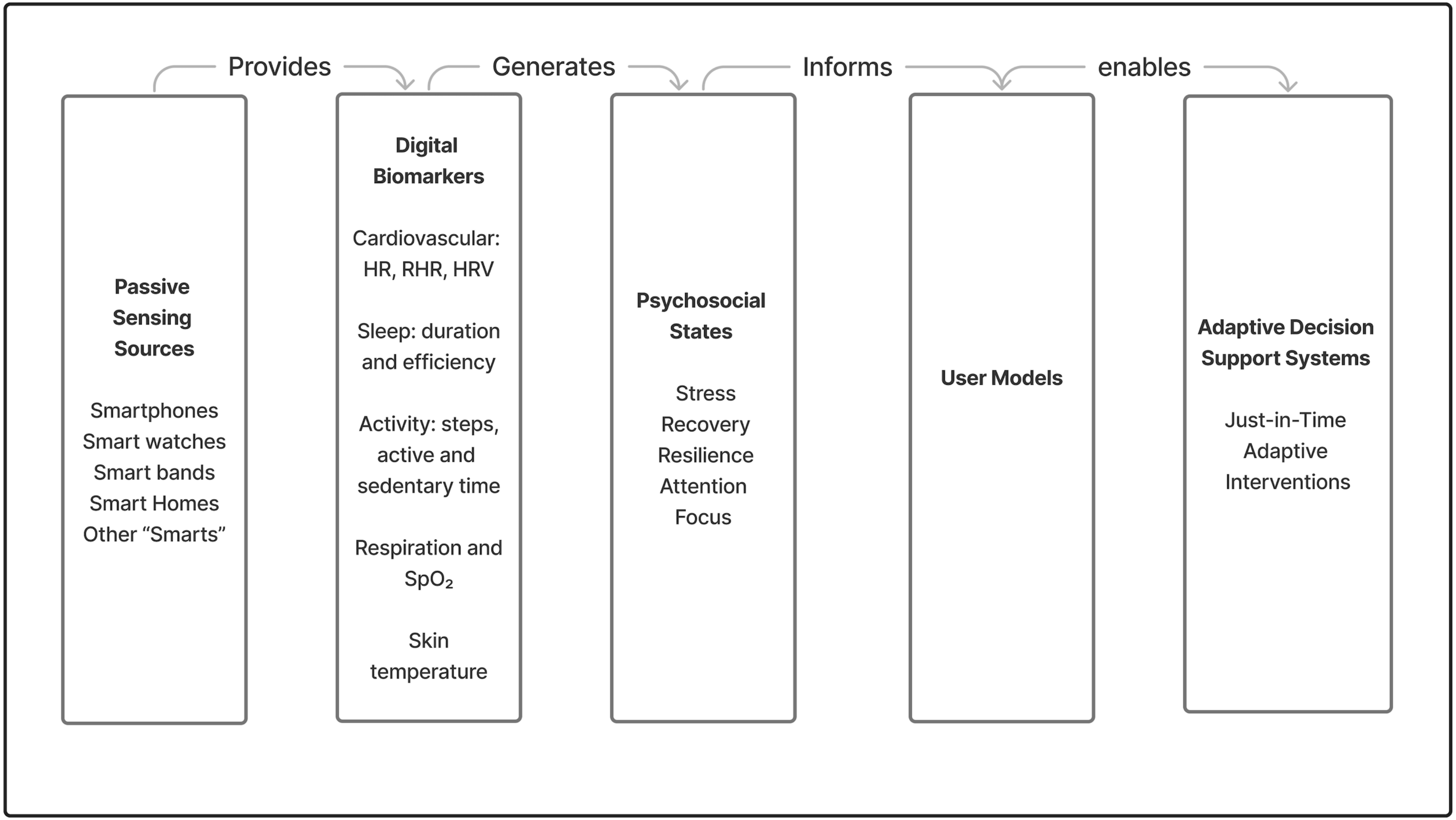
Introduction & Context

- Digital health behaviour interventions use mobile and wearable technologies to support health behaviour change through personalised support delivered when users are most receptive (Keller et al., 2022).
- Adaptive decision support systems (ADSS) and Just-In-Time Adaptive Interventions, adapt support to users’ changing states, needs, and contexts (Hardeman et al., 2019).
- User models are digital representations of users' behaviours, preferences, habits, cognitive and emotional states.
- User models also enable *adaptation and personalisation*: when to intervene, how to intervene, and what type of support to provide

Problem Space

- Snapshots: User models often rely on one-time assessments and predefined traits, making it difficult to capture how users' behavioural and psychosocial states evolve over time.
- Limited integration: Objective data from wearables and smartphones are often not fully integrated with subjective user experience.
- Limited temporal representation: Existing models may not adequately represent patterns, transitions, and changes across time.
- Limited interpretability: User states are often difficult to represent in a way that is meaningful and actionable for adaptive decision-making.
- We need user models that are dynamic, multimodal, longitudinal, and interpretable.

