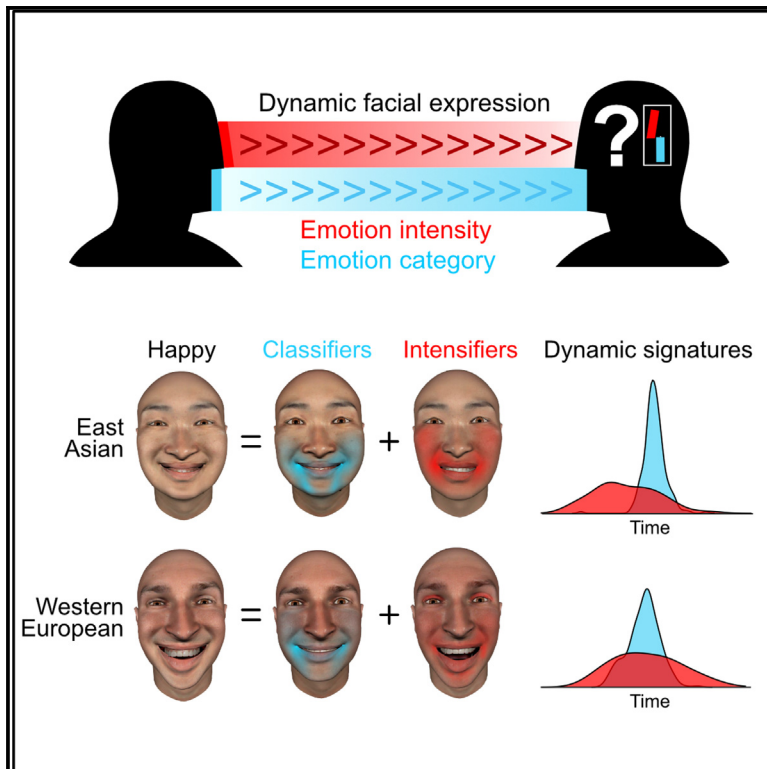# Cultural facial expressions dynamically convey emotion category and intensity information

Graphical abstract

Authors

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In brief

Chen et al. examine how facial expressions dynamically represent emotion category and intensity information. Using a perception-based data-driven method and information-theoretic analyses, they reveal, in two distinct cultures, that facial expressions represent emotion and intensity information using a specific compositional dynamic structure.

Highlights

- Emotion categories and intensity are represented by specific facial movements

- Emotion classifier facial movements are highly distinct; intensifiers are not

- Emotion classifiers and intensifiers have distinct temporal signatures

- Cultural variance in facial signals may impact cross-cultural communication

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Report

Cultural facial expressions dynamically convey emotion category and intensity information

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SUMMARY

Communicating emotional intensity plays a vital ecological role because it provides valuable information about the nature and likelihood of the sender's behavior.[1–3] For example, attack often follows signals of intense aggression if receivers fail to retreat.[4,5] Humans regularly use facial expressions to communicate such information.[6–11] Yet how this complex signaling task is achieved remains unknown. We addressed this question using a perception-based, data-driven method to mathematically model the specific facial movements that receivers use to classify the six basic emotions—"happy," "surprise," "fear," "disgust," "anger," and "sad"—and judge their intensity in two distinct cultures (East Asian, Western European; total n = 120). In both cultures, receivers expected facial expressions to dynamically represent emotion category and intensity information over time, using a multi-component compositional signaling structure. Specifically, emotion intensifiers peaked earlier or later than emotion classifiers and represented intensity using amplitude variations. Emotion intensifiers are also more similar across emotions than classifiers are, suggesting a latent broad-plus-specific signaling structure. Cross-cultural analysis further revealed similarities and differences in expectations that could impact cross-cultural communication. Specifically, East Asian and Western European receivers have similar expectations about which facial movements represent high intensity for threat-related emotions, such as "anger," "disgust," and "fear," but differ on those that represent low threat emotions, such as happiness and sadness. Together, our results provide new insights into the intricate processes by which facial expressions can achieve complex dynamic signaling tasks by revealing the rich information embedded in facial expressions.

RESULTS AND DISCUSSION

In human societies, communicating emotions and their intensity is often achieved using the information-rich, dynamic signals of facial expressions.[6,8,10,11] For example, different smiles distinguish contentment from delight,[7,12,13] while different snarls distinguish irritation from fury[14] (see also Bachorowski et al.[15] and Scherer et al.[16] for vocal expressions and Dael et al.[17] and Wallbott[18] for body movements). Yet, how facial expressions achieve the complex task of dynamically conveying emotion category and intensity information simultaneously remains unknown. Existing knowledge suggests that, as multi-component signals, facial expressions could represent such information using specific compositions of different facial movements (called action units [AUs][19]) as emotion classifiers and emotion intensifiers, as illustrated in Figure 1A. For example, to communicate

the emotion message "I am very happy," the sender would encode it in a dynamic facial expression composed of different facial movements (i.e., AUs): cheek raising (cheek raiser, AU6, in red) and smiling (lip corner puller, AU12, in blue; color saturation represents AU amplitude over time). When communication is successful, the receiver accurately decodes the message "they are very happy" from the facial expression signal by comparing it with their prior knowledge (represented by the color-coded signal in the receiver's mind). Thus, here, the smile (lip corner puller, AU12) elicited in the receiver the perception of the emotion "happy," while the cheek raiser (cheek raiser, AU6 in red) elicited the perception of "strong" intensity.[7,12,20–24] In addition, specific temporal features—such as when facial movements are activated and how strongly they are activated—could also contribute to communicating emotion intensity (see Hess et al.,[13] Nowicki and Carton,[25] Orgeta and
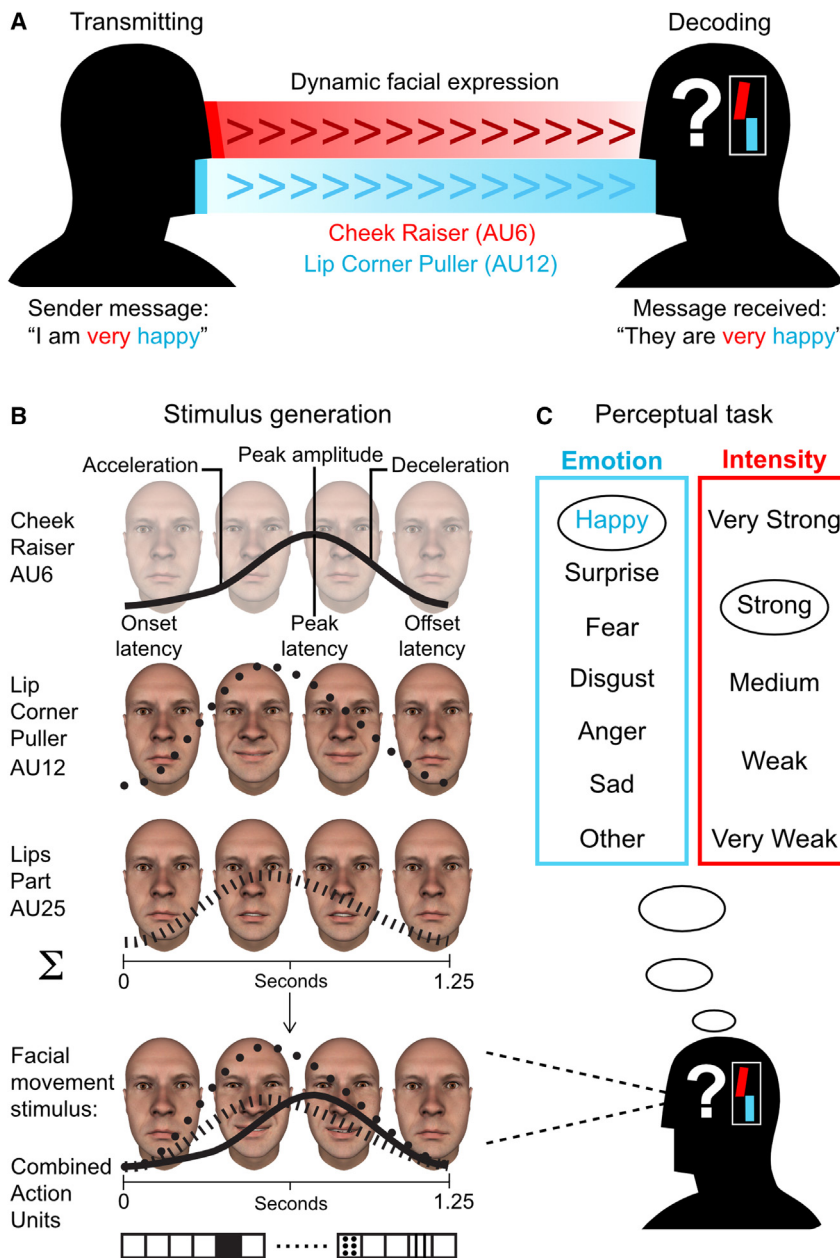
Figure 1. Illustration of communication framework and data-driven method used to model the facial movements that represent emotion and intensity

(A) General framework of facial expression communication. To communicate the emotion message "I am very happy," the sender encodes it in a dynamic facial expression signal—here, the signal comprises two facial movements (i.e., action units [AUs][19]): cheek raiser (cheek raiser, AU6 in red) and smiling (lip corner puller, AU12, in blue; color saturation represents peak amplitude over time). Successful communication relies on mutual expectations of social signals (here, facial expressions) between the sender and receiver. Here, the receiver accurately decodes the message, "they are very happy," from the dynamic signal using their prior knowledge (represented by the color-coded signals in the receiver's mind). Specifically, the receiver perceived the emotion category "happy" based on lip corner puller (AU12) and perceived "strong" emotion intensity based on cheek raiser (AU6).

(B) Stimulus generation. On each experimental trial, we sampled a random combination of facial movements (i.e., AUs, median = 3 AUs across trials) from a core set of 41 AUs and assigned a random movement to each AU using 6 temporal parameters (see labels illustrating the solid black curve). In this illustrative trial, three AUs are randomly selected—cheek raiser (AU6), lip corner puller (AU12), and lips part (AU25)—and each is activated with a random movement (see solid, dotted, and dashed curves representing each AU). The AUs are then combined to produce a photorealistic facial animation, shown here as four snapshots across time (see bottom row of faces; see also Video S1 for another illustrative stimulus). The resulting facial animation is shown below as four snapshots across time; the vector represents the three AUs randomly sampled in this example trial.

(C) Perceptual task. The receiver classifies the facial expression stimulus as one of the six emotions—"happy," "surprise," "fear," "disgust," "anger," or "sad" (blue box)—and rates its intensity on a 5-point scale from "very weak" to "very strong" (red box)—only if they perceived that the facial animation represents that emotion and intensity to the receiver, otherwise selecting "other." Here, this receiver perceived this facial expression stimulus as representing "happy" at "strong" intensity (see ellipses). Each receiver (60 Western European, 60 East Asian) completed 2,400 such trials with all facial expressions displayed on same-ethnicity male and female face identities.

Phillips,[26] and Biele and Grabowska[27] for smiles). Finally, culture-specific values and preferences often lead to different interpretations of intense facial expressions of emotion,[28–32] suggesting differences in how emotion intensity is communicated across cultures.

