Four not Six: Revealing Culturally Common Facial Expressions of Emotion

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Abstract

As a highly social species, humans generate complex facial expressions to communicate a diverse range of emotions. Since Darwin's work, identifying amongst these complex patterns which are common across cultures and which are culture-specific has remained a central question in psychology, anthropology, philosophy, and more recently machine vision and social robotics. Classic approaches to addressing this question typically tested the cross-cultural recognition of theoretically motivated facial expressions representing six emotions, and reported universality. Yet, variable recognition accuracy across cultures suggests a narrower cross-cultural communication, supported by sets of simpler expressive patterns embedded in more complex facial expressions. We explore this hypothesis by modelling the facial expressions of over 60 emotions across two cultures, and segregating out the latent expressive patterns. Using a multi-disciplinary approach, we first map the conceptual organization of a broad spectrum of emotion words by building semantic networks in two cultures. For each emotion word in each culture, we then model and validate its corresponding dynamic facial expression, producing over 60 culturally valid facial expression models. We then apply to the pooled models a multivariate data reduction technique, revealing four latent and culturally common facial expression patterns that each communicates specific combinations of valence, arousal and dominance. We then reveal the face movements that accentuate each latent expressive pattern to create complex facial expressions. Our data questions the widely held view that six facial expression patterns are universal, instead suggesting four latent expressive patterns with direct implications for emotion communication, social psychology, cognitive neuroscience, and social robotics.

Keywords: facial expressions, emotion, communication, culture, psychophysics.

Humans are one of the most socially sophisticated species on the planet (Wilson, 2012) and regularly exchange complex information to support the functioning of individual lives and broader society. Of critical importance in such exchanges is the communication of emotions, which provides predictive information about the environment and allows others to adapt their own cognitions and behaviors accordingly. To communicate the wide range of nuanced emotions that are required for sophisticated social interactions, humans are equipped with a complex and powerful tool – the face (but see also voice, e.g., Belin, Fillion-Bilodeau, & Gosselin, 2008; Cordaro, Keltner, Tshering, Wangchuk, & Flynn, 2015; Sauter, Eisner, Ekman, & Scott, 2010; Scheiner & Fischer, 2011) (and body posture, e.g., de Gelder, 2009). With numerous independent muscles, each of which can be combined at different intensities over time, the face can generate myriad intricate dynamic patterns – i.e., facial expressions.

Since Darwin's groundbreaking theory on the evolutionary origins of facial expressions (Darwin, 1999/1872) a fundamental aim in emotion communication is to identify which specific facial expression patterns are universal across cultures and which are culture-specific. Yet, since the face is a complex, high dimensional dynamic information space (Jack & Schyns, 2015) doing so represents a genuine empirical challenge, as reflected by many attempting the task. For example, Ekman's observation that "*the sources of cultural variability are so many that it is exceedingly difficult to observe the common facial expressions of emotion across cultures*" (Ekman, 1972, pg. 234) closely mirrors those of Labarre "*it is frequently difficult to analyze out and segregate* [culture-specific from universal face movements]" (Labarre, 1947, pg. 57).

Amongst the most notable in addressing this challenge is the pioneering work of Ekman who, based on Darwin's biological and evolutionary account of the origins of facial expressions of emotion (see also e.g., Andrew, 1963; Susskind et al., 2008), proposed that a specific set of facial expressions accurately communicated six basic emotions – 'happy,'

‘surprise,’ ‘fear,’ ‘disgust,’ ‘anger’ and ‘sad’ – across all cultures. Specifically, each facial expression comprised a face movement pattern derived from theory and naturalistic observation (see Ekman, Friesen, & Hagar, 1978 for prototypes and major variants) and described according to the Facial Action Coding System (FACS, Ekman & Friesen, 1976) – an objective system that comprehensively describes most visible facial movements called Action Units (AUs, Ekman & Friesen, 1978). For example, following Ekman’s characterization of the six basic facial expressions of emotion, FACS describes ‘happy’ as comprising Cheek Raiser (AU6) and Lip Corner Puller (AU12), whereas ‘sad’ comprises Inner Brow Raiser (AU1), Brow Lowerer (AU4) and Lip Corner Depressor (AU15). In a series of cross-cultural recognition studies (e.g., Ekman, 1972; Izard, 1971) these specific AU patterns consistently elicited above chance recognition performance (>16.7% in a standard 6-alternative forced choice task, i.e., 1/6) across cultures, resulting in the widespread conclusion that these facial expressions of emotion are universal (see Izard, 1994 for a review).

While the work of Darwin, Ekman and many others (e.g., Izard, 1994; Tomkins, 1962, 1963) undoubtedly made several significant advances in the field, the main approaches used cast a relatively narrow light on how facial expressions communicate emotions within and across cultures (see also Elfenbein & Ambady, 2002b; Jack, 2013; Russell, 1994 for further discussion). First, the threshold of above chance performance (i.e., >16.7% in a standard 6-alternative forced choice task) is too low to demonstrate typical recognition because communication critically relies on the majority of participants making few, not many, errors (e.g., Dukas, 1998; Slater & Halliday, 1994). Rather, where an individual makes errors on a majority of occasions performance likely indicates (within a given culture) a significant cognitive deficit – i.e., atypical performance (e.g., see Duchaine & Nakayama, 2006). The threshold of above chance performance is therefore also not sensitive enough to

detect specific patterns of differences in recognition performance across observer groups. For example, certain AU patterns representing ‘fear’ or ‘disgust’ consistently elicit high recognition in Western cultures, but systematically lower recognition accuracy in non-Western cultures (e.g., Biehl et al., 1997; Chan, 1985; Ekman et al., 1987; Ekman, Sorenson, & Friesen, 1969; Jack, Blais, Scheepers, Schyns, & Caldara, 2009; see Jack, 2013 for a review and global map of recognition accuracy of facial expressions widely considered universal; Matsumoto, 1992; Matsumoto & Ekman, 1989; Moriguchi et al., 2005). Using a threshold of above chance performance to demonstrate universality would therefore mask these statistically significant systematic differences by simply classifying and reporting both cultural performances as the same – i.e., above chance. Rather, in line with the expertise hypothesis (Tanaka & Taylor, 1991) variability in recognition accuracy across cultures could reflect the cultural diversification and specialization of facial expressions of emotion arising from widespread migration and increasing social and cognitive sophistication (Dunbar, 1993, 1998). Thus, it remains an empirical question as to which AU patterns reliably communicate emotions in non-Western cultures.

Second, classic recognition studies show that only a subset of facial expressions is recognized with comparably high accuracy across cultures – namely ‘happy,’ ‘surprise,’ ‘anger’ and ‘sad’ – which suggests that cross-cultural emotion communication via facial expressions might comprise fewer than six categories (see also Jack, Garrod, & Schyns, 2014; Jack, Garrod, Yu, Caldara, & Schyns, 2012). Interestingly, this subset does not include ‘fear’ or ‘disgust,’ both of which are widely considered primitive on the basis of their biological origins (e.g., Susskind et al., 2008) and rapid processing by deep brain structures (e.g., J. S. Morris et al., 1996; Phillips et al., 1997). Specifically, ‘fear’ and ‘disgust’ tend to be miscategorized as ‘surprise’ and ‘anger,’ respectively outside of Western culture (Jack et al., 2009; Matsumoto & Ekman, 1989; Moriguchi et al., 2005). Instead, cross-cultural

recognition of a smaller subset of facial expressions, characterized by specific confusions between semantically and physically similar facial expression patterns (e.g., 'disgust' and 'anger') suggests that specific *latent components* of facial expressions – i.e., simpler expressive patterns used by early humans embedded in the more complex facial expressions used today – could support cross-cultural emotion communication. Specifically, with comparatively simpler social sophistication, early humans might have communicated broader social concepts (e.g., approach, avoidance, negative, positive) using simpler facial expression patterns that exploited the evolving sensitivities of the visual brain (Guilford & Dawkins, 1991). For example, the rapid transmission of high contrast signals such as the sclera (a uniquely human feature, see Kobayashi & Kohshima, 1997) or nose wrinkling are highly detectable by the visual brain, and could therefore act as 'attention grabbers' to quickly communicate general information about types of threat (Cott, 1940; Niedenthal, Mermillod, Maringer, & Hess, 2010; Senju & Johnson, 2010). With increasing social and cognitive sophistication, the subsequent evolving communication needs could be met by developing a more nuanced and diverse range of facial expressions built from these simpler expressive patterns. Thus, the evidence from classic recognition studies suggests that to uncover the expressive patterns that are common across cultures and those that are culture-specific requires a broader approach motivated by both theoretical and empirical considerations.

A third limitation is that, as described above, facial expressions are dynamic patterns of information (see E. G. Krumhuber, Kappas, & Manstead, 2013 for a review) where the temporal unfolding of diagnostic face movements provide specific information for emotion categorization (e.g., E. Krumhuber & Kappas, 2005). Yet, with few exceptions (e.g., van der Schalk, Hawk, Fischer, & Doosje, 2011) the facial expression patterns studied have been static (i.e., facial expression images), which provides no characterization of their temporal dynamics (e.g., when in time each AU peaks, its acceleration, deceleration, and so on). Such

an important omission is noted in early works highlighting the importance of dynamics: *"The photograph congeals this motion into a still which is never entirely adequate as a recognizable affective response"* (Silvan S. Tomkins & R. McCarter, 1964, pg. 126).

Finally, a more fundamental limitation of the classic approach is that the proposed AU patterns correspond to only the six emotion categories. Yet, observation of daily social functioning or casual corpus analyses shows that this selection represents only a small proportion of the broad spectrum of emotions that support complex social interactions (Cunningham, Kleiner, Bülthoff, & Wallraven, 2004). In analogy to language (Fay, Garrod, Roberts, & Swoboda, 2010) and as highlighted above, facial expressions of emotion likely evolved from a simpler set of expressive patterns that communicated a small set of relevant categories (e.g., approach, avoid, threat) into a more numerous and complex set of facial expressions designed to support more diverse communication needs (e.g., irritation, skepticism, anxiety; Darwin, 1999/1872; Hasson, 1997; Hebets & Papaj, 2005; Maynard Smith & Harper, 1995). As with the restricted exploration of AU patterns just discussed, restricting investigation to few emotion categories limits knowledge of facial expressions of emotion to a small set of selected emotion categories and their recognition. Instead, a better understanding of the emotion concepts that are routinely communicated in different cultures would reveal the true diversity of facial expression patterns in each culture, and show which expressive patterns are culturally common and which are culture-specific.

Here, we address the limitations described above using a combination of cultural psychology and social cognition, dynamic structural face computer graphics, vision science and psychophysical methods, and mathematical psychology. Using this multidisciplinary approach, we will first characterize the conceptual organization of emotions in two different cultures (Western and East Asian) using a broad range of emotion words in each native language (English and Chinese). Using the psychophysical method of reverse correlation

(Ahumada & Lovell, 1971), we will then model the dynamic facial expressions associated with each emotion word, and use multivariate data reduction techniques to identify the latent facial movement patterns that are common across cultures and segregate out any culture-specific accents. Consequently, we show that four distinct and latent facial movement patterns are common across cultures, two of which comprise face movements that regulate sensory exposure and thus have likely biological origins (e.g., Chapman, Kim, Susskind, & Anderson, 2009; Shariff & Tracy, 2011; Susskind et al., 2008). We also reveal the specific face movements that accentuate each culturally common expressive pattern, thereby proving a precise characterization of the grammar of facial expressions of emotion across cultures.

