Using computer-vision and machine learning to automate facial coding of positive and negative affect intensity

Nathaniel B. Haines[1], Matthew W. Southward[1], Theodore Beauchaine[1], Jennifer S. Cheavens[1], Woo-Young Ahn[2]

[1]Department of Psychology, The Ohio State University, [2]Department of Psychology, Seoul National University

Author Contact: haines.175@osu.edu

Introduction

Background

Facial expressions are fundamental to human interaction, including the conveyance of threat, cooperative intent, and internal emotional states. In studies of human behavior, *facial expressions are typically rated manually by human coders–this method is both laborious and inefficient*.

Novel work using computer vision and machine learning (**CVML**) has allowed researchers to *automatically decode facial expressions*, with specific applications including the detection of pain[1], depression[2], and emotional valence intensity[3].

Current Gap

While there has been work on decoding human-rated emotional valence intensities from facial expressions, the *prediction accuracy reported in previous studies is not ideal* (e.g., *r* between human and model-predicted ratings = 0.58 and 0.23 for positive and negative ratings, respectively[3]), partly because *most studies examine valence along a single continuum*. These limitations may play a role in why CVML is not widely used outside of computer science. Moreover, it is *unclear if CVML can be used to make inference* on how people generate perceptual ratings of positive and negative affect intensity.

Here we show that CVML can rate continuous positive and negative emotion intensities in a human-like manner. Additionally, we show that ML models can be used to identify specific multivariate patters of facial expression that human coders use when generating emotion ratings.

Methods: Data

Computer Vision Tool

This study used an emotion-decoding algorithm called FACET (Emotient Analytics, San Diego, CA) to analyze 4,648 videos of facial expressions. FACET generates time-series (30Hz) of evidence scores for each of 20 Action Units (AU) based on the well-validated Facial Action Coding System[4].

