Reading Tells

Using Facial Expression Analysis to Track Emotional States in Depression

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2025-03-25

Reading tells

Charles Darwin's Contributions

- *The Expression of the Emotions in Man and Animals* (1872)
- Proposed that emotions evolved for adaptive and social functions
- Noted similarities in emotional expressions across species
- Established an observational basis for scientific study of emotions

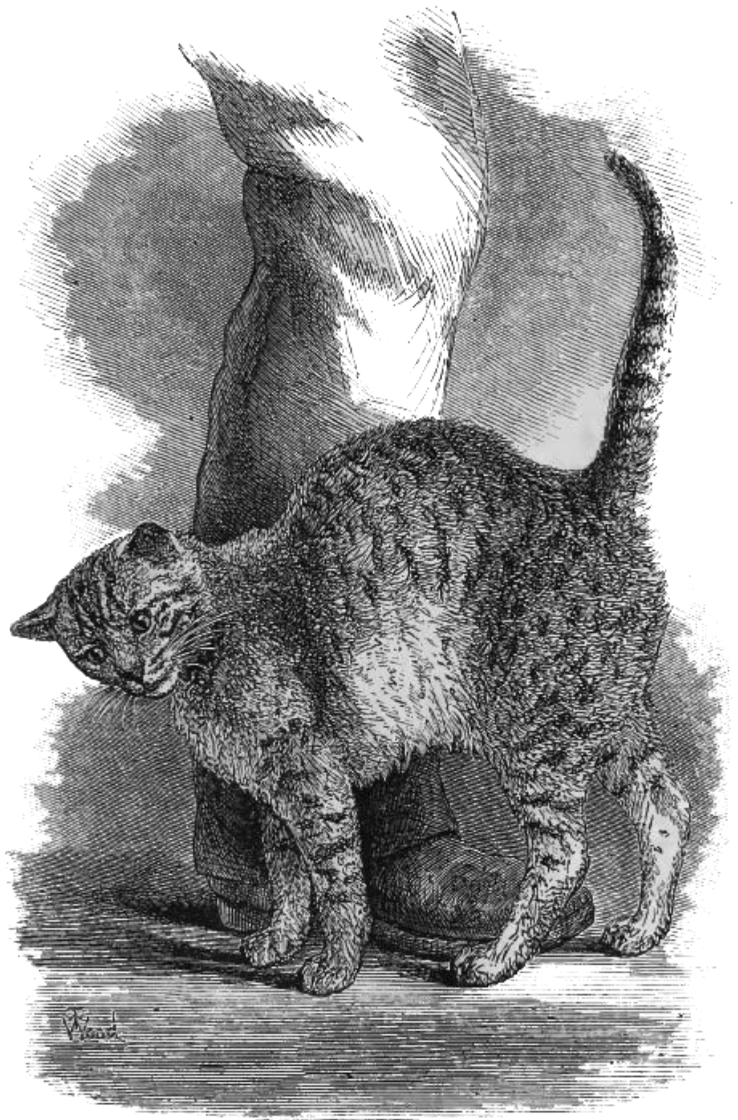


Fig. 10. Cat in an affectionate frame of mind. By Mr. Wood.

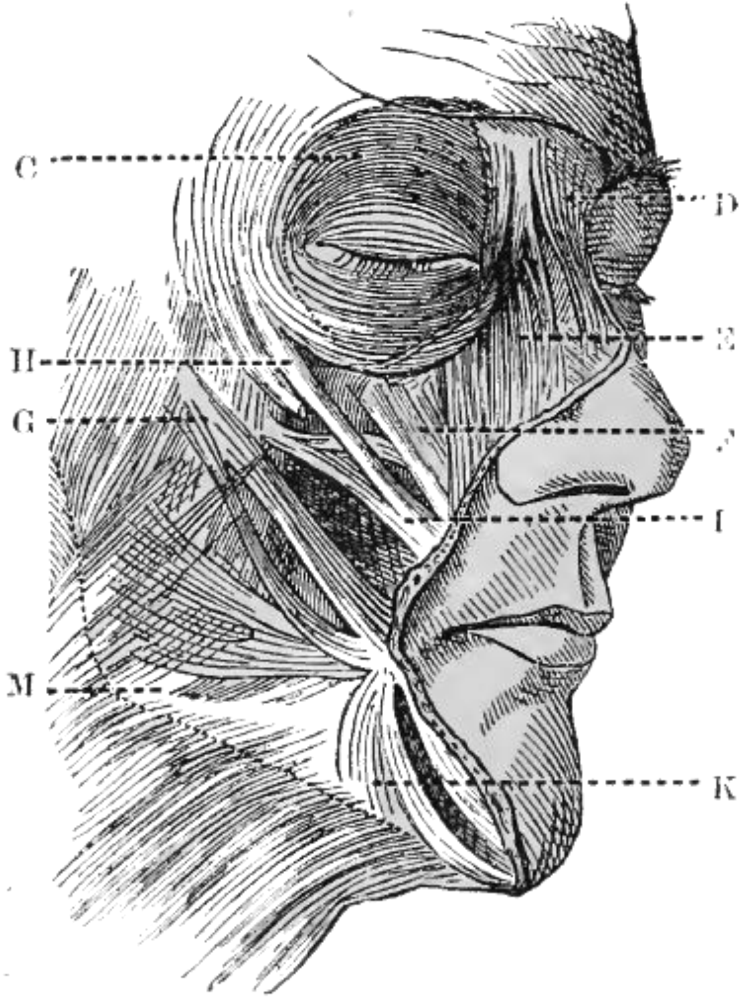
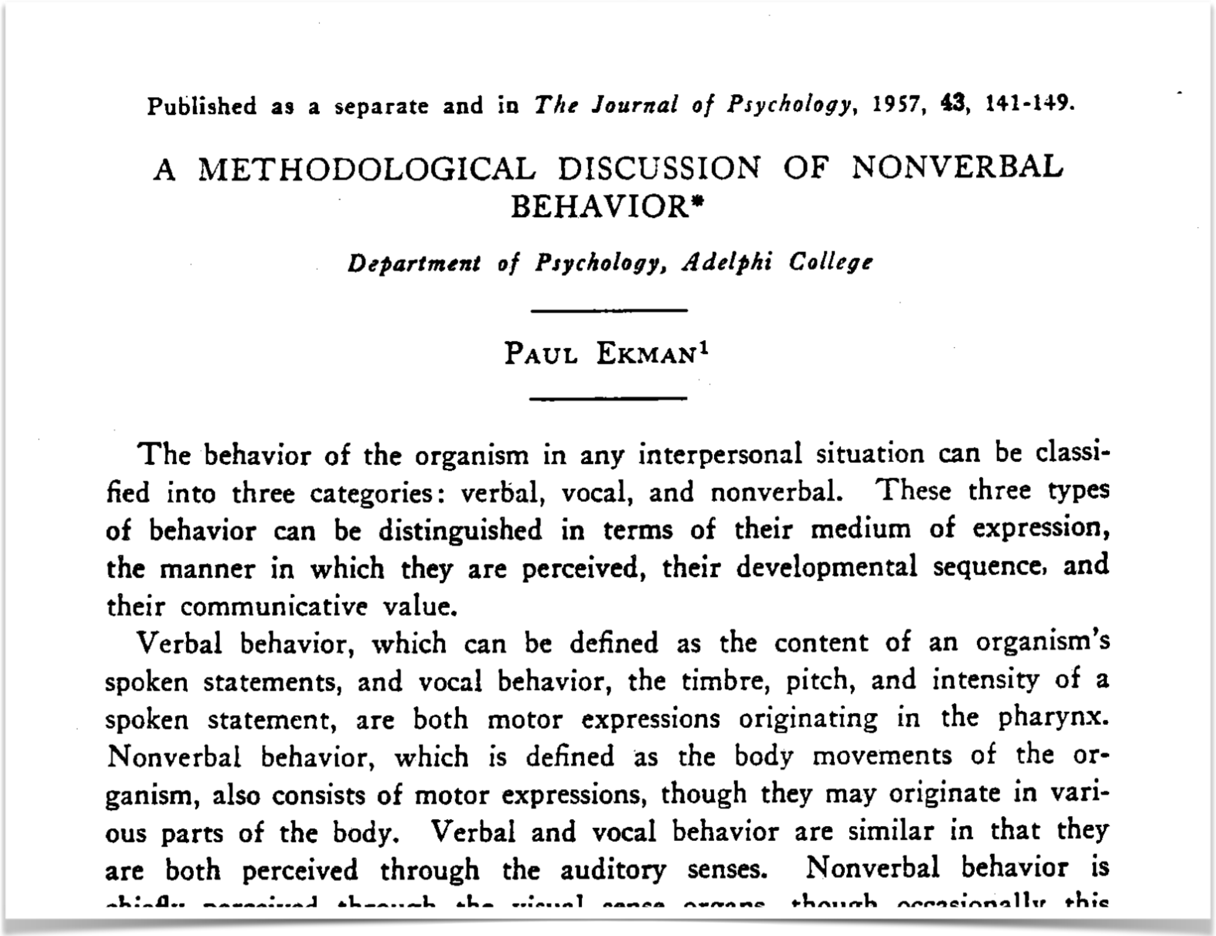