We focus our cultural comparisons on Western and East Asian cultures for several reasons. First, each culture is computer literate, which allows each observer to interact easily and independently (i.e., without social presence of the experimenter) with modern equipment typically used for data collection (e.g., see Sauter et al., 2010 for an illustration of the challenges using such equipment in developing countries). Second, it is well documented that Western and East Asian cultures show marked contrasts in general visual processing (Nisbett & Masuda, 2003), which plays a central role in communication – i.e., the receiving of transmitted visual information patterns (see Jack & Schyns, 2015). Finally, understanding similarities and differences in East Asian and Western social communication is critical in developing the digital economy. For all experiments, we tested all observers in the UK and used strict criteria to select Western and East Asian observers with minimal exposure to and engagement with other cultures (De Leersnyder, Mesquita, & Kim, 2011) as assessed by screening questionnaire (see *Supplemental Materials – Screening Questionnaire*). Specifically, all Western and East Asian observers had never lived in or visited a non-Western/East Asian country before, had never had any close relationships with a non-Western/non-East Asian culture individual (e.g., boy/girlfriend) or had any interest in non-

Western/East Asian culture (e.g., sports or art societies). All East Asian observers were Chinese nationals of Chinese heritage, who had arrived in the UK for the first time, had a maximum UK residence of 2.5 months at the time of testing, and possessed a minimum International English Testing System (IELTS) score of 6.0 (Competent user). All Western observers were British nationals of white Caucasian ethnicity. All observers had normal or corrected-to-normal vision and were free from any lexical, reading, language (e.g., dyslexia) or emotion related atypicalities (e.g., Autism Spectrum Disorder, depression, anxiety) as per self-report, and typically from a student population. We paid each observer £6 per hour, and obtained their written informed consent. The University of Glasgow College of Science and Engineering Ethics Committee authorized the experimental protocol.

Experiment 1

Mapping the Conceptual Landscape of Emotions in Different Cultures. As noted by the poet Friedrich von Schiller, language is the mirror of a nation where language is used as a medium to communicate concepts within a given culture, with words comprising the smallest elements of meaning. For example, the indigenous circumpolar Saami people have a rich vocabulary for snow, ice and reindeer (Magga, 2006), which in line with the Sapir-Whorf hypothesis (Sapir, 1929; Whorf, 1956), reflects not only their specific experiences interacting with the Arctic environment, but also which categories are salient in their culture. Therefore, examining the distribution of words or phrases and their associated meaning (i.e., semantics) within a language can provide insights into the relevance of different concepts and categories across cultures. Here, we will examine the distribution and semantic associations of emotion words in Western (British English) and East Asian (Chinese) cultures to map the conceptual organization of emotions in each. To do this, we first derived a core set of highly familiar and highly typical emotion words in each language, measured the perceived semantic similarity

between all word pairs to derive a semantic network of emotion words in each culture, then used a graph-theoretic clustering method to identify groups of conceptually related words.

Method

To generate a core set of highly familiar and highly typical emotion words in each language, we proceeded in five steps.

1. Extracting emotion words from key sources. First, we compiled a comprehensive list of emotion words in British English and Chinese separately, sourced from established corpuses (e.g., British National Corpus – BNC), word lists (Cai & Brysbaert, 2010) and literature sources (Averill, 1983; Bedford, 2004; Davitz, 1969; de Rivera, 1977; Ho, Fu, & Ng, 2004; Li, Wang, & Fischer, 2004; Ortony & Turner, 1990; Parrott, 2001; Plutchik, 1980).

2. Word familiarity and emotion typicality rating task. To extract highly familiar and highly typical emotion words, we first obtained measures of familiarity and emotion typicality using a rating task with native speakers. We recruited a new group of 50 native English speakers (50 British, 25 male, mean age 21.5 years, SD 2.5 years) and 50 native Chinese speakers (50 Chinese, 26 male, mean age 24.1 years, SD 1.7 years). On each experimental trial, native speakers viewed a single word in their native language and rated it according to a) familiarity on a 7-point Likert scale (‘totally unfamiliar’ to ‘highly familiar’) or b) emotion typicality on a 7-point Likert scale (‘definitely not an emotion’ to ‘definitely an emotion’) including ‘I don’t know this word’ using a Graphic User Interface (GUI). We presented all words in random order across the experiment and blocked and counterbalanced the tasks of familiarity and emotion typicality across native speakers in each group. We presented all words in lower case white font (MS Sans Serif for English; MS Song for Chinese) on a black background in the center of the screen, with all Chinese words presented in simplified form. Following the experiment, we then selected words rated as both highly

familiar and highly typical of emotion (i.e., >=6 on both scales) by a large majority of native speakers (85%). See *Supplemental Materials – Table S1* and *S2* for the proportion of native speakers rating each word as highly familiar and highly typical of emotion for English and Chinese words, respectively.

3. Commonly used emotion terms. Finally, to relate our data to the majority of existing literature, we retained any emotion words that are widely discussed in the literature – e.g., 'happy,' 'surprise,' 'fear,' 'disgust,' 'anger,' 'sad,' 'shame,' 'contempt,' 'pride' and 'embarrassment.' Specifically, for English we retained six such emotion words – 'surprise', 'disgust,' 'shame,' 'contempt,' 'pride,' and 'embarrassment.' For Chinese, we retained five such emotion words (as determined by closest match translation provided by a professional translator) – 'disgusted'/厌恶, 'shame'/羞愧, 'contempt'/鄙视, 'pride'/骄傲 and 'embarrassment'/尴尬.

4. Semantic similarity of emotion words in each language. Next, to understand the semantic relations between the emotion words in each language, we instructed a new set of 49 native English speakers (23 male, mean age 22.5 years, SD 2.2 years) and 50 native Chinese speakers (25 male; mean age 23.0 years, SD 1.9 years) to rate the semantic similarity of all word pairs in their own language. On each experimental trial, native speakers viewed a word pair (e.g., 'happy' and 'fury') and rated it according to similarity of meaning on a 7-point bipolar scale ranging from 'very different' to 'very similar.' Each native speaker rated all possible word pair combinations (excluding identical word pairs and including word order reversal) using a GUI, with words presented in random order across the experiment and positioned side-by-side in lower case white font (MS Sans Serif for English; MS Song for Chinese) on a black background in the center of the screen.

5. Clusters of semantically similar emotion words in each language. To identify clusters of semantically similar emotion words in each language, we first computed a semantic network of emotion words by calculating the average (mode) similarity of each word pair across native speakers in each group separately. In Figures 1 and 2, color-coded similarity matrices show the semantic relationship between all word pairs in English (Figure 1) and Chinese (Figure 2) where lighter squares indicate high similarity (e.g., in English, 'delighted' and 'joy') and darker squares indicate low similarity between word pairs (e.g., in Chinese, 'anguish'/苦闷 and 'pleasantly surprised'/惊喜). We then applied a graph-theoretic clustering method (Pavan & Pelillo, 2007) to each similarity matrix, revealing several clusters in each. In Figures 1 and 2, green brackets to the left of each matrix show the emotion words that form each cluster (i.e., words that are highly semantically similar) in each language.

6. Valence, arousal and dominance of emotion words in each language. To interpret each emotion word cluster, we obtained ratings of three main components of emotion – valence (e.g., pleasantness or unpleasantness), arousal (e.g., excited or calm) and dominance (e.g., in control or being controlled) for each word in both languages. For the English words, we extracted data from an existing database (Warriner, Kuperman, & Brysbaert, 2013). In the absence of a comparable database for Chinese words, we recruited a new set of 32 native Chinese speakers (15 male, mean age 23.3 years, SD 1.7 years) and instructed each to rate the valence, arousal and dominance of each Chinese emotion word used in the semantic network above using a similar procedure as in Warriner et al. (2013). On each experimental trial, native speakers viewed a single word in their native language and rated it according to valence, arousal or dominance on a 9-point Likert scale ranging from happy [excited/ dominated] to unhappy [calm/dominant] (depending on the dimension) using a Graphic User Interface (GUI). We blocked the dimensions of valence, arousal and dominance, with blocks presented in random order across the experiment. All Chinese words appeared in each block

and presented in random order for each block. Thus, each native speaker completed 159 trials (53 words x 3 dimensions). We presented all words in white font (MS Song) simplified form on a black background in the center of the screen. To compute the average valence, arousal and dominance ratings for each Chinese word, we first normalized each native speakers responses across each dimension separately. We then computed the median valence, arousal and dominance rating across all native speakers for each word (see *Supplemental Materials – Table S3* for a full list of values). In Figures 1 and 2, color-coded circles next to each word shows the average perceived valence (red – high; blue – low), arousal (green – high; yellow – low) and dominance (magenta – high; cyan – low; see key to left of labels) as judged by native speakers in each group.

[FIGURE 1 HERE]

[FIGURE 2 HERE]

Results

At this juncture, it is worth highlighting that although these semantic networks cannot comprise an exhaustive representation of all emotion words in each language (e.g., Allport & Odbert, 1936 identified >4,500 English emotion words), each nevertheless represents a core set of highly familiar and highly typical emotion words – i.e., those used frequently to communicate emotion concepts within each language. From these semantic networks, a number of similarities and differences across cultures are observed.

Broad emotion categories. First, as shown by the green brackets in Figure 1, the English emotion words form eight clusters, broadly comprising the six classic emotion categories – ‘happy,’ ‘surprise,’ ‘fear,’ ‘disgust,’ ‘anger’ and ‘sad’ (see asterisks in Figure 1) – plus two

clusters corresponding to ‘pride’ and ‘shame.’ Whereas the Chinese emotion words form more clusters (see green brackets in Figure 2), they also largely comprise the six classic emotions (see asterisks in Figure 2) including two clusters of surprise (one high valence/arousal/dominance, one neutral), two clusters of ‘fear,’ and four further singleton clusters – ‘embarrassment’/尴尬, ‘shame’/羞愧, ‘pride’/骄傲, and ‘despise’/蔑视. Thus, in both languages the semantic groupings largely correspond to the emotion categories typically discussed in the literature – i.e., the classic six emotions, plus ‘shame’ and ‘pride,’ the latter two of which are increasingly considered basic emotions (e.g., Tracy & Robins, 2004, 2008). Such correspondence broadly supports the view that certain main emotion concepts are shared across cultures.

Underlying continuous dimensions of valence, arousal and dominance. Second, as shown by the color-coded circles in Figures 1 and 2, discrete emotion word clusters in each culture tend to be characterized by distinct ratings on the continuous dimensions of valence, arousal and dominance. Specifically, clusters in both cultures tend to be either high or low valence emotions, which supports theoretical and empirical accounts suggesting that valence is a main dimension of semantic similarity in emotion (Fontaine, Scherer, Roesch, & Ellsworth, 2007; Russell, 1980; Scherer, 1999). In both cultures, negative emotion word clusters are also more numerous than positive emotion word clusters, which in line the Sapir-Whorf hypothesis (Sapir, 1929; Whorf, 1956), could reflect a heightened relevance and social salience of negative emotion words in each language (see also Lindquist & Gendron, 2013 for a review). In contrast, the distribution of arousal and dominance ratings across the emotion words shows some cultural differences. Across the English emotion words, valence and dominance are positively correlated (Pearson’s correlation, $r = .87$, $P < 0.01$), such that high valence words tend to be associated with high dominance, and low valence words tend to be associated with low dominance. However, across the Chinese emotion words

dominance is positively correlated with arousal (Pearson's correlation, $r = .37$, $P < 0.01$) whereby high dominance tends to be associated with high arousal, whereas low dominance tends to be associated with low arousal.