Here, we addressed the ecologically important question of how facial expressions represent emotions and their intensity by modeling the dynamic compositions of facial movements that represent the six basic emotions—"happy," "surprise," "fear," "disgust," "anger," and "sad"—and their intensity in two cultures with known differences in facial expression perception—Western

European and East Asian.[29,33–35] Specifically, we modeled these signals using the perceptual expectations of receivers because understanding any system of communication fundamentally relies on explaining what specific signals drive the receivers' perceptual responses,[9,36–38] thus reflecting the symbiotic relationship between signal production and perception.[4,6,39–43] We used an established approach[14,33,34,44–48] that combines classic reverse correlation methods used in ethology,[39] vision science,[49,50] neuroscience,[51–53] and engineering[36,54–56] with a modern computer-graphics-based generative model of human facial movements,[34] subjective human perception,[33,34,46] and

information-theoretic analysis tools.[57] Figures 1B and 1C illustrates the approach.

On each experimental trial, we used a generative model of human facial movements[58] to agnostically generate a facial expression. Specifically, we pseudo-randomly sampled a biologically plausible combination of AUs from a set of 41 core AUs and assigned a random movement to each AU (see Figure 1B and stimuli and procedure, STAR Methods). The receiver viewed the random facial animation and classified it as one of the six basic emotions—"happy," "surprise," "fear," "disgust," "anger," or "sad"—and rated its intensity on a 5-point scale from "very weak" to "very strong" only if they perceived that the facial animation accurately represented the emotion and intensity to them. Otherwise, they selected "other." Each receiver (60 Western European, 60 East Asian, see participants, STAR Methods) completed 2,400 such trials with all facial animations displayed on same-ethnicity photorealistic face identities of real people (see stimuli and procedure, STAR Methods). Therefore, on each experimental trial, we captured the dynamic facial movements that elicit the perception of a given emotion category and its intensity—e.g., "happy" at "strong" intensity—in each individual receiver in each culture. Following the experiment, we measured the statistical relationship between the facial movements presented on each trial (i.e., the dynamic AUs) and the receiver's emotion category and intensity responses separately. using the general measure of mutual information (MI).[57,59] This analysis produced a statistically robust model of the facial movements that elicit the perception of each emotion category and its intensity for each receiver—that is, a quantitative estimate of the physical form of specific AUs and their temporal parameters based on a space of 41 AUs × 6 temporal parameters (see modeling emotion classifier and intensifier facial movements, STAR Methods). Thus, our data-driven approach can objectively and precisely characterize the facial movements that receivers use to classify emotions and judge their intensity by using the implicit prior knowledge they have developed from interacting with their environment.[36,60,61]

Emotions and their intensity are represented by specific facial movements

We used the above method to model the facial movements that communicate the six basic emotions and their intensity in two distinct cultures and validated each facial expression model (see validating emotion classifier and intensifier facial movements, STAR Methods and Figure S1B). To ensure the resulting AUs from the within-receiver analysis reflect the estimated effects in the sampled population, we computed the Bayesian estimate of population prevalence and retained for further analysis the AUs with effects observed for receiver numbers above the population prevalence threshold (see Bayesian estimate of population prevalence, STAR Methods). Figure 2A shows the composition of emotion classifier and intensifier facial movements for each emotion, using East Asian receivers as an example (Figure S1A shows both cultures).

Emotion classifiers and intensifiers have distinct dynamic signatures

Given their potentially different communicative roles, emotion classifier and intensifier signals could also have distinct dynamic signatures, such as differences in the order in which they are activated[44,62] and how strongly they are activated.[13,25–27] To test this, we first analyzed the dynamics of the classifier and intensifier facial movements separately for each of the six emotions and each culture (see temporal analysis of emotion classifier and intensifier facial movements, STAR Methods). Figure 2B shows the results using East Asian receivers as an example (Figure S2 shows both cultures). For each emotion, color-coded plots on the left show the estimated distribution of peak amplitude times of emotion classifiers (blue) and intensifiers (red) across time. Comparison of their distributions showed statistically significant differences (p < 0.05 for all emotions and both cultures, except "sad" in East Asian culture; see Figure S2). Next, we examined the relationship between the peak amplitude of emotion classifiers and intensifiers and the receivers' emotion intensity judgments (see relationship between facial movement amplitude and emotion intensity judgments, STAR Methods and Table S2). Figure 2B shows the results using boxplots, with individual points representing individual receivers. Results show that emotion intensifier amplitudes are statistically significantly more strongly associated with emotion intensity judgments than emotion classifier amplitudes are (p < 0.05 for all emotions and both cultures, except "sad" for Western European receivers; see Table S2). Thus, in line with existing accounts of general communication,[4,5,63,64] our results show that, in each culture, receivers expect facial expressions of emotion to represent emotion categories and their intensity, using a multicomponent signal that has a distinctive temporal signature and latent structure for broad and specific signaling.

Emotion classifier facial movements are more distinct than emotion intensifiers

Across emotions, a visual inspection of Figure 2A suggests that emotion classifier facial movements are more distinct than emotion intensifiers. For example, East Asian receivers classify the emotions of "surprise," "fear," and "anger" according to different facial movements—i.e., eyebrow raising (inner-outer brow raising, AU1-2), lip stretching (lip stretcher, AU20), and lip raising (upper lip raiser, AU10), respectively—but perceive their high intensity using similar facial movements, such as wide-open eyes (upper lid raiser, AU5) and mouth gaping (mouth stretch, AU27). Formal analyses confirmed this observation (see signal distinctiveness of classifier and intensifier facial movements across emotions, STAR Methods). Figure 3 shows the results. In Figure 3A, the color-coded matrix on the left shows the percentage of shared AUs across each pair of emotions. Higher color saturation indicates more similarity (see color bar to right; exact percentages are shown in each square). Boxplots on the right show that the average similarity of emotion intensifiers across emotions is statistically significantly higher than that of emotion classifiers (p < 0.05, two-sample t test). Figure 3B shows examples of AUs that intensify several emotions—for example, in Western receivers, the wide-open eyes (upper lid raiser, AU5) and gaping mouth (mouth stretch, AU27) intensify both "surprise" and "fear." In Figure 3C, red squares indicate the emotions that each AU intensifies, with the total number of emotions shown on the right. For example, for East Asian receivers, lip pulling with cheek raising (lip corner puller-cheek raiser, AU12-6) intensifies five of the six emotions (i.e., "happy," "surprise," "fear," "disgust," and "sad"). Thus, our results show

A Emotion classifiers and intensifiers

Classifiers   Intensifiers

Happy

Surprise

Fear

Disgust

Anger

Sad

No.
receivers   0   58   0   50

B Dynamic signatures: timing & amplitude

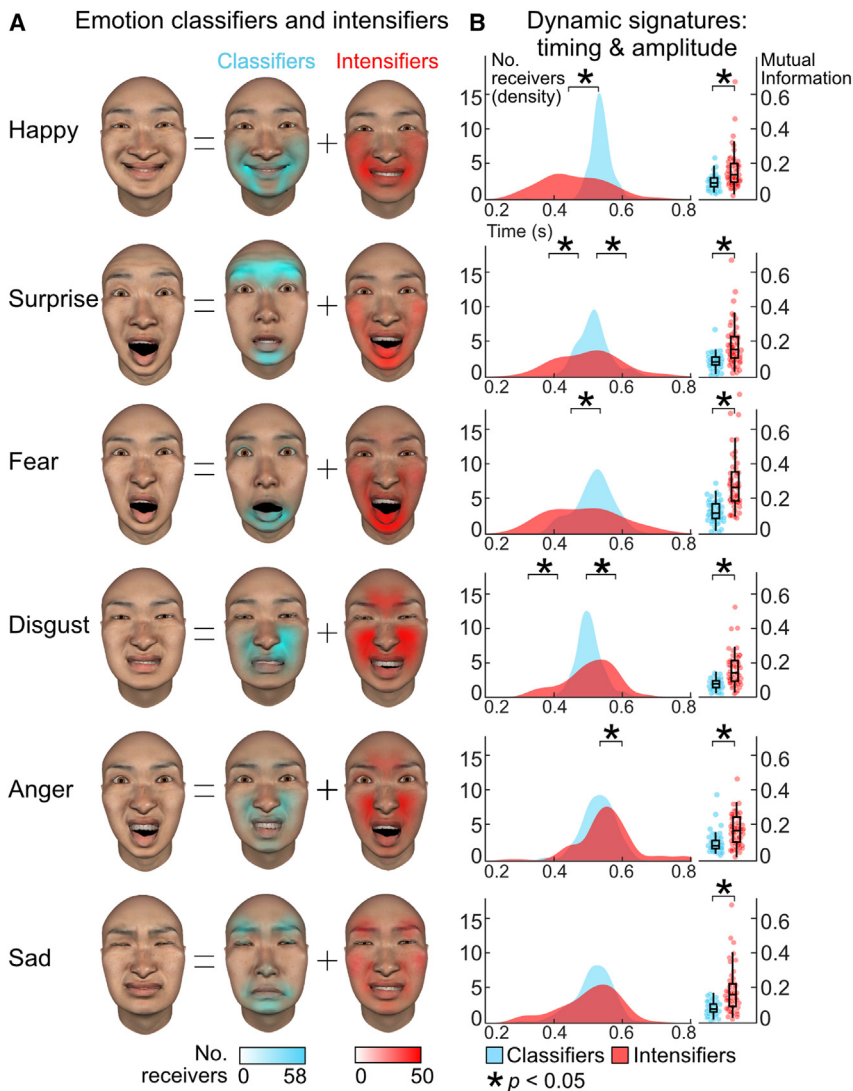□ Classifiers ■ Intensifiers
✱ p < 0.05

Figure 2. Facial expressions are composed of emotion classifiers and intensifiers

(A) Emotion classifiers and intensifiers. Color-coded face maps show the composition of emotion classifier (blue) and intensifier (red) facial movements for each emotion, using East Asian receivers as an example (see Figure S1 for both cultures). Color saturation shows the number of receivers showing the effect (see color bar below; see modeling emotion classifier and intensifier facial movements, STAR Methods). For example, "anger" is classified using lip raising (upper lip raiser, AU10) and intensified using snarling (nose wrinkle, AU9), wide-open eyes (upper lid raiser, AU5), and mouth gaping (mouth stretch, AU27).

