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Request for Information (RFI) on Public and Private Sector Uses of Biometric Technologies: Responses

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Inferring Emotions From Physical Signals

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Executive Summary

You cannot detect a person’s emotional state (i.e., angry, sad, fearful, remorseful, etc.) from patterns of facial signals, physiological signals, or neural signals, according to peer-reviewed scientific articles. Scowling in anger, smiling in happiness, frowning in sadness, - all these are stereotypes of emotional expressions. They reflect common beliefs about emotional “expressions,” beliefs held by people who live in western countries, but these beliefs don’t correspond to how people actually express emotion in real life. And these stereotypes don’t generalize to cultures that are very different from ours. Any technology that claims to read emotion in physical movements, physiological signals, or neural signals is misrepresenting what it can do, according to the best available, peer-reviewed scientific evidence. Inferring a person’s mood or affect (e.g., sleepiness during driving) via such signals may hold more promise.

Background

Research in psychological science, computer science, neuroscience, and physiology attempt to identify emotional states in humans and non-human animals by measuring signals in behavior (e.g., facial muscle movements, postural changes, vocalizations, word use, etc.), signals in the brain (e.g., brain imaging patterns) and signals in peripheral physiology (e.g., autonomic nervous system changes in heart rate, skin conductance, etc.). These efforts are referred to as **emotion inference** (the term used in this document), emotion perception, emotion detection, or more commonly, emotion recognition. Machine learning (ML) algorithms are trained to detect patterns for the purpose of inferring the presence of emotional states, such as anger, happiness, sadness, and fear. ML is a powerful family of techniques that allow scientists to program and train a computer model on one set of observations, identify data patterns, and assess how well these patterns generalize to a new set of observations. In emotion inference efforts, human raters view a sample of signals (e.g., photographs or videos of people making facial movements) and label them with emotion words; this becomes the ML training set. Once a pattern is identified for each emotional state, it is used to diagnose the presence of that state in a new sample of signals.

Emotion inference can be distinguished from **affect inference** which uses similar data and ML approaches to infer the presence of affective states such as pleasure, boredom, sleepiness,

arousal, distress and interest. Methods to infer emotion and affect are collectively referred to as **affective computing** or **emotion artificial intelligence** (a.k.a. “emotion AI”).

The global market for emotion and affect inference products is projected to double by 2024 to reach \$56 billion.¹ Efforts to infer affect and emotion can be found in every commercial, educational, medical, and governmental sector (summarized in Table 1). Large companies have established R&D projects and made major acquisitions in emotion AI including Apple², Amazon,³ IBM,⁴ Google,⁵ Facebook,⁶ and Microsoft.⁷ Several of these companies have released software platforms for others to attempt to build emotion AI products. Major car companies have significant emotion and affect inference efforts to infer driver inattentiveness and/or sleepiness and to estimate levels of frustration and joy.⁸ Many startups are also building new recording methods and inference models for specific use cases.⁹

Emotion AI Applications¹⁰

Business & Industry	Health Care & Education	Consumer and Entertainment	Government, Police, Military, Legal
<p>Marketing & Advertising</p> <ul style="list-style-type: none"> Targeted advertising Customer purchase monitoring¹¹ Smart billboards <p>Customer Service</p> <ul style="list-style-type: none"> Chatbots Customer experience monitoring <p>Human Resources</p> <ul style="list-style-type: none"> Job interviews and hiring decisions Productivity monitoring Team functioning <p>Safety & Quality Control</p> <ul style="list-style-type: none"> Factory monitoring Vehicle safety features (e.g., monitoring driver 	<p>Diagnostics</p> <p>Patient Monitoring</p> <ul style="list-style-type: none"> Symptoms monitoring^{15,16} Suicide prevention <p>Treatment</p> <ul style="list-style-type: none"> Mental health chatbots Wellness apps <p>Schools</p> <ul style="list-style-type: none"> Learning, attention, distraction & motivation^{17,18,} 	<p>Consumer Apps</p> <ul style="list-style-type: none"> Personal wellness apps Dating apps <p>Entertainment</p> <ul style="list-style-type: none"> Gaming & AR/VR Companion robots Adult entertainment 	<p>Police</p> <ul style="list-style-type: none"> Parole monitoring Crowd control & protest monitoring Threat assessment <p>Courts & Criminal Justice</p> <ul style="list-style-type: none"> Sentencing Parole board decisions <p>Security Screening & Counterterrorism</p> <ul style="list-style-type: none"> Behavioral profiles Lie detection Interrogation <p>Elections & Political Campaigns</p> <ul style="list-style-type: none"> Political ads