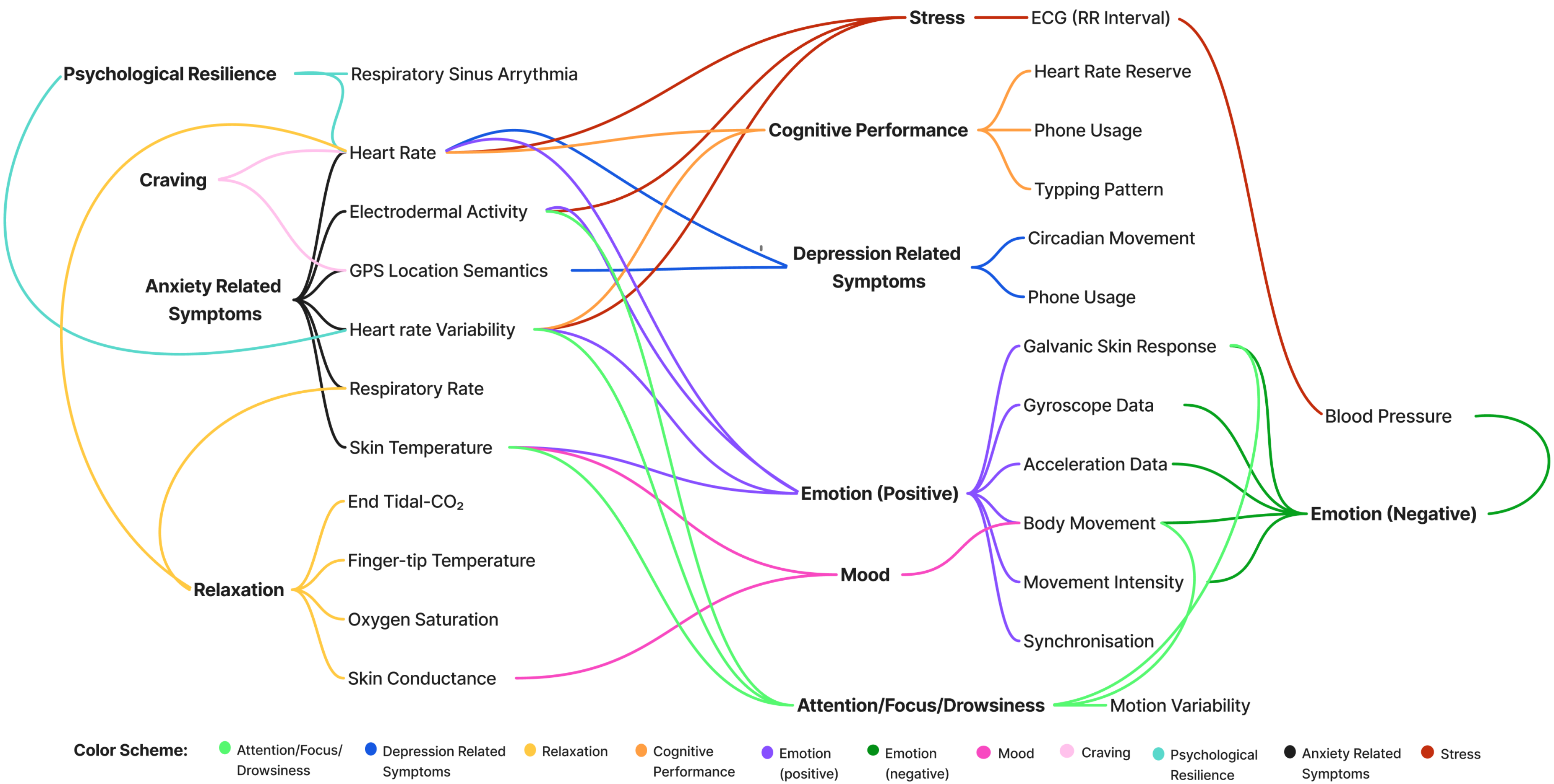
→ This motivates enhancing user models with digital biomarkers.


Provides
Generates
Informs
enables
Passive Sensing Sources
Smartphones
Smart watches
Smart bands
Smart Homes
Other "Smarts"
Digital Biomarkers
Cardiovascular: HR, RHR, HRV
Sleep: duration and efficiency
Activity: steps, active and sedentary time
Respiration and SpO2
Skin temperature
Psychosocial States
Stress
Recovery
Resilience
Attention
Focus
User Models
Adaptive Decision Support Systems
Just-in-Time Adaptive Interventions

Enhancing user models with digital biomarkers…

- Which combinations of digital biomarker data collected from popular wearable devices can be effectively leveraged to infer a range of psychosocial factors?
- How can we use biomarker-inferred psychosocial states to construct interpretable user models of psychosocial wellbeing?
- To what extent do biomarker-derived psychosocial states align with self-reported wellbeing measures?

- Which combinations of digital biomarker data collected from popular wearable devices can be effectively leveraged to infer a range of psychosocial factors?



Aishah Shah, Danial Hooshyar, and Vladimir Tomberg. 2026. From Wrists and Pockets to Interventions: Leveraging Digital Biomarkers to Infer Psychosocial Factors—A Systematic Review. ACM Trans. Comput. Healthcare 7, 2, Article 32 (April 2026), 44 pages. https://doi.org/10.1145/3797877

- Most used analytical methods for predicting psychosocial factors from digital biomarker data

Traditional ML (most common):

- Support Vector Machines (SVM) - stress, anxiety, emotional states, depression
- Logistic Regression - stress, mood, depressive symptoms
- Random Forest - stress prediction, craving, drowsiness
- k-Nearest Neighbors (kNN) - attention, arousal, emotional states

Regression approaches:

- Linear/Multiple Linear Regression - mood, stress levels, activity contexts
- Gradient Boosting - cognitive and emotional responses

Deep Learning (emerging):

- CNNs and LSTMs - stress and emotional state classification
- Feed-forward ANNs - stress state classification

Key finding:

- **Support Vector Machines (SVM)** 18 studies: stress, anxiety, emotional states, depression
- **Logistic Regression** 12 studies: stress, mood, depressive symptoms
- **Random Forest** 8 studies: stress prediction, craving, drowsiness
- **Emerging approaches:** Deep learning (CNNs, LSTMs) for temporal sequence modeling

Primary outcomes modeled: Stress (most frequent), emotional states, depression/anxiety, mood, cognitive performance, engagement, and arousal
Trend: Studies predominantly use ensemble methods (Random Forest, SVM) and traditional classifiers, with recent work exploring deep learning for temporal sequences.