(B) Dynamic signatures: timing and amplitude. Color-coded plots show the distribution of emotion classifiers (blue) and intensifiers (red) across time for each emotion. Distribution height represents the kernel density estimation of the number of receivers at each time point (see Figure S2 for individual data points and both cultures). Asterisks indicate a statistically significant difference (p < 0.05; see more details in Figure S2). Results show that emotion classifiers and intensifiers reach their peak amplitude at significantly different times (see temporal analysis of emotion classifier and intensifier facial movements, STAR Methods). Color-coded points and boxplots to the right show the relationship between the amplitude of emotion classifiers (blue) or intensifiers (red) and emotion intensity judgments, measured using mutual information (MI). Each point represents individual receivers, averaged across all classifiers or intensifiers. Boxplots show the distribution of MI values across receivers, for classifiers and intensifiers separately. Asterisks indicate a statistically significant difference (p < 0.05, see more details in Table S2). Results show that the amplitude of emotion intensifiers has a stronger relationship with emotion intensity judgments than the amplitude of emotion classifiers do (see relationship between facial movement amplitude and emotion intensity judgments, STAR Methods).
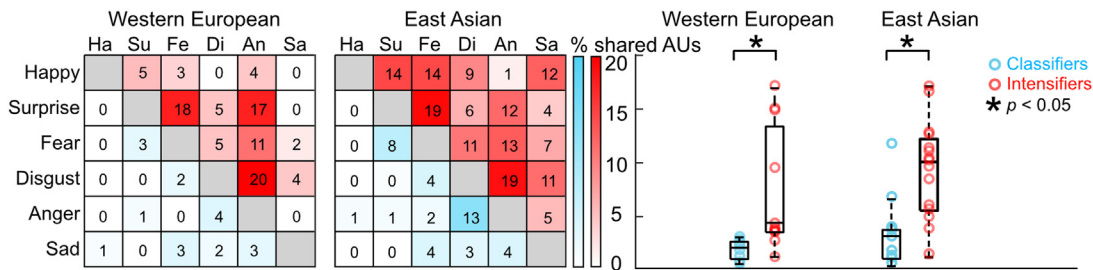
that, in both cultures, emotion classifier facial movements are more distinct across emotions than emotion intensifiers are. This suggests that they could play different communicative roles, with classifiers representing finer-grained emotion categories that enable precise adaptive action while intensifiers represent broader, attention-grabbing information that could quickly signal potential threats and trigger avoidance behaviors.[20,63–65]

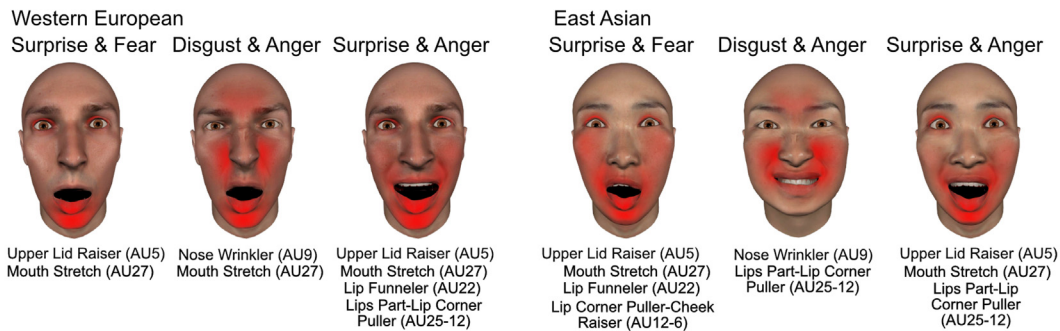### Emotion classifier and intensifier facial movements vary across cultures

In line with current knowledge of cultural variance in facial expressions,[9,10,33–35,66,67] a visual inspection of our results suggests that emotion classifiers and intensifiers might differ across cultures, which could impact cross-cultural communication. To test this, we compared the facial expression dynamic temporal signatures across cultures using a Bayesian classifier approach. Specifically, we trained naive Bayesian classifiers to classify either the six emotion categories or high intensity for each emotion, using the classifier and intensifier facial movements

from each culture. We applied this procedure both for within-culture and cross-culture classification using a half-split method (see cross-cultural classification of emotion and intensity, STAR Methods). Figure 4 shows the results using one example train-test set (see also Figure S3A). For each emotion, color-coded lines (dashed represents cross-culture results; solid represents within-culture results for comparison) show the average (mean) Bayesian classifier performance for the emotion category (blue) and its high intensity (red) at each time point of the unfolding dynamics of facial movements (x axis). Asterisks and vertical lines indicate when cross-cultural accuracy is significantly lower than within-culture accuracy. Overall, results show that cross-culture classification accuracy is lower than the within-culture classifications—for example, "happy," "surprise," and "sad" are classified accurately across cultures but their intensity is not. The opposite pattern is observed for "anger"—its intensity is classified accurately across cultures, but the emotion is not (see Figure S3B for specific confusions). "Disgust" and "fear" show an overall lower cross-cultural accuracy.

A Similarity of classifiers and intensifiers across emotions

B Examples of shared intensifiers

Western European

Surprise & Fear — Upper Lid Raiser (AU5) Mouth Stretch (AU27)

Disgust & Anger — Nose Wrinkler (AU9) Mouth Stretch (AU27)

Surprise & Anger — Upper Lid Raiser (AU5) Mouth Stretch (AU27) Lip Funneler (AU22) Lips Part-Lip Corner Puller (AU25-12)

East Asian

Surprise & Fear — Upper Lid Raiser (AU5) Mouth Stretch (AU27) Lip Funneler (AU22) Lip Corner Puller-Cheek Raiser (AU12-6)

Disgust & Anger — Nose Wrinkler (AU9) Lips Part-Lip Corner Puller (AU25-12)

Surprise & Anger — Upper Lid Raiser (AU5) Mouth Stretch (AU27) Lips Part-Lip Corner Puller (AU25-12)

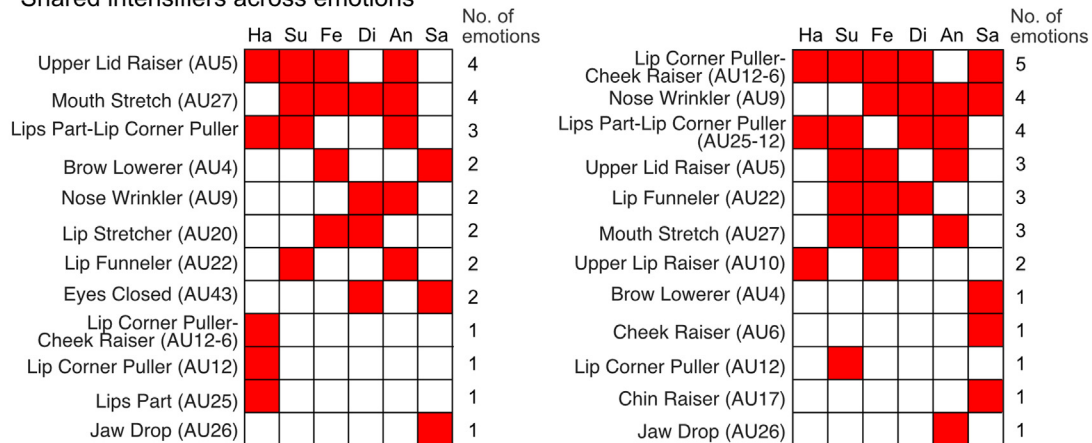## C Shared intensifiers across emotions

Figure 3. Similarity of classifiers and intensifiers across emotions

(A) For each culture, the color-coded matrix shows the percentage of emotion classifiers (blue) and intensifiers (red) that are shared across each emotion pair. Higher color saturation indicates more similarity (see color bar next to the matrices); exact percentages are shown in each square. Color-coded circles and boxplots to the right show the data aggregated across emotion pairs; individual circle represents each emotion pair as shown in the matrix. Asterisks indicate a statistically significant difference. Results show that emotion intensifiers are significantly more similar across emotions than classifiers are ($p < 0.05$, two-sample t test, see signal distinctiveness of classifier and intensifier facial movements across emotions, STAR Methods).

(B) Examples of shared intensifiers. For each culture, face maps show examples of intensifier AUs (labels below) that are shared across emotion pairs. For example, for East Asian receivers, the wide-open eyes (upper lid raiser, AU5), gaping mouth (mouth stretch, AU27), and lip pulling (lips part-lip corner puller, AU25-12) intensify both "surprise" and "anger."

(C) Shared intensifiers across emotions. For each culture, red squares in the matrix show the emotion(s) that each AU intensifies. The total number of emotions is shown on the right. Intensifiers are ranked from the highest to lowest number of emotions. For example, for Western receivers, the wide-open eyes (upper lid raiser, AU5) and gaping mouth (mouth stretch, AU27) intensify 4 out of 6 emotions. For East Asian receivers, lip pulling with cheek raising (lip corner puller-cheek raiser, AU12-6), nose wrinkling (nose wrinkler, AU9), and lip pulling with open mouth (lips part-lip corner puller, AU12-25) each intensifies at least 4 emotions.

To identify the specific facial movements that drive this performance, we used a leave-one-out approach (see cross-cultural classification of emotion and intensity, STAR Methods). In Figure 4, color-coded face maps show the results (see also Table S3). For example, "sad" is classified accurately across cultures based on culturally shared emotion classifier facial
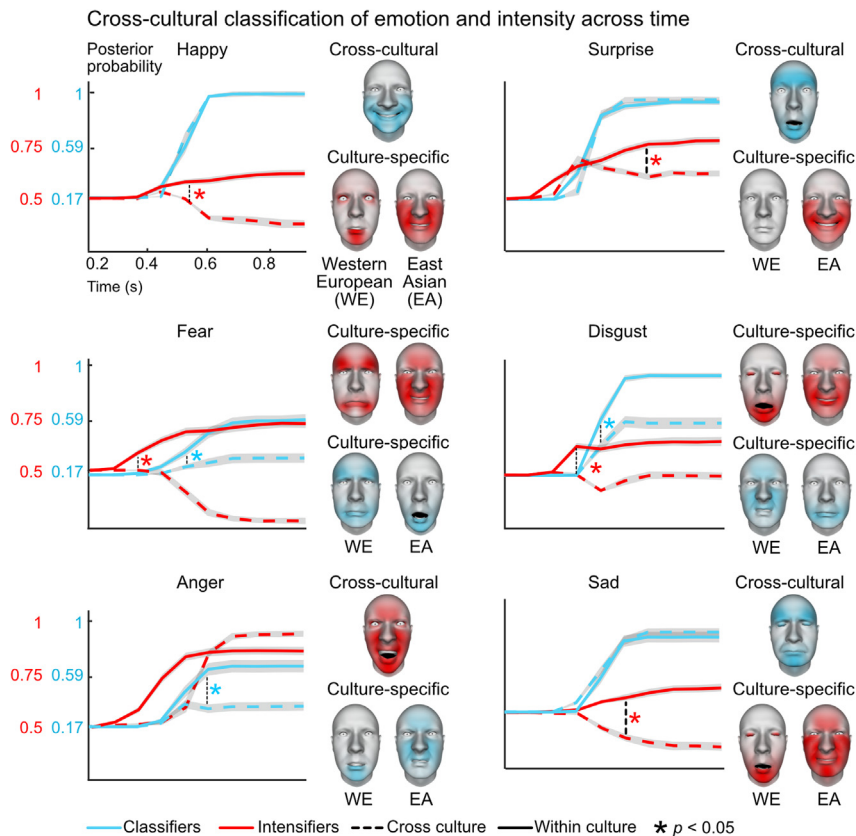
Figure 4. Cross-cultural classification of emotion and intensity across time
Each line plot shows the average (mean) Bayesian classifier performance (i.e., posterior probability) over time for the emotion category (blue) and intensity (red; see legend below). Dashed lines represent cross-culture results; solid lines represent within-culture results for comparison (see also Figure S3). Shaded areas show the standard error of the mean (SEM) across the test samples. Asterisks and vertical lines show when cross-cultural accuracy is statistically significantly lower compared with within-culture performance (p < 0.05; see more details in cross-cultural classification of emotion and intensity, STAR Methods). Face maps to the right show the AUs that drive high cross-cultural accuracy ("cross-cultural") or those contribute to low cross-cultural accuracy ("culture-specific"). For example, "sad" is classified accurately across cultures based on culturally shared emotion classifiers, brow lowering (brow lowerer, AU4), and lip pursing (chin raiser, AU17, lip pressor, AU24), whereas its intensity is misclassified based on culture-specific intensifiers (e.g., Western European: mouth opening, jaw drop, AU26; East Asian: cheek raising (cheek raiser, AU6); see Table S3 for AU results).

movements, brow lowering (e.g., brow lowerer, AU4) and chin raising (chin raiser, AU17). However, its intensity is misclassified due to culture-specific emotion intensifiers (e.g., Western European: eyes closed, AU43 and jaw drop, AU26; East Asian: lip corner puller-cheek raiser, AU12-6 and nose wrinkler, AU9). In contrast, "anger" is misclassified based on culture-specific emotion classifiers (e.g., Western European: lower lip depressor, AU16; East Asian: upper lip raiser left/right, AU10L/R). However, its intensity is classified accurately based on culturally shared emotion intensifiers (e.g., upper lid raiser, AU5; nose wrinkler, AU9; mouth stretch, AU27). Our results reveal systematic cultural similarities and differences in the facial movements that represent emotion categories and their intensity. This suggests that emotion communication may be less nuanced across cultures than within culture.

