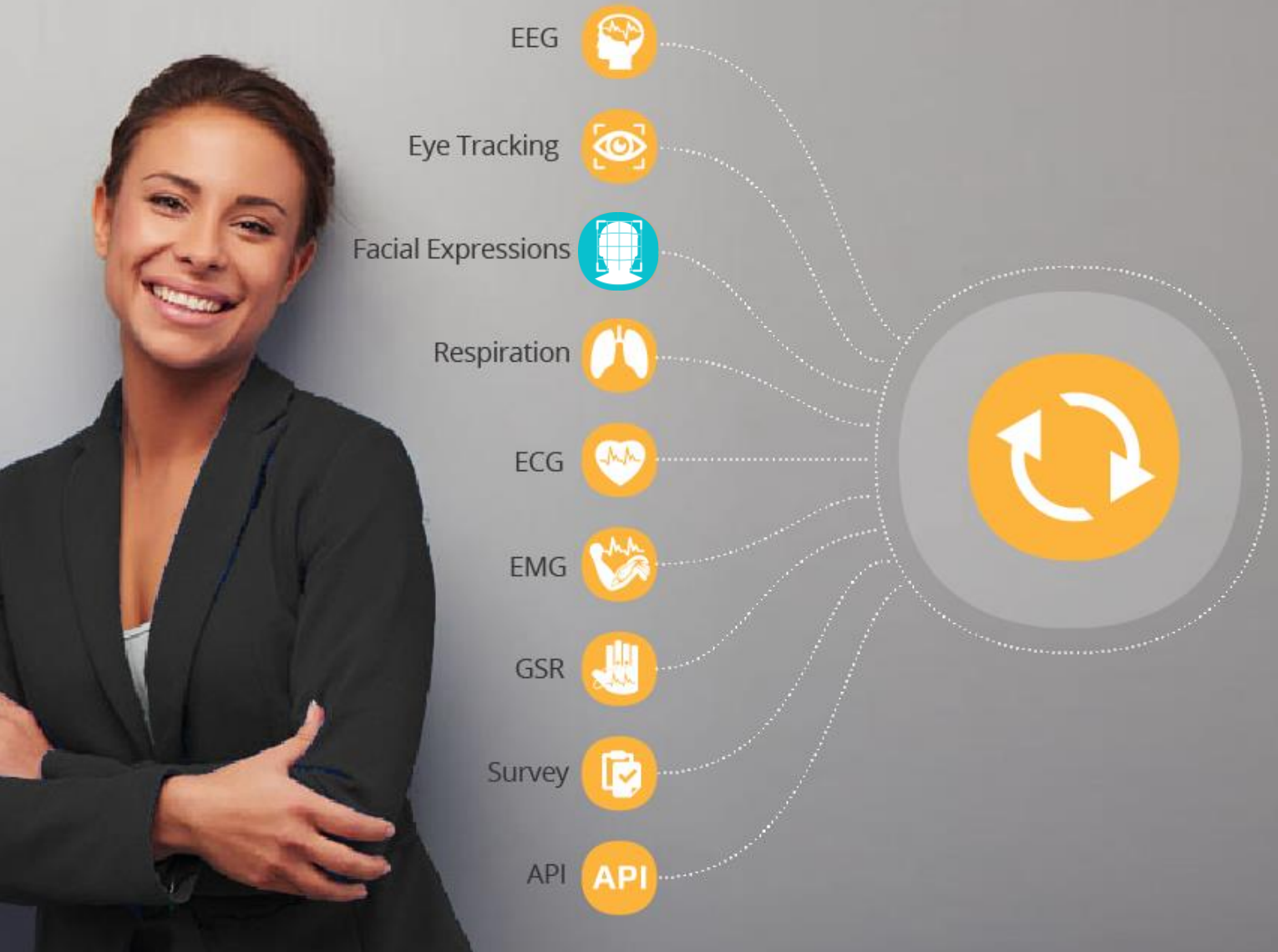


Module: Affectiva

Facial Expression Emotion Analysis

Pre-requisite: iMotions Core License



sales@imotions.com

Your face tells everything

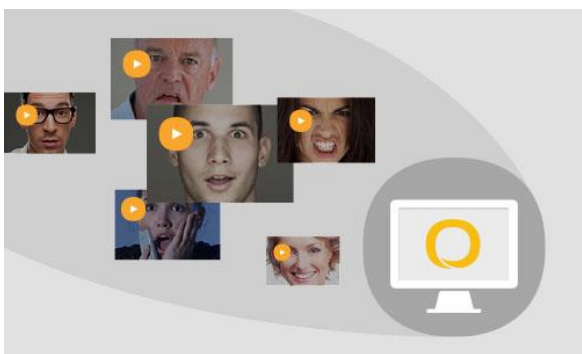
Analyze facial expressions to understand emotional reactions