Fig. 2. Diagram from Henle.

Darwin's Legacy in Modern Research



Published as a separate and in *The Journal of Psychology*, 1957, **43**, 141-149.

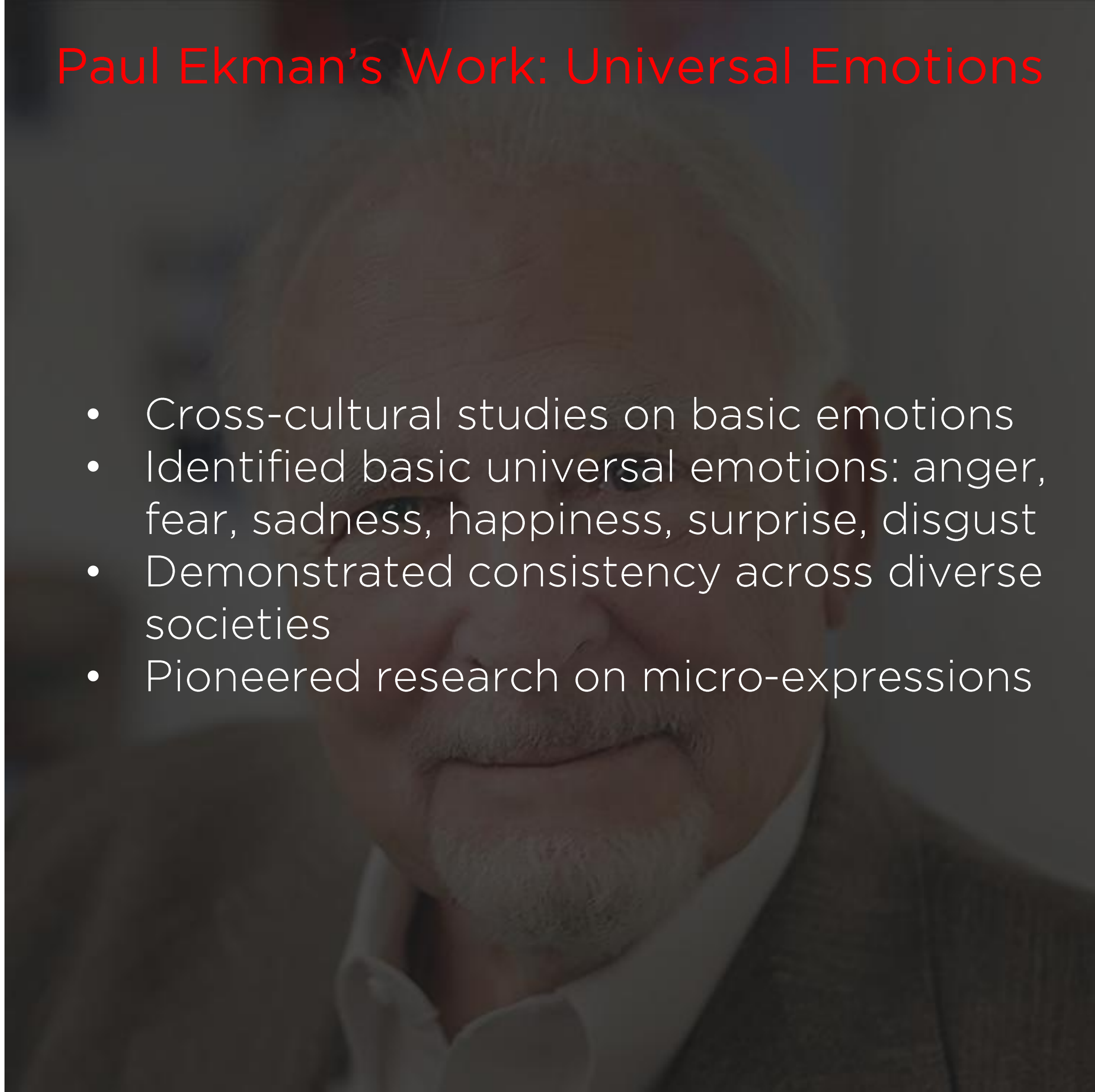
A METHODOLOGICAL DISCUSSION OF NONVERBAL BEHAVIOR*

Department of Psychology, Adelphi College

Paul Ekman[1]

The behavior of the organism in any interpersonal situation can be classified into three categories: verbal, vocal, and nonverbal. These three types of behavior can be distinguished in terms of their medium of expression, the manner in which they are perceived, their developmental sequence, and their communicative value.