Relatedness of emotion word clusters. Third, there are clear cultural differences in the relatedness of the emotion clusters. For example, in English the large high valence/dominance emotion word cluster is highly distinct from all low valence/dominance emotion clusters but shows some semantic similarity with 'pride' and 'surprise' on the basis of high valence. Similarly, all low valence emotion word clusters show varying levels of similarity between them. For example, the clusters containing 'disgust' and 'anger' overlap considerably and share characteristics of high arousal and neutral dominance; the clusters containing 'fear,' 'sad' and 'shame' also overlap and share characteristics of high dominance but differ according to arousal. Such semantic similarities and differences could reflect differences in behavioral response. For example, the clusters containing 'disgust' and 'anger' that share characteristics of negative valence and high arousal could quickly elicit avoidance behaviors to reduce harmful encounters with the expresser or the environment. In contrast, the overlapping negative, low dominance clusters containing 'fear,' 'sad,' and 'shame' could elicit approach behaviors, whereby expressions of 'sad' and 'shame' could reflect a non-aggressive negative internal state where social contact (i.e., approach by the perceiver) would re-instate the expressers emotional and/or social homeostasis. Specifically, 'shame' – a typical response to social rejection – could signal remorse and therefore willingness for social re-integration as initiated by other group members. Finally, 'fear' could indicate that the expresser has knowledge of the location or nature of a threat, thereby inciting others to mirror their behaviors for adaptive response (e.g., escape in the same direction).

In contrast, the Chinese semantic network shows much more distinctiveness between the negative emotion word clusters. Although sharing characteristics of valence, arousal, and

dominance, the increased representation of and distinctiveness between negative emotion word clusters could reflect a heightened importance of communicating negative events compared to English speaking cultures. That is, detecting, communicating and responding to negative events could be more important (i.e., more costly or beneficial) in Chinese than English speaking cultures. For example, the Chinese semantic network contains a large cluster of various types of sadness compared to the English semantic network, suggesting the greater social relevance of communicating nuances of this emotion. Similarly, the Chinese semantic network contains two separate (but related) 'surprise' clusters – one high in valence and arousal, one more neutral – whereas only a singleton 'surprise' cluster in the English semantic network represents the same emotion.

Here, cultural differences in the relative number and distinctiveness of negative emotion word clusters are consistent with cultural accounts of social organization whereby individualism (e.g., Western culture) and collectivism (e.g., East Asian culture) modulate the importance of social cohesion and harmony (and therefore the communication of costly events). For example, in collectivist cultures, which rely on interdependence between individuals, inaccurate social communication would have greater impact compared to individualistic cultures. Thus, cultural interdependence could be inversely related to conceptual similarity of emotion (and/or social) categories.

Experiment 2

Modelling Dynamic Facial Expressions of Emotion. Having identified the clusters of semantically similar emotion words in the Western and East Asian cultures, we now characterize the facial expressions that communicate each of these emotions (if they exist as independent facial expressions). To determine which dynamic facial expression patterns communicate emotions to individual observers in a given culture, we used a 3D dynamic

Generative Face Grammar (GFG; Yu, Garrod, & Schyns, 2012) combined with reverse correlation (Ahumada & Lovell, 1971) and subjective perception (see Dotsch, Wigboldus, Langner, & van Knippenberg, 2008; Gosselin & Schyns, 2003 for similar applications; Kontsevich & Tyler, 2004). Figure 3 illustrates our method using an example trial.

[FIGURE 3 HERE]

Method

To illustrate, consider that we aim to identify in a specific culture (e.g., East Asian) the facial movements that communicate different types of aggression (e.g., 'fury,' 'rage', 'livid', and 'anger') at different levels of intensity. On each experimental trial, a dynamic facial expression generation platform (the Generative Face Grammar - GFG; Yu et al., 2012) creates a stimulus by randomly selecting a biologically plausible combination of AUs from a core set of 42 AUs using a binomial distribution (minimum 1 AU, maximum 6 AUs, median 3 AUs). As shown in Figure 3, on this illustrative trial three AUs are selected – Upper Lid Raiser (AU5) color-coded in red, Nose Wrinkler (AU9) color-coded in green, and Upper Lip Raiser (AU10) color-coded in blue. The GFG then assigns a random movement to each AU by selecting random values for each of six temporal parameters (onset latency, acceleration, peak latency, peak amplitude deceleration, and offset latency; see labels illustrating the blue curve) from a uniform distribution. The dynamic AUs are then combined to produce a photo-realistic random facial movement, illustrated here with four snapshots. The cultural observer categorizes the stimulus according to a specific emotion (here, 'rage') at a given intensity (here, 'strong') if the face movements form a pattern that correlates with their prior knowledge (i.e. mental representation) of that facial expression of emotion at that intensity (here, 'strong rage'). If the pattern does not correspond to any of the categories provided, the

observer selects ‘other.’ In other words, as illustrated in Figure 3, this specific dynamic pattern of facial movements has elicited in this observer the response (i.e., categorical perception) ‘strong rage.’ Over many such trials, other patterns might correspond to the other emotion categories (here, ‘fury’, ‘livid’ and ‘anger’) at different levels of intensity. Following the experiment, we can therefore measure the relationship between the dynamic AUs presented on each trial and the observer’s responses, from which we can precisely identify the combinations of AUs (i.e. facial expressions) that reliably correlate with perception of different types of aggression (here, ‘fury’, ‘rage’, ‘livid,’ ‘anger’).

Here, we use this approach to determine which dynamic facial expression patterns communicate emotions to individual observers in a given culture. To appreciate the strength of the approach and its potential to inform emotion communication (i.e., the transmission and decoding of facial expressions) it is worthwhile highlighting the symbiotic link between the production and perception of information. As discussed in detail in human (e.g., Scott-Phillips, 2008), animal (e.g., Dukas, 1998; Slater & Halliday, 1994) and man-made (e.g., Shannon, 2001) communication systems, information produced that supports communication is inextricably shaped by the perceptual capabilities of the observer. For example, due to fixed retinal density, the human eye is capable of detecting detailed information only at relatively short distances. Therefore, transmitting detailed information (e.g., the high spatial frequency, high contrast of the sclera) over a long viewing distance would not support communication (Smith & Schyns, 2009). Similarly, if the transmitted information is unknown to the observer (i.e., it does not correspond with their prior knowledge), or sender and observer do not share the same meaning of the transmitted information (e.g., direct eye contact in Western versus East Asian culture, Jack, Caldara, & Schyns, 2011; see also Labarre, 1947; D. Morris, 1979; Turnbull, 1813). Consequently, any such ineffective transmissions would become extinct from the communication system and replaced with information that is

both detectable and meaningful to the observer (see also Jack & Schyns, 2015). Thus, the production of information that is used for communication is inextricably shaped by the perceptual capabilities of the observer, thereby creating an intimate correlation between the two.

In recognizing the fundamental link between production and perception, the approach of using the observer to inform knowledge of facial expressions – one pioneered by Darwin (Darwin, 1999/1872) – has remained one of the most popular methods in the field. Here, we develop this classic method in one significant way. As described above, rather than using a top-down theoretical selection of specific AU patterns for testing on observers, we agnostically select AU patterns and then probe the visual system to determine which patterns communicate emotions to individual observers in a given culture. Adopting such a data-driven approach – i.e., without *a priori* assumptions about which facial expression patterns might communicate emotions – allows an exploration of a much broader set of possible facial expressions as candidates for emotion communication. That is, we can model reconstruct, visualize, quantify and compare the cultural facial expressions (i.e. dynamic AU patterns) associated with each emotion word (i.e., concept) in Figures 1 and 2 (e.g., ‘delighted,’ ‘rage,’ ‘anxious,’ ‘depressed’).

To model the cultural facial expressions associated with each emotion word, we proceeded in two stages involving within and between cluster categorization tasks. Each stage is detailed below.

1. Within cluster categorization task. First, we modeled the cultural facial expressions associated with the emotion words in each non-singleton cluster (in the English group, 6 non-singleton clusters comprising a total of 28 words; in the Chinese group, 7 non-singleton clusters comprising 48 words) using the method illustrated in Figure 3. We recruited a new set of 36 native English speakers (18 male, mean age 21.5 years, SD 2.9 years), and 32 new

native Chinese speakers (16 male, mean age 22.6 years, SD 2.2 years). For each observer, we presented each random facial animation on one of 8 same-race face identities (white Caucasian: 4 male, mean age 23 years, SD 4.1 years; Chinese: 4 male, mean age 22.1 years, SD 0.99 years) using the procedures described in (Yu et al., 2012) and used in (Gill, Garrod, Jack, & Schyns, 2014; Jack et al., 2014; Jack et al., 2012). Observers view the random facial animation and categorize it according to one of the emotion words comprising one of the clusters of semantically similar emotion words derived above using cluster analysis (e.g., see Figure 1 and 2), or selects 'other.' For example, in Figure 3, on this illustrative trial the cluster of semantically similar emotion words – response options – comprises 'fury,' 'rage,' 'livid,' and 'anger.' Observers also rate the perceived emotional intensity on a 5-point Likert scale ('very weak' to 'very strong'). Each observer categorized 2400-2800 such facial animations. We presented the same response options – cluster of semantically similar emotion words – for 200 consecutive trials, and randomized the order of the emotion words clusters across the experiment. We presented each facial animation on a black background in the observers' central visual field and displayed on a flat 17-inch panel monitor with a refresh rate of 60 Hz and resolution of 1280 × 1024. We played each animation only once for a duration of 1.25s. A chin rest ensured a constant viewing distance of 73cm, with images (average size 18.3 × 12 cm) subtending 14.29° (vertical) and 9.38° (horizontal) of visual angle, thereby reflecting the average size of a human face (Ibrahimagi•-` eper, • elebi•, Petri•evi•, & Selimovi•, 2006) during typical social interaction (Hall, 1966).