Conclusions and future directions
We aimed to understand how facial expressions achieve the complex task of dynamically signaling multi-layered emotion messages—i.e., emotion categories and their intensity. Using a perception-based, data-driven approach within a communication theory framework, we show that, in two distinct cultures, receivers expect facial expressions of emotion to comprise multi-component signals that play two distinct communicative roles—representing finer-grained emotion information (i.e., classifiers) and coarser-grained intensity information (i.e., intensifiers)—with distinct dynamic signatures. Further, cultural variance in these expectations suggests that communicating emotions across cultures could be less nuanced than within a culture.

Together, our results provide new insights into understanding how facial expressions dynamically represent complex emotion information to receivers in different cultures and raise new questions about how the brain dynamically parses these complex signals. We expand on these points below.

In each culture, emotion classifier facial movements are more distinct across emotions whereas emotion intensifiers are more similar.[23,65] This suggests that specific facial movements represent finer-grained emotion category information while others represent coarser-grained intensity information.[44,47] These results provide further support for theories proposing that facial expressions represent both specific and broad emotion information.[9,47,65,66,68] Further, these results address the seeming paradox of why some facial expressions of emotion comprise similar facial movements, which should reduce signal specificity.[9] Rather, our results show that such facial movements likely play the different role of representing broad intensity information while other more distinct facial movements represent emotion categories. Relatedly, because our results quantify the strength of the statistical relationship between a specific facial movement and emotion category or intensity perception, this provides an effect size of the causal relationship between stimulus features and perception on the common scale of bits. Consequently, our facial expression models can be used to generate predictions of emotion categorizations and explain the casual role of individual AUs.[48]

Receivers in each culture also expected emotion classifier and intensifier facial movements to be displayed in a particular temporal order, which largely mirrors the results of studies examining produced facial expressions in laboratory[69] and real-world settings.[70,71] Understanding the temporal dynamics of facial movements has important implications for theories of emotion

processing in relation to models of visual attention. Specifically, the human visual system is a bandwidth-limited information channel in which attention (covert and overt) "guides" the accrual of task-relevant stimulus information for categorical decision making.[72–74] Our results suggest that attention is deployed in space and time—i.e., reading out different facial movements at different time points—to guide the accrual of information. By contrast, certain events could "grab" a receiver's attention and interrupt this accrual[72]—for example, the eye whites (upper lid raiser, AU5), which are known to grab attention,[75,76] are dynamically represented in the occipito-ventral pathway before those of other facial features lower down the face.[53,77–79] Therefore, the expected temporal decoupling of emotion classifier and intensifier facial movements could reflect a symbiotic adaptation between the receiver's bandwidth-limited information channel that must accrue dynamic visual information[77,78] and the sender's transmission of a multi-component emotion message. Technological developments in facial expression analysis tools[80–82] will enable future work to precisely code these temporal dynamics in real-time production and further examine the relationship between production and perception. How these temporally distinct expressive facial features are processed in the brain is now the focus of ongoing studies.[77,83]

Cross-cultural analysis showed similarities and differences in the facial movements that receivers expect to represent emotions and their intensity. In line with existing theories,[32,35,84–86] this suggests that emotion communication could be less nuanced across cultures than within due to culture-specific accents and/or dialects in facial expressions (but see Gosselin and Larocque[87]). Further, some facial movements served different communicative roles across cultures—for example, lip corner puller-cheek raiser (AU12-6) is primarily an emotion classifier in Western European receivers but an intensifier in East Asian receivers. This suggests that the communicative function of human facial movements is not fixed,[88] highlighting the potential role of culture in shaping facial expression signals.[28,33,35] Equally, we found clear cultural similarities in facial movements—specifically, for "happy," "surprise," and "sad," and high intensity for "anger"—that could reflect the preservation of high priority threat-related messages. For example, intense "anger" is a costly-to-miss signal because it is critically related to the high likelihood of threat.[4,64] In contrast, intensity is relatively less important for low-threat emotions, such as "happy" and "sad" (but see Schmidt et al.[89]), compared with their specific emotion category information that would enable different adaptive responses.[90,91] Therefore, these results suggest that facial expressions could have evolved to preserve the communication of high priority messages across cultures using similar facial movements, possibly with biological roots.[92,93] For example, our results show that facial movements such as eye constriction and mouth gaping intensify several emotions in both cultures, mirroring existing work on cross-cultural intensifier signals.[7,12,20] Together, these results provide new insights into the cultural diversity of facial expressions and support existing theories that highlight the importance of cultural accents[9,32,33,35,94,95] and the breadth of cultural differences.[13,28,29,34,96,97]

Finally, facial expressions in the real world are typically presented alongside other sources of information—including the sender's ethnicity,[98–104] age[105–108] and sex,[109–112] their voice,[113]

gestures and body movements,[114,115] and the social and cultural context[9,116–120]—under various constraints of the communication channel, including proximal versus distal[121] and clear versus occluded[122] conditions, all of which could influence how facial expressions are produced and perceived. Future research should further investigate how the precise interplay of different sources of face information (i.e., shape, complexion, movements) contributes to emotion perception.[36,45,103,106,123,124]

In sum, by revealing the complexities of their dynamic signaling, our results show how facial expressions can perform the complex task of representing multi-component emotion messages. Together, our results provide new insights into the longstanding goal of deciphering the communicative system of human facial expressions, with implications for existing theories of emotion communication within and across cultures and the design of culturally sensitive socially interactive artificial agents.[125,126]

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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  - Signal distinctiveness of classifier and intensifier facial movements across emotions
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AUTHOR CONTRIBUTIONS

P.G.S., D.S.M., and R.E.J. designed the research; R.E.J. collected the Western European receiver data in the UK; Cheng Chen collected the East Asian receiver data in China; O.G.B.G. and P.G.S. developed the facial movement generator; Y.D. and R.A.A.I. developed the analytical tools of mutual information; Chaona Chen analyzed and interpreted the data under the supervision of R.E.J., P.G.S., and D.S.M.; Chaona Chen prepared the figures; Chaona Chen and R.E.J. wrote the paper; and P.G.S., D.S.M., Y.D., R.A.A.I., Cheng Chen, H.Y., and O.G.B.G. provided feedback on the manuscript draft.

DECLARATION OF INTERESTS

P.G.S. is on the advisory board of this *Current Biology*.

REFERENCES

1. Frijda, N.H., Ortony, A., Sonnemans, J., and Clore, G.L. (1992). The Complexity of Intensity: Issues Concerning the Structure of Emotion Intensity (Sage Publications, Inc).

2. Ortony, A., Clore, G., and Collins, A. (1988). The Cognitive Structure of Emotions (Cambridge University Press).

3. Ben-Ze'ev, A. (2001). The Subtlety of Emotions (MIT Press).

4. Bradbury, J.W., and Vehrencamp, S.L. (1998). Principles of Animal Communication (Sinauer Associates).

5. Seyfarth, R.M., and Cheney, D.L. (2003). Signalers and receivers in animal communication. Annu. Rev. Psychol. *54*, 145–173.

6. Darwin, C. (1872). The Expression of the Emotions in Man and Animals, Third Edition (Oxford University Press).

7. Messinger, D.S., Fogel, A., and Dickson, K.L. (2001). All smiles are positive, but some smiles are more positive than others. Dev. Psychol. *37*, 642–653.

8. Andrew, R.J. (1963). Evolution of facial expression. Science *142*, 1034–1041.

9. Barrett, L.F., Adolphs, R., Marsella, S., Martinez, A.M., and Pollak, S.D. (2019). Emotional expressions reconsidered: challenges to inferring emotion from human facial movements. Psychol. Sci. Public Interest *20*, 1–68.

10. Fridlund, A.J. (2014). Human Facial Expression: An Evolutionary View (Academic Press).

11. Russell, J.A., Bachorowski, J.A., and Fernández-Dols, J.M. (2003). Facial and vocal expressions of emotion. Annu. Rev. Psychol. *54*, 329–349.

12. Ekman, P., Davidson, R.J., and Friesen, W.V. (1990). The Duchenne smile: emotional expression and brain physiology. II. J. Pers. Soc. Psychol. *58*, 342–353.

13. Hess, U., Blairy, S., and Kleck, R.E. (1997). The intensity of emotional facial expressions and decoding accuracy. J. Nonverbal Behav. *21*, 241–257.

14. Jack, R.E., Sun, W., Delis, I., Garrod, O.G., and Schyns, P.G. (2016). Four not six: revealing culturally common facial expressions of emotion. J. Exp. Psychol. Gen. *145*, 708–730.

15. Bachorowski, J.-A. (1999). Vocal expression and perception of emotion. Curr. Dir. Psychol. Sci. *8*, 53–57.

16. Scherer, K.R., Johnstone, T., and Klasmeyer, G. (2003). Vocal Expression of Emotion (Oxford University Press).

17. Dael, N., Mortillaro, M., and Scherer, K.R. (2012). Emotion expression in body action and posture. Emotion *12*, 1085–1101.

18. Wallbott, H.G. (1998). Bodily expression of emotion. Eur. J. Soc. Psychol. *28*, 879–896.

19. Ekman, P., and Friesen, W.V. (1978). Manual for the Facial Action Coding System (Consulting Psychologists Press).

20. Messinger, D.S., Mattson, W.I., Mahoor, M.H., and Cohn, J.F. (2012). The eyes have it: making positive expressions more positive and negative expressions more negative. Emotion *12*, 430–436.

21. Girard, J.M., Shandar, G., Liu, Z., Cohn, J.F., Yin, L., and Morency, L.P. (2019). Reconsidering the Duchenne smile: indicator of positive emotion or artifact of smile intensity? In 2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII) (IEEE), pp. 594–599.

22. Messinger, D.S., Cassel, T.D., Acosta, S.I., Ambadar, Z., and Cohn, J.F. (2008). Infant smiling dynamics and perceived positive emotion. J. Nonverbal Behav. *32*, 133–155.

23. Malek, N., Messinger, D., Gao, A.Y.L., Krumhuber, E., Mattson, W., Joober, R., Tabbane, K., and Martinez-Trujillo, J.C. (2019). Generalizing Duchenne to sad expressions with binocular rivalry and perception ratings. Emotion *19*, 234–241.

24. Miller, E.J., Krumhuber, E.G., and Dawel, A. (2022). Observers perceive the Duchenne marker as signaling only intensity for sad expressions, not genuine emotion. Emotion *22*, 907–919.

25. Nowicki, S., Jr., and Carton, J. (1993). The measurement of emotional intensity from facial expressions. J. Soc. Psychol. *133*, 749–750.

26. Orgeta, V., and Phillips, L.H. (2008). Effects of age and emotional intensity on the recognition of facial emotion. Exp. Aging Res. *34*, 63–79.

27. Biele, C., and Grabowska, A. (2006). Sex differences in perception of emotion intensity in dynamic and static facial expressions. Exp. Brain Res. *171*, 1–6.

28. Tsai, J.L., Blevins, E., Bencharit, L.Z., Chim, L., Fung, H.H., and Yeung, D.Y. (2019). Cultural variation in social judgments of smiles: the role of ideal affect. J. Pers. Soc. Psychol. *116*, 966–988.