Verbal behavior, which can be defined as the content of an organism's spoken statements, and vocal behavior, the timbre, pitch, and intensity of a spoken statement, are both motor expressions originating in the pharynx. Nonverbal behavior, which is defined as the body movements of the organism, also consists of motor expressions, though they may originate in various parts of the body. Verbal and vocal behavior are similar in that they are both perceived through the auditory senses. Nonverbal behavior is

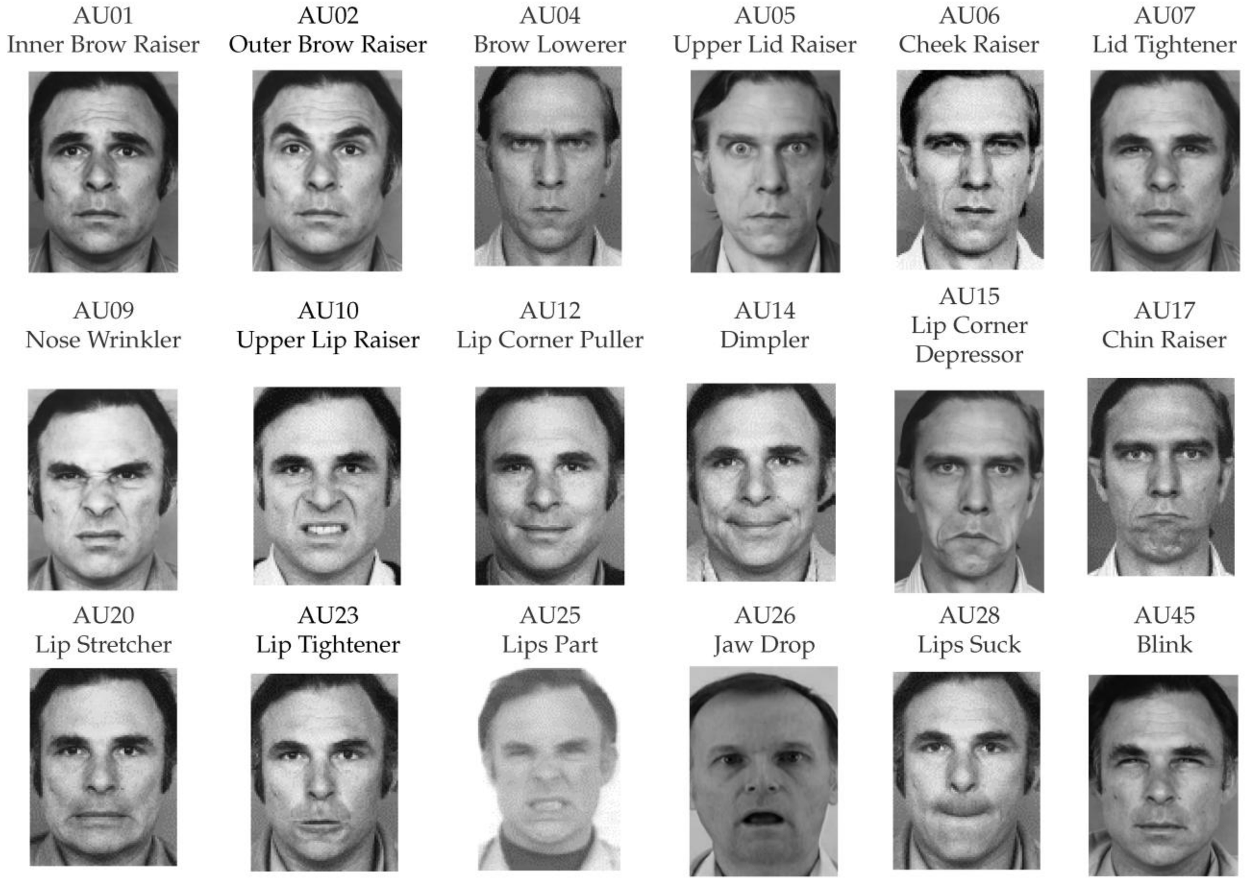


Paul Ekman's Work: Universal Emotions

- Cross-cultural studies on basic emotions
- Identified basic universal emotions: anger, fear, sadness, happiness, surprise, disgust
- Demonstrated consistency across diverse societies
- Pioneered research on micro-expressions

Facial Action Coding System (FACS)

- Developed by Paul Ekman and Wallace Friesen
- Breaks down facial movements into “Action Units” (AUs)
- Provided a standardized, objective measure of expressions
- Basis for modern automated emotion-detection tools



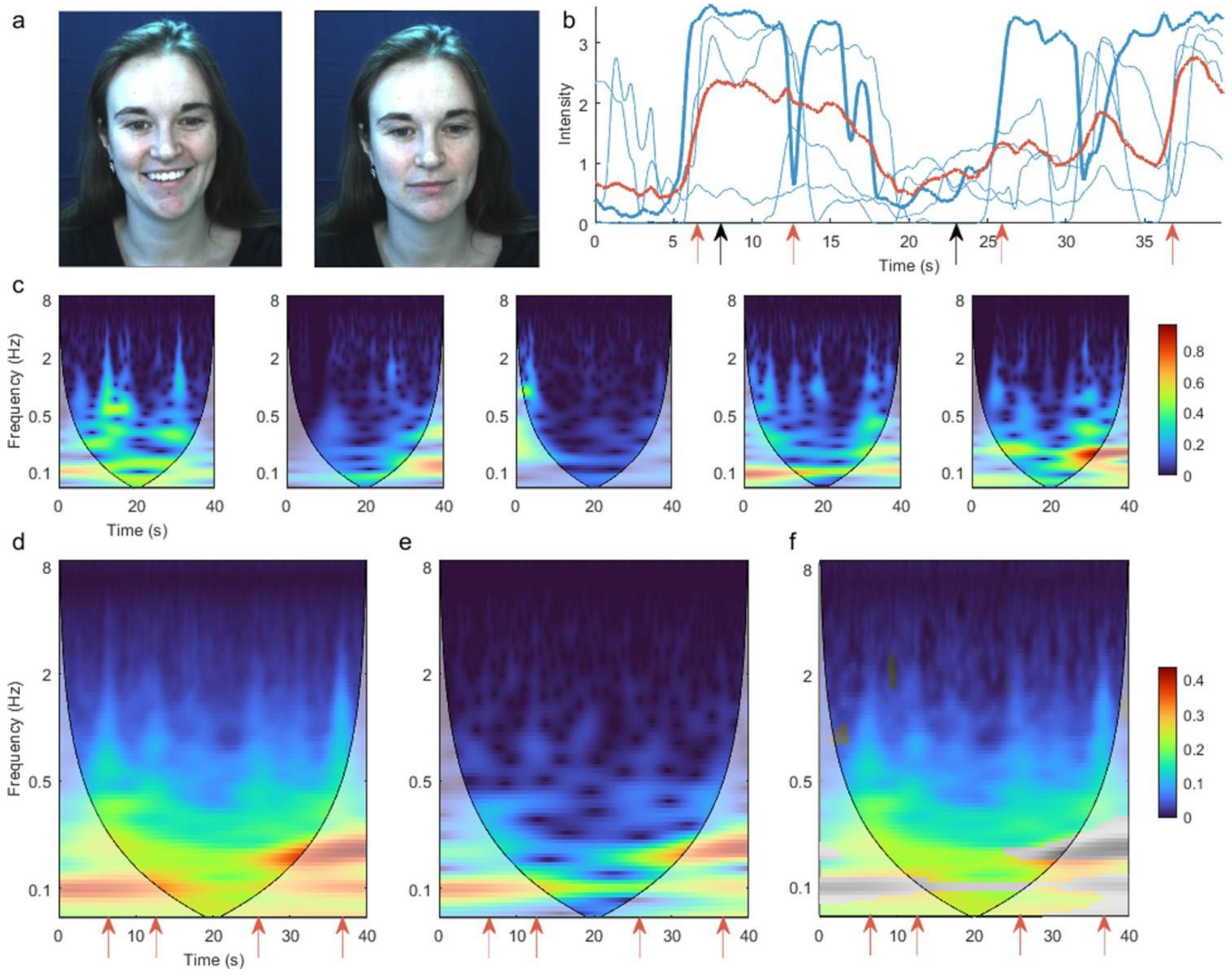
Microexpressions and Subtle Displays

- Brief, involuntary facial movements
- Reveal concealed or rapidly changing emotions
- Typically last 1/25 to 1/5 of a second
- High clinical relevance in mood disorders

Paul Ekman analyzed a 2007 interview of Alex Rodriguez with Katie Couric, pointing out certain gestural slips, unilateral contempt, and microfear.