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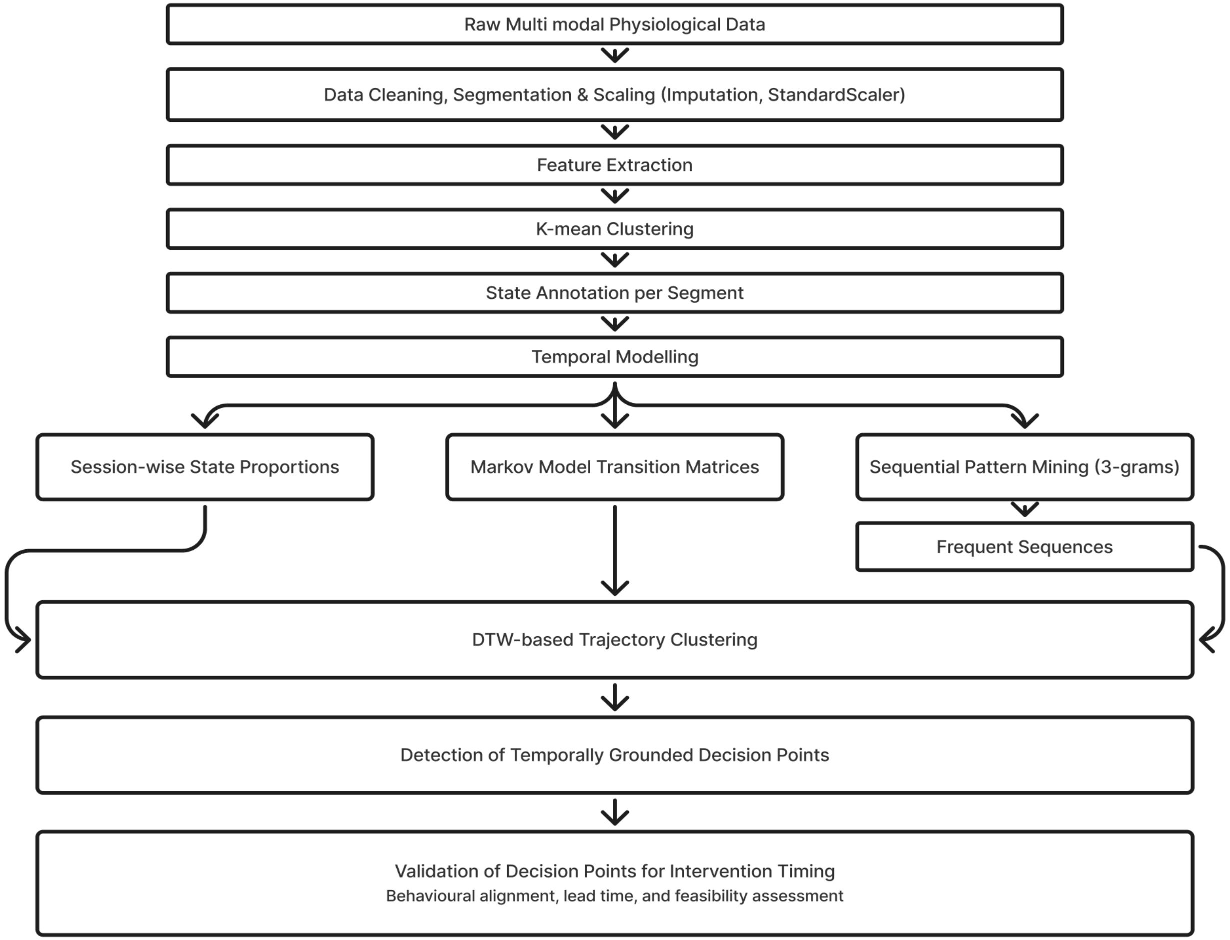
- How can we use biomarker-inferred psychosocial states to construct interpretable user models of psychosocial wellbeing?

Cluster	Biomarkers (Features)	Behavioural Markers
Stress	High EEG slope & power (frontal/parietal), high HR, elevated EDA, unstable BVP/IBI, lower temperature, high motion variability	Low accuracy, long RT
Focus	Moderate EEG activity, balanced HR & EDA, regulated BVP/IBI, stable temperature, moderate motion	High accuracy, fast RT
Relaxation	Low EEG power & slope, low HR, reduced EDA, stable BVP/IBI, higher temperature, low motion	Medium accuracy, stable RT



- **Dataset: Fekri Azgomi, H., Branco, L., Amin, M. R., Khazaei, S., & Faghih, R. T. (2023). Regulation of Brain Cognitive States through Auditory, Gustatory, and Olfactory Stimulation with Wearable Monitoring (version 1.0.0). *PhysioNet*. RRID:SCR_007345. https://doi.org/10.13026/jr6f-wc85**

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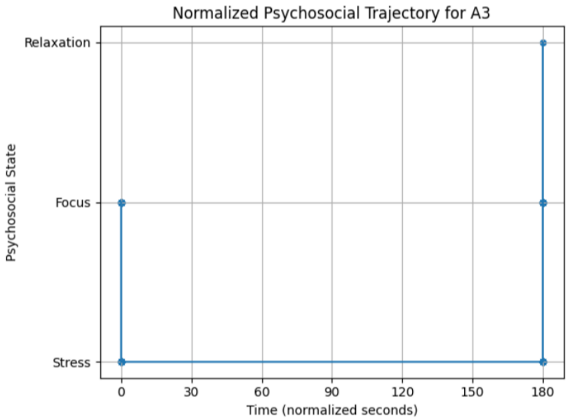
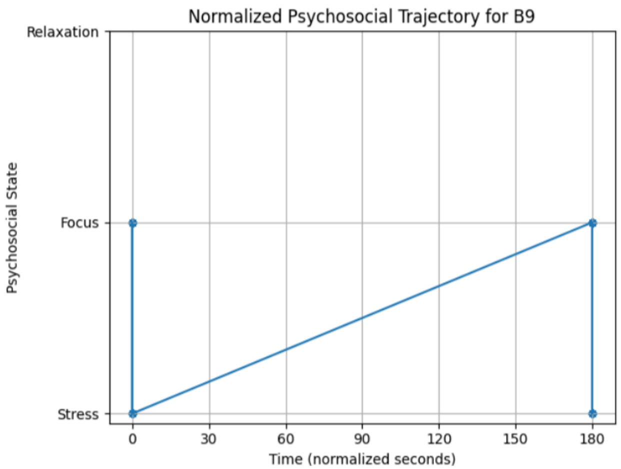
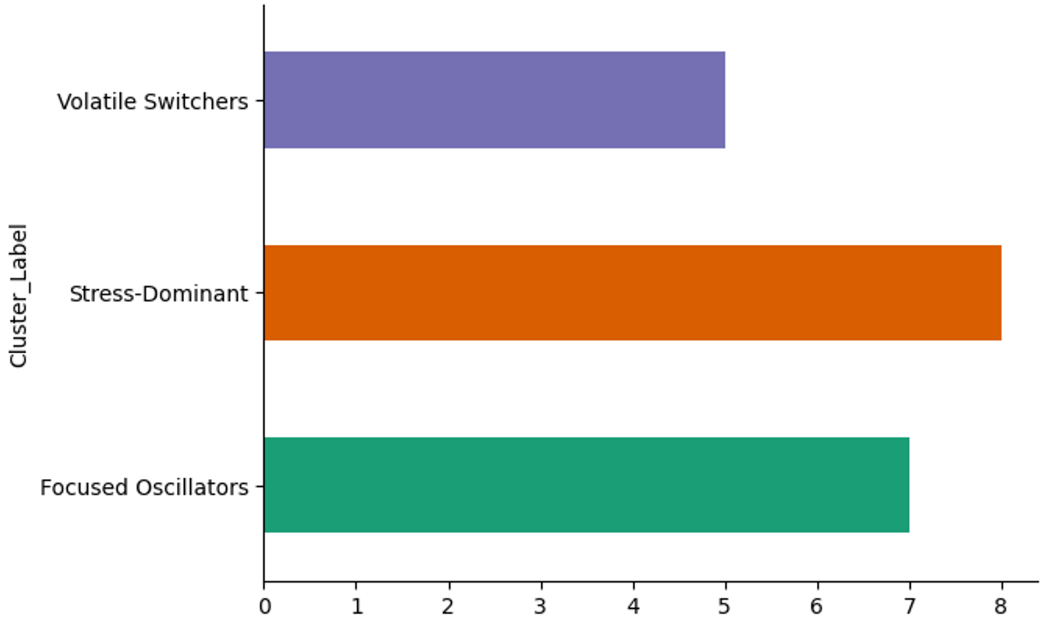
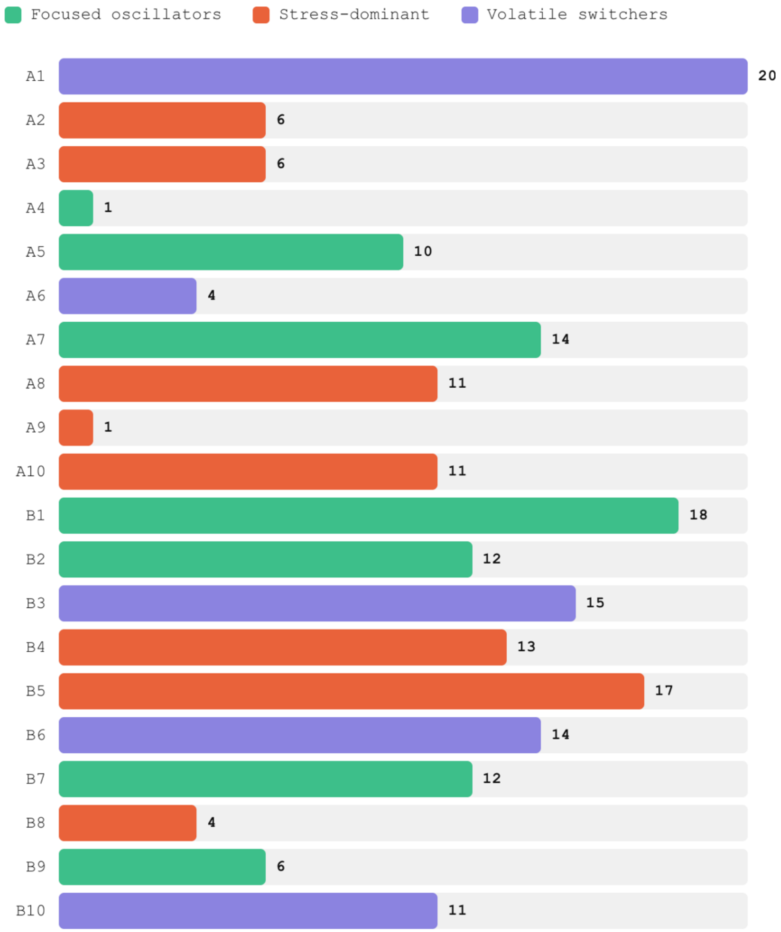