29. Matsumoto, D., and Ekman, P. (1989). American-Japanese cultural differences in intensity ratings of facial expressions of emotion. Motiv. Emot. *13*, 143–157.

30. Engelmann, J.B., and Pogosyan, M. (2013). Emotion perception across cultures: the role of cognitive mechanisms. Front. Psychol. *4*, 118.

31. Krys, K., -Melanie Vauclair, C.-M., Capaldi, C.A., Lun, V.M.-C., Bond, M.H., Domínguez-Espinosa, A., Torres, C., Lipp, O.V., Manickam, L.S.S., Xing, C., et al. (2016). Be careful where you smile: culture shapes judgments of intelligence and honesty of smiling individuals. J. Nonverbal Behav. *40*, 101–116.

32. Hess, U., Beaupré, M.G., and Cheung, N. (2002). Who to whom and why–cultural differences and similarities in the function of smiles. In An Empirical Reflection on The Smile, *4* (The Edwin Mellen), p. 187.

33. Jack, R.E., Garrod, O.G.B., Yu, H., Caldara, R., and Schyns, P.G. (2012). Facial expressions of emotion are not culturally universal. Proc. Natl. Acad. Sci. USA *109*, 7241–7244.

34. Chen, C., Crivelli, C., Garrod, O.G.B., Schyns, P.G., Fernández-Dols, J.M., and Jack, R.E. (2018). Distinct facial expressions represent pain and pleasure across cultures. Proc. Natl. Acad. Sci. USA *115*, E10013–E10021.

35. Elfenbein, H.A. (2013). Nonverbal dialects and accents in facial expressions of emotion. Emot. Rev. *5*, 90–96.

36. Jack, R.E., and Schyns, P.G. (2017). Toward a social psychophysics of face communication. Annu. Rev. Psychol. *68*, 269–297.

37. Schyns, P.G., Zhan, J., Jack, R.E., and Ince, R.A.A. (2020). Revealing the information contents of memory within the stimulus information representation framework. Philos. Trans. R. Soc. Lond. B Biol. Sci. *375*, 20190705.

38. Krakauer, J.W., Ghazanfar, A.A., Gomez-Marin, A., MacIver, M.A., and Poeppel, D. (2017). Neuroscience needs behavior: correcting a reductionist bias. Neuron *93*, 480–490.

39. Tinbergen, N. (1948). Social releasers and the experimental method required for their study. Wilson Bull. *60*, 6–51.

40. Shannon, C.E. (2001). A mathematical theory of communication. ACM SIGMOBILE Mob. Comput. Commun. Rev. *5*, 3–55.

41. Guilford, T., and Dawkins, M.S. (1993). Receiver psychology and the design of animal signals. Trends Neurosci. *16*, 430–436.

42. Edelman, G.M., and Gally, J.A. (2001). Degeneracy and complexity in biological systems. Proc. Natl. Acad. Sci. USA *98*, 13763–13768.

43. McGregor, P.K. (2005). Animal Communication Networks (Cambridge University Press).

44. Jack, R.E., Garrod, O.G.B., and Schyns, P.G. (2014). Dynamic facial expressions of emotion transmit an evolving hierarchy of signals over time. Curr. Biol. *24*, 187–192.

45. Gill, D., Garrod, O.G., Jack, R.E., and Schyns, P.G. (2014). Facial movements strategically camouflage involuntary social signals of face morphology. Psychol. Sci. *25*, 1079–1086.

46. Rychlowska, M., Jack, R.E., Garrod, O.G.B., Schyns, P.G., Martin, J.D., and Niedenthal, P.M. (2017). Functional smiles: tools for love, sympathy, and war. Psychol. Sci. *28*, 1259–1270.

47. Liu, M., Duan, Y., Ince, R.A.A., Chen, C., Garrod, O.G.B., Schyns, P.G., and Jack, R.E. (2022). Facial expressions elicit multiplexed perceptions of emotion categories and dimensions. Curr. Biol. *32*, 200–209.e6.

48. Snoek, L., Jack, R.E., Schyns, P.G., Garrod, O.G.B., Mittenbühler, M., Chen, C., Oosterwijk, S., and Scholte, H.S. (2023). Testing, explaining, and exploring models of facial expressions of emotions. Sci. Adv. *9*, eabq8421.

49. Mangini, M.C., and Biederman, I. (2004). Making the ineffable explicit: estimating the information employed for face classifications. Cogn. Sci. *28*, 209–226.

50. Murray, R.F. (2011). Classification images: a review. J. Vis. *11*, 2.

51. Hubel, D., and Wiesel, T.N. (1959). Receptive fields of single neurons in the cat's striate visual cortex. J. Physiol. *148*, 574–591.

52. Nishimoto, S., Ishida, T., and Ohzawa, I. (2006). Receptive field properties of neurons in the early visual cortex revealed by local spectral reverse correlation. J. Neurosci. *26*, 3269–3280.

53. Zhan, J., Ince, R.A.A., Van Rijsbergen, N., and Schyns, P.G. (2019). Dynamic construction of reduced representations in the brain for perceptual decision behavior. Curr. Biol. *29*, 319–326.e4.

54. Thompson, W.B., Owen, J.C., Germain, H.de S., Stark, S.R., and Henderson, T.C. (1999). Feature-based reverse engineering of mechanical parts. IEEE Trans. Robot. Autom. *15*, 57–66.

55. Volterra, V., and Whittaker, E.T. (1959). Theory of Functionals and of Integral and Integro-Differential Equations (Dover Publications).

56. Wiener, N. (1958). Nonlinear Problems in Random Theory Cambridge (The Massachusetts Institute of Technology Press).

57. Ince, R.A., Giordano, B.L., Kayser, C., Rousselet, G.A., Gross, J., and Schyns, P.G. (2017). A statistical framework for neuroimaging data analysis based on mutual information estimated via a gaussian copula. Hum. Brain Mapp. *38*, 1541–1573.

58. Yu, H., Garrod, O.G.B., and Schyns, P.G. (2012). Perception-driven facial expression synthesis. Comput. Graphics *36*, 152–162.

59. Cover, T.M., and Thomas, J.A. (2012). Elements of Information Theory (John Wiley & Sons).

60. Jack, R.E., Crivelli, C., and Wheatley, T. (2018). Data-driven methods to diversify knowledge of human psychology. Trends Cogn. Sci. *22*, 1–5.

61. Jack, R.E., and Schyns, P.G. (2015). The human face as a dynamic tool for social communication. Curr. Biol. *25*, R621–R634.

62. Delis, I., Jack, R., Garrod, O., Panzeri, S., and Schyns, P. (2014). Characterizing the manifolds of dynamic facial expression categorization. J. Vis. *14*, 1384.

63. Endler, J.A. (1993). Some general comments on the evolution and design of animal communication systems. Philos. Trans. R. Soc. Lond. B Biol. Sci. *340*, 215–225.

64. Guilford, T., and Dawkins, M.S. (1991). Receiver psychology and the evolution of animal signals. Anim. Behav. *42*, 1–14.

65. Messinger, D.S. (2002). Positive and negative: infant facial expressions and emotions. Curr. Dir. Psychol. Sci. *11*, 1–6.

66. Ekman, P. (2006). Darwin and Facial Expression: A Century of Research (The Institute for the Study of Human Knowledge).

67. Chen, C., and Jack, R.E. (2017). Discovering cultural differences (and similarities) in facial expressions of emotion. Curr. Opin. Psychol. *17*, 61–66.

68. Fujimura, T., Matsuda, Y.T., Katahira, K., Okada, M., and Okanoya, K. (2012). Categorical and dimensional perceptions in decoding emotional facial expressions. Cogn. Emot. *26*, 587–601.

69. Krumhuber, E.G., Skora, L., Küster, D., and Fou, L. (2017). A review of dynamic datasets for facial expression research. Emot. Rev. *9*, 280–292.

70. Jeganathan, J., Campbell, M., Hyett, M., Parker, G., and Breakspear, M. (2022). Quantifying dynamic facial expressions under naturalistic conditions. eLife *11*, e79581.

71. Bartlett, M.S., Littlewort, G., Frank, M., Lainscsek, C., Fasel, I., and Movellan, J. (2006). Fully automatic facial action recognition in spontaneous behavior. In 7th International Conference on Automatic Face and Gesture Recognition (FGR06) (IEEE), pp. 223–230.

72. Pratto, F., and John, O.P. (1991). Automatic vigilance: the attention-grabbing power of negative social information. J. Pers. Soc. Psychol. *61*, 380–391.

73. Lachter, J., Forster, K.I., and Ruthruff, E. (2004). Forty-five years after Broadbent (1958): still no identification without attention. Psychol. Rev. *111*, 880–913.

74. Smith, M.L., Cottrell, G.W., Gosselin, F., and Schyns, P.G. (2005). Transmitting and decoding facial expressions. Psychol. Sci. *16*, 184–189.

75. Jessen, S., and Grossmann, T. (2014). Unconscious discrimination of social cues from eye whites in infants. Proc. Natl. Acad. Sci. USA *111*, 16208–16213.

76. Whalen, P.J., Kagan, J., Cook, R.G., Davis, F.C., Kim, H., Polis, S., McLaren, D.G., Somerville, L.H., McLean, A.A., Maxwell, J.S., et al. (2004). Human amygdala responsivity to masked fearful eye whites. Science *306*, 2061.

77. Schyns, P.G., Petro, L.S., and Smith, M.L. (2007). Dynamics of visual information integration in the brain for categorizing facial expressions. Curr. Biol. *17*, 1580–1585.

78. Schyns, P.G., Petro, L.S., and Smith, M.L. (2009). Transmission of facial expressions of emotion co-evolved with their efficient decoding in the brain: behavioral and brain evidence. PLoS One *4*, e5625.

79. Duan, Y., Zhan, J., Gross, J., Ince, R.A.A., and Schyns, P.G. (2022). Network mechanisms of dynamic feature selection for flexible visual categorizations. Preprint at arXiv.

80. Li, S., and Deng, W. (2020). Deep facial expression recognition: a survey. IEEE Trans. Affect. Comput. *13*, 1195–1215.

81. Jacob, G.M., and Stenger, B. (2021). Facial action unit detection with transformers. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7680–7689.

82. Zhang, X., Yin, L., Cohn, J.F., Canavan, S., Reale, M., Horowitz, A., and Liu, P. (2013). A high-resolution spontaneous 3d dynamic facial expression database. In 2013 10th IEEE International Conference and

Workshops on Automatic Face and Gesture Recognition (FG) (IEEE), pp. 1–6.

83. Liu, M., van Rijsbergen, N., Garrod, O., Ince, R., Jack, R., and Schyns, P. (2021). Semantic decoding of affective face signals in the brain is temporally distinct. J. Vision *21*, 2589.

84. Elfenbein, H.A., Beaupré, M., Lévesque, M., and Hess, U. (2007). Toward a dialect theory: cultural differences in the expression and recognition of posed facial expressions. Emotion *7*, 131–146.

85. Marsh, A.A., Elfenbein, H.A., and Ambady, N. (2003). Nonverbal "accents": cultural differences in facial expressions of emotion. Psychol. Sci. *14*, 373–376.

86. Marsh, A.A., Elfenbein, H.A., and Ambady, N. (2007). Separated by a common language nonverbal accents and cultural stereotypes about Americans and Australians. J. Cross Cult. Psychol. *38*, 284–301.

87. Gosselin, P., and Larocque, C. (2000). Facial morphology and children's categorization of facial expressions of emotions: a comparison between Asian and Caucasian faces. J. Genet. Psychol. *161*, 346–358.