Quantitative Measures

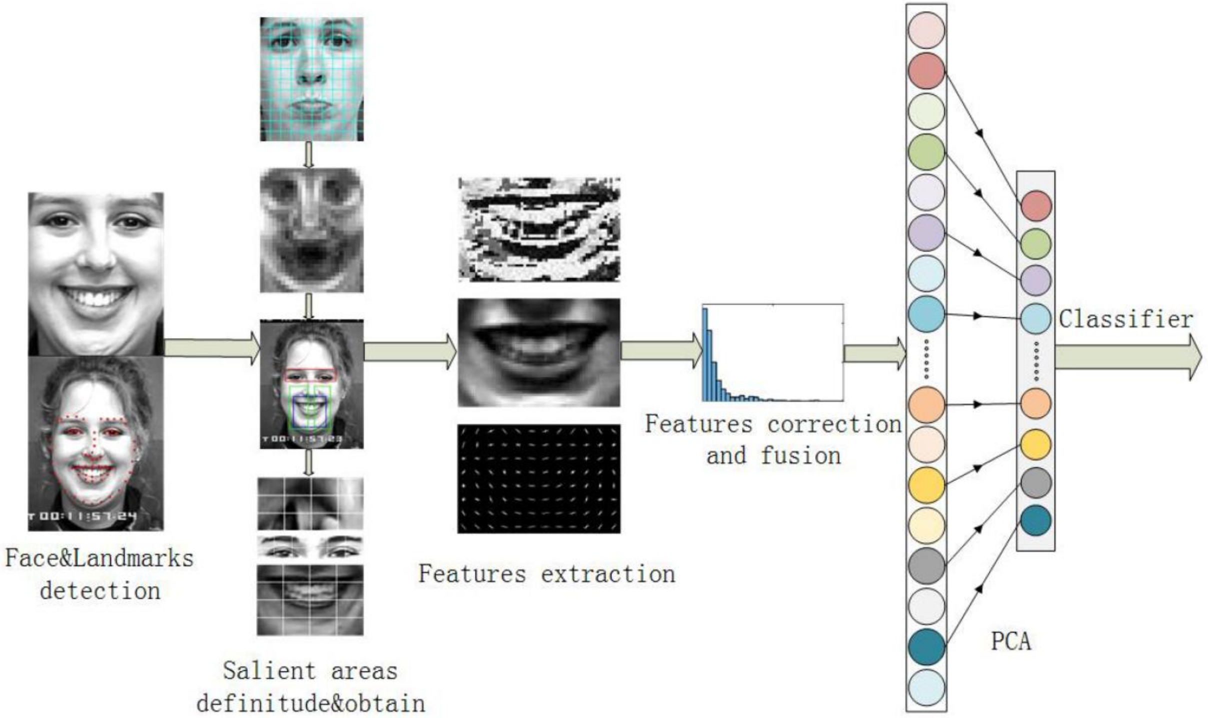
- Coding frequency and intensity of Action Units
- Measuring positive vs negative affect balance
- Applications in longitudinal depression studies



Jeganathan, et al., *eLife*, 2022

Qualitative Observation to Algorithmic Detection

- Manual FACS coding: expert-driven, time-intensive
- Transition to machine-based analysis for scalability
- AI algorithms (CNNs, RNNs) identify facial landmarks and AUs



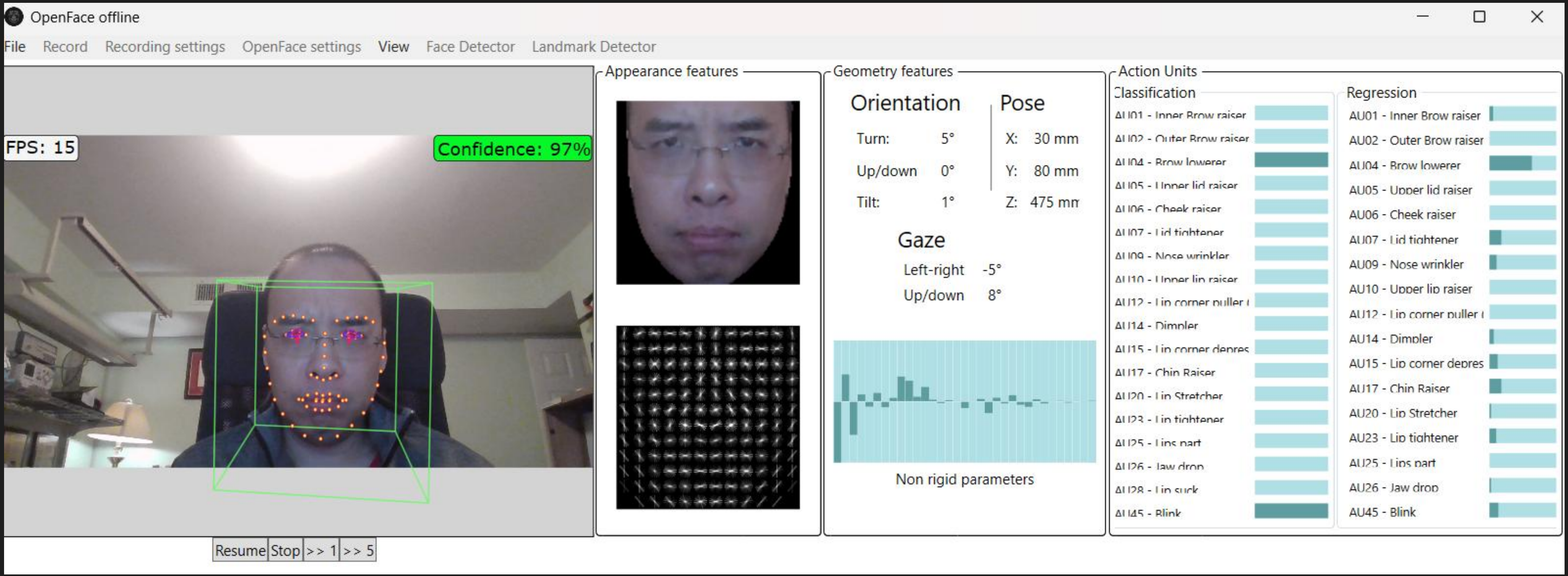
Data Collection Methods

- Controlled lab setups (high-resolution cameras)
- Naturalistic environments (webcams, mobile devices)
- Video vs. still image capture
- Consideration: lighting, subject positioning, privacy