2. Between cluster categorization task. To model the dynamic facial expressions of the remaining singleton word clusters in each culture (i.e., 'surprise' and 'pride' in the English group, and in the Chinese group 'embarrassment'/尴尬, 'shame'/羞愧, 'pride'/骄傲, 'despise'/蔑视 and 'disgust'/厌恶), we used a between cluster categorization task. We recruited 32 new native English speakers (16 male; mean age 20.4 years, SD 2.9 years), and

32 native Chinese speakers (16 male, mean age 23 years, SD .7 years). We used the same stimulus generation and task procedure as in the *within cluster categorization task*, except the response options. On each trial, the response options comprised all singleton cluster words (e.g., in English, 'surprise' and 'pride'), plus the highest frequency word from each of the non-singleton clusters, identified using the BNC for English words and Chinese National Corpus for Chinese words. Response options for the English group therefore comprised 8 emotion words – 'surprise,' 'pride,' 'love,' 'fear,' 'hate,' 'anger,' 'sad,' and 'shame' – with the Chinese response options comprising 12 emotion words 'embarrassment'/尴尬, 'shame'/羞愧, 'pride'/骄傲, 'despise'/蔑视, 'disgust'/厌恶, 'glad'/高兴, 'pleasantly surprised'/惊喜, 'surprised'/惊讶, 'panic'/恐慌, 'anxiety'/害怕, 'anger'/生气, and 'suffering'/痛苦). Each observer categorized 2400-2800 such facial animations presented on the same face identities used in the *between cluster categorization task.*

3. Modelling dynamic facial expressions of emotion. For both the *between* and *within cluster categorization task*, we then identified, for each culture, the dynamic face movements significantly associated with each emotion word shown in Figures 1 and 2. Specifically, we reverse correlated the observer's categorical responses (e.g., 'rage') with the AUs and their temporal parameters using established model fitting procedures (Yu et al., 2012). For the *within cluster categorization task*, for each emotion word within a cluster, we pooled together all trials from all observers for each culture separately, and performed a Pearson correlation between the binary vector detailing the presence vs. absence of each AU on each trial and the corresponding binary vectors detailing the response of the observers. Consequently, we obtained for each emotion word in each culture, a 1 X 42-dimensional vector detailing the correlation coefficients for each AU. We then obtained bootstrap confidence intervals (95%, 1000 shuffled samples) for the resulting Pearson correlation coefficients, thereby producing a 1 X 42-dimensional binary vector detailing the composition of significant AUs for each

emotion word in each culture. To model the dynamic components of each model, we then performed a linear regression between each of the emotional intensity response variables and the six temporal parameters for each AU. We then obtained bootstrap confidence intervals (95%, 1000 samples) for the resulting linear regression coefficients, thereby producing a 6 (temporal parameters) X 42 (AUs) matrix detailing the significant temporal parameter values for each of the significant AU derived previously. Finally, we combined the significantly correlated AUs with the temporal parameters derived from the regression coefficients, thereby an animation for each facial expression model. For the *between cluster categorization task*, for each singleton cluster word (e.g., 'surprise' and 'pride' in English), we used the same procedure as above where the set of response options (e.g., in English, 'surprise,' 'pride,' 'love,' 'fear,' 'hate,' 'anger,' 'sad,' and 'shame') comprises a single cluster. By combining the results of the within and between cluster categorization tasks, we derived 30 dynamic facial expressions of emotion for the Western group and 52 dynamic facial expressions of emotion for the East Asian group ('sad'/悲 produced no significant Action Units).

4. Validation of models of dynamic facial expressions of emotions. Our method aimed to provide an accurate representation of the cultural dynamic facial expressions that communicate the emotions represented in the clusters of Figures 1 and 2. Before analyzing the resulting dynamic facial expression models (henceforth, 'model'), we submitted each to a within-culture verification task using a new set of observers (henceforth 'validators.') We recruited 29 new Western white Caucasian native English speakers (14 male; mean age 20.8, SD 2.2 years), and 28 Chinese native Chinese speakers (13 male, mean age 22.9, SD 1.5) years).

On each experimental trial, validators viewed one of the emotion words presented in Figures 1 or 2 followed by a model from their own culture. Validators then indicated (using a

yes/no key response) whether the emotion word accurately described the facial expression displayed. For each validator, half of the trials comprised correct (i.e., within cluster) word and facial expression pairs (e.g., 'fury' word + 'livid' facial expression) and half of the trials comprised incorrect (i.e., between cluster) word and facial expression pairs (e.g., 'fury' word + 'happy' facial expression). We presented each word for 1 second in lower case white font (Arial Unicode MS) on a black screen and played each facial expression stimulus once for 1.25s, followed again by a black screen. Observers responded using a keyboard only after the facial expression animation had finished. We displayed all models (30 Western and 52 East Asian) by mapping them onto a new set of 50 same-race identities (white Caucasian: 25 male, mean age 25 years, SD 4.2 years; Chinese: 25 male, mean age 24 years, SD 1.6 years) captured using standard procedures (Yu et al., 2012). We used standard procedure to render all stimuli (Yu et al., 2012), resulting in a total of 1500 (30 models X 50 identities) Western facial expression stimuli and 2600 (52 models X 50 identities) East Asian facial expression stimuli. Each validator completed a sub-sample of trials randomly sampled (with replacement) from the pool of culture-specific stimuli, presented in random order across the experiment. Each Western validator completed 300 such trials; East Asian validators completed 520 such trials. All validators viewed all stimuli on a black background, presented in the center of their visual field and displayed on a flat 17-inch panel monitor with a refresh rate of 60 Hz and resolution of 1280 × 1024. A chin rest ensured a constant viewing distance of 68cm, with facial expression stimuli (average size 17 × 11.5 cm) subtending 14.28° (vertical) and 9.69° (horizontal) of visual angle.

Results

D-prime. To extract the models that each culture could accurately identify, we computed the between-cluster discrimination performance (d-prime; Macmillan & Creelman,

2004) of each model in each culture. D-prime values ranged from -0.29 to 3.02 (mean 1.53, SD 0.81) in the Western group and -0.37 to 2.7 (mean 1.35, SD 0.88) in the East Asian group. Table 1 below shows all d-prime values for all Western and East Asian facial expression models.

[TABLE 1 HERE]

We then extracted all models with a d-prime > 1 (indicated with an asterisk in Table 1), resulting in 25/30 (83.33%) Western models and 37/52 (71.15%) East Asian models. Five Western facial expression models and 15 East Asian models had a d-prime < 1.

Experiment 3

Common and Culture-specific Action Unit Patterns. In each culture, we identified a core set of emotion words, their semantic relations, and their corresponding dynamic AU patterns. As discussed earlier, Darwin's theory of the biological and evolutionary origins of facial expressions of emotion formed the basis of a longstanding view that facial expressions of emotion are universal. Specifically, Darwin's account proposed that certain facial movements that once served a physiologically adaptive function, such as widening the eyes to increase visual input, evolved as social signals based on their visual salience (e.g., the high contrast of the eye whites unique to humans; Kobayashi & Kohshima, 1997) and consistent association with states of the environment (e.g., approaching threat) and group members (e.g., fear). Consequently, although facial expressions evolved into more complex and numerous patterns to support increasingly sophisticated social interactions, they could still retain these physiologically adaptive facial movements, thereby supporting the recognition of certain emotions across distinct cultures. On the basis of Darwin's evolutionary account, Ekman and

colleagues proposed that a specific set of facial expressions (i.e., AU patterns) communicated six basic emotions – ‘happy,’ ‘surprise, ‘fear, ‘ disgust,’ ‘anger,’ and ‘sad’ – across all cultures, and reported above chance recognition performance across several cultures to support their claims.

However, as discussed above, the highly variable recognition performance of these AU patterns across cultures question the true extent of their cultural validity. Rather, recognition accuracies below typical (e.g., see Duchaine & Nakayama, 2006) but above chance performance in non-Western cultures suggest that specific *latent components* of facial expressions (i.e., specific embedded AU patterns) could support a more fundamental level of emotion communication across cultures. For example, biologically adaptive facial movements (e.g., eye widening; Ekman et al., 1978) embedded in different facial expressions of emotion (e.g., ‘fear’ and ‘surprise;' Ekman et al., 1978; Jack et al., 2014) could communicate more general information that is shared across the emotion categories (e.g., that an immediate response is required). Thus, as suggested by Darwin’s account, facial expressions of emotion in different cultures could share a common set of embedded AU patterns, on which cultural evolution has built more complex and numerous patterns to support sophisticated social interactions. Such cultural specificities – called ‘accents’ or ‘dialects’ (Elfenbein, 2013; Elfenbein, Beaupre, Levesque, & Hess, 2007; Marsh, Elfenbein, & Ambady, 2003; Silvan S. Tomkins & Robert McCarter, 1964), or ‘modifiers’ in animal communication (Jenssen, 1977, 1979) – are widely discussed in the literature (Ekman, 1972; Elfenbein, 2013; Matsumoto, Yoo, & Fontaine, 2008; Mesquita & Frijda, 1992). For example, Japanese nationals and Japanese Americans are reliably distinguished on the basis of expressive but not neutral facial expressions (Marsh et al., 2003), suggesting the embedding of cultural accents (see also Marsh, Elfenbein, & Ambady, 2007). Yet, segregating culturally common AU patterns (i.e., basis AUs) from those that are culture

specific (i.e., modifier AUs) has remained challenging as detailed above (Labarre, 1947).

Method

To explore the *latent components plus cultural accents* hypothesis, we used a multivariate data reduction technique (Non-negative Matrix Factorization – NMF; Lee & Seung, 1999) to separate culturally common and culture specific AU patterns from each modeled facial expression. Specifically, NMF performs factorization on non-negative values data to separate them into their main parts, where the parts (i.e., factors) are multivariate AU patterns. In other words, NMF applied here can identify the most common AU patterns in our data set. Each facial expression model can thus be expressed as the addition of weighted factors (i.e., common AU patterns) plus a residual (i.e., 'accent' AU patterns)

Model = linear_coefficients * Common AU patterns + Accent AU pattern (1)

NMF therefore provides an intuitive representation of each facial expression as the combination of parts (i.e., specific AU patterns) to form a whole.

A. Common Action Unit patterns. To extract the AU patterns common across cultures, we proceeded in two steps. First, we pooled together the 25 Western and 37 East Asian facial expression models (each represented as a 1 X 42 vector detailing the coefficients of each AU's positive correlation with the categorization responses), resulting in a 62 (all facial expressions across cultures) X 42 (AUs) matrix of real valued correlation data. To identify the optimal (i.e., minimum) number of factors to represent the data (i.e., pooled Western and East Asian facial expressions), we applied NMF in an iterative manner (k = 2 to 20 factors, 1000 replicates per iteration), computed the variance explained at each iteration, and identified the minimum of the curve of variance explained as the best fit (Cattell, 1966). Our analysis revealed that four factors best represent the pooled Western and East Asian facial expressions of emotion (see *Supplemental Materials – Figure S1*). Figure 4 shows the four

NMF factors (i.e., latent AU patterns) resulting from this analysis, each displayed as color-coded face maps, where red indicates a stronger AU presence and blue indicates weaker AU presence in the factor (i.e., the factor weights, normalized separately for each factor).

[FIGURE 4 HERE]

Results

As shown in Figure 4, the color-coded face maps show four distinct AU patterns – whereas AU pattern 1 involves Lip Corner Puller (AU12) and Cheek Raiser (AU6), AU pattern 2 includes Brow Lowerer (AU4), Lip Stretcher (AU20) and Eyes Closed (AU43), AU pattern 3 includes Upper Lid Raiser (AU5) and Jaw Drop (AU26), and AU pattern 4 involves Nose Wrinkler (AU9) and Upper Lip Raiser (AU10). See *Supplemental Materials – Table S4* for all AUs corresponding to each factor. Gray-scale shapes to the right of each face map indicate the AU pattern (i.e. factor) that contributes mostly to Western (circles) and East Asian (diamonds) culturally validated facial expression models (i.e., d-prime > 1). Lighter shapes indicate a higher strength of the contribution (i.e., the linear coefficient value), with darker shapes indicating a lower contribution (values are normalized across each AU pattern separately). Corresponding emotion labels are shown next to each shape. For example, AU pattern 1 contributes more to the Western facial expression of 'happy' (light circle) than the East Asian facial expression of 'feel well'/爽 (dark diamond). As shown by the heterogeneity of the shapes associated with each AU pattern, each AU pattern contributes similarly to both Western (circles) and East Asian (diamonds) facial expression models (see *Supplemental Materials – Table S5* for the median linear coefficient values and numbers of models and per factor and culture). Below each face map, magenta bars with standard error show the average coefficient values for each of the four factors (median computed across all facial expressions

listed on the right of each face map). Note from the distributions that most facial expression models comprise one main factor (i.e., AU pattern), with minimal contribution from the other three factors. We will thus forth refer to these main factors as 'basis AU patterns.'