88. Thibault, P., Levesque, M., Gosselin, P., and Hess, U. (2012). The Duchenne marker is not a universal signal of smile authenticity - but it can be learned! Soc. Psychol. *43*, 215–221.

89. Schmidt, K., Levenstein, R., and Ambadar, Z. (2012). Intensity of smiling and attractiveness as facial signals of trustworthiness in women. Percept. Mot. Skills *114*, 964–978.

90. Baron-Cohen, S., Leslie, A.M., and Frith, U. (1985). Does the autistic child have a "theory of mind"? Cognition *21*, 37–46.

91. LeMoult, J., Joormann, J., Sherdell, L., Wright, Y., and Gotlib, I.H. (2009). Identification of emotional facial expressions following recovery from depression. J. Abnorm. Psychol. *118*, 828–833.

92. Susskind, J.M., Lee, D.H., Cusi, A., Feiman, R., Grabski, W., and Anderson, A.K. (2008). Expressing fear enhances sensory acquisition. Nat. Neurosci. *11*, 843–850.

93. Lee, D.H., Mirza, R., Flanagan, J.G., and Anderson, A.K. (2014). Optical origins of opposing facial expression actions. Psychol. Sci. *25*, 745–752.

94. Matsumoto, D. (2006). Culture and nonverbal behavior. In Handbook of Nonverbal Communication (Sage), pp. 219–235.

95. Tsai, J.L. (2007). Ideal affect: cultural causes and behavioral consequences. Perspect. Psychol. Sci. *2*, 242–259.

96. Wallraven, C., Hur, D.-C., and Shin, A. (2015). Across cultures: a cognitive and computational analysis of emotional and conversational facial expressions in Germany and Korea. In Recent Progress in Brain and Cognitive Engineering (Springer), pp. 97–108.

97. Hess, U., Blaison, C., and Kafetsios, K. (2016). Judging facial emotion expressions in context: the influence of culture and self-construal orientation. J. Nonverbal Behav. *40*, 55–64.

98. McKone, E., Dawel, A., Robbins, R.A., Shou, Y., Chen, N., and Crookes, K. (2023). Why the other-race effect matters: poor recognition of other-race faces impacts everyday social interactions. Br. J. Psychol. *114* (*Suppl 1*), 230–252.

99. Lipp, O.V., Craig, B.M., and Dat, M.C. (2015). A happy face advantage with male Caucasian faces: it depends on the company you keep. Soc. Psychol. Pers. Sci. *6*, 109–115.

100. Craig, B.M., Mallan, K.M., and Lipp, O.V. (2012). The effect of poser race on the happy categorization advantage depends on stimulus type, set size, and presentation duration. Emotion *12*, 1303–1314.

101. Hugenberg, K. (2005). Social categorization and the perception of facial affect: target race moderates the response latency advantage for happy faces. Emotion *5*, 267–276.

102. Hugenberg, K., and Bodenhausen, G.V. (2004). Ambiguity in social categorization: the role of prejudice and facial affect in race categorization. Psychol. Sci. *15*, 342–345.

103. Hedgecoth, N., Strand, N., and Adams, R.B., Jr. (2023). The intersection of race, gender/sex, and age in emotion perception from faces and bodies. In Emotion Communication by the Aging Face and Body: A Multidisciplinary View, *106* (Cambridge University Press).

104. Adams, R.B., Albohn, D.N., Hedgecoth, N., Garrido, C.O., and Adams, K.D. (2022). Angry white faces: a contradiction of racial stereotypes and emotion-resembling appearance. Affect. Sci. *3*, 46–61.

105. Van Rijsbergen, N., Jaworska, K., Rousselet, G.A., and Schyns, P.G. (2014). With age comes representational wisdom in social signals. Curr. Biol. *24*, 2792–2796.

106. Hess, U., Adams, R.B., Jr., Simard, A., Stevenson, M.T., and Kleck, R.E. (2012). Smiling and sad wrinkles: age-related changes in the face and the perception of emotions and intentions. J. Exp. Soc. Psychol. *48*, 1377–1380.

107. Fölster, M., Hess, U., and Werheid, K. (2014). Facial age affects emotional expression decoding. Front. Psychol. *5*, 30.

108. Freudenberg, M., Adams, R.B., Jr., Kleck, R.E., and Hess, U. (2015). Through a glass darkly: facial wrinkles affect our processing of emotion in the elderly. Front. Psychol. *6*, 1476.

109. Palermo, R., and Coltheart, M. (2004). Photographs of facial expression: accuracy, response times, and ratings of intensity. Behav. Res. Methods Instrum. Comput. *36*, 634–638.

110. Becker, D.V., Kenrick, D.T., Neuberg, S.L., Blackwell, K.C., and Smith, D.M. (2007). The confounded nature of angry men and happy women. J. Pers. Soc. Psychol. *92*, 179–190.

111. Hess, U., Adams, R.B., Jr., Grammer, K., and Kleck, R.E. (2009). Face gender and emotion expression: are angry women more like men? J. Vis. *9*, 19.1–19.8.

112. Craig, B.M., and Lipp, O.V. (2018). The influence of multiple social categories on emotion perception. J. Exp. Soc. Psychol. *75*, 27–35.

113. Ponsot, E., Burred, J.J., Belin, P., and Aucouturier, J.J. (2018). Cracking the social code of speech prosody using reverse correlation. Proc. Natl. Acad. Sci. USA *115*, 3972–3977.

114. Aviezer, H., Trope, Y., and Todorov, A. (2012). Body cues, not facial expressions, discriminate between intense positive and negative emotions. Science *338*, 1225–1229.

115. Noroozi, F., Corneanu, C.A., Kamińska, D., Sapiński, T., Escalera, S., and Anbarjafari, G. (2021). Survey on emotional body gesture recognition. IEEE Trans. Affect. Comput. *12*, 505–523.

116. Barrett, L.F., Mesquita, B., and Gendron, M. (2011). Context in emotion perception. Curr. Dir. Psychol. Sci. *20*, 286–290.

117. Carroll, J.M., and Russell, J.A. (1996). Do facial expressions signal specific emotions? Judging emotion from the face in context. J. Pers. Soc. Psychol. *70*, 205–218.

118. De Leersnyder, J., Boiger, M., and Mesquita, B. (2015). Cultural differences in emotions. In Emerging Trends in the Social and Behavioral Sciences: An Interdisciplinary, Searchable, and Linkable Resource (Wiley), pp. 1–15.

119. Berry, J.W. (2017). Theories and models of acculturation. In The Oxford Handbook of Acculturation and Health (Oxford University Press), pp. 15–28.

120. Mesquita, B., and Boiger, M. (2014). Emotions in context: a sociodynamic model of emotions. Emot. Rev. *6*, 298–302.

121. Smith, F.W., and Schyns, P.G. (2009). Smile through your fear and sadness: transmitting and identifying facial expression signals over a range of viewing distances. Psychol. Sci. *20*, 1202–1208.

122. Li, S.Z., Jain, A.K., Tian, Y.-L., Kanade, T., and Cohn, J.F. (2005). Facial expression analysis. In Handbook of Face Recognition (Springer), pp. 247–275.

123. Adams, R.B., Jr., Nelson, A.J., Soto, J.A., Hess, U., and Kleck, R.E. (2012). Emotion in the neutral face: a mechanism for impression formation? Cogn. Emot. *26*, 431–441.

124. Hess, U., Adams, R.B., Jr., and Kleck, R.E. (2004). Facial appearance, gender, and emotion expression. Emotion *4*, 378–388.

125. Swartout, W.R., Gratch, J., Hill, R.W., Jr., Hovy, E., Marsella, S., Rickel, J., and Traum, D. (2006). Toward virtual humans. AI Mag. *27*, 96.

126. Lee, J., and Marsella, S. (2006). Nonverbal behavior generator for embodied conversational agents. In Intelligent Virtual Agents. IVA 2006. Lecture Notes in Computer Science (Springer), pp. 243–255.

127. Ince, R.A., Paton, A.T., Kay, J.W., and Schyns, P.G. (2021). Bayesian inference of population prevalence. eLife *10*, e62461.

128. Rousselet, G.A., Pernet, C.R., and Wilcox, R.R. (2017). Beyond differences in means: robust graphical methods to compare two groups in neuroscience. Eur. J. Neurosci. *46*, 1738–1748.

129. Crivelli, C., and Fridlund, A.J. (2018). Facial displays are tools for social influence. Trends Cogn. Sci. *22*, 388–399.

130. Parkinson, B. (2005). Do facial movements express emotions or communicate motives? Pers. Soc. Psychol. Rev. *9*, 278–311.

131. Martin, J., Rychlowska, M., Wood, A., and Niedenthal, P. (2017). Smiles as multipurpose social signals. Trends Cogn. Sci. *21*, 864–877.

132. Du, S., Tao, Y., and Martinez, A.M. (2014). Compound facial expressions of emotion. Proc. Natl. Acad. Sci. USA *111*, E1454–E1462.

133. Russell, J.A. (1994). Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. Psychol. Bull. *115*, 102–141.

134. Ekman, P., Sorenson, E.R., and Friesen, W.V. (1969). Pan-cultural elements in facial displays of emotion. Science *164*, 86–88.

135. Chen, C., Garrod, O.G.B., Ince, R.A.A., Foster, M.E., Schyns, P.G., and Jack, R.E. (2020). Building culturally-valid dynamic facial expressions for a conversational virtual agent using human perception. In Proceedings of the 20th ACM International Conference on Intelligent Virtual Agents, pp. 1–3.

136. Poldrack, R.A. (2017). Precision neuroscience: dense sampling of individual brains. Neuron *95*, 727–729.

137. Naselaris, T., Allen, E., and Kay, K. (2021). Extensive sampling for complete models of individual brains. Curr. Opin. Behav. Sci. *40*, 45–51.

138. Smith, P.L., and Little, D.R. (2018). Small is beautiful: in defense of the small-N design. Psychon. Bull. Rev. *25*, 2083–2101.

139. Dailey, M.N., Joyce, C., Lyons, M.J., Kamachi, M., Ishi, H., Gyoba, J., and Cottrell, G.W. (2010). Evidence and a computational explanation of cultural differences in facial expression recognition. Emotion *10*, 874–893.

140. Matsumoto, D. (2002). Methodological requirements to test a possible in-group advantage in judging emotions across cultures: comment on Elfenbein and Ambady (2002) and evidence. Psychol. Bull. *128*, 236–242.

141. Ibrahimagić-Šeper, L., Čelebić, A., Petričević, N., and Selimović, E. (2006). Anthropometric differences between males and females in face dimensions and dimensions of central maxillary incisors. Med. Glas. *3*, 58–62.

142. Hall, E.T. (1966). The Hidden Dimension (Doubleday & Co.).

143. Nichols, T.E., and Holmes, A.P. (2002). Nonparametric permutation tests for functional neuroimaging: a primer with examples. Hum. Brain Mapp. *15*, 1–25.

144. Bouma, G. (2009). Normalized (pointwise) mutual information in collocation extraction. In Proceedings of GSCL, *30*, pp. 31–40.

145. Ince, R.A.A., Kay, J.W., and Schyns, P.G. (2022). Within-participant statistics for cognitive science. Trends Cogn. Sci. *26*, 626–630.

146. Chen, C., Hensel, L.B., Duan, Y., Ince, R.A.A., Garrod, O.G.B., Beskow, J., Jack, R.E., and Schyns, P.G. (2019). Equipping social robots with culturally-sensitive facial expressions of emotion using data-driven methods. In 2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019), pp. 1–8.