¹<https://findbiometrics.com/biometrics-news-marketsandmarkets-projects-emotion-recognition-market-double-next-four-years-020508/>

²<https://9to5mac.com/2016/01/07/apple-emotient/>

³<https://www.wired.com/story/amazon-detect-fear-face-you-scared/>

⁴<https://www.washingtonpost.com/business/2019/07/31/emotion-detection-ai-is-billion-industry-new-research-says-it-cant-do-what-it-claims/>

⁵<https://www.techradar.com/news/internet/cloud-services/you-can-now-try-google-s-emotion-detecting-image-api-for-yourself-1315249>

⁶<https://techcrunch.com/2016/11/16/facial-gesture-controls/>

⁷<https://blogs.microsoft.com/ai/happy-sad-angry-this-microsoft-tool-recognizes-emotions-in-pictures/>

⁸<https://singularityhub.com/2020/07/29/what-if-cars-could-read-and-react-to-your-emotions-soon-they-will/>

⁹<https://resource.affectlab.io/top-10-emotional-artificial-intelligence-startups-that-have-created-a-global-disruption/>

¹⁰ Modified with permission; Fridman, J., Winterberg, S. (2021). Responsibly assessing and investing in affective computing technologies *IEEE Transactions on Affective Computing*, submitted.

¹¹<https://thecounter.org/walgreens-kroger-testing-cameras-that-guess-shoppers-age-gender/>

¹⁵<https://www.empatica.com/blog/embrace2-receives-fda-clearance-for-children-ages-6-and-up-edce647ef610.html>

¹⁶<https://winterlightlabs.com/news/isctm-2020-news-update>

¹⁷<https://www.telegraph.co.uk/news/2018/05/17/chinese-school-uses-facial-recognition-monitor-student-attention/>

¹⁸<https://www.theverge.com/2017/5/26/15679806/ai-education-facial-recognition-nestor-france>

attention, sleepiness & distraction) ^{12,13,14} <ul style="list-style-type: none"> Air traffic control safety (e.g., monitoring controller attention, sleepiness & distraction) 	19		<ul style="list-style-type: none"> Crowd monitoring²⁰ Governance and Regulation <ul style="list-style-type: none"> Monitoring citizens²¹
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Assessment

To date, peer-reviewed scientific articles indicate that patterns of facial signals, physiological signals, or neural signals have limited reliability, specificity, and generalizability to infer the presence of a particular emotional state (e.g.,^{22,23,24,25}). (Most ML technology in industry is proprietary and without access to the code, it is difficult to assess their function.) Here is a brief summary of notable peer-reviewed findings:

- An interdisciplinary team of senior scientists, commissioned by the Association for Psychological Science, reviewed over 1,000 peer-reviewed scientific papers and came to a consensus view: the common assumption “that a person’s emotional state can be readily inferred from his or her facial movements” has no scientific support.²² For example, it has been assumed that scowling is the universal facial expression of anger. Yet studies consistently show that humans who live in urban culture settings scowl only about 30% of the time when angry, which is considered low reliability. The other 70% of the time, they express anger in other meaningful and context-specific ways (frowning, crying, smiling, etc.). People also scowl to express other states, including confusion, concentration, humor at a bad joke, stomach upset, etc., so scowling has low specificity as a marker of anger. Scowling is not a universal expression of anger; it is a Western stereotype. No stereotypical facial expression (smiling in happiness, frowning in sadness, etc.) is a reliable, specific, and generalizable predictor of emotional state. Therefore, it is inaccurate to refer to facial

¹² <https://www.fastcompany.com/90368804/emotion-sensing-cars-promise-to-make-our-roads-much-safer>

¹³ <https://blog.affectiva.com/affectiva-automotive-ai-building-emotionally-aware-cars-with-in-cabin-sensing>

¹⁴ Eyben, F., Wöllmer, M., Poitschke, T., Schuller, B., Blaschke, C., Färber, B., & Nguyen-Thien, N. (2010). Emotion on the road—necessity, acceptance, and feasibility of affective computing in the car. *Advances in human-computer interaction*, 2010.