The face reveals both conscious and non-conscious reactions. iMotions integrates Affectiva's Affdex technology to gain deeper insight into human emotional reactions via facial expressions. The powerful algorithms give you metrics for many different nuanced facial expressions and key emotions.



Non-intrusive research method

A face video recorded from a standard webcam is all you need. Get facial emotional reactions in sync with all type of stimuli such as images, videos, websites, ads, TV programs, products and/or use it for video interviews.



Analyze previously recorded faces

Batch upload previously recorded videos of respondents to iMotions and extract all facial expression and emotion data as if collected live. See table of outputs on next page.



Visualize, aggregate & export

Visualize frame-by-frame synchronization of all facial emotion channels with stimuli on a timeline. Segment, make annotations, aggregate across participants and export all raw data to any statistical or data analysis program for further analysis.

The Affectiva Module is available in 3 packages



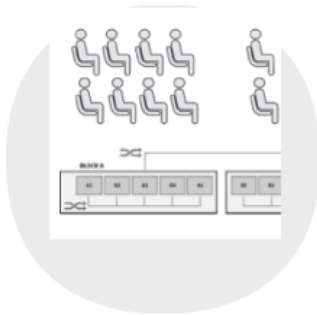
OUTPUTS	BASE	RESEARCH	BEHAVIORAL
Valence: A measure of the positive or negative nature of the recorded person experience. The range of values for the metric is between -100 to 100.	X	X	
Engagement: A measure of facial muscle activation that illustrates the subject's expressiveness. The range of values is between 0 and 100.	X	X	
7 Basic Emotions: Joy, Anger, Surprise, Fear, Sadness, Disgust, Contempt. Emotion metrics scores indicate when users express a specific emotion, along with the degree of confidence. The metrics can be thought of as detectors: as the emotion occurs, the score rises from 0 (no expression) to 100 (expression fully present).	X	X	
21 Facial Expressions (Action Units): Attention, Brow Furrow, Brow Raise, Inner Brow Raise, Eye Closure, Nose Wrinkle, Upper Lip Raise, Lip Suck, Lip Pucker, Lip Press, Mouth Open, Lip Corner Depressor, Chin Raise, Smirk, Smile, Cheek Raise, Dimpler, Eye Widen, Eye Tighten, Lip Stretch, and Jaw Drop. Expression metrics, also known as Action Units (AUs) in the FACS methodology, scores indicate when users make a specific expression (e.g., a smile) along with the degree of confidence. The metrics can be thought of as detectors: as the facial expression occurs and becomes more apparent, the score rises from 0 (no expression) to 100.		X	
33 Facial Landmarks: The indices of the elements in the face points array correspond to specific locations on a face. Click here to see an explanation of the locations corresponding to each index.		X	
Interocular Distance: Distance between the two outer eye corners.			X
Head Orientation: Estimation of the head position in a 3-D space in Euler angles (pitch, yaw, roll).			X

The Affectiva Module has the iMotions Core License as pre-requisite, which allows you to:



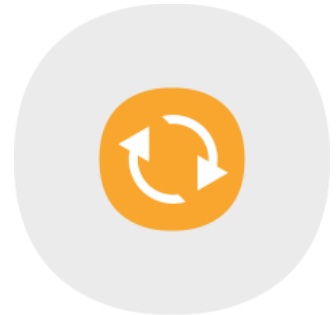
Present all Type of Stimuli

Present images, videos, websites, screen & scene recordings, real world products and surveys.



Create Sophisticated Studies

Full flexibility to design any study setup with randomizations, block designs, test plans, group rotations and more.



Real-Time Synchronization

Affdex data, stimuli and any other sensor data streams are real time synchronized.