Software

- OpenFace, Py-FEAT: Open-source FACS-based analysis
- Affectiva: Commercial SDK/APIs for emotion AI
- Microsoft Azure Face API: Cloud-based facial recognition and emotion detection
- Emotient/iMotions: Integrations for eye tracking and biometric data

OpenFace



- Face detection & alignment: locate faces, correct for orientation
- Feature extraction: Identify facial landmarks and Action Units

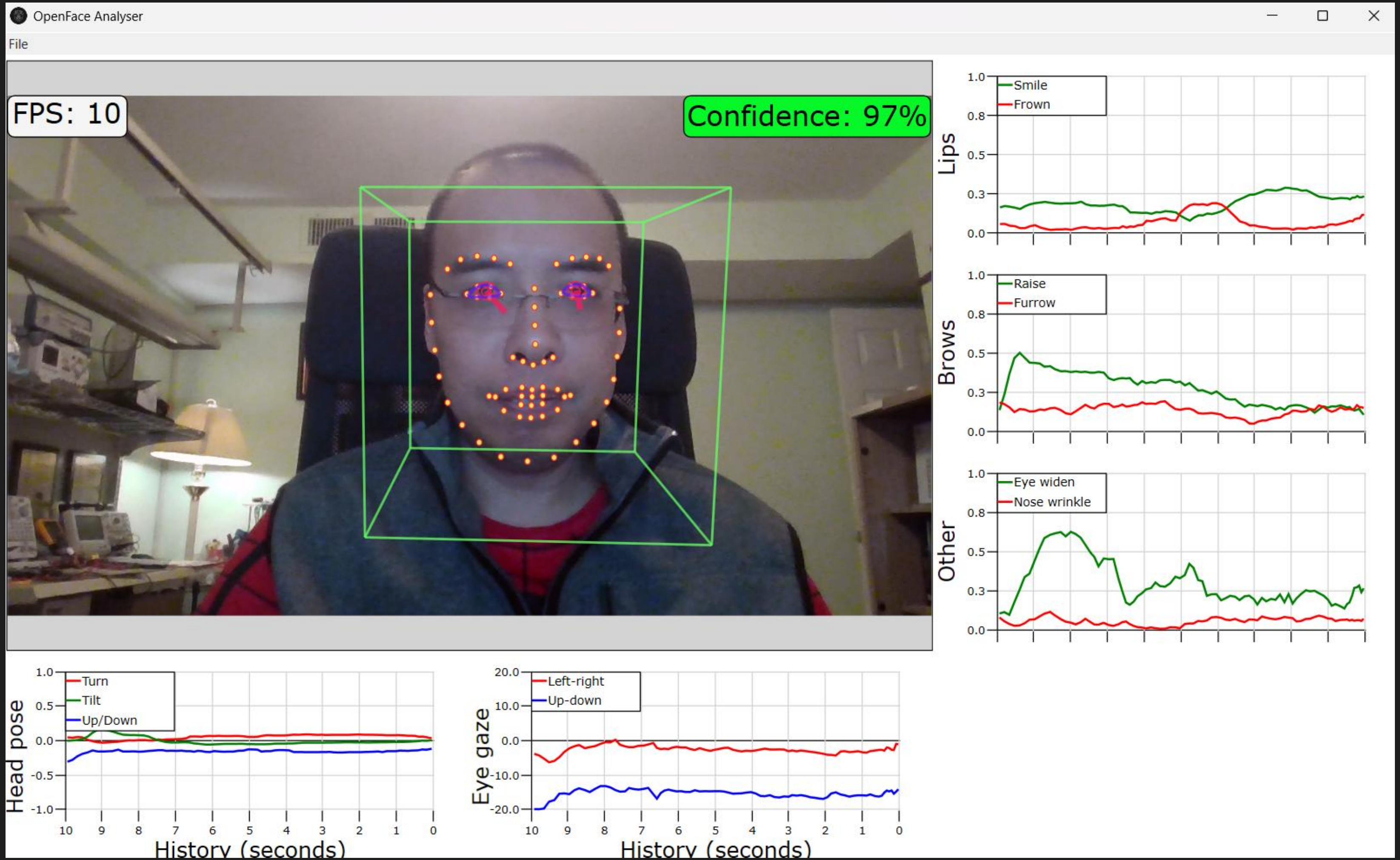
Real-Time vs. Offline Analysis

Real-Time (Live feeds)

- Immediate feedback (telemedicine, interactive apps)
- Challenges: computational load, network stability

Offline (Batch processing)

- Detailed post-session analysis
- Less resource-intensive in the moment
- Trade-offs in accuracy, practicality, and clinical workflow



Facial Expression Patterns in Depression

- Reduced frequency and intensity of positive expressions
- Possible flat or blunted affect
- Subtle negative indicators (microexpressions of sadness)
- Variability based on individual and cultural factors

Monitoring Treatment Efficacy

- Longitudinal data collection: weekly or daily face recordings
- Automated alerts: flagging atypical expression patterns
- Correlational & predictive analytics: Linking expression data to clinical scales