Meaning of basis Action Unit patterns across the dimensions of valence, arousal and dominance.

Next, to understand the message that each basis AU pattern conveys, we examined the ratings of three main dimensions of emotion – valence (e.g., pleasantness or unpleasantness), arousal (e.g., excited or calm) and dominance (e.g., in control or being controlled) – for each emotion word with a culturally validated facial expression model (i.e., d-prime > 1). Our aim is to understand whether the four basis AU patterns convey specific fundamental messages of valence, arousal and/or dominance, which could characterize the compositionality of facial expressions of emotion according to few basis AU patterns plus a variety of cultural accents. Our analyses will reveal that each basis AU pattern is associated with specific messages of valence, arousal and/or dominance within and across cultures. In Figure 5, each basis AU pattern is displayed as a color-coded face map with a color-coded outline. Underneath, we list and number all the associated emotion words with a culturally validated facial expression model that comprises that basis AU pattern as main contributor, as explained above.

[FIGURE 5 HERE]

To visualize the relationship between the facial expressions comprising each basis AU pattern and the dimensions of valence, arousal and dominance, we plotted each emotion word with a culturally valid facial expression model in a 3-dimensional space according to its average valence (x-axis), arousal (z-axis) and dominance (y-axis) rating. In Figure 5, the 3-dimensional plot shows the results where each number represents an emotion word (see list

below each AU pattern) color-coded according to the basis AU pattern of its corresponding facial expression model (see color-coded outline of each basis AU pattern). As shown by the distribution of colors, each basis AU pattern is associated with specific ratings of valence, arousal and/or dominance. For example, basis AU pattern 1 (color-coded in orange) is associated primarily with emotion words rated as high valence, high arousal, and high dominance such as 'happy,' 'pride' and 'feel well'/爽. In contrast, basis AU pattern 4 (color-coded in green) is associated primarily with emotion words rated as low valence, high arousal, and varying levels of dominance, such as 'bristle with anger'/怒发冲冠, 'disgust,' and 'hate.' See *Supplemental Materials – Figure S3* for corresponding 2 dimensional plots.

To identify the main clusters of facial expressions according to valence, arousal and dominance, we applied a k-means cluster analysis to the ratings of valence, arousal and dominance of each word in an iterative manner (k = 2 to 10 clusters, 1000 replicates per iteration), computed the total within-cluster point-to-centroid distances (squared Euclidean distance) at each iteration, and identified the maximum of the curve as the best fit (Cattell, 1966). Our analysis showed that three clusters best represent the data (see *Supplemental Materials – Figure S2*), with each cluster representing a specific combination of valence, arousal, and dominance ratings. In Figure 5, red shapes (diamond, square, star) in the 3-dimensional plot indicate the location of each centroid (i.e., the cluster's average valence, arousal and dominance rating which are reported in the gray-scale matrix underneath together with the spread. Lighter to darker squares indicate high to low average ratings, see colorbar below). The gray-scale coding reveals that cluster 1 (diamond) comprises high valence, high arousal, and high dominance emotions, cluster 2 (square) comprises low valence, high arousal and varying dominance emotions, and cluster 3 (star) comprises low valence, low arousal, and varying dominance emotions.

In Figure 5, the color-coded matrix shows the proportion of facial expression models associated with each basis AU pattern (see color-coding above) assigned to each cluster, where color brightness indicates a higher proportions of facial expression models with that basis AU pattern (e.g., 85% of the facial expression models with basis AU pattern 1, color-coded in orange, are present in cluster 1, represented by the diamond). As shown by the distributions of basis AU pattern colors across the three clusters, some basis AU patterns are associated with specific combinations of valence, arousal and dominance, suggesting high specificity in the messages they communicate. For example, basis AU pattern 1 (color-coded in orange) is primarily associated with high valence, high arousal, and high dominance emotions, whereas basis AU 4 (color-coded in green) is mostly associated with low valence, high arousal emotions. In contrast, basis AU patterns 2 (color-coded in cyan) and 3 (color-coded in magenta) distribute across several different clusters, indicating more flexibility in the messages they can communicate. For example, basis AU pattern 2 is associated with low valence emotions of both low and high arousal, suggesting that this expressive pattern communicates a general message of negativity. Similarly, basis AU pattern 3 is associated with high arousal emotions of both low and high valence, which suggests that this expressive pattern 3 communicates a general message of high arousal.

Here, we identified four distinct AU patterns that each forms the basis of a broad range of facial expressions of emotion in different cultures, and which are associated with specific fundamental messages of valence, arousal and/or dominance within and across cultures. Our results are consistent with previous cross-cultural recognition studies showing that only four facial expressions of discrete emotions are recognized across cultures (i.e., ‘happy,’ ‘surprise,’ ‘anger’ and ‘sad’), with consistent confusions between semantically and physically similar facial expressions – i.e., ‘surprise’ and ‘fear,’ and ‘disgust’ and ‘anger’ (see Jack, 2013 for a review). Consequently, our results question the widely held view that

the six facial expression patterns corresponding to discrete emotion categories – i.e. 'happy,' 'surprise,' 'fear,' 'disgust,' 'anger,' and 'sad' – are universal (Ekman et al., 1969). Rather, our results suggest that four distinct and latent expressive patterns, which each conveys more fundamental emotion messages (e.g., negative, high arousal) represent the culturally common basis of emotion communication. Thus, our data suggests an alternative theoretical account of facial expressions of emotion that combines categorical and continuous theories of emotion, which we will return to in the General Discussion.

B. Accent Action Unit patterns. From the NMF factorization, we can represent each facial expression model as additive (i.e. linear) combination of the basis AU patterns (each weighted by a coefficient value detailing its contribution) to the facial expression, plus a residual (i.e., accent AU patterns). Since most facial expression models comprise one main basis AU pattern (i.e., the other three factors contribute minimally; see magenta bars in Figure 4), we can represent each model as a composition of one main basis AU pattern plus its accent (cf. Equation 1). Thus, to reveal the accent AU pattern of each facial expression model, we simply subtracted from the original real-valued facial expression model the main basis AU pattern contribution (gray-scale shapes in Figure 4 indicating contribution strength). Figure 6 shows the results using one illustrative example.

[FIGURE 6 HERE]

Results

The central color-coded face map represents basis AU pattern 1 (e.g., Lip Corner Puller – AU12, Cheek Raiser – AU6, Dimpler – AU14, Sharp Lip Puller – AU13), which contributes most to the facial expressions of 6 Western and 8 East Asian emotions (see

emotion labels, which also corresponds to the list in Figure 5). Below each emotion word, smaller face maps show the accent AU pattern of the corresponding facial expression. Color-coded circles below each face map show the proportion of accent AUs that correspond to each of the other three basis AU patterns (see color key in Figure 5), where brighter colors indicate higher proportions. For example, the Western accent AU pattern in 'delighted' comprises Outer Brow Raiser (AU2), Upper Lid Raiser (AU5) and Jaw Drop (AU26) – i.e. aspects of basis AU pattern 3 (color-coded in magenta). Visual inspection of the face maps shows that basis AU pattern 1 is mostly accented with AUs that correspond to basis AU pattern 3, which is primarily associated with high arousal emotion words. A small proportion of accents also correspond to basis AU 2 (color-coded in cyan) – e.g., 'contempt,' 'embarrassment'/尴尬 and 'pride'/骄傲 – which is associated with low valence emotion words. Together, these data illustrate how the combination of basis AU patterns with specific accents can finely modulate, via a grammatical composition, the emotion message transmitted by the face (e.g., by arousal or valence) to produce complex facial expressions for sophisticated social interactions. We will now examine the accent AU patterns associated with the remaining three basis AU patterns, as show in Figures 7-9 below.

[FIGURE 7 HERE]

As in Figure 6, Figure 7 shows that basis AU pattern 2 (e.g., Brow Lowerer – AU4, Lip Stretcher – AU20, Eyes Closed – AU43, Lip Pressor – AU24) contributes most to the facial expressions of 9 Western and 14 East Asian emotions. Smaller face maps below each emotion word show the corresponding accent AU pattern as explained before. As shown by the distribution of color-coded circles, basis AU pattern 2 tends to be combined with accents

that correspond to basis AU pattern 1 (color-coded in orange), which is associated primarily with high valence, high arousal emotions. Some accents also comprise AUs from basis AU pattern 3 (color-coded in magenta) and AU pattern 4 (color-coded in green), each of which are associated with high arousal emotions. Such diversity in accent AU patterns suggests that basis AU pattern 2, which is associated with low valence emotion words (see Figure 5 for cluster assignments), can be flexibly manipulated to create a broad range of nuanced negative emotions.

[FIGURE 8 HERE]

As above, Figure 8 shows basis AU pattern 3 (e.g., Upper Lid Raiser – AU5, Mouth Stretch – AU27, Jaw Drop – AU26 and Outer Brow Raiser – AU2), which contributes most to the facial expressions of 5 Western and 6 East Asian emotions. As shown by the distribution of color-coded circles beneath each face map, basis AU pattern 3 is combined with accents from all other basis AU patterns in similar proportions. Thus, as with basis AU pattern 2 (see Figure 7 above), the diversity in accent AU patterns reflects that basis AU pattern 3, which is associated with high arousal emotions, can be flexibly manipulated to create a complex array of high arousal facial expression of emotion.

[FIGURE 9 HERE]

Finally, Figure 9 shows the basis AU pattern (e.g., Nose Wrinkler – AU9, Upper Lip Raiser – AU10, Lower Lip Depressor – AU16 and Lip Funneler – AU22) that contributes most to the facial expressions of 5 Western and 9 East Asian emotions. As shown by the distribution of color-coded circles, basis AU pattern 4 is combined with AU accents from all

other basis AU patterns in similar proportions. Thus, as with basis AU patterns 2 and 3 (see Figures 7 and 8 above), the diversity in accent AU patterns reflects that basis AU pattern 4 forms the basis of a complex array of low valence, high arousal facial expression of emotion.

In sum, our analysis reveals that each facial expression model comprises a culturally common basis AU pattern to which specific accent AUs are added to refine the message transmitted. Specifically, the four basis AU patterns form latent variables that convey fundamental emotion messages of differing valence, arousal and dominance – basis AU pattern 1 (e.g., Lip Corner Puller – AU12, Cheek Raiser – AU6, color-coded in orange) is primarily associated with high valence, high arousal and high dominance emotions; basis AU pattern 2 (e.g., Brow Lowerer – AU4, Lip Stretcher – AU20, Eyes Closed – AU43, color-coded in cyan) is associated more generally with low valence emotions; basis AU pattern 3 (e.g., Upper Lid Raiser – AU5, Jaw Drop – AU26, color-coded in magenta) is associated with high arousal emotions; and basis AU pattern 4 (e.g., Nose Wrinkler – AU9, Upper Lip Raiser – AU10) is associated with low valence, high arousal emotions. As shown by the distribution of color-coded circles in Figure 6-9, each basis AU pattern is then combined with an array of specific AU accents to create the range of nuanced emotion signals required for sophisticated social interactions. Our data therefore suggest that facial expressions of emotion are characterized by a grammatical structure, whereby each facial expression comprises one main basis AU pattern that communicates a broad message shared across cultures, and which is accentuated by additional AUs to refine the message.