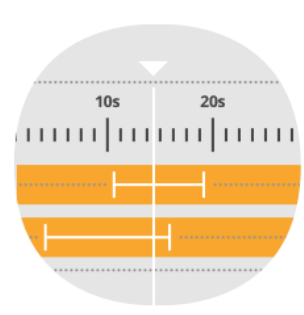
Export Raw Data

Export all collected Affdex data in sync with stimuli and other sensors in .txt format for easy import into MatLab and other statistical programs.



Get Quality Assurance

Monitor data collection quality at any given time to ensure the validity of the studies.



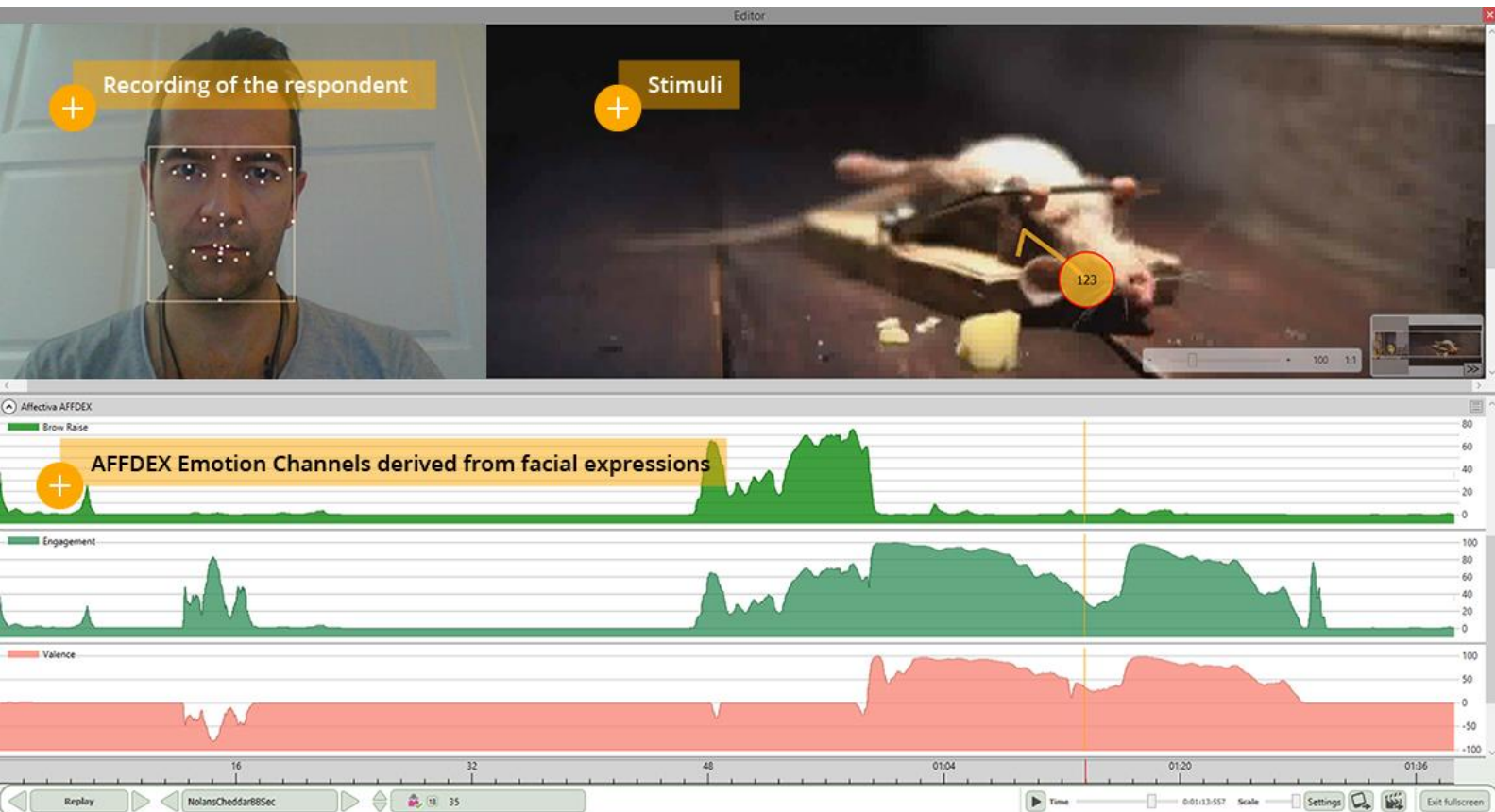
Create Live or Post Markers

Mark important happenings during data collection or in replay mode to facilitate the analysis.