Task Design

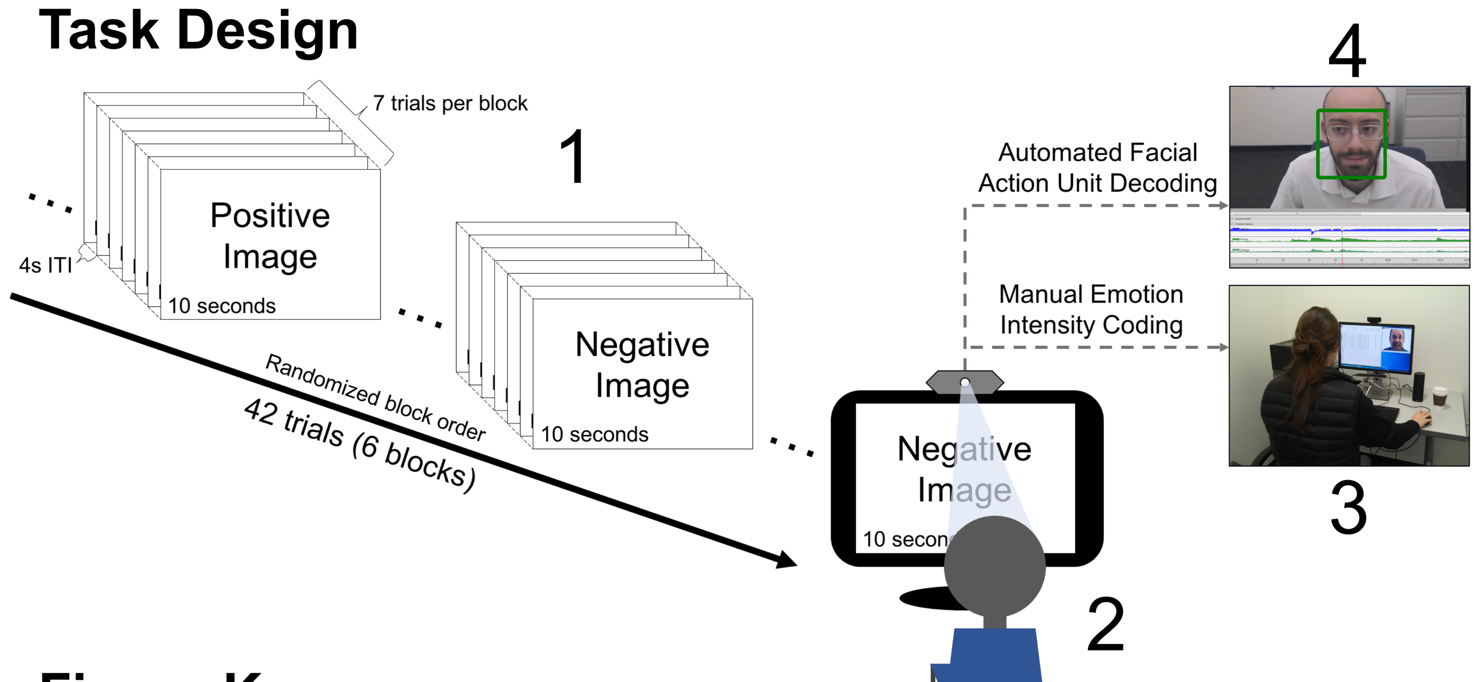
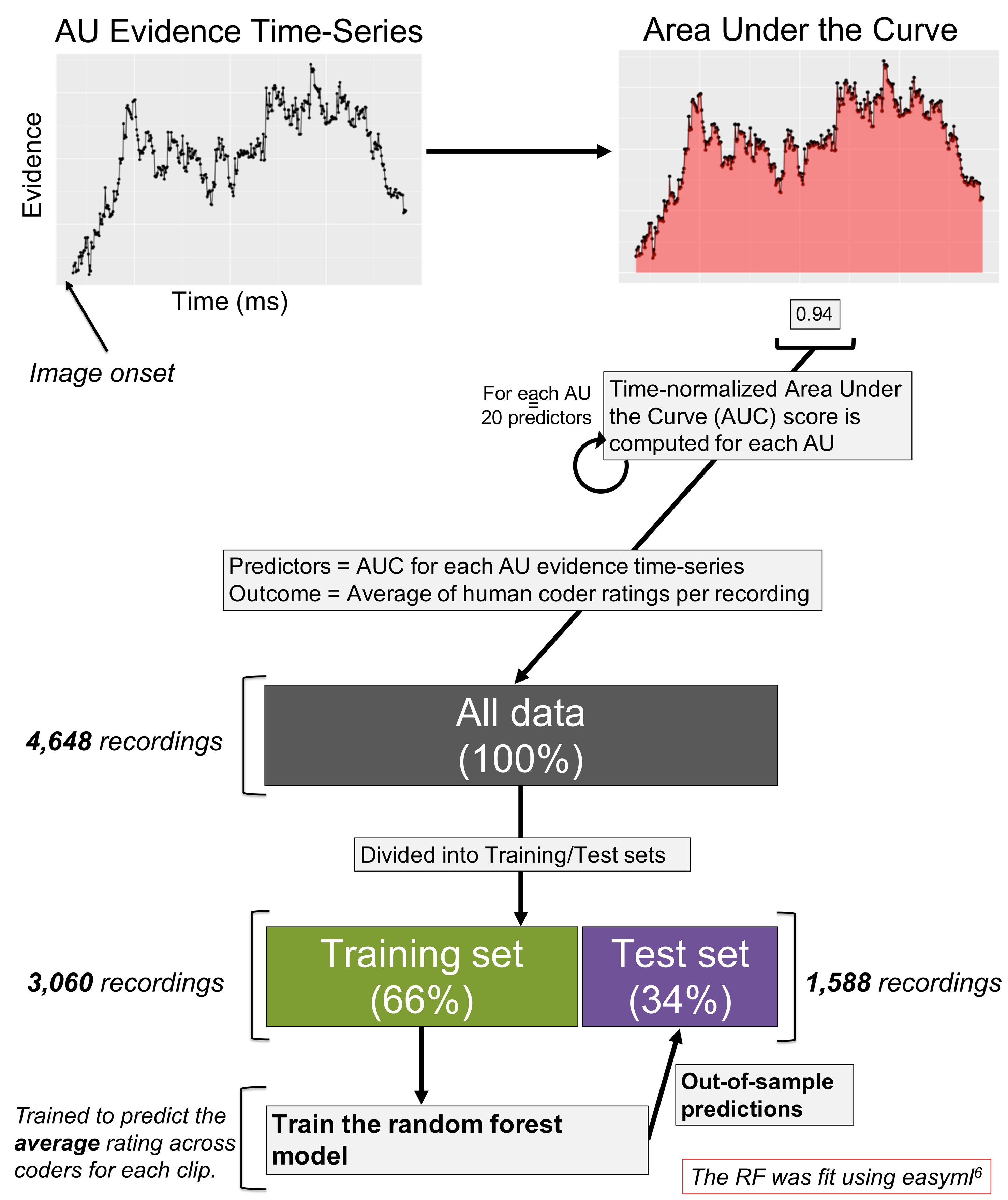