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited Data		
Deposited data	This paper	https://osf.io/3m95w/
Software and Algorithms		
MATLAB R2021a	MathWorks	RRID: SCR_001622
Psychtoolbox-3	http://psychtoolbox.org/	RRID: SCR_002881
Custom Code for analyses	This paper	https://osf.io/3m95w/
Bayesian inference of population prevalence	Ince et al.[127]	https://doi.org/10.1016/j.tics.2022.05.008
Shift function	Rousselet et al.[128]	https://doi.org/10.1111/ejn.13610

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Chaona Chen (Chaona.Chen@glasgow.ac.uk).

Materials availability
This study did not generate new unique reagents.

Data and code availability
Data reported in this study and the custom code for analyses are deposited at Open Science Framework https://osf.io/3m95w/. Custom code for experiment and visualization are available by request to the Lead Contact.

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

Participants
We recruited a total of 120 human participants (referred to in the main text as *receivers*)—60 white Western European (59 European, 1 North American, 31 females, mean age = 22 years, *SD* = 1.71 years) and 60 East Asians (60 Chinese, 24 females, mean age 23 years, *SD* = 1.55 years). To control for the possibility that the perception of facial expressions could be influenced by cross-cultural experiences, we recruited participants with minimal exposure to and engagement with other cultures, as per self-report (see Screening questionnaire below). We recruited all Western participants in the UK and collected the data at the University of Glasgow. We recruited all East Asian participants in China and collected the data at the University of Electronic Science and Technology of China using the same experimental settings. All East Asian participants had a minimum International English Testing System score of 6.0 (competent user). All participants had normal or corrected-to-normal vision and were free of any emotion-related atypicalities (autism spectrum disorder, depression, anxiety), learning difficulties (e.g., dyslexia), synesthesia, and disorders of face perception (e.g., prosopagnosia), as per self-report. We obtained each participant's written informed consent before testing and paid £6 or ¥50 per hour for their participation. The University of Glasgow and the University of Electronic Science and Technology of China authorized the experimental protocol (reference ID 300160203 and 1061422030722173, respectively).

Screening questionnaire
To control for the effects of exposure to/experience of other cultures, each potential receiver completed the following questionnaire. We selected only those answering "no" to all questions for participation in the experiments.
Western European receivers
Have you ever:

  i) lived in a non-Western* country before (e.g., on a gap year, summer work, move due to parental employment)?
  ii) visited a non-Western country (e.g., vacation)?
  iii) dated a non-Westerner?
  iv) had a very close friendship with a non-Westerner?
  v) been involved with any non-Western culture societies/groups?

*by Western groups/countries, we are referring to Europe (East and West), USA, Canada, United Kingdom, Australia and New Zealand.

East Asian receivers

Have you ever:

  i) lived in a non-East Asian* country before (e.g., on a gap year, summer work, move due to parental employment)?
  ii) visited a non-East Asian country (e.g., vacation)?
  iii) dated a non-East Asian person?
  iv) had a very close friendship with a non-East Asian person?
  v) been involved with any non-Eastern culture societies/groups?

*by East Asian groups/countries, we are referring to China, Japan, Korea, Thailand and Taiwan.

METHOD DETAILS

Stimuli and procedure

We modelled the dynamic compositions of facial movements that represent the six basic emotions and their intensity in two cultures using the perceptual expectations of receivers. Therefore, we aim to examine the relationship between facial movement signals and the receiver's perceptual responses rather than the relationship between internal emotion states and external facial displays.[9,129–131] To do so, we generated random combinations of facial movements on each experimental trial, we used a dynamic facial movement generator comprised of a library of individual 3D facial Action Units (AUs)[19] captured using a stereoscopic system from real people who are trained to accurately produce individual Action Units on their face (see Yu et al.[58] for full details). On each experimental trial, the facial movement generator randomly selected a set of individual AUs from a core set of 41 AUs using a binomial distribution (i.e., minimum = 1, maximum = 5 on each trial, median = 3 AUs across trials). A random movement is then applied to each AU separately using random values selected for each of six temporal parameters (onset latency, acceleration, peak amplitude, peak latency, deceleration, and offset latency—see labels illustrating the solid black curve in Figure 1B). These dynamic AUs are then combined to produce a photo-realistic facial animation. The receiver viewed the random facial animation and categorized it according to one of the six basic emotion categories—i.e., "happy," "surprise," "fear," "disgust," "anger" or "sad"—and rated its intensity on a 5-point scale from "very weak" to "very strong". If the receiver did not perceive that the facial animation accurately represented any of the six emotions, including if it represented a compound or blended emotion,[132] such as "happily disgusted," we instructed receivers to select '"other" without rating intensity. Therefore, we explicitly used a behavioral task that does not force receivers to select facial expressions that they do not perceive as representing the six basic emotion categories and their intensity levels (see Russell[133] for discussion on methodology; see Darwin[6] and Ekman et al.[134] for similar applications, see Jack et al.,[14] Jack et al.,[33] Chen et al.,[34] and Liu et al.[47] for validation examples). Each receiver completed 2,400 such trials. We based the number of trials per receiver on previous research using a similar generative model of facial movements, sampling procedure, experimental task, data-driven reverse correlation method, and modelling procedure to derive statistically robust and validated facial expression models.[14,33,34,44–48,135] We also used a dense sampled design[127,136–138] for a thorough exploration of the relationship between stimulus features and each receiver's perception. To control for the potential influence of face ethnicity on the perception on facial expression,[139,140] we displayed all facial expression stimuli on the same set of same-ethnicity face identities for all receivers in each culture. All face identities are of real people, captured using a high-resolution 3D face capture system (see Yu et al.[58] for full details). For Western European receivers, we used 8 white Western European face identities (4 males, 4 females, mean age = 23 years, SD = 4.10 years); for East Asian receivers, we used 8 Chinese face identities (4 males, 4 females, mean age = 22.1 years, SD = 0.99 years). We displayed all stimuli on a black background using a 19-inch flat panel Dell monitor (60 Hz refresh rate, 1024 × 1280-pixel resolution) in the center of the receiver's visual field. Each facial animation played for 1.25 s followed by a black screen. A chin rest maintained a constant viewing distance of 68 cm, with stimuli subtending 14.25° (vertical) × 10.08° (horizontal) of visual angle to represent the average visual angle of a human face[141] during typical social interaction.[142] Each receiver completed the experiment over a series of eighteen ∼20-minute sessions with a short break (∼5 min) after each session and a longer break (at least 1 hour) after 3 consecutive sessions.

QUANTIFICATION AND STATISTICAL ANALYSIS

Modelling emotion classifier and intensifier facial movements

To identify the facial movements (i.e., AUs) that receivers used to classify the six basic emotions and judge their intensity, we measured the statistical relationship between each AU and each receiver's emotion classification and intensity responses separately, using Mutual Information (MI).[57,59] We computed MI to derive emotion classifier facial movements and intensifier facial movements as follows.

Classifier facial movements

To identify the facial movements that receivers used to classify each of the six emotion categories, we computed the MI between each AU (present vs. absent on each trial) and each receiver's emotion classification responses (e.g., the individual trials categorized as "happy" vs. those were not categorized as "happy"). Table S1 shows the average proportion of emotion responses across

receivers in both cultures. A high MI value would indicate a strong relationship between the AU and the receiver's response of the emotion. A low MI value would indicate a weak relationship. To establish statistical significance, we derived a chance level distribution for each receiver using a non-parametric permutation test and maximum statistics.[143] Specifically, we randomly shuffled the receiver's emotion category responses across the 2400 trials, repeated this for 1,000 iterations, computed the maximum MI across all AUs at each iteration to control the family-wise error rate (FWER) over AUs, and used the 95th percentile of the resulting distribution of maximum MI values as a threshold for inference (FWER $p < 0.05$ within receiver test). For AUs with statistically significantly high MI values, we identified those with a positive relationship with the receiver's emotion responses (i.e., the receiver categorized a given emotion when the AU is present) using Point-wise Mutual Information (PMI).[144] Specifically, a positive PMI value indicates that the presence (vs absence) of an AU (e.g., Lip Corner Puller—AU12) increases the probability of observing a specific emotion response (e.g., selecting "happy") in the receiver.

Intensifier facial movements

To identify the AUs that intensify each emotion, we first extracted the individual trials that each receiver categorized as a given emotion (e.g., "anger"), normalized the intensity ratings across these trials for each receiver and emotion separately to ensure that the intensity ratings reflected each receiver's relative judgements of intensity of each emotion. We then computed, for each emotion and receiver separately, the Mutual Information (MI) between each AU (present vs. absent on each trial) and each receiver's corresponding intensity ratings. A high MI would indicate a strong relationship between the AU and the receiver's judgments of intensity of each emotion. A low MI value would indicate a weak relationship. To establish statistical significance, we used the same non-parametric permutation test with maximum statistics as described above and identified the AUs with statistically significantly high MI values (FWER $p < 0.05$ within-receiver test). We then identified AUs with a positive relationship with the receiver's high intensity responses using PMI as described above. Here, a positive PMI value indicates that the presence (vs absence) of an AU (e.g., Upper Lid Raiser—AU5) increases the probability of the receiver perceiving that a given emotion (e.g., "anger") is highly intense.

Bayesian estimate of population prevalence

To obtain a population inference from the within-receiver results, we used Bayesian estimate of population prevalence.[127] In this approach, we model the population from which our experimental receivers are sampled with a binary property: each possible receiver either would, or would not, show a true positive effect in the specific test considered (e.g., that the observer uses a specific AU to classify an emotion). A certain proportion of the population possesses this binary effect. We then perform an inference against the null hypothesis that the value of this population proportion parameter—i.e., the prevalence—is 0. For example, with 60 receivers in each culture as considered, at $p < 0.05$ with Bonferroni corrections over all AUs, we can reject the null hypothesis that the proportion of the population with the effect is 0 when significant within-receiver results are observed in at least 10 out of the 60 receivers. We therefore retained for further analysis AUs with effects observed in the number of receivers above this population prevalence threshold (e.g., 10/60 receivers).

Validating emotion classifier and intensifier facial movements

We derived the classifier and intensifier facial movements using a highly powered and statistically robust within-receiver analysis[145] where results are based on the analysis of trials categorized by each individual receiver separately (vs aggregating across receivers). We demonstrate the validity of our within-receiver modelling approach using an external validation task with a new group of human validators[14,34,46,135,146] (see also Chen et al.[34] and Snoek et al.[48] for cross-validation of the approach with production data). Here, we further validated the results of classifier and intensifier facial movements using a naïve Bayesian classifier machine learning approach as follows.

Emotion classifier facial movements

To validate the emotion classifier facial movements in each culture, we built a naïve Bayesian classifier to classify AU patterns according to the six emotion categories in a six-alternative forced choice task using a split-half method. First, for each individual receiver in each culture, we trained a Bayesian classifier using a randomly sampled half of the stimulus AU patterns (i.e., randomly generated facial expressions presented on each experimental trial) that the receiver categorized as each of the six emotions. To ensure a balanced training set across the six emotions, we randomly selected for each emotion the same number of experimental trials (on average 167 trials per receiver per emotion) across all emotions based on the lowest number of trials across emotions. We then used the trained Bayesian classifier to classify the other half of the experimental trials as three testing sets: (1) with the full set of AUs presented on each experimental trial, (2) with the classifier AUs removed from each experimental trial, and (3) with the intensifier AUs removed from each experimental trial. Thus, if the classifier AUs contribute to accurately classifying the six emotions, classification accuracy (i.e., posterior probabilities) would decrease more when the classifier AUs are removed compared to the full set of AUs (set 1) or when the intensifier AUs are removed (set 3). We repeated this procedure for 1,000 iterations and computed the averaged posterior probability over the iterations. To examine the differences in the posterior probabilities of the three test sets, we applied a one-way ANOVA for each emotion and each culture separately, with multiple-comparison tests between each of the two test sets. Results show that in both cultures, the posterior probability of correctly classifying each emotion significantly decreased with the classifier AUs removed compared to the full set of AUs or with the intensifier AUs removed ($p < 0.05$ with Bonferroni corrected over emotions). On average, with classifier AUs removed, the posterior probabilities decreased by 14.31% for Western European receivers and 14.29% for East Asian receivers across emotions (see Figure S1B for more details).