Accuracy & Cultural Differences

The Affectiva emotion metrics are trained and tested on very difficult datasets. Affectiva sampled the test set, comprising hundred of thousands of facial frames, from nearly 4 million facial videos. This data is from more than 75 countries, representing real-world, spontaneous facial expressions, made under challenging conditions, such as varying lighting, different head movements, and variances in facial features due to ethnicity, age, gender, facial hair and glasses. This has hardened the technology to account for cultural differences with high accuracy.

Facial Expression Emotion & Analysis Output

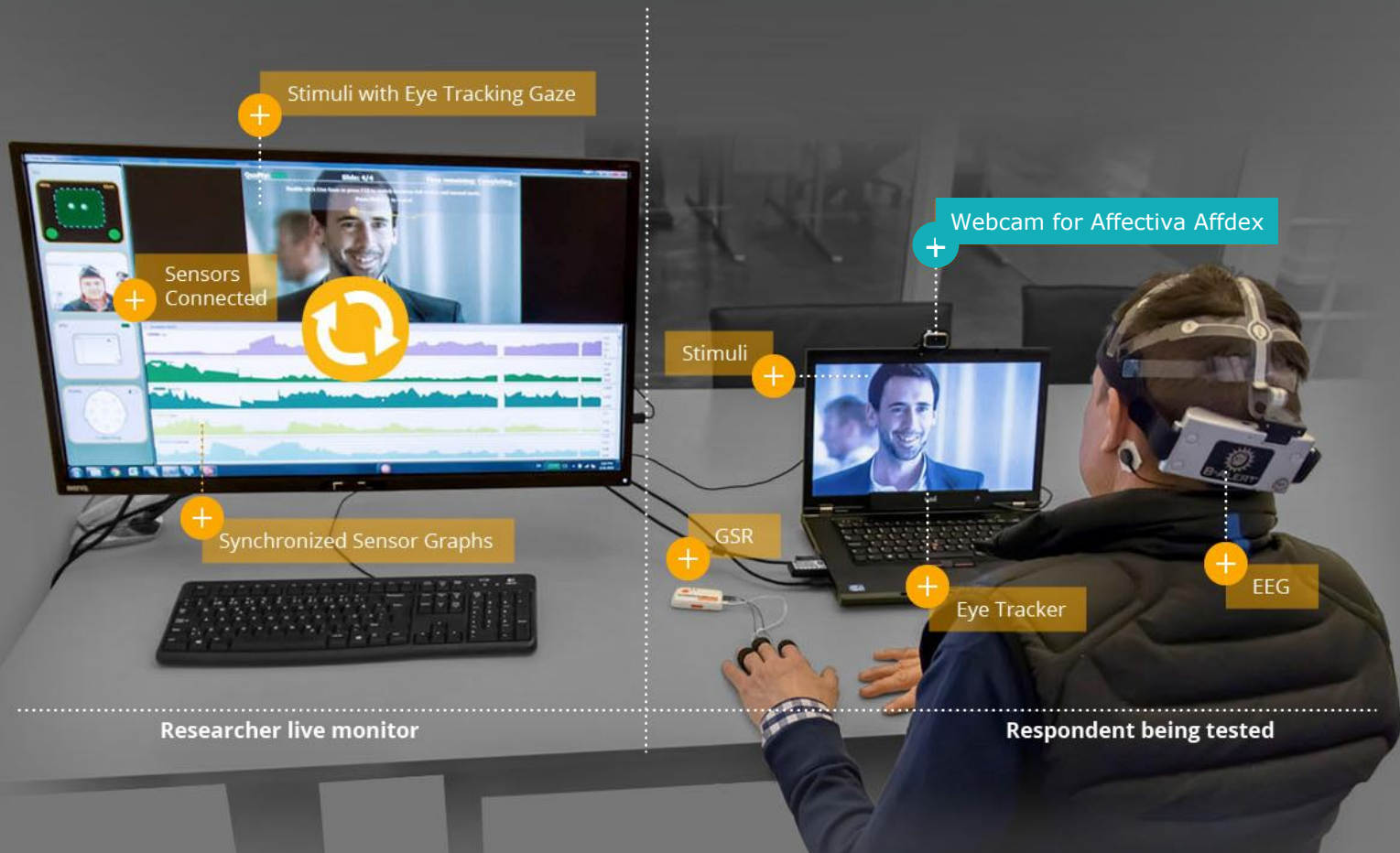


Raw Data Output

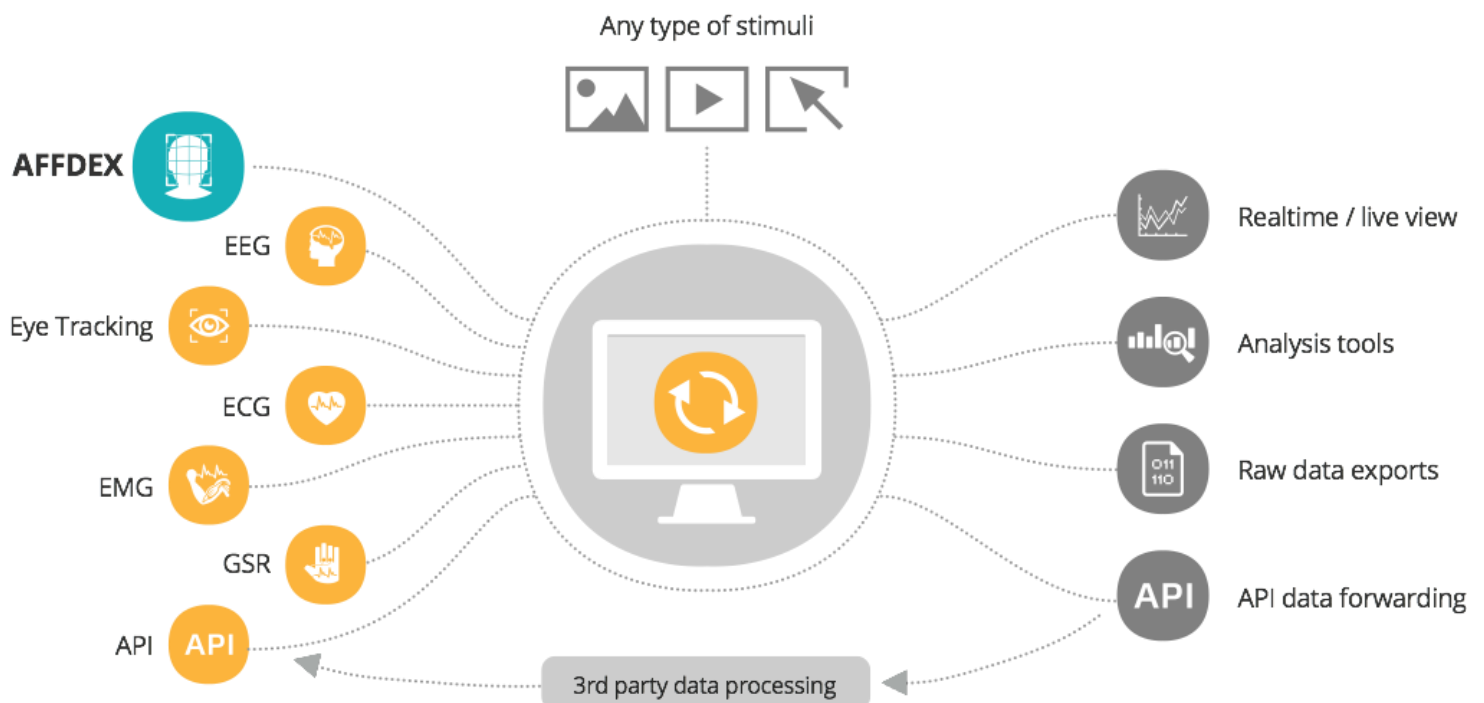
	I	J	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	
7	Timestamp	MediaTime	row	Furrow	Brow Raise	Engagement	Lip Corner	Smile	Valence	Number of	feature id	feature-x	feature-y	feature id	feature-x	feature-y	feature id	feature-x
8	11537	0	1.31E-10	0.001236	0.001236	8.35E-10	2.94E-05	2.94E-05	34	0	262.9432	263.6705	1	281.2834	306.9061	2	322.751	
9	11568	0	5.80E-11	0.001509	0.001509	8.74E-10	2.40E-05	2.40E-05	34	0	263.1234	266.8395	1	281.9147	304.1014	2	323.4996	