Article

Cingulate dynamics track depression recovery with deep brain stimulation

https://doi.org/10.1038/s41586-023-06541-3

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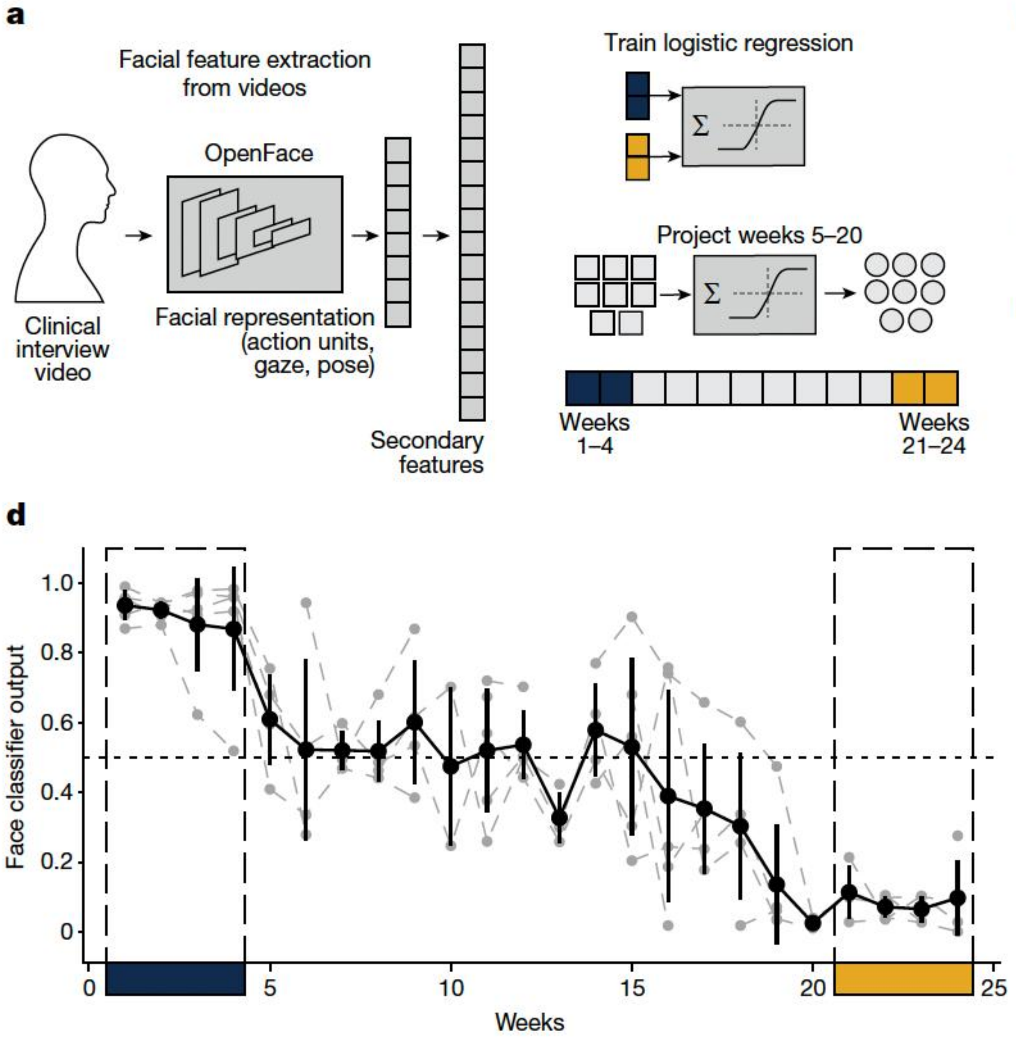
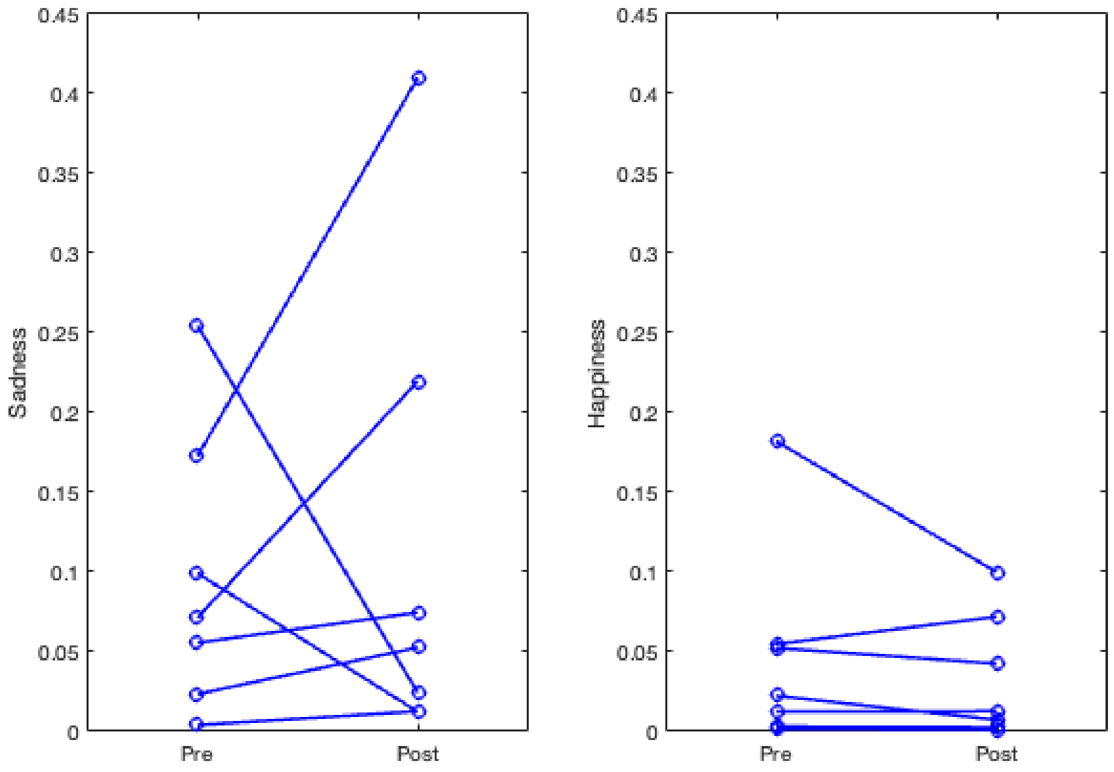
Deep brain stimulation (DBS) of the subcallosal cingulate (SCC) can provide long-term symptom relief for treatment-resistant depression (TRD)[1]. However, achieving stable recovery is unpredictable[2], typically requiring trial-and-error stimulation adjustments due to individual recovery trajectories and subjective symptom reporting[3]. We currently lack objective brain-based biomarkers to guide clinical decisions by distinguishing natural transient mood fluctuations from situations requiring intervention. To address this gap, we used a new device enabling electrophysiology recording to deliver SCC DBS to ten TRD participants (ClinicalTrials.gov identifier NCT01984710). At the study endpoint of 24 weeks, 90% of participants demonstrated robust clinical response, and 70% achieved remission. Using SCC local field potentials available from six participants, we deployed an explainable artificial intelligence approach to identify SCC local field potential changes indicating the patient's current clinical state. This biomarker is distinct from transient stimulation effects, sensitive to therapeutic adjustments and accurate at capturing individual recovery states. Variable recovery trajectories are predicted


a
Facial feature extraction
from videos
OpenFace
Clinical
interview
video
Facial representation
(action units,
gaze, pose)
Secondary
features
Train logistic regression
Project weeks 5–20
Weeks
1–4
Weeks
21–24
b
True positive rate
False positive rate
Mean ROC
(AUC = 0.95 ± 0.05)
Chance
± 1 s.d.
c
AU1
AU4
AU7
AU6
AU10
AU12
d
Face classifier output
Weeks
e
Face classifier output
Spectral discriminative component
f
τ = 0.89*
Face transition weeks
LFP transition weeks
P002
P003
P004
P005
P006

Ketamine

- 7 depressed patients treated with IV ketamine
- Recorded videos of structured interviews comprising questions derived from Beck's cognitive triad
- Using Py-FEAT, AUs and emotional expression probabilities were extracted for each frame of the video
- Averaged emotional expression probabilities across all frames to assess general emotional tone



Challenges in Translating to Clinical Practice

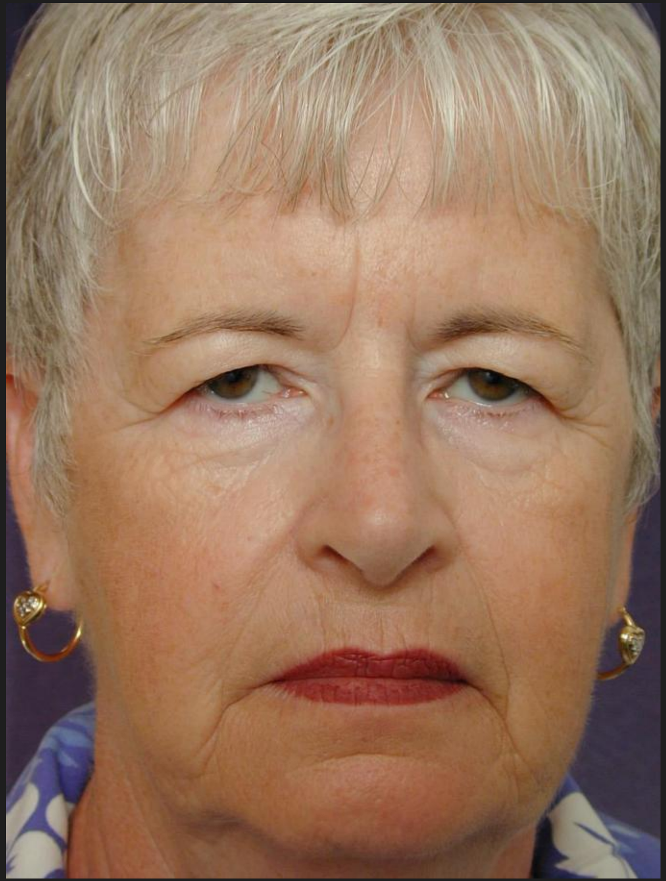
- Workflow integration: Time, training, and tech adoption
- Data management: Privacy, security, and storage
- Cost & accessibility: Equipment, software licenses, IT infrastructure
- Acceptance: Trust in AI, added workload concerns
- Regulatory & ethical barriers: Compliance with health data laws