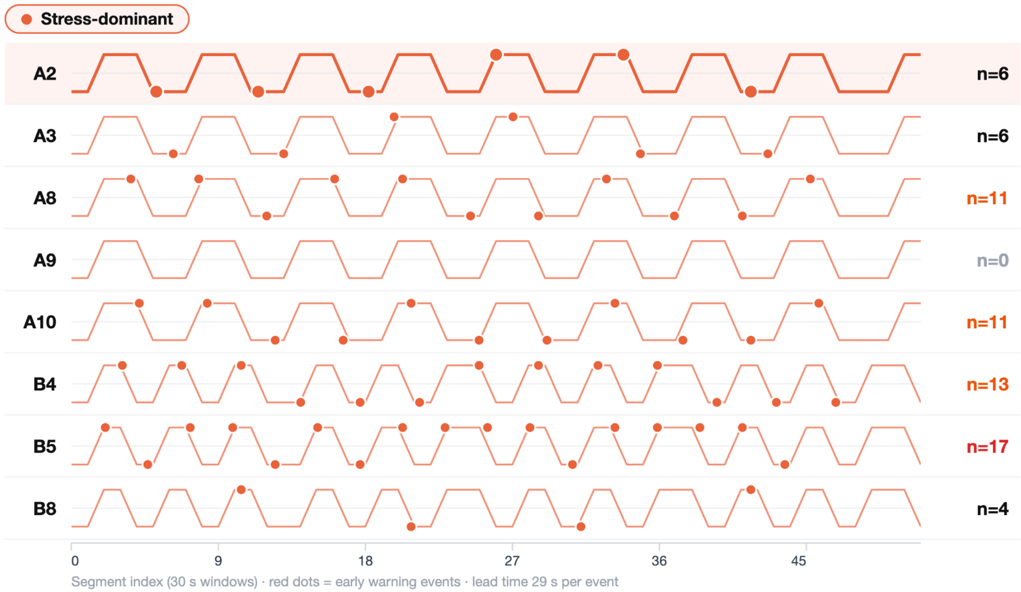




Key finding: We need to infer user states at **segment-level (stress/focus/relaxation…) and model participant-level patterns (volatile/stress-dominant/focused…)** so that the interventions, and intervention timing is tuned to each user's trajectory and archetype rather than population averages.

- How can we use biomarker-inferred psychosocial states to construct interpretable user models of psychosocial wellbeing?