10	11600	0	8.98E-10	0.000789	0.000789	3.63E-09	1.59E-05	1.59E-05	34	0	260.4611	266.7928	1	279.6588	305.4049	2	322.9208	
11	11632	0	5.03E-07	0.000654	0.000654	2.29E-09	1.73E-05	1.68E-05	34	0	261.353	268.9203	1	280.6978	307.783	2	323.3754	
12	11664	0	1.66E-06	0.000733	0.000733	1.74E-09	2.15E-05	1.98E-05	34	0	262.8487	266.5692	1	280.7923	305.9268	2	322.8087	
13	11696	0	7.74E-07	0.001025	0.001025	1.53E-09	2.94E-05	2.86E-05	34	0	262.3969	268.8913	1	280.7675	306.976	2	323.2076	
14	11728	0	4.15E-07	0.001511	0.001511	1.03E-09	4.92E-05	4.88E-05	34	0	262.0877	268.2392	1	282.0513	306.8156	2	323.6277	
15	11760	0	1.95E-07	0.002058	0.002058	8.55E-10	6.28E-05	6.26E-05	34	0	263.1465	267.6401	1	281.921	306.2422	2	323.2233	
16	11793	0	3.18E-08	0.00274	0.00274	8.81E-10	8.66E-05	8.66E-05	34	0	262.511	265.949	1	281.5397	305.1618	2	323.1579	
17	11824	0	1.00E-08	0.003816	0.003816	9.72E-10	9.71E-05	9.70E-05	34	0	261.9542	265.8148	1	280.9771	305.0693	2	322.6039	
18	11856	0	1.99E-09	0.004053	0.004053	8.67E-10	8.34E-05	8.34E-05	34	0	261.6271	263.8626	1	280.7608	304.1898	2	322.5801	
19	11910	0	6.29E-10	0.004884	0.004884	6.85E-10	8.16E-05	8.16E-05	34	0	261.9604	264.8217	1	281.3117	304.2974	2	322.636	