Figure Key

1. 42 positive and negative images from the International Affective Picture System (IAPS) were displayed in blocks. Each block contained all positive or all negative images.
2. 125 subjects were video-recorded while observing all 42 images[5]. They were asked to either: 1) *Express*, 2) *React normally*, or 3) *Suppress* their emotions. Instructions were given by block, so that each valence (positive or negative) was paired once with each instruction (Express, React normally, or Suppress).
3. 3 independent coders rated each recorded clip for positive and negative emotion intensity, from 1 (no emotion) to 7 (extreme emotion). They demonstrated **high agreement**: intraclass correlation coefficient [ICC] = .88 for positive emotions and ICC = .94 for negative emotions.
4. We used FACET to generate AU time-series for each recorded clip.

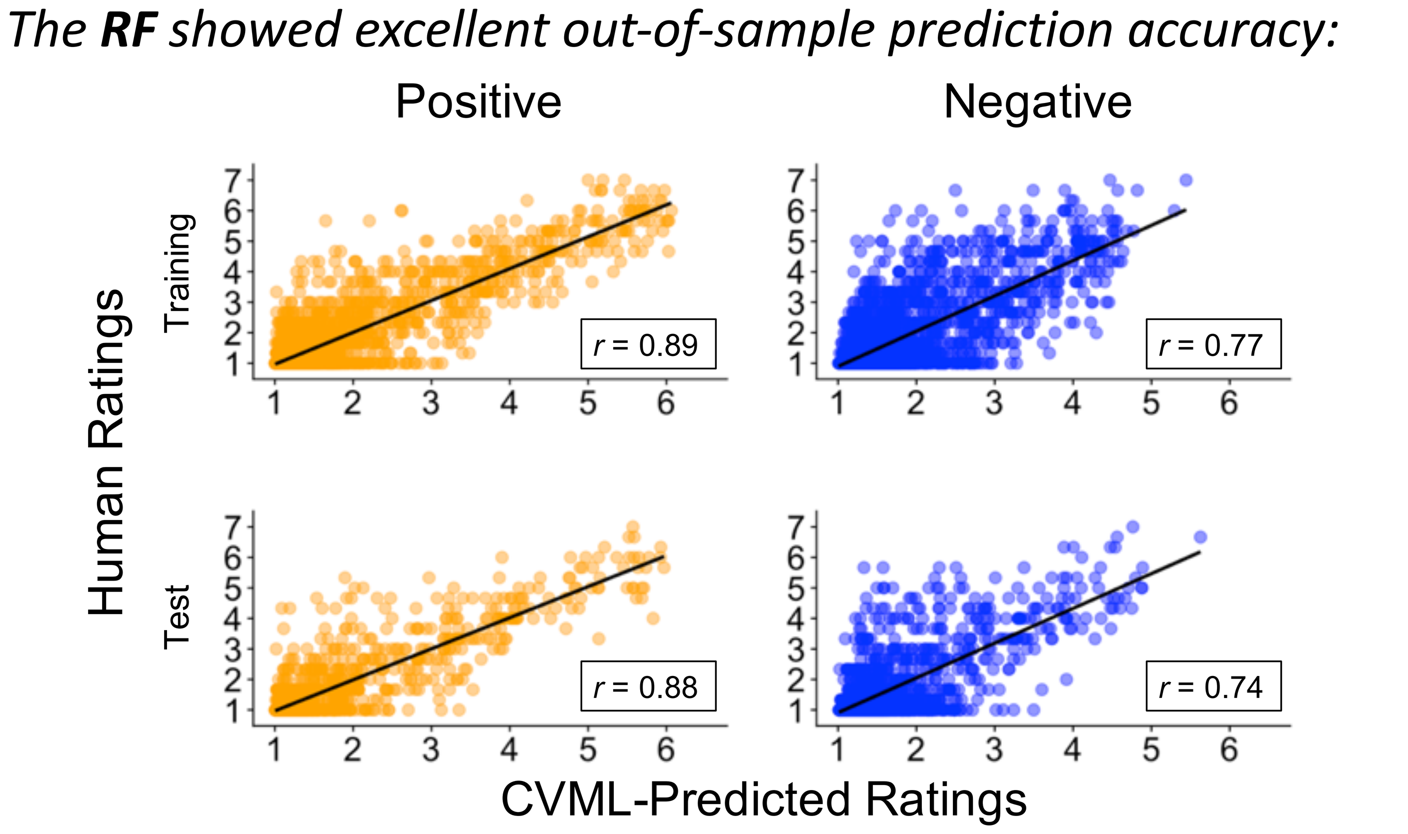
Methods: Analysis



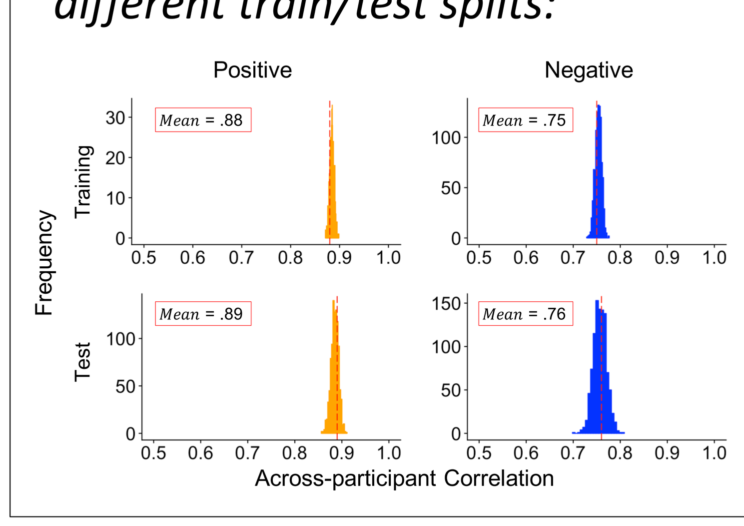
Results

❖ Can CVML achieve human-like emotion intensity ratings?

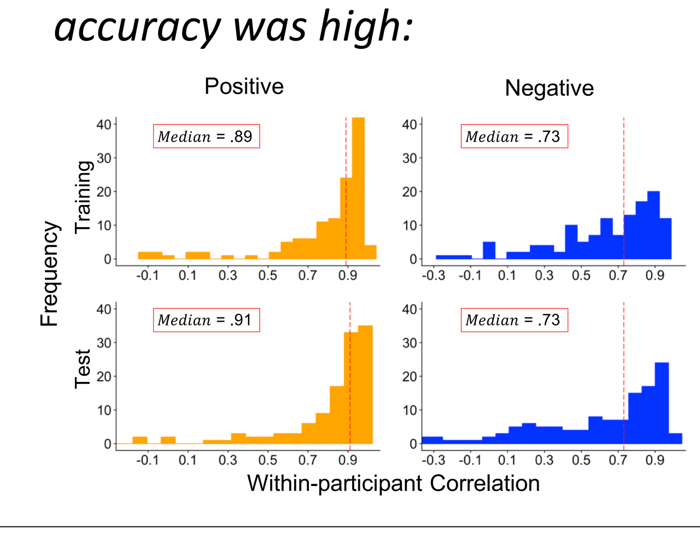
*The **RF** showed excellent out-of-sample prediction accuracy:*