General Discussion

Here, we used a multidisciplinary approach that combines cultural psychology and social cognition, dynamic structural face computer graphics, vision science and psychophysical methods, and mathematical psychology to address the empirical challenge of understanding

how the face – a complex high dimensional dynamic information space – communicates emotions across cultures. To summarize our results, we first identified a core set of emotion words in each culture that represent a broad spectrum of emotions, and used them to identify clusters of semantically similar emotion words in each language. Next, using reverse correlation combined with a dynamic facial expression generator, we modeled the dynamic facial expressions associated with all such emotion words in each culture. Following within culture validation of the resulting dynamic facial expression models, we applied a multivariate data-reduction analysis (Non-negative Matrix Factorization) and showed that four basis AU patterns (i.e., specific latent components of facial expressions of emotion) are common across cultures. Analysis of the ratings of valence, arousal, and dominance associated with each basis AU pattern showed that each basis AU pattern communicates a specific fundamental emotion message (e.g., negative, high arousal). Finally, by extracting the basis AU patterns from each of the original facial expression models, we revealed their culture-specific accent AU patterns. Thus, our results provide for the first time a broad spectrum of over 60 culturally valid dynamic facial expressions of emotion and reveal that four basis AU patterns are common across cultures. Furthermore, we reveal the compositionality of each expression model as a culturally common basis AU pattern plus a cultural accent. Consequently, our data extends knowledge beyond the classic six static facial expressions on which much of knowledge of cultural similarities and difference are currently based, with direct implications across several fields of psychology including emotion communication, social psychology, cognitive neuroscience, and social robotics.

In the field of emotion communication, one of the main aims is to identify which specific facial expression patterns are common across cultures and which are culture-specific. Here, using a much broader set of culturally validated facial expressions than used previously, we show that a latent set of four basis AU patterns is common across cultures, thereby

questioning the common view of six universal facial expression patterns. Our data suggest that emotion communication via facial expressions is based on four main categories, each of which could reflect different functions of broadly similar meaning across cultures. For example, basis AU pattern 4 (Nose Wrinkler, Upper Lip Raiser) is associated exclusively with low valence emotions in both cultures (e.g., ‘rage’ and ‘furious’/暴怒), and comprises face movements associated with rejecting noxious contaminants (Susskind et al., 2008), moral disgust (Chapman et al., 2009) and aggression (Andrew, 1963), which could elicit avoidance behaviors to protect from harm. Basis AU pattern 2 (Eyes Closed, Lip Stretcher, Brow Lowerer) is also associated exclusively with low valence emotions in both cultures (e.g., ‘shame’ and ‘anguish’/苦闷), but could instead reflect a non-aggressive negative internal state that elicits approach behaviors to re-establish social contact (e.g., to restore the expressers emotional and/or social status). Thus, while each AU pattern is associated exclusively with negative emotions, each specific facial pattern could elicit different behaviors of approach or avoidance. Similarly, basis AU pattern 1 (Lip Corner Puller, Cheek Raiser) is associated primarily with high valence emotions in both cultures (e.g., ‘joy’ and ‘pleasantly surprised’/惊喜) and therefore likely elicits approach behaviors but where the social function (e.g., affiliation, enjoyment) is distinct from the negatively related approach behaviors elicited by basis AU pattern 2 (Eyes Closed, Lip Stretcher, Brow Lowerer). Finally, basis AU pattern 3 (Upper Lid Raiser, Jaw Drop) is not associated exclusively with negative or fear related emotions, as predicted on account of the wide-open eyes, but is also associated with high valence (e.g., ‘ecstatic’) and neutral emotions (e.g., ‘amazed’/吃惊) across both cultures. Rather, the visually salient eye whites present in a variety of different emotions such as ‘surprise,’ ‘excited,’ ‘terrified,’ ‘amazed’/吃惊 could act as an ‘attention grabber’ (Niedenthal et al., 2010; Senju & Johnson, 2010) for rapid action, or to convey intensity similar to grammatical facial movements used in sign languages. Our data therefore raise new

questions to understand the fundamental conceptual dimensions that distinguish these four basis AU patterns. Our results are also consistent with recent work showing that dynamic facial expressions of the six classic emotions transmit information in a hierarchical manner over time, where early AU patterns support the discrimination of only four emotion categories – 'happy,' 'sad,' 'surprise'/'fear,' 'disgust'/'anger' – with all six emotion categories discriminated only later based on the transmission of diagnostic AUs (e.g., 'surprise' is discriminated from 'fear' on the basis of the Inner/Outer Brow Raiser – AU1-2) (Jack et al., 2014).

The prominence of these four basis AU patterns across the cultures considered here also raises the possibility of a grammar of facial expressions. That is, individual facial expressions could syntactically comprise one main basis AU pattern that communicates a broad message that is shared across cultures, which is accentuated by additional AUs (i.e., accent AU patterns) that refine the message and which could be subject to the influence of culture. We also predict that the syntax of facial expression production would have a dynamic order such that basis AU patterns (i.e., the main message) would be transmitted before the accent AU pattern is added to refine meaning. Thus, we expect cultural commonalities (i.e., basis AU patterns) early in the transmission of information followed by social and cultural diversity (i.e., accent AU patterns) later in the transmission of information. We aim to explore this hypothesis in further studies.

Here, we show that four distinct basis AU patterns are common across cultures. Although such commonalities are typically used to support claims that facial expressions of emotion are innate and hard-wired, on their own they are insufficient to draw such conclusions. For example, cultural similarities in facial expression patterns could arise due to convergent evolution (i.e., independent emergence) based on the relatively high similarity of facial musculature across the human species, and similar social pressures across cultures.

Also, as with spoken language, humans could have a common genetic predisposition to learn the visual language of facial expressions of emotion generally, but where the specifics of the language learned could vary by culture/country (Ladd, Dediu, & Kinsella, 2008). For example, we show culture-specific accent AU patterns that could indicate the role of cultural learning, as is demonstrated by the distinct accents of animals of the same species located in different geographical regions (Slabbekoorn & den Boer-Visser, 2006) only are found only in species that learn their vocalizations from others. In addition to identifying the genetic basis of facial expression production and perception, understanding whether and how certain learned facial expression 'feature vocabularies' (Schyns, Goldstone, & Thibaut, 1998; Schyns & Rodet, 1997) could facilitate or hinder the learning of new facial expressions could further inform knowledge of human social communication and the challenges of cross-cultural integration.

We also anticipate that by providing a broad spectrum of over 60 culturally valid dynamic facial expressions of emotions, our data will form the basis of new research to develop empirical and theoretical knowledge of emotion communication. For example, a detailed exploration of the facial expressions that communicate different forms of aggression, such as 'fury,' 'rage,' 'livid,' and 'anger,' in a given culture could reveal the precise accent AU patterns that communicate different intensities thereby modulating the observer's behavior (e.g., attack or flee). Similarly, analysis of different smile types such as those used to establish friendship, dominance or show pleasure (Niedenthal et al., 2010) could reveal which specific accent AU patterns communicate these different social functions, and thereby influence related judgments such as trustworthiness or attractiveness. Our culturally accented dynamic facial expressions of emotion could also be combined with different in- and out-group face identifiers such as skin pigmentation or facial morphology to address remaining questions relating to the in-group advantage hypothesis (Elfenbein & Ambady, 2002a;

Matsumoto, 2002).

Our results also provide a theoretical mid-way point between the continuous space of the dimensions of valence, arousal and dominance (Russell, 1980) and the discrete classic categories (Ekman et al., 1969). Here, we showed that the basis AU patterns clustered around specific values of the dimensions of valence, arousal and dominance, where the variance (and therefore coverage) of the 3-dimensional continuous space can be attributed to culture-specific accents that modulate the transmitted message. However, we also note that in certain quadrants of the 3D continuous space, few or no facial expression models were projected (e.g., high valence, low arousal, any value of dominance). Since the face transmits myriad social messages of which emotions are a subset, it is possible that facial expressions associated with social traits (Gill et al., 2014) or mental states (Bavelas, Coates, & Johnson, 2000; Chen, Garrod, Schyns, & Jack, 2015) would populate these quadrants. We aim to study the coverage of the continuous space by basis AU patterns, cultural accents and discrete facial expression categories in further studies.

In cognitive neuroscience, the vast majority of knowledge of human cognition, including how emotion information is processed by the brain, is based on Western, Educated, Industrial, Rich and Democratic (WEIRD) populations (Henrich, Heine, & Norenzayan, 2010) using classic facial expression stimuli. As in emotion communication, developing a comparable understanding of non-Western brain processes, a necessary first step involves developing culturally valid facial expression stimuli. Thus, we anticipate that our dynamic facial expressions will be used to show how the non-Western brain processes specific face information to perform recognition of same- and other-culture facial expressions (LeDoux, 2015; Pessoa & Adolphs, 2011; Schyns, Petro, & Smith, 2007), particularly when communication breaks down. For example, which specific face information contributes to decision-making processes when interpreting culturally unfamiliar or ambiguous facial

expressions? To what extent are reward and fear brain centers involved in these processes (Dolan & Dayan, 2013)? In turn, new questions arise about the complexities of emotion communication within cultures. For example, a prominent issue in affective neuroscience is that the amygdala responds strongly to the wide opened eyes of fearful facial expressions (Gamer, Schmitz, Tittgemeyer, & Schilbach, 2013; Whalen et al., 2004). However, here we show that many more facial expressions, including negative, positive and neutral emotions, display the sclera. Should we expect similar amygdala responses to these facial expressions, as predicted by its proposed specialization to the sclera (Adolphs, Tranel, Damasio, & Damasio, 1995)? Relatedly, where the sclera is expected early, such as in 'surprise,' or late such as in 'ecstatic,' does the amygdala respond similarly to these facial expressions? Thus, we anticipate that our dynamically precise culturally valid facial expression stimuli will be used to address these questions.

Finally, understanding human emotion communication also has direct implications for the development of the digital economy, which currently supports the rise of globalization and cultural integration. Consequently, cross-cultural social communication particularly via computing technologies such as life sized socially interactive avatars or 3D holograms are increasingly part of modern society. One of the main challenges in designing social robots and avatars is to equip them with knowledge of the system of human emotion communication – that is, which specific patterns of transmitted information communicate different emotions and which patterns should be transmitted in response. Thus, by providing a precise characterization of the system of emotion communication across different cultures, and identifying why communication breaks down between cultures, can inform the design of culturally aware social robots and avatars.

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Table 1. D-prime Values for Western and East Asian Facial Expression Models.

Table 1. D-prime Values for Western and East Asian Facial Expression Models.