Ethical and Privacy Considerations

- Data security & consent: Storing and sharing sensitive facial data
- Risk of surveillance & misuse: Potential unethical applications
- Patient autonomy: Transparency, voluntary participation, opt-out
- Bias & fairness: Ensuring diverse, representative datasets

Biases in Automated Emotion Detection

- Training data limitations: Underrepresentation of certain demographics
- Cultural & contextual variations: Expressions can differ across regions
- Algorithmic bias: Tendency to misclassify
- Implications for clinical accuracy & fairness
- Example: Older demographics may be subject to overdetection of lip corner depressor, which is a key component of sadness

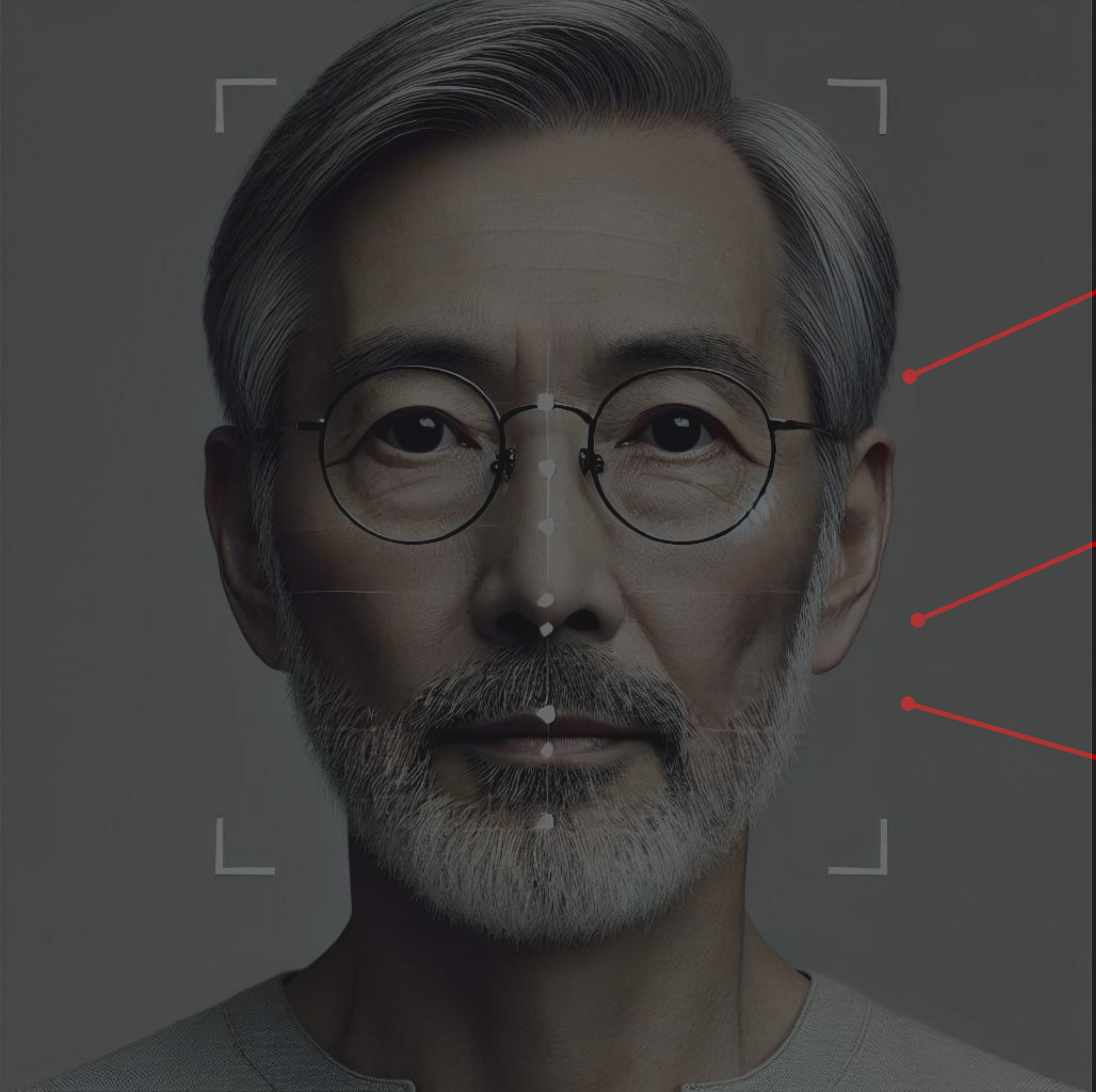


Interpretation Pitfalls

- Overreliance on single cues (e.g., one Action Unit)
- Cultural & situational contexts overlooked
- Emotional masking or co-occurring conditions
- Risk of false positives/negatives without additional data

Towards Personalized Interventions

- Adaptive treatment strategies guided by individual facial expression “baseline”
- Identifying unique triggers, emotional patterns, and relapse risks
- Real-time feedback loops for therapists and patients
- Also… how about filming the therapist as well?
- Integration with digital health platforms for ongoing support



Multimodal data integration

Video

Pupil dilation
Eye tracking
Head movement
Blood flow
Respiration
Response time

Micro-expressions
Cognitive load
Emotional response
Eyelid ptosis
Temperature change
Articulation