*The **RF** was robust across 1,000 different train/test splits:*



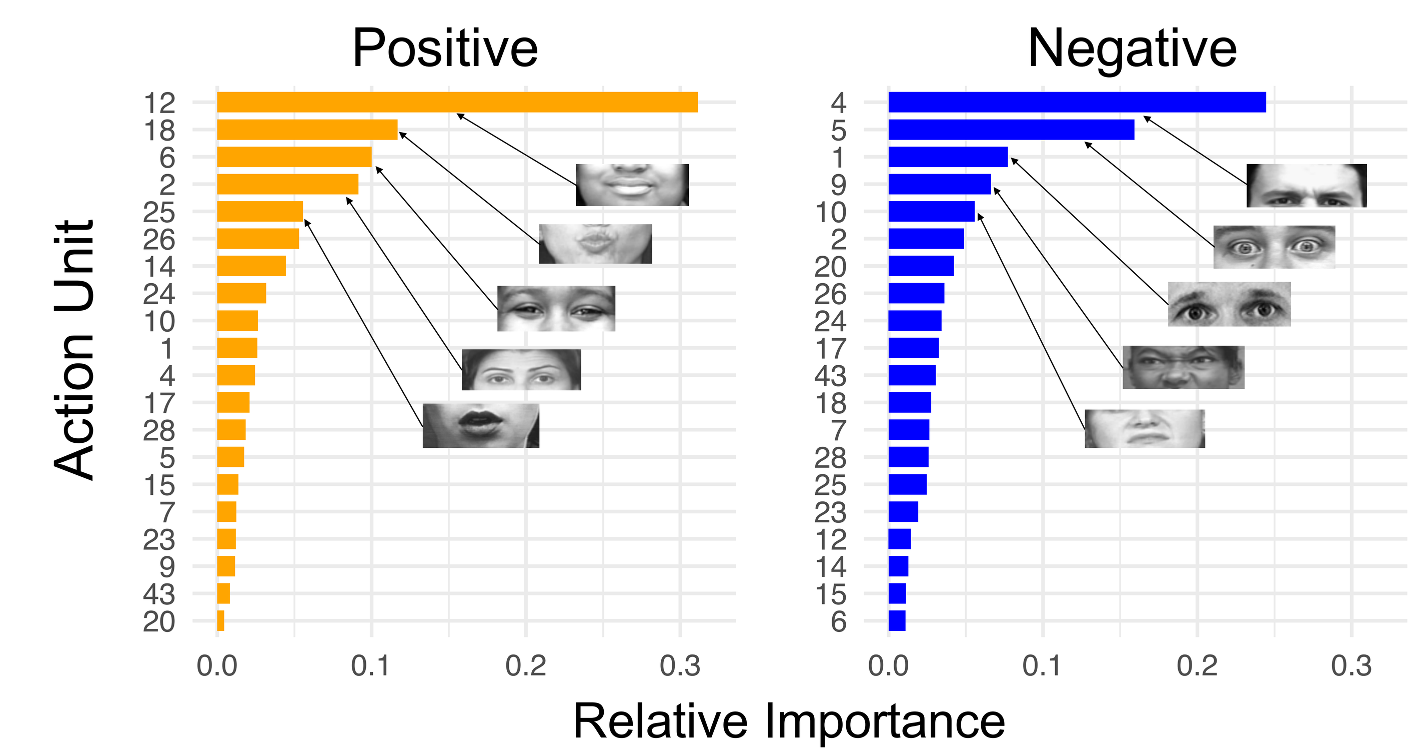
*Median **within-subject** prediction accuracy was high:*