¹⁹ <https://syncedreview.com/2020/01/16/emotioncues-ai-knows-whether-students-are-paying-attention/>

²⁰ <https://www.wsj.com/articles/trumps-rallies-arent-just-part-of-his-campaign-they-are-the-campaign-11571753199?mod=searchresults&page=1&pos=1>

²¹ <https://www.ft.com/content/68155560-fbd1-11e9-a354-36acbbb0d9b6>

²² Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A., & Pollak, S. (2019). Emotional expressions reconsidered: Challenges to inferring emotion in human facial movements. *Psychological Science in the Public Interest*, 20, 1-68; Le Mau, T., Hoemann, K., Lyons, S.H., Fugate, J. M. B., Brown, E. N., Gendron, M., & Barrett, L. F.* (2021). Professional actors demonstrate variability, not stereotypical expressions, when portraying emotional states in photographs. *Nature Communications*, 12, <https://doi.org/10.1038/s41467-021-25352-6>

²³ Azari, B., Westlin, C., Satpute, A.B. *et al.* Comparing supervised and unsupervised approaches to emotion categorization in the human brain, body, and subjective experience. *Sci Rep* 10, 20284 (2020). <https://doi.org/10.1038/s41598-020-77117-8>

²⁴ Siegel, E. H., Sands, M. K., Van den Noortgate, W., Condon, P., Chang, Y., Dy, J., *Quigley, K. S., & *Barrett, L. F. (2018). [Emotion fingerprints or emotion populations? A meta-analytic investigation of autonomic features of emotion categories](#). *Psychological Bulletin*, 144(4), 343-393.

²⁵ Gendron, M., Crivelli, C., & Barrett, L. F. (2018). [Universality reconsidered: Diversity in meaning making of facial expressions](#). *Current Directions in Psychological Science*, 27, 211-219; Gendron, M., Hoemann, K., Crittenden, A. N., Mangola, S. M., Ruark, G., & Barrett, L.F. (2020). Emotion perception in Hadza hunter-gatherers. *Scientific Reports*, 10 3867. <https://doi.org/10.1038/s41598-020-60257-2>.

movements, such as a scowl, as “anger expressions” or even “emotional expressions.” Such terms confuse a movement with its (possible) emotional meaning. Many reports, both peer-reviewed and from industry, claim that emotion AI technology can accurately detect emotions. This is not the case. Under optimal conditions, such technology can detect facial *movements*, but the emotional *meanings* of these movements is incorrectly assumed rather than tested.

- A similar pattern of findings exists for measures of the autonomic nervous system and brain. In an individual study, certain patterns of signals might distinguish one emotion from another, but these patterns are not reliable (do not replicate) across different statistical methods and studies.^{23,24}
- Facial movements, vocalizations, and gestures have significant cultural differences.²⁵
- Using emotion stereotypes to infer emotions also increases the likelihood of racial bias from emotion AI technology.²⁶
- Even humans do not “recognize” or “detect” emotions in one another. Rather, people make educated guesses based on context, including the immediate situation, the state of their own bodies, their own past learning history, and their cultural learning. This means that in machine learning, third-party labels that are applied to training data are inferences, not objective “readings.” When “emotion AI” algorithms are evaluated for their ability to predict with consistency relative to human inferences, high values do not reflect the objective accuracy or validity of the algorithm to detect an emotional state.

Monitoring techniques involving many different signals (more than just two or three), known as multimodal monitoring, may hold more promise for emotion inference, provided ML algorithms model and predict patterns *within a given individual* over time (e.g., ²⁷), search for *multiple patterns* for each emotion category (e.g., ²⁸), and then examine whether any of the patterns predict across individuals and situations. Robust and generalizable inferences will require many signals collected simultaneously for the same person across many contexts, with their active and willing participation. Algorithms for affective inferences in certain circumstances, e.g., sleepiness during driving, may hold more promise, in part because the training data can be labeled objectively (e.g., did the person fall asleep or not).

²⁶ https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3281765

²⁷ Hoemann, K., Khan, Z., Feldman, M.J. *et al.* Context-aware experience sampling reveals the scale of variation in affective experience. *Sci Rep* 10, 12459 (2020). <https://doi.org/10.1038/s41598-020-69180-y>

²⁸ Khalaf, A., Nabian, M., Fan, M., Yin, Y., Wormwood, J., Siegel, E., Quigley, K. S., Barrett, L. F., Akcakaya, M., Chou, C-A., & Ostadabbas, S. (2020). Analysis of multimodal physiological signals within and between individuals to predict psychological challenge vs. threat. *Expert Systems with Applications*, 140, <https://doi.org/10.1016/j.eswa.2019.112890>.