Business value applications

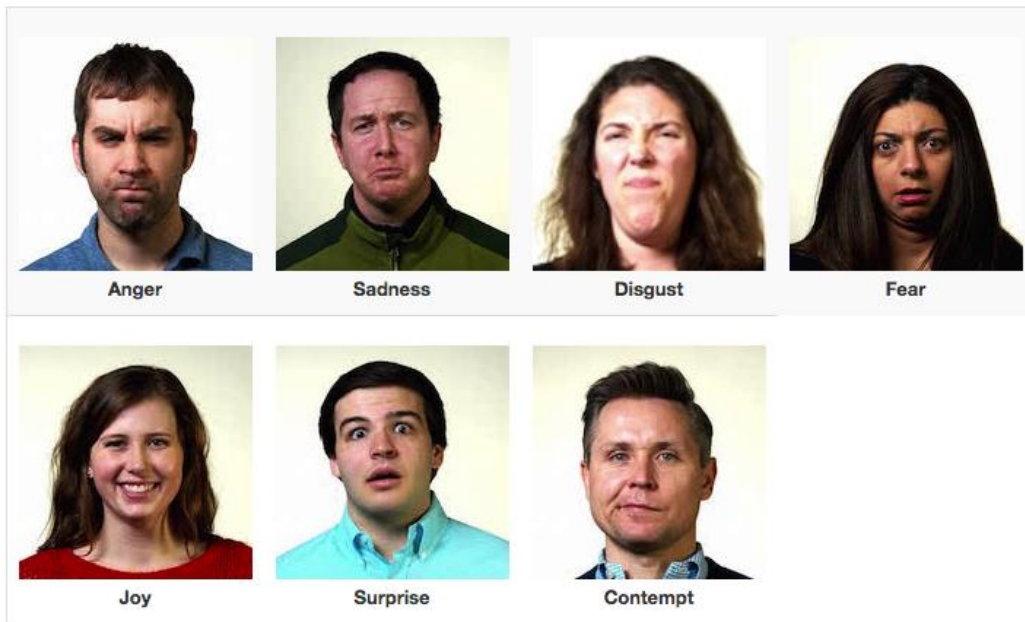
- Media and entertainment test labs conducting market research to better evaluate audience emotion engagement with TV and movie content.
- Brand marketers evaluating product features and their communication to have more successful product launches and better stand against competition.
- Academic labs researching behavioral science and wellbeing in a diversity of areas.
- Digital interaction labs testing website performance, software and app usability and gaming user experience and playtesting.