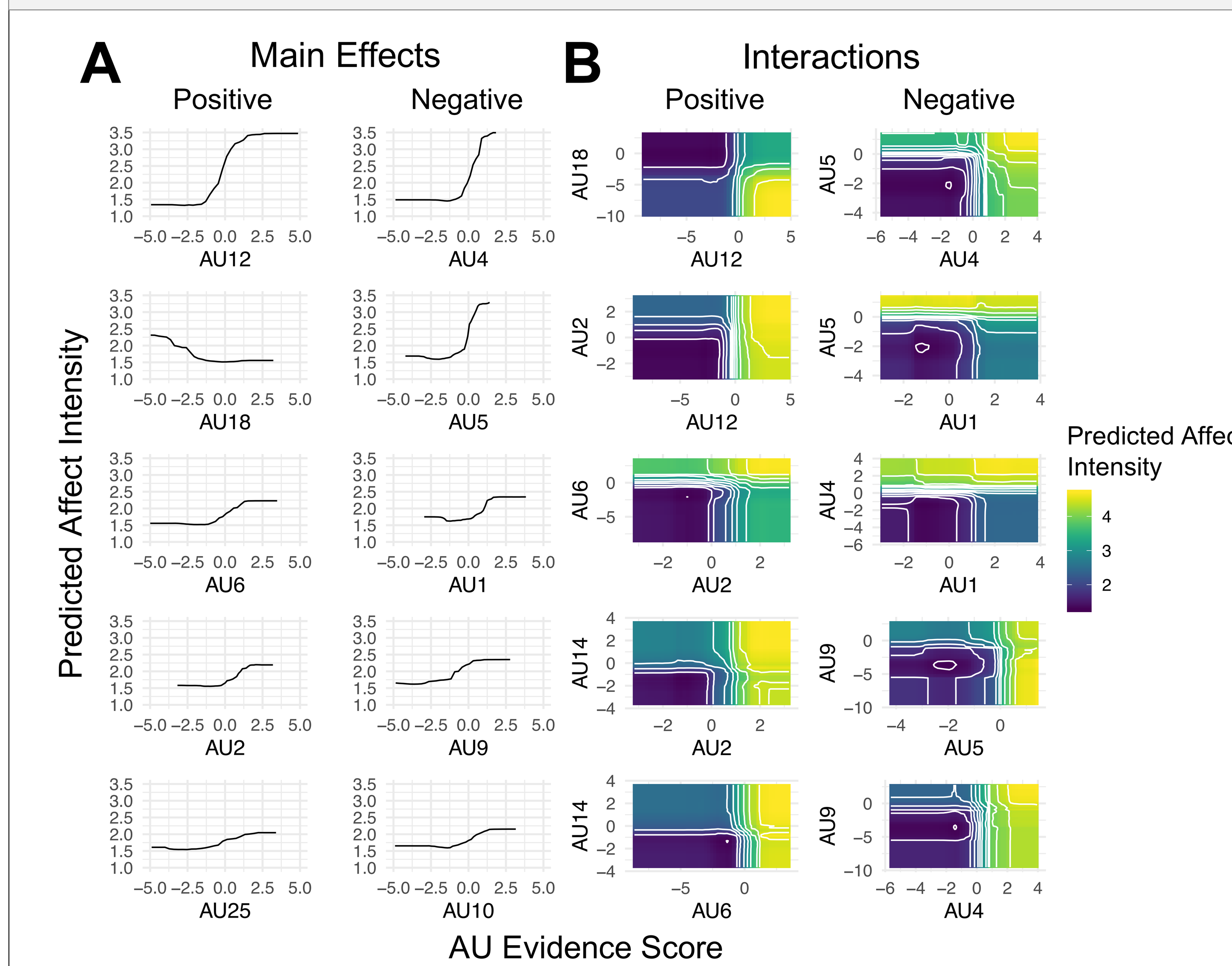
Results Continued

❖ *What facial expressions do people attend to when rating positive and negative emotion?*

Importance of AUs for Positive vs. Negative Affect



Directional and Interactive Effects



Conclusion & Future Directions

Our results provide ***strong support for the use of CVML*** in rating positive and negative emotion intensity. Additionally, we provide a methodology which can be used to ***identify multivariate patterns of facial AUs*** that human raters use to generate emotion ratings.

There was no overlap between the facial expressions that were most predictive of positive and negative emotions, bolstering previous evidence suggesting that positive and negative emotions occupy separate dimensions.

Future research should investigate how AU attention may be related to individual difference measures. Doing so may help provide a more mechanistic understanding of the impaired processing of facial expressions experienced by multiple psychiatric populations.

References

1. Sikka, K. *et al. PEDIATRICS* **136,** e124–e131 (2015).
2. Dibeklioğlu, H., Hammal, Z., Yang, Y. & Cohn, J. F. *ICMI*. 307–310 (2015).
3. Bailenson, J. N. *et al. International Journal of Human-Computer Studies* **66,** 303–317 (2008).
4. Ekman, P., Friesen, W. V., & Hager, J. *Palo Alto: Consulting Psychologists* (1978).
5. Southward, M. W. & Cheavens, J. S. *Journal of Social and Clinical Psychology* **36,** 142–157 (2017).
6. Ahn WY, Hendricks P, Haines N. Easyml: Easily Build and Evaluate Machine Learning Models. bioRxiv. (2017)