Speech

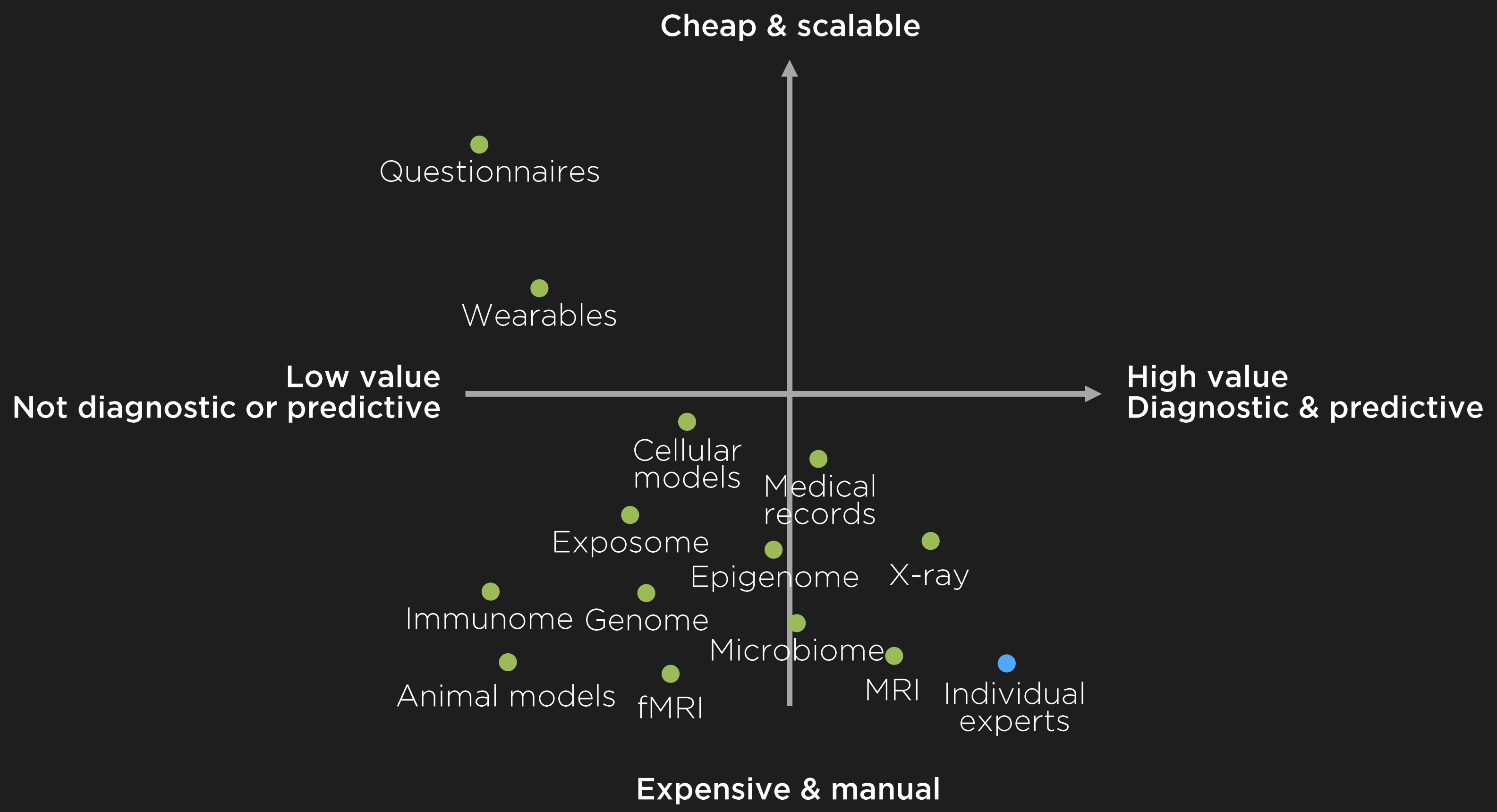
Word choice
Sentence structure
Personality traits
Speech patterns
Education level
Engagement
Vocabulary

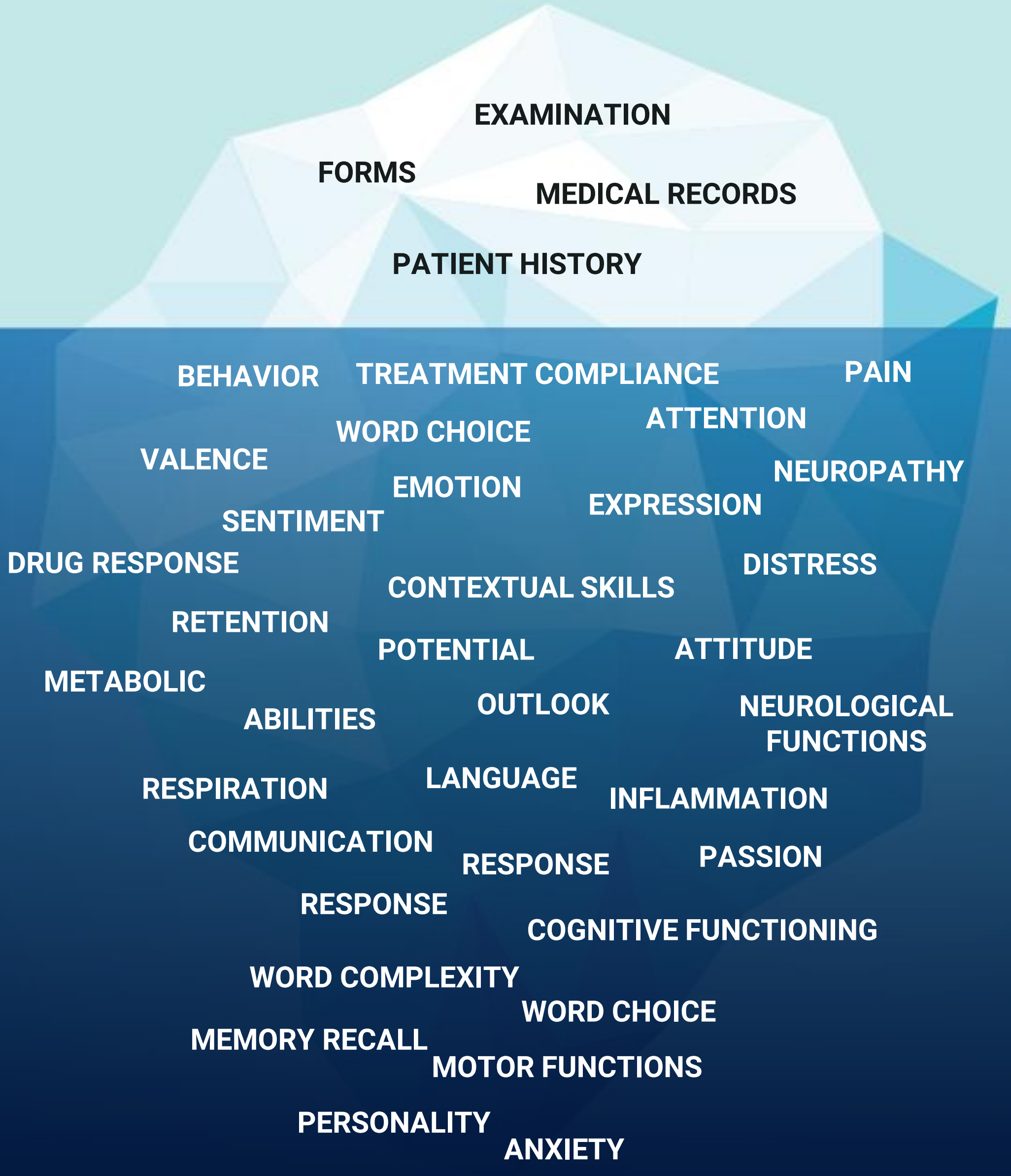
Time stamping
Utterances
Sentiment
Thought patterns
Frequency
Complexity
Outlook

Audio

Vocal micro-tremors
Pitch & tone changes
Pronunciation
Valence
Stress

Opportunities





Old world

Patient Data

EHR records, forms, surveys, wet lab tests.

New world

Intelligent Patient Data

Behavior, sentiment, and expression.
Clinical interview data.