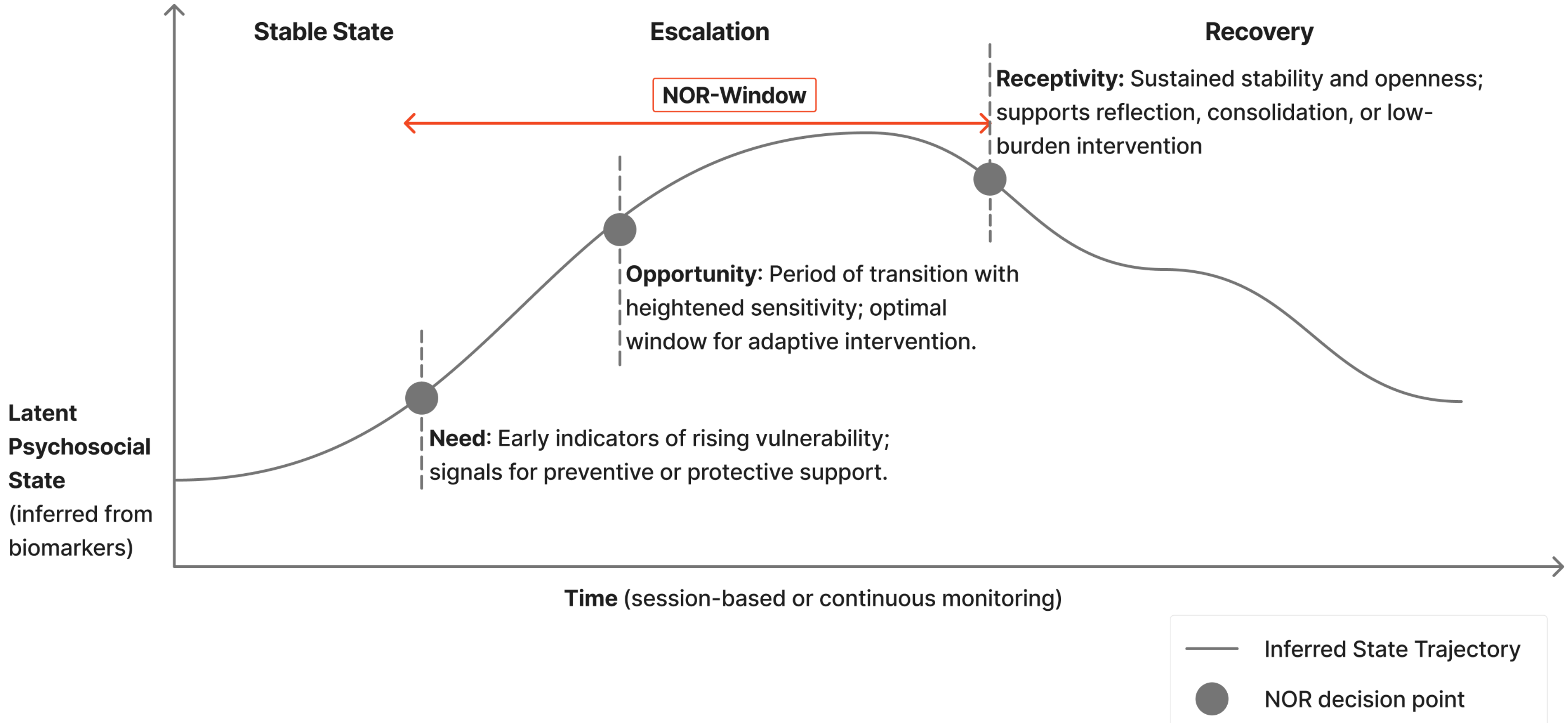




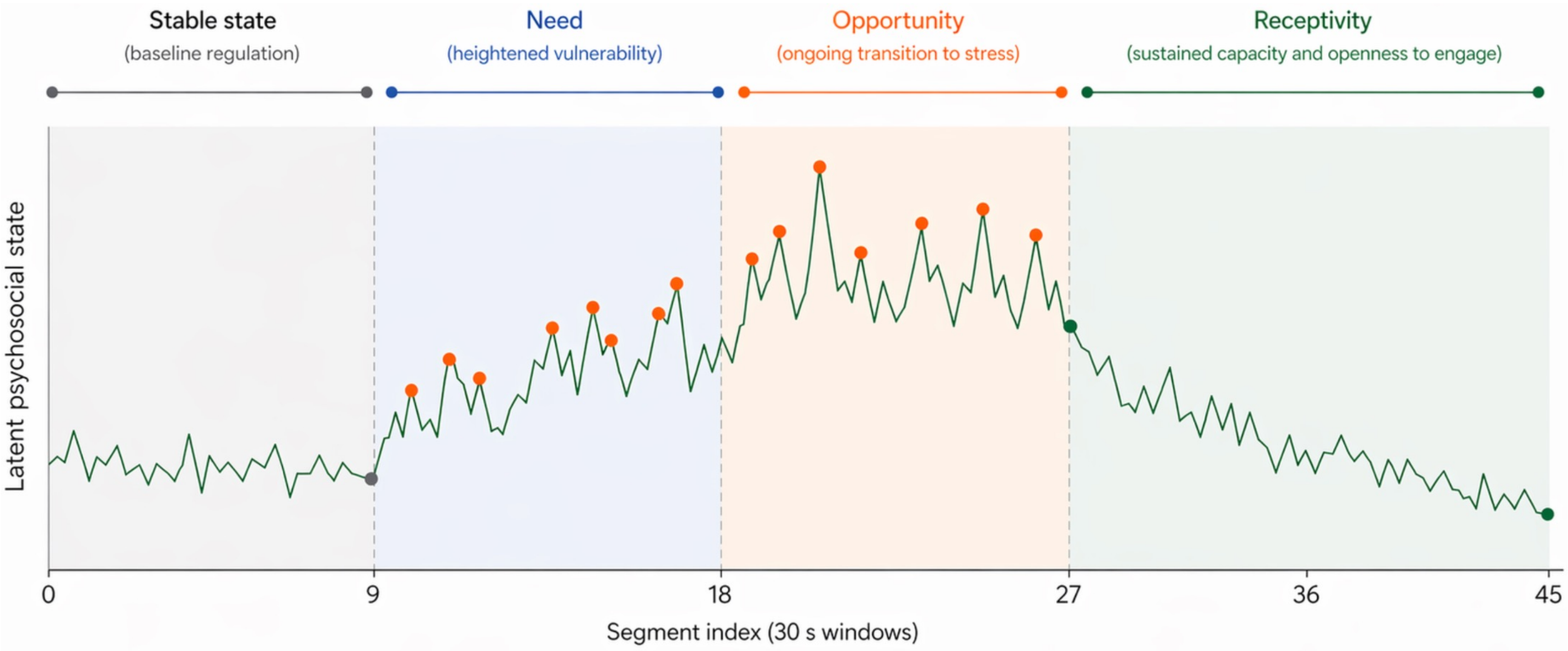
- **Key finding:** A total of 36,318 stress runs were identified across all participants, of which 11,181 were classified as long stress peaks.
- From these combined conditions *(biomarkers + reaction time + task accuracy)*, the system identified 205 early warning events
- The **early warning events** serve as temporally grounded decision points for intervention timing in JITAIs *(Events were confirmed against behavioral ground truth (task accuracy and reaction time), demonstrating alignment between biomarker-detected stress transitions and observable performance changes.)*

- **Extended BESC paper submitted to Journal on Image and Video Processing: AI-empowered Multimedia Processing for Behavioral and Social Computing (currently in peer review)**

- Just In Time: Modelling NOR-Windows (Need, Opportunity, and Receptivity) for JITAI
- Operationalising intervention timing through NOR-Windows: Need, Opportunity, and Receptivity, as conceptualized in the JITAI literature.