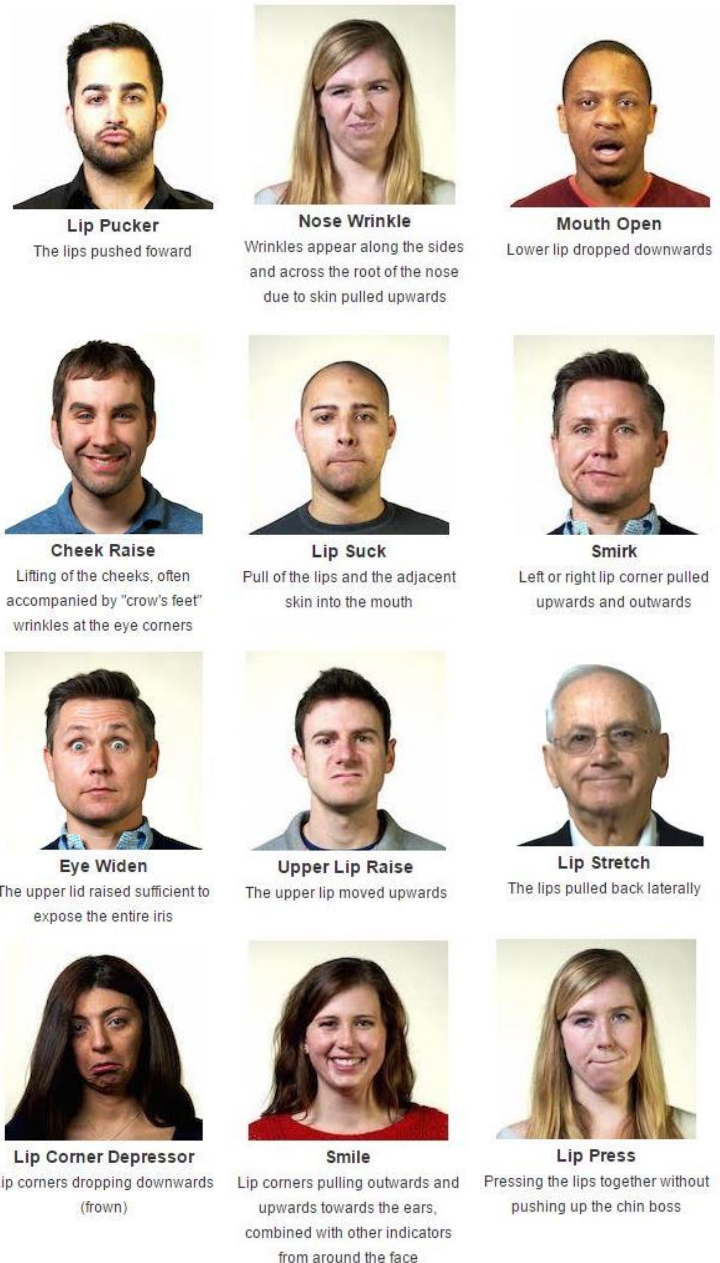
Combine AFFDEX's Facial Expression Emotion Analysis with Stimuli, Eye tracking, EEG, GSR & more



Emotions



Facial Expressions



Affectiva peer-reviewed publications

McDuff, D., El Kaliouby, R., & Picard, R. W. (2015, September). Crowdsourcing facial responses to online videos. In *Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on* (pp. 512-518). IEEE.

[Crowdsourcing facial responses to online videos](#)

McDuff, D., Kaliouby, R., Senechal, T., Amr, M., Cohn, J., & Picard, R. (2013). Affectiva-mit facial expression dataset (am-fed): Naturalistic and spontaneous facial expressions collected. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* (pp. 881-888).