*d' > 1

Western		East Asian		
Emotion	**d-prime**	**Emotion**		**d-prime**
delighted *	1.83	joyful *	欢喜	2.33
joy *	2.78	delighted *	喜	2.40
ecstatic *	1.55	happy & pleased *	喜悦	2.00
happy *	2.58	glad *	高兴	2.54
cheerful *	3.02	excitement	兴奋	0.14
euphoric	-0.19	feel well *	爽	1.97
love	-0.30	tears of joy	喜极而泣	-0.15
excited *	1.18	pleasantly surprised *	惊喜	1.93
surprise *	2.10	nice surprise	惊喜不已	0.81
fear *	2.38	amazed *	吃惊	2.71
scared *	2.17	greatly surprised *	大吃一惊	1.57
frightened *	2.11	surprised *	惊讶	2.03
terrified *	1.92	shock	震惊	0.22
anxious *	2.10	alarmed & panicky *	惊恐	1.30
contempt *	1.51	scared *	惊慌	1.52
jealous	0.16	panic	恐慌	0.46
hate *	1.73	fear *	恐惧	1.19
disgust *	2.38	afraid *	恐	1.48
fury *	1.62	anxiety *	害怕	1.26
rage *	1.77	terrified	惶恐	-0.17
livid	0.67	disgusted *	厌恶	1.21
anger *	1.16	bristle with anger *	怒发冲冠	1.87
unhappy	0.60	furious *	暴怒	1.49
upset *	1.81	wild wrath *	大怒	1.44
miserable *	1.30	storm of fury *	怒气冲冲	1.54
sad *	1.48	storm of anger *	气冲冲	1.40
depressed *	1.24	indignant *	气愤	1.37
shame *	1.08	wrath *	怒	2.18
embarrassment *	1.18	rage *	愤怒	1.73
pride *	1.08	angry	生气	0.61
		irritated & furious	恼怒	-0.30
		grief & indignation	悲愤	-0.08
		sorrow	伤悲	-0.37
		distressed *	哀伤	1.83
		heart-broken *	伤心	2.40
		sorrow & sadness *	悲伤	1.62
		painfully sad	悲痛	-0.05
		have a hard time *	难过	2.56
		suffering	痛苦	0.19
		grieve to the extent of wishing to die	痛不欲生	0.07
		grief *	哀	2.17
		give up all hope *	绝望	0.82
		dismay *	沮丧	1.73
		anguish *	苦闷	1.69
		worry *	忧	2.46
		vexed *	苦恼	1.88
		unhappy *	不开心	1.72
		annoyed	懊恼	0.15
		embarrassment *	尴尬	1.55
		shame *	羞愧	1.17
		pride *	骄傲	2.15
		despise *	蔑视	2.61

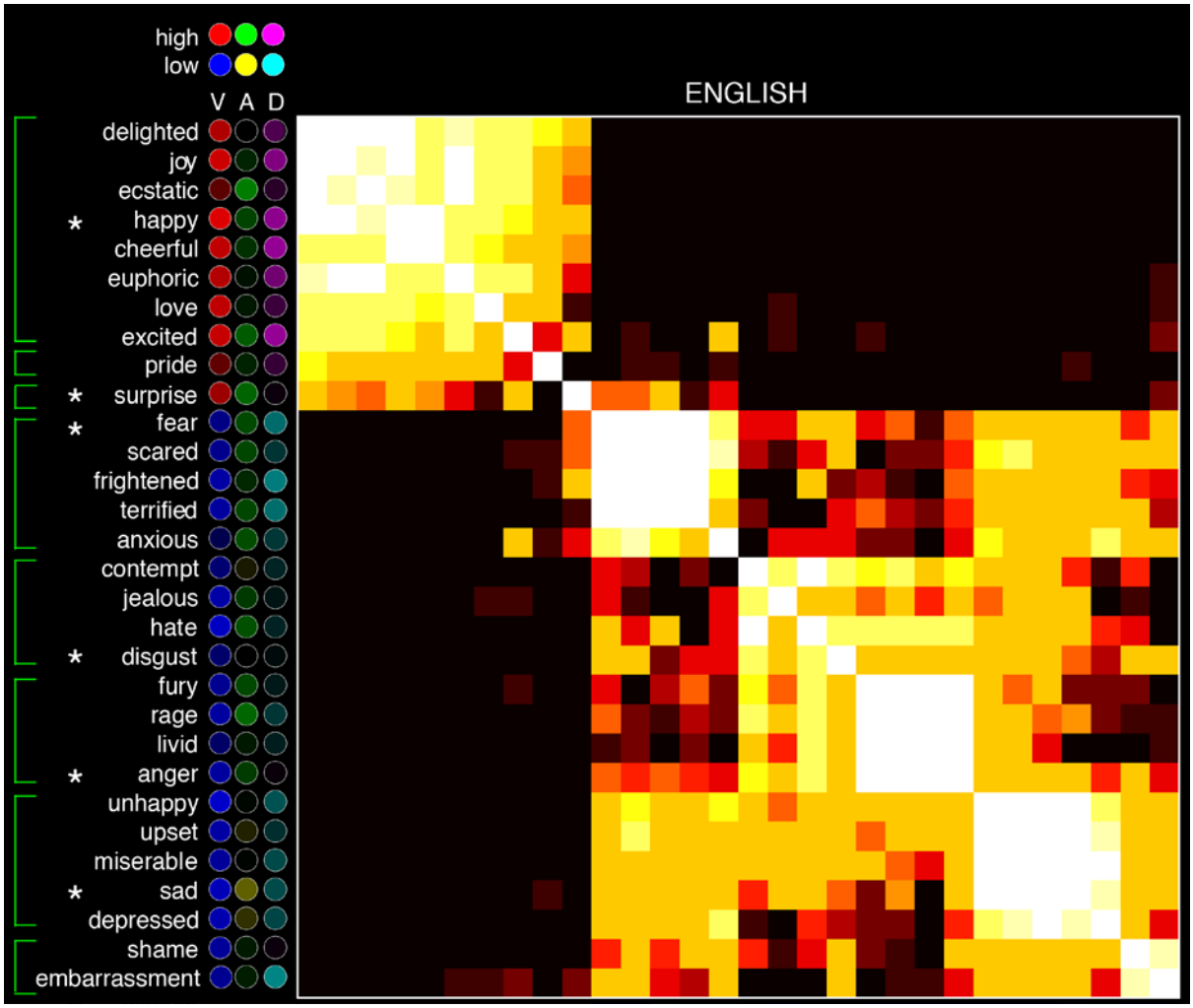

Figure 1. Clusters of Semantically Similar English Emotion Words Each Rated by Valence, Arousal and Dominance. The color-coded matrix shows the average (mode, computed across 50 native speakers) semantic similarity between each pair of emotion words in English. Lighter squares indicate high semantic similarity between word pairs (e.g., ‘delighted’ and ‘joy’) whereas darker squares indicate low similarity (e.g., ‘disgust’ and ‘pride’). To objectively identify clusters of semantically similar emotion words, we applied a graph-theoretic clustering algorithm (Pavan & Pelillo, 2007) to the matrix. Green brackets to the left indicate the emotion words that form clusters (e.g., ‘contempt,’ ‘jealous,’ ‘hate,’ and ‘disgust’ form one cluster). Asterisks indicate the location of the six classic emotions. Color-coded circles next to each word axis shows the average (mean) valence (red – high; blue – low), arousal (green – high; yellow – low) and dominance (magenta – high; cyan – low; see

key to left of labels) as judged by native English speakers (Warriner et al., 2013). As shown by the distribution of color-coded circles, all word clusters are either high valence (red circles) and high dominance (magenta circles), or low valence (blue circles) with varying levels of lower dominance (cyan circles), where the latter type as most numerous (5/8 [62.5%] clusters). Arousal varies across all clusters, where high arousal (green circles) is more numerous than low arousal (yellow circles).

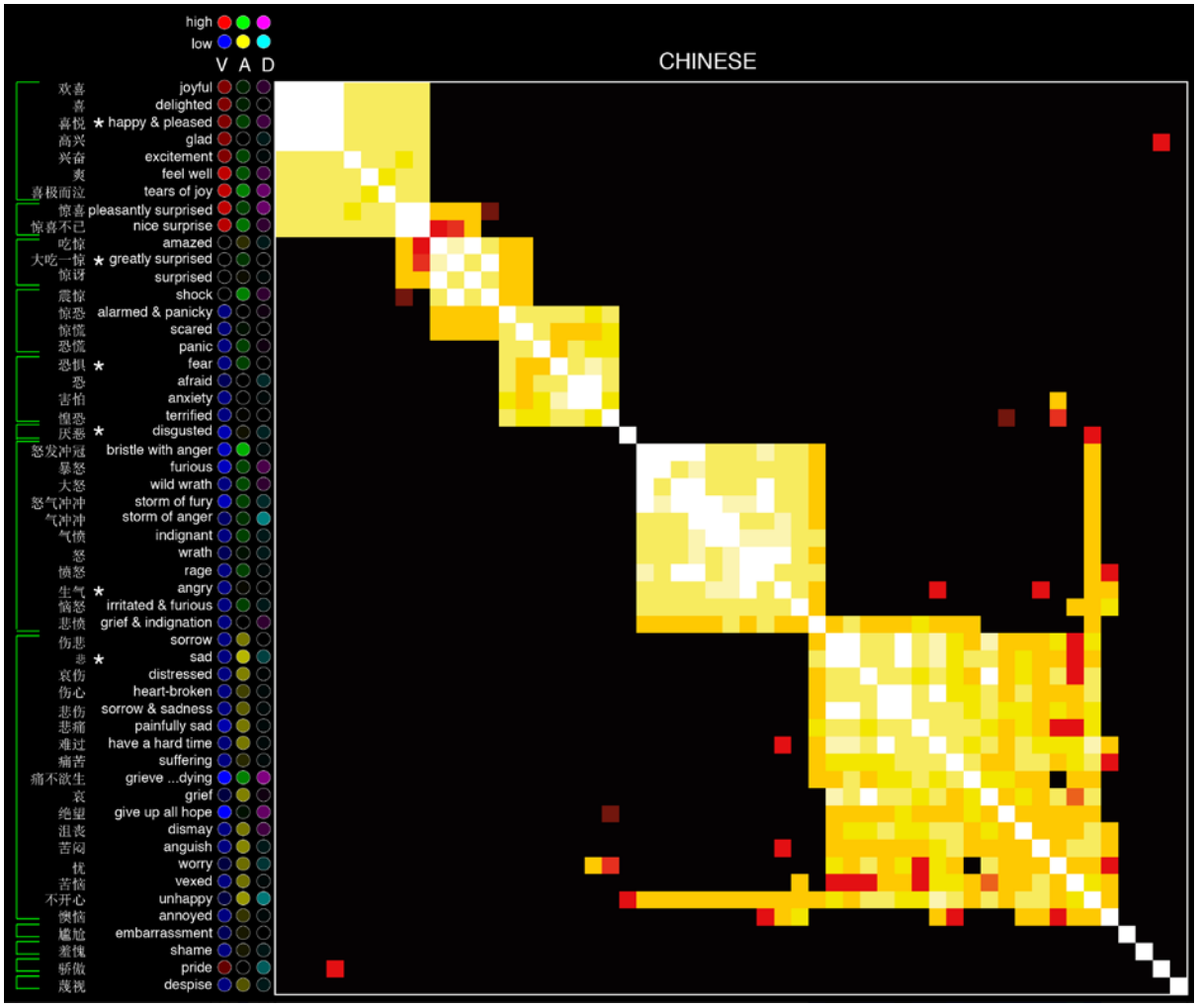

Figure 2. Clusters of Semantically Similar Chinese Emotion Words Each Rated by Valence, Arousal and Dominance. As in Figure 1 above, the color-coded matrix shows the average (mode, computed across 50 native speakers) semantic similarity between each pair of Chinese emotion words. Lighter squares indicate high semantic similarity between word pairs (e.g., ‘joyful’/欢喜 and ‘delighted’/喜) whereas darker squares indicate low similarity (e.g., ‘anguish’/苦闷 and ‘pleasantly surprised’/惊喜). To objectively identify clusters of semantically similar emotion words, we applied a graph-theoretic clustering algorithm (Pavan & Pelillo, 2007) to the matrix. Green brackets to the left indicate the emotion words that form clusters in each group (e.g., ‘fear’/恐惧, ‘afraid’/恐, ‘anxiety’/害怕, ‘terrified’/惶恐 form one

cluster). Asterisks indicate the location of the six classic emotions, as determined by closest match translation (‘happy’/喜悦, 惊讶, ‘fear’/恐惧, ‘disgust’/厌恶, ‘anger’/生气 and ‘sad’/悲). Color-coded circles next to each word show the average (median) perceived valence (red – high; blue – low), arousal (green – high; yellow – low) and dominance (magenta – high; cyan – low; see key to left of labels) as judged by 32 native Chinese speakers (see *Supplemental Materials – Table S3* for a full list of values). As shown by the distribution of color-coded circles, most clusters are homogenously high valence (red circles) and high arousal (green circles), or low valence (blue circles) with varying levels of arousal (green through yellow circles). Dominance (magenta through cyan circles) varies across all clusters. Low valence (blue circles) clusters are more numerous (10/12 [83.33%] clusters) than high valence clusters (red circles).