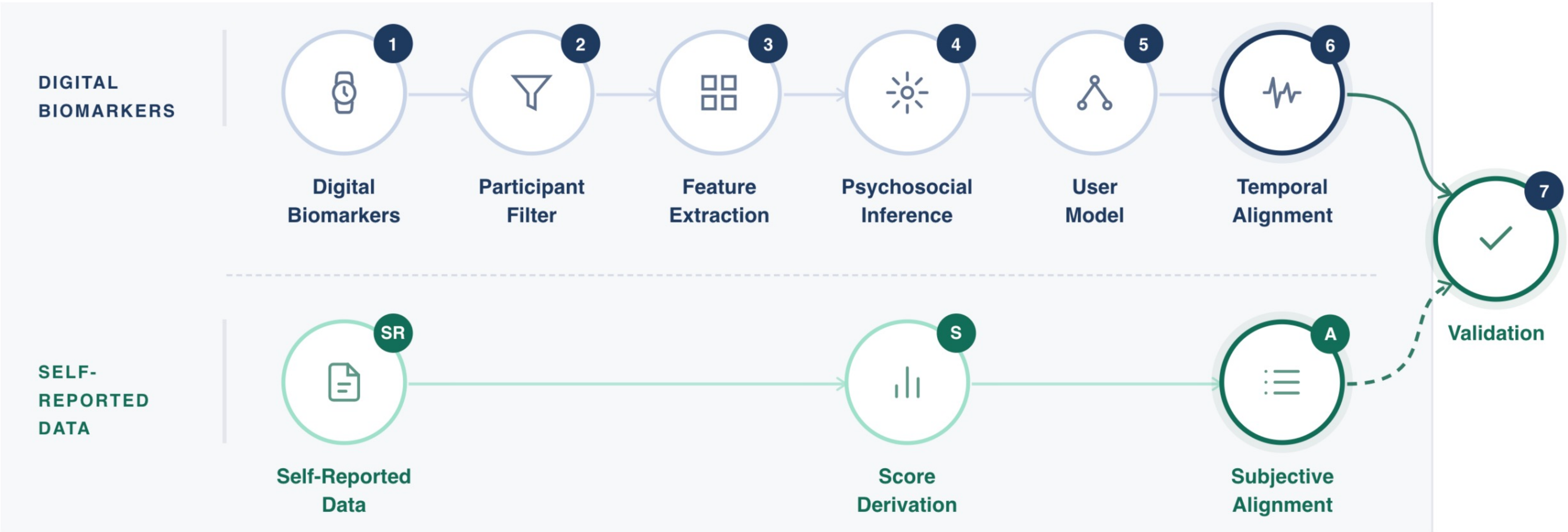
- Just In Time: Modelling NOR-Windows (Need, Opportunity, and Receptivity) for JITAI



- **Key finding:** Illustration of how NOR-Windows emerge from temporal psychosocial state dynamics (Example trajectory for participant B1)
- It shows stress trajectory for participant B1, derived from biomarker data and segmented into 30-second windows (x-axis), with the corresponding state intensity on the yaxis. This example represents the dynamics observed during one task; when monitoring a user over longer periods, multiple NOR-Windows may emerge across different activities and context

- To what extent do biomarker-derived psychosocial states align with self-reported wellbeing measures?

Bridging Objective and Subjective Psychosocial States: Validating Digital Biomarker-Based User Models with Self-Reported Wellbeing



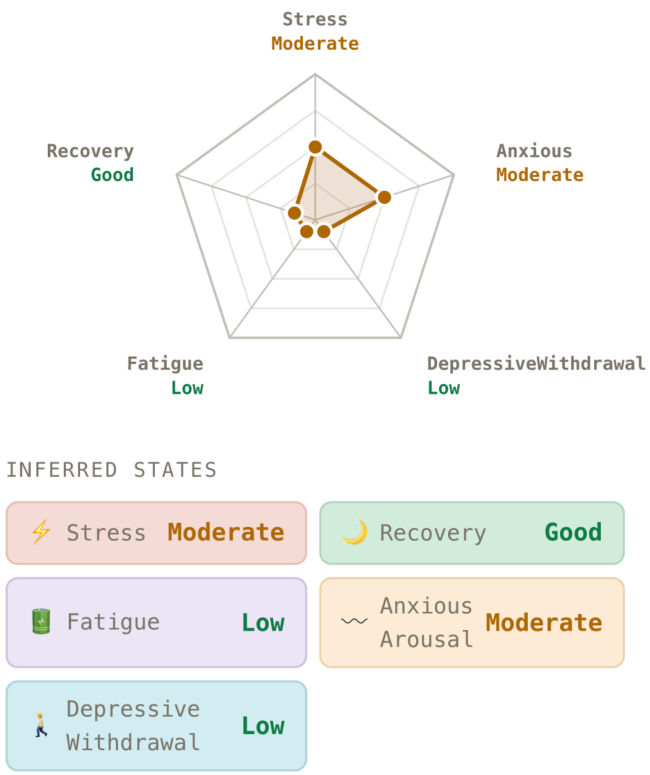
- Dataset from Mentastic (Heba Clinic): Garmin for passive data, and self reports

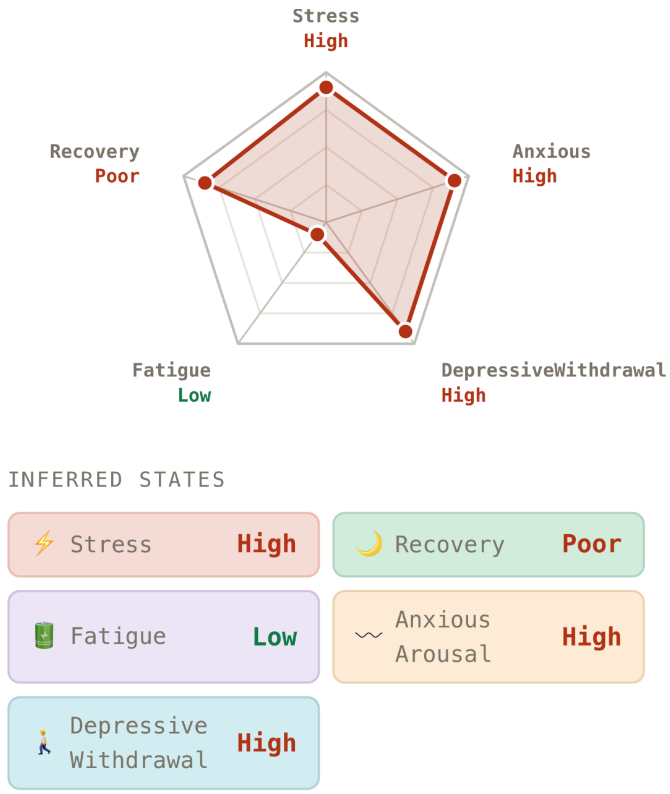
■ Bridging Objective and Subjective Psychosocial States