[Naturalistic and Spontaneous Facial Expressions Collected In-the-Wild](#)

McDuff, D., El Kaliouby, R., Demirdjian, D., & Picard, R. (2013, April). Predicting online media effectiveness based on smile responses gathered over the internet. In *Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on* (pp. 1-7). IEEE.

[Predicting Online Media Effectiveness Based on Smile Responses Gathered Over the Internet. \(Face & Gesture 2013\)](#)

Sénéchal, Thibaud, Jay Turcot, and Rana El Kaliouby. "Smile or smirk? automatic detection of spontaneous asymmetric smiles to understand viewer experience." *Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on*. IEEE, 2013.

[Smile or Smirk? Automatic Detection of Spontaneous Asymmetric Smiles to Understand Viewer Experience. \(Face & Gesture 2013\)](#)

McDuff, D., El Kaliouby, R., & Picard, R. (2011, November). Crowdsourced data collection of facial responses. In *Proceedings of the 13th international conference on multimodal interfaces* (pp. 11-18). ACM.

[Crowdsourced Data Collection of Facial Responses \(First-ever online facial coding study – FORBES; International Conference on Multimodal Interfaces, 2011\)](#)

McDuff, D., El Kaliouby, R., Senechal, T., Demirdjian, D., & Picard, R. (2014). Automatic measurement of ad preferences from facial responses gathered over the internet. *Image and Vision Computing*, 32(10), 630-640.

[Automatic Measurement of Ad Preferences from Facial Responses Gathered Over the Internet](#)

McDuff, D., El Kaliouby, R., Kodra, E., & Picard, R. (2013, September). Measuring Voter's Candidate Preference Based on Affective Responses to Election Debates. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on* (pp. 369-374). IEEE.

[Measuring Voter's Candidate Preference Based on Affective Responses to Election Debate](#)

McDuff, D., El Kaliouby, R., Cohn, J. F., & Picard, R. W. (2015). Predicting ad liking and purchase intent: Large-scale analysis of facial responses to ads. *Affective Computing, IEEE Transactions on*, 6(3), 223-235.

[Predicting Ad Liking and Purchase Intent: Large-scale Analysis of Facial Responses to Ads](#)

Teixeira, T., Picard, R., & El Kaliouby, R. (2014). Why, when, and how much to entertain consumers in advertisements? A web-based facial tracking field study. *Marketing Science*, 33(6), 809-827.

[Why, When and How Much to Entertain Consumers in Advertisements? \(Marketing Science\)](#)

Senechal, T., McDuff, D., & Kaliouby, R. (2015). Facial Action Unit Detection using Active Learning and an Efficient Non-Linear Kernel Approximation. In *Proceedings of the IEEE International Conference on Computer Vision Workshops* (pp. 10-18).

[Facial Action Unit Detection using Active Learning and an Efficient Non-Linear Kernel Approximation](#)

Affective peer-reviewed publications

Kodra, E., Senechal, T., McDuff, D., & El Kaliouby, R. (2013, April). From dials to facial coding: Automated detection of spontaneous facial expressions for media research. In *Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on* (pp. 1-6). IEEE.

[From Dials to Facial Coding: Automated Detection of Spontaneous Facial Expressions for Media Research. \(Face & Gesture 2013\)](#)

Osman, A., Turcot, J., & El Kaliouby, R. (2015, May). Supervised learning approach to remote heart rate estimation from facial videos. In *Automatic Face and Gesture Recognition (FG), 2015 11th IEEE International Conference and Workshops on* (Vol. 1, pp. 1-6). IEEE.

[Supervised learning approach to remote heart rate estimation from facial videos](#)

Vandal, T., McDuff, D., & El Kaliouby, R. (2015, May). Event detection: Ultra large-scale clustering of facial expressions. In *Automatic Face and Gesture Recognition (FG), 2015 11th IEEE International Conference and Workshops on* (Vol. 1, pp. 1-8). IEEE.

[Event detection: Ultra large-scale clustering of facial expressions](#)

Not peer-reviewed but worth reading

McDuff, D., El Kaliouby, R., & Picard, R. W. (2015, September). Crowdsourcing facial responses to online videos. In *Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on* (pp. 512-518). IEEE.

[Crowdsourcing Facial Responses to Online Videos. \(IEEE Transactions on Affective Computing\)](#)