Emotion intensifier facial movements

To validate the emotion intensifier facial movements, we used the same approach described above by training a naïve Bayesian classifier to classify high intensity emotions. We first re-binned each receiver's intensity ratings (from 1 to 5) into low and high intensity with an equal-population transformation (i.e., towards an equal number of trials in low and high intensity bins). Specifically, this iterative heuristic procedure combines the smallest bin with its smallest neighbor to reduce the number of bins while maintaining as equal sampling as possible, without splitting the trials from its original bin. We applied this procedure to ensure that the intensity ratings reflected each receiver's relative judgements of intensity of each emotion. For each emotion, we then trained a classifier to clarify the high intensity emotion using a two-alternative forced choice task (i.e., high intensity or not). We examined the differences in the posterior probabilities to correctly classify high intensity in the three test sets using the same analysis described above. Here, if the intensifier AUs contribute to classifying high intensity, the posterior probabilities would decrease more when the intensifier AUs are removed compared to the full set of AUs or when the classifier AUs are removed. Results show that in both cultures, the posterior probability to correctly classify high intensity significantly decreased with intensifier AUs removed compared to the full set of AUs or with classifier AUs removed ($p < 0.05$ with Bonferroni corrected over emotions). On average, performance decreased by 11.71% for Western European receivers and 12.50% for East Asian receivers across emotions (see Figure S1B for more details).

Influence of face ethnicity and individual identity

We also examined whether the ethnicity or the individual identity of the face stimuli influenced the reported results—i.e., whether the AUs represent emotion category and intensity information independent of the face they are displayed on. To do so, we conducted two separate analyses.

Face ethnicity. In our current design, participants in each culture viewed facial expressions displayed on same-ethnicity faces; therefore, it is possible that any differences in the AUs attributed to culture could instead be due to differences in the face stimuli. To test this, we analyzed an existing data set from a study[33] that used the same data-driven reverse correlation method, the same behavioral task (i.e., emotion categorization and intensity ratings), the same receiver group cultures and ethnicities (i.e., 15 white Western European and 15 Chinese East Asian) and a fully balanced stimulus set (i.e., all receivers viewed the same set of same- and other-ethnicity face identities). We repeated the same analysis procedure using Mutual Information (MI) as described in modelling emotion classifier and intensifier facial movements, STAR methods, for each face ethnicity separately. We then used these two MI values to compute the Conditional Mutual Information (CMI)[57,59] between each AU and each receiver's emotion classification responses given a specific face ethnicity. By its statistical definition, CMI is the sum of the MI values of each condition weighted by the probability of each condition. In this case, CMI equals the average (mean) of the two MI values because each receiver viewed the same number of trials displayed on same- and other-ethnicity face identities. A high CMI value (with respect to the unconditional MI calculated over all trials) would indicate that the relationship between an AU and the receiver's responses is biased by the ethnicity of the face stimuli. A low CMI value would indicate that it is not. We established a statistical threshold using non-parametric permutation testing (i.e., by randomly re-shuffling the same- or other face ethnicity of individual trials) with maximum statistics. Results showed that a maximum of 3 out of 15 Western European receivers and 3 out of 15 East Asian receivers showed a statistically significant effect (e.g., Western European receivers: Mouth Stretch—AU27 for "anger"; East Asian receivers: Mouth Stretch for "surprise"; see per AU results in Additional Information available on the Open Science Frame repository, https://osf.io/3m95w/). We then obtained a population prevalence inference from these within-receiver results using the population prevalence as described in Bayesian estimate of population prevalence, STAR Methods. With 15 receivers per culture in this study as considered, at $p < 0.05$ with Bonferroni corrections over all AUs, we can reject the null hypothesis that the proportion of the population with the effect is 0 when significant within-receiver results are observed in at least 4 out of the 15 receivers. In both cultures, the number of receivers showing a statistically significant effect is below this population prevalence threshold ($n < 4$ in each culture). Failure to reject the null hypothesis does not provide conclusive proof that there is no effect related to face ethnicity but does suggest that any such effect is too weak to introduce a meaningful confound in our results.

Face identity. We similarly examined whether the individual identity of the face stimuli influenced our results using the current data set and the same CMI analysis described above. Results showed that a maximum of 1 out of 60 Western European receivers and 2 out of 60 East Asian receivers showed a statistically significant effect (e.g., Western European receivers: Inner Brow Raiser—AU1 for "anger"; East Asian receivers: Lid Tightener Left—AU7L for "happy"; see per AU results in Additional Information available on the Open Science Frame repository, https://osf.io/3m95w/). In both cultures, the number of receivers showing a statistically significant effect is below the population prevalence threshold ($n < 10$ in each culture). Thus, the modulating effect of face identity is not expected to be prevalent in the populations sampled. Together, our results show that the perception of AUs as emotion classifiers and intensifiers is not modulated by face ethnicity or face identity, which corresponds with existing work showing that facial movements can override the social perceptions derived from static, non-expressive faces.[45]

Temporal analysis of emotion classifier and intensifier facial movements

To examine the temporal distribution of the emotion classifier and intensifier facial movements we compared their peak latencies—i.e., when in time the AU reached its peak amplitude. To do so, for each emotion classifier/intensifier AU and each receiver, we first extracted its individual trial peak latencies where the receiver had categorized the stimulus as the emotion in question or rated it as high intensity. Given that the peak latencies comprise continuous values and the way we measured the relationship between the AU presence and the receiver's responses (i.e., using Mutual Information and Point-wise Mutual Information, as described in modelling emotion classifier and intensifier facial movements, STAR Methods) is more suitable for measuring the relationship between discrete

variables, we computed the average (median) AU peak latency across these experimental trials and compared the distributions of classifier and intensifier AUs using the shift function.[128] Specifically, the shift function estimates the difference between two distributions using each quantile with a bootstrap estimation of the standard errors, thus enabling comparisons using the entire range of the distributions (versus group averages). Here, we compared the distributions of the peak latencies of the emotion classifier AUs and the emotion intensifier AUs. We applied this analysis to receivers who showed a significant effect for the AU in question (i.e., based on the results of modelling emotion classifier and intensifier facial movements, STAR Methods). Figure S2 shows the temporal distribution of the classifier and intensifier facial movements in each culture, pooled across receivers. Specifically, in each decile, we computed the 95% bootstrap confidence interval (CI) of the AU peak latencies to identify any statistically significant differences (i.e., where CIs do not include 0). If the CIs > 0, this suggests that the intensifier AUs peaked before the classifier AUs; if the CIs < 0, this suggests that the intensifier AUs peaked after the classifier AUs (see Figure S2).

Relationship between facial movement amplitude and emotion intensity judgments

To examine the relationship between the amplitude of facial movements and emotion intensity judgements, we computed the Mutual Information (MI) between the amplitude of each emotion classifier and intensifier AU (re-binned into 5 bins using the equal-population transformation) and each individual receiver's emotion intensity ratings (i.e., low vs high intensity; see modelling emotion classifier and intensifier facial movements). High MI values indicate a strong relationship between the amplitude of facial movement and emotion intensity judgement. Low MI values indicate a weak relationship. We then computed the averaged (mean) MI values across the AUs for classifier and intensifiers separately. In Figure 2B, color-coded boxplots on the right show the results, with individual points representing individual receivers (see Table S2 for both cultures). In each emotion and each culture, we identified any statistically significant differences using a paired-sample *t*-test (two-tailed, Bonferroni corrected over emotions; $p < 0.05$, see asterisks in Figure 2B and Table S2).

Signal distinctiveness of classifier and intensifier facial movements across emotions

To examine the distinctiveness of the emotion classifier and intensifier facial movements across emotions, we computed the average (mean) percentage of shared AUs between each pair of emotions (e.g., "happy" and "surprise") for classifiers and intensifiers separately, and for each culture. Specifically, we computed the average percentage of shared AUs between each emotion (e.g., "anger" and "disgust") for all within- and between-receiver pairs within each culture, for each emotion pair separately. Results show that, in each culture, intensifiers are more similar across emotions than classifiers are (two-tailed two-sample *t*-tests; Western European: $t(17) = 2.56$, $p = 0.02$, East Asian: $t(23) = 3.41$, $p = 0.003$).

Cross-cultural classification of emotion and intensity

To compare the dynamic signaling of emotion categories and their intensity across cultures, we used a machine learning approach. Specifically, we built at each of 10 time points a naïve Bayesian classifier to perform one of two tasks—to classify the six emotion categories or to classify high intensity for each emotion. For the emotion classification task, we trained the Bayesian classifier at each time point using all classifier AUs that had reached their peak amplitude up until that time point, derived from one culture and tested the classifier's performance using the corresponding classifier AUs from the other culture (and vice versa). For the intensity classification task, we trained the Bayesian classifiers at each time point to discriminate facial expression intensity using the classifier-plus-intensifier AUs (high intensity) and classifier-only AUs (not high intensity) for each emotion, tested it using the corresponding AUs from the other culture (and vice versa). For each test set, we computed the posterior probability of each test sample (i.e., the facial expression model from each individual receiver). Line plots in Figure 4 show the averaged (mean) posterior probabilities and stand error of the mean (SEM) across test samples. Next, we compared the cross-cultural classification accuracy to the within-cultural accuracy classification, derived by training the Bayesian classifiers for the same tasks within each culture using a half-split method. Specifically, for each culture separately, we randomly sampled half of the data for training and tested on the other half. We repeated this for 1,000 iterations and computed the averaged posterior probability of each test sample across iterations. To examine whether cross-culture accuracy differs from within-culture accuracy at each time point, we compared the posterior probabilities of cross-culture and within-culture test samples using a two-sample *t*-test ($p < 0.05$ with Bonferroni correction over emotions; see Figure S3A). We then identified the first time point at which the (1) within-culture classification accuracy is significantly higher than chance (derived by randomly re-shuffling the emotion categories or intensity) and the (2) cross-culture classification accuracy is significantly lower than the within-culture classification accuracy (see asterisks in Figures 4 and S3A). We further examined the cross-cultural misclassifications by analyzing the specific emotion confusions across time. As shown in Figure S3B, we identified when the cross-cultural misclassifications between emotions is significantly higher than the within-culture misclassifications between emotions (two-sampled *t*-test, two-tailed, $p < 0.05$ with Bonferroni correction over emotions). Results showed statistically significant cross-cultural confusions between emotions—for example, "fear" is often misclassified as "disgust" across cultures.

Next, we identified the AUs that drive statistically significantly lower vs. accurate cross-culture performance using a leave-one-out approach. In each test, we removed one AU from the train and test set and measured the change in cross-culture classification accuracy. If removing the AU decreased cross-cultural accuracy, we can infer that the AU is cross-cultural; if removing an AU decreased cross-cultural misclassifications, we can infer that the AU is culture specific. In Figure 4, color-coded face maps show the AUs that, when removed, impose a statistically significant change in cross-cultural classification performance (two-tailed two-sample *t*-test, $p < 0.05$; see Table S3 for individual AU results).