Key finding: *This was done using Mentastic data.*
Digital biomarkers enable construction of interpretable user models through a multi-stage process:

- **State inference:** Biomarker combinations infer current psychosocial states (stress, focus, relaxation..)
- **Trajectory modeling:** States aggregate into behavioral patterns over time (volatile/stress-dominant/focused…)
- **Visualization:** User models represent state + trajectory at any point in time
- **Validation:** Inferred states traced back to biomarker features and aligned with self-reported wellbeing

Validated user models provide interpretable representations ready for intervention mapping





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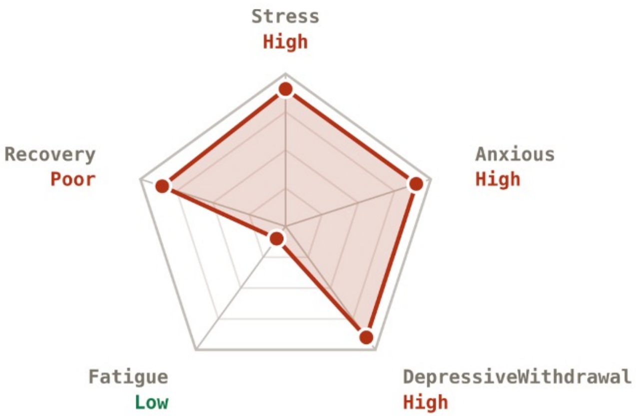
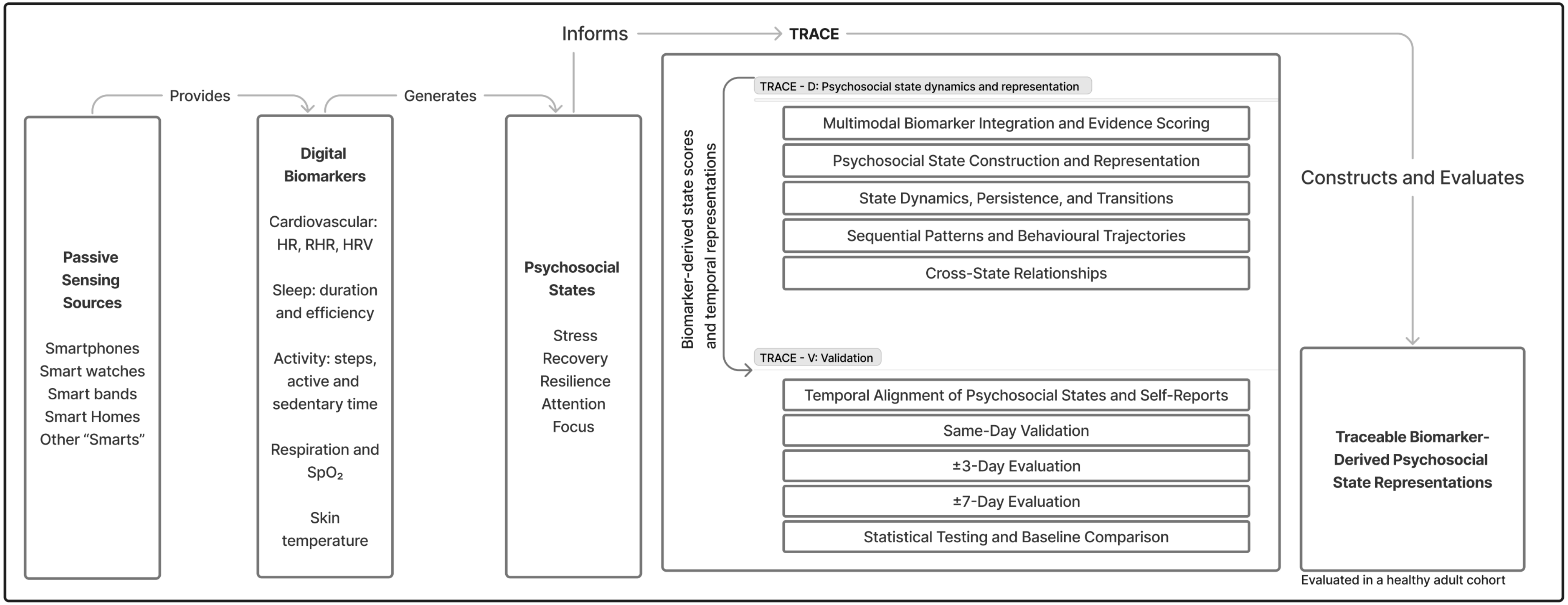


- wearable risk 0.80; self-report distress 0.88. Physiology and subjective state agree.

Commercial applications catch distress when the body shows it, but miss it when someone is physiologically "fine" yet subjectively struggling confirming the objective–subjective gap. **This is why we need to enhance user models with biomarkers, behavioral patterns and individual state trajectories so the intervention can be tailored to each user rather than the population baseline.**

- To what extent do biomarker-derived psychosocial states align with self-reported wellbeing measures?

TRACE: Temporal Representation, Alignment, and Continuity Evaluation

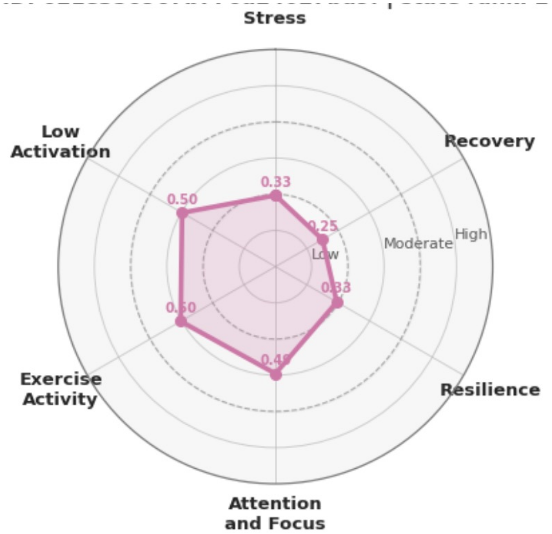


- Dataset: LifeSnaps: a 4-month multi-modal dataset capturing unobtrusive snapshots of our lives in the wild
https://zenodo.org/records/6832186