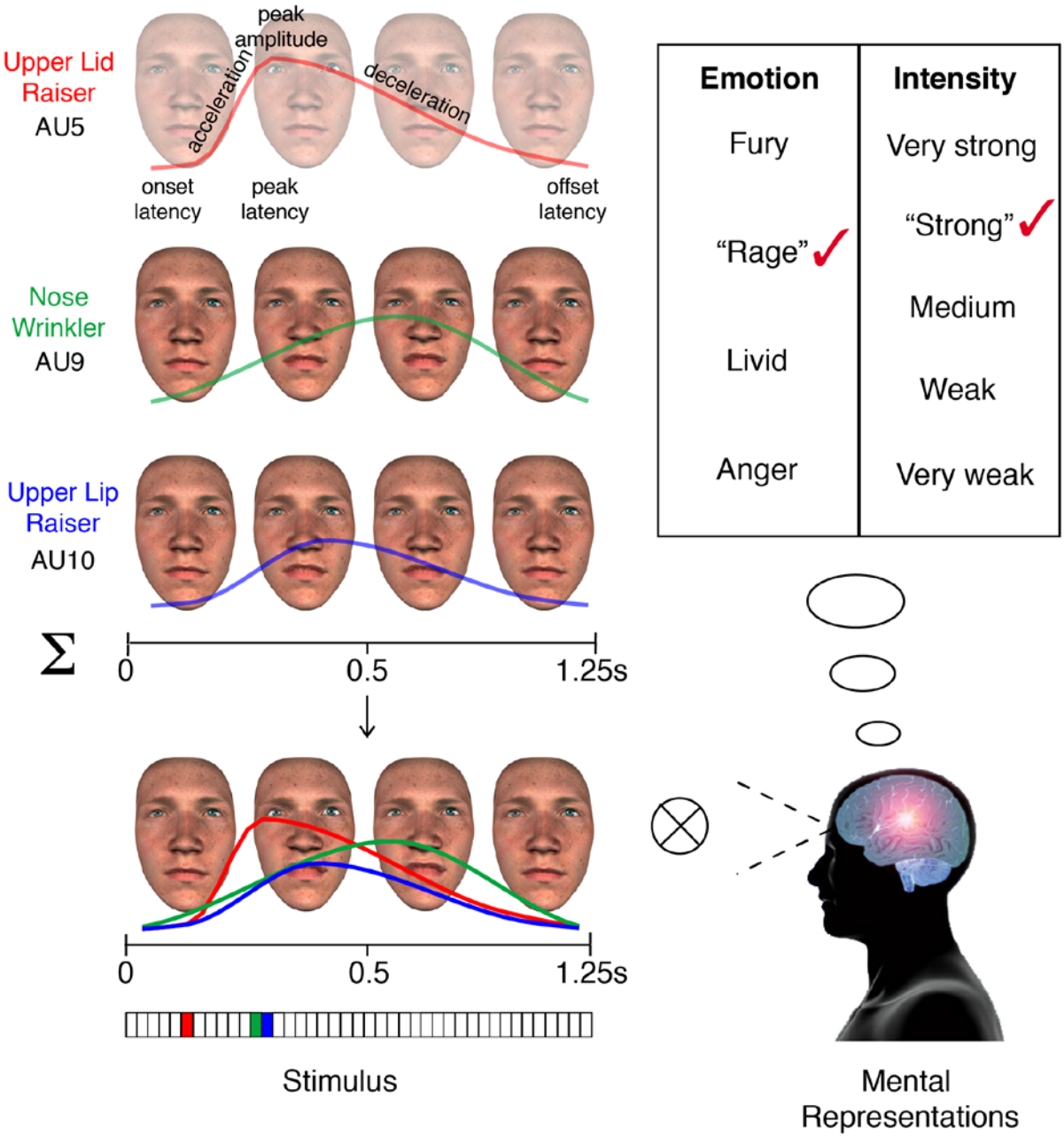

Figure 3. Modelling Dynamic Facial Expressions of Emotion Using Reverse Correlation. *Stimulus.* On each experimental trial, a Generative Face Grammar (GFG; Yu et al., 2012) randomly selects a subset of facial movements called Action Units (AUs; Ekman & Friesen, 1978) (here, Upper Lid Raiser – AU5 color-coded in red, Nose Wrinkler – AU9 in green, and Upper Lip Raiser – AU10 in blue) from a set of 42 AUs and random values for each of six temporal parameters per AU (see parameter labels in top row and color-coded temporal curves for each AU). The randomly chosen dynamic AUs are then combined to create a 4D facial animation presented here with four snapshots across time (duration 1.25s). The color-

coded vector below represents the 3 randomly selected AUs comprising the stimulus in this illustrative experimental trial. *Mental Representations.* The observer views and categorizes each random animation according to an aggression category (e.g., ‘fury,’ ‘rage,’ ‘livid,’ and ‘anger’) and rates the emotional intensity perceived from ‘very strong’ to ‘very weak.’ Observers categorize the stimulus as expressive when the random facial movements form a pattern that correlates with their mental representations (i.e., perceptual expectations) of an aggressive emotion at a given intensity (here, ‘rage,’ ‘strong’), otherwise selecting ‘other.’

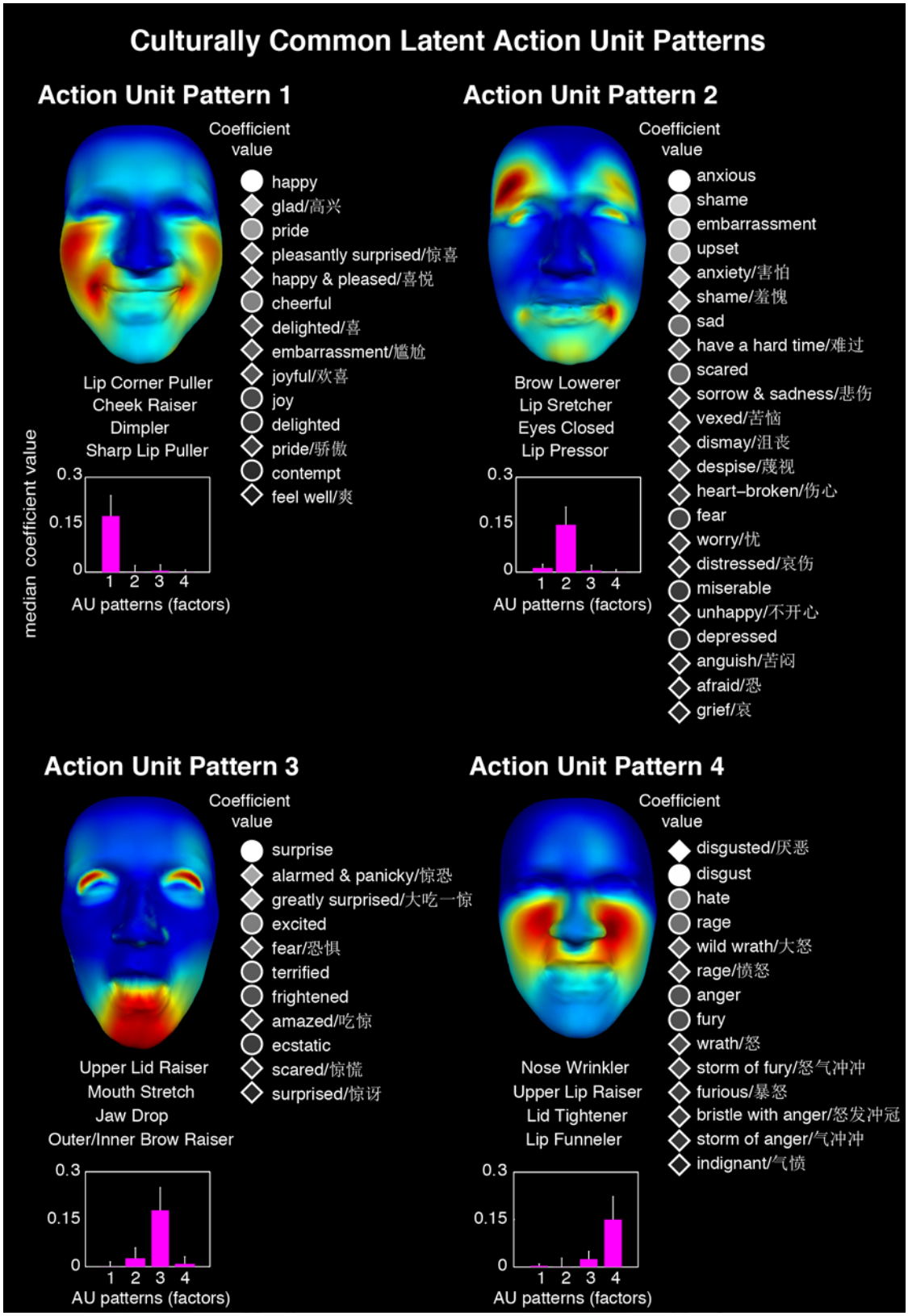

Figure 4. Culturally Common Latent Action Unit Patterns in Facial Expressions of Emotion. Color-coded face maps show the four common AU patterns (i.e., factors) extracted from 62 culturally validated Western and East Asian facial expressions models using non-

negative matrix factorization (NMF; Lee & Seung, 1999). Red color-coding indicates stronger AU presence (i.e., factor weight) and blue indicates weaker AU presence (weights are normalized per factor). Corresponding AU labels appear below each face map. As shown by the face maps, the four factors comprise distinct AU patterns: AU pattern 1 comprises Lip Corner Puller (AU12) and Cheek Raiser (AU6), AU pattern 2 includes Brow Lowerer (AU4) and Eyes Closed (AU43), AU pattern 3 includes Upper Lid Raiser (AU5) and Jaw Drop (AU26), and AU pattern 4 involves Nose Wrinkler (AU9) and Upper Lip Raiser (AU10). See *Supplemental Materials – Table S4* for all AUs corresponding to each factor). Gray-scale shapes to the right of each face map show the distribution of Western (circles) and East Asian (diamonds) culturally validated facial expression models to which the AU pattern contributes most out of the four. Lighter shapes indicate a higher AU pattern contribution (i.e., the linear coefficient value, values are normalized per factor). Corresponding emotion labels are shown next to each shape. Heterogeneity of the shapes associated with each AU pattern shows that each contributes similarly to both Western and East Asian facial expression models (see *Supplemental Materials – Table S5* for the median linear coefficient values and numbers of models per factor and culture). Below each face map, magenta bars with standard error show the average coefficient value for each of the four factors (median computed across all facial expression models listed on right of each face map). On average, most facial expression models comprise one main AU pattern, with minimal contributions from the other three AU patterns.