Psychosocial state	Biomarkers/features and evidence direction	Mean evidence score	SD
Stress	Higher HR, RHR, stress score, breathing rate, and temperature variation; lower RMSSD	0.221	0.221
Recovery	Longer sleep duration, higher sleep efficiency and SpO_2; stable temperature variation	0.200	0.232
Resilience	Higher RMSSD; lower RHR and stress score	0.196	0.225
Exercise Activity	Higher steps, distance, calories, and light, moderate, and vigorous active minutes	0.426	0.267
Low Activation	Higher sedentary minutes; lower sleep efficiency	0.359	0.173
Attention and Focus	Stable HR; higher RMSSD and sleep efficiency	0.246	0.246


Stress
Recovery
Resilience
Attention and Focus
Exercise Activity
Low Activation
Low
Moderate
High
0.31
0.30
0.42
0.34


Stress
Recovery
Resilience
Attention and Focus
Exercise Activity
Low Activation
Low
Moderate
High
0.27
0.09

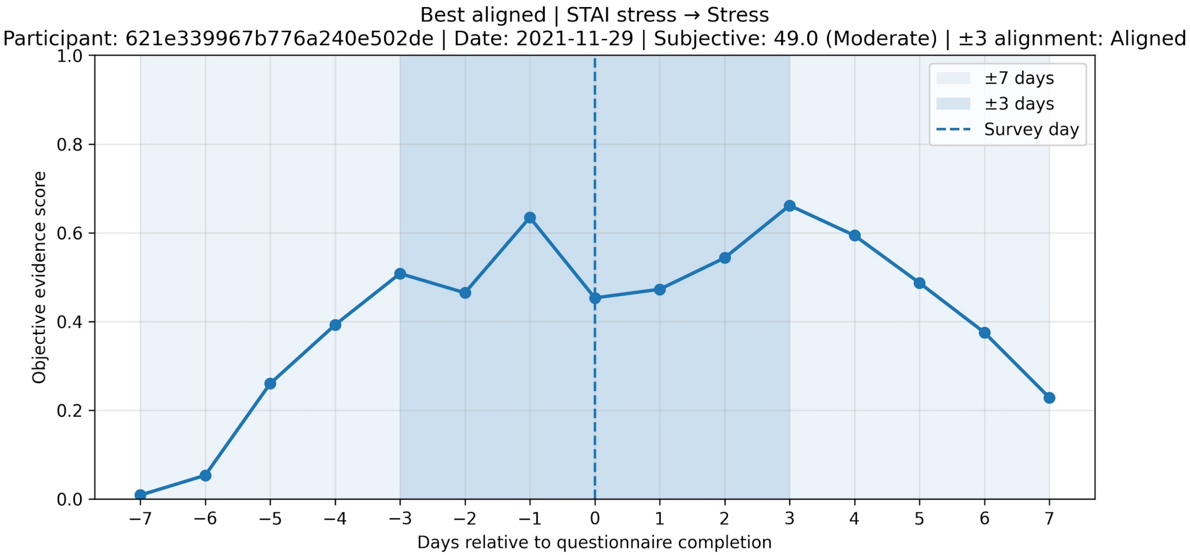

Stress
Recovery
Resilience
Attention and Focus
Exercise Activity
Low Activation
Low
Moderate
High
0.33
0.50
0.25

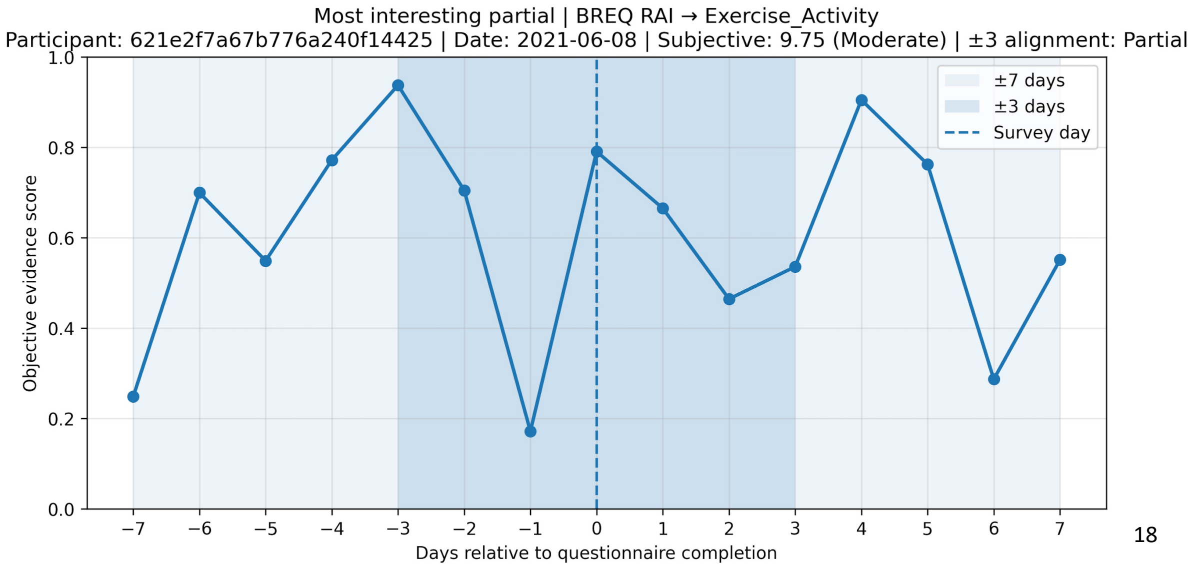

Stress
Recovery
Resilience
Attention and Focus
Exercise Activity
Low Activation
Low
Moderate
High
0.45
0.47
0.33
0.45

- To what extent do biomarker-derived psychosocial states align with self-reported wellbeing measures?

- TRACE-V's windowed performance was not reproduced by reducing each window to a single average score.
- Instead, retaining information about the occurrence, distribution, and persistence of state evidence provided substantially greater correspondence with the subjective categories.

Window	N	TRACE-V alignment (%)	Naïve smoothing (%)	p
±3 days	1,989	57.52	33.58	<0.001
±7 days	1,993	65.78	34.32	<0.001





Opportunities & Challenges

- Data quality shapes the nuance of user models
- Passive sensing can provide continuous behavioural and physiological data without requiring constant user input.
- Collecting subjective, contextual, and behavioural information still requires user engagement, creating a trade-off between data richness and user burden.
- How can we combine passive sensing, minimal active input, and intelligent sampling to obtain the data needed to build meaningful user models?
- Richer user models → better understanding of changing users → more appropriate adaptive decisions and JITAIs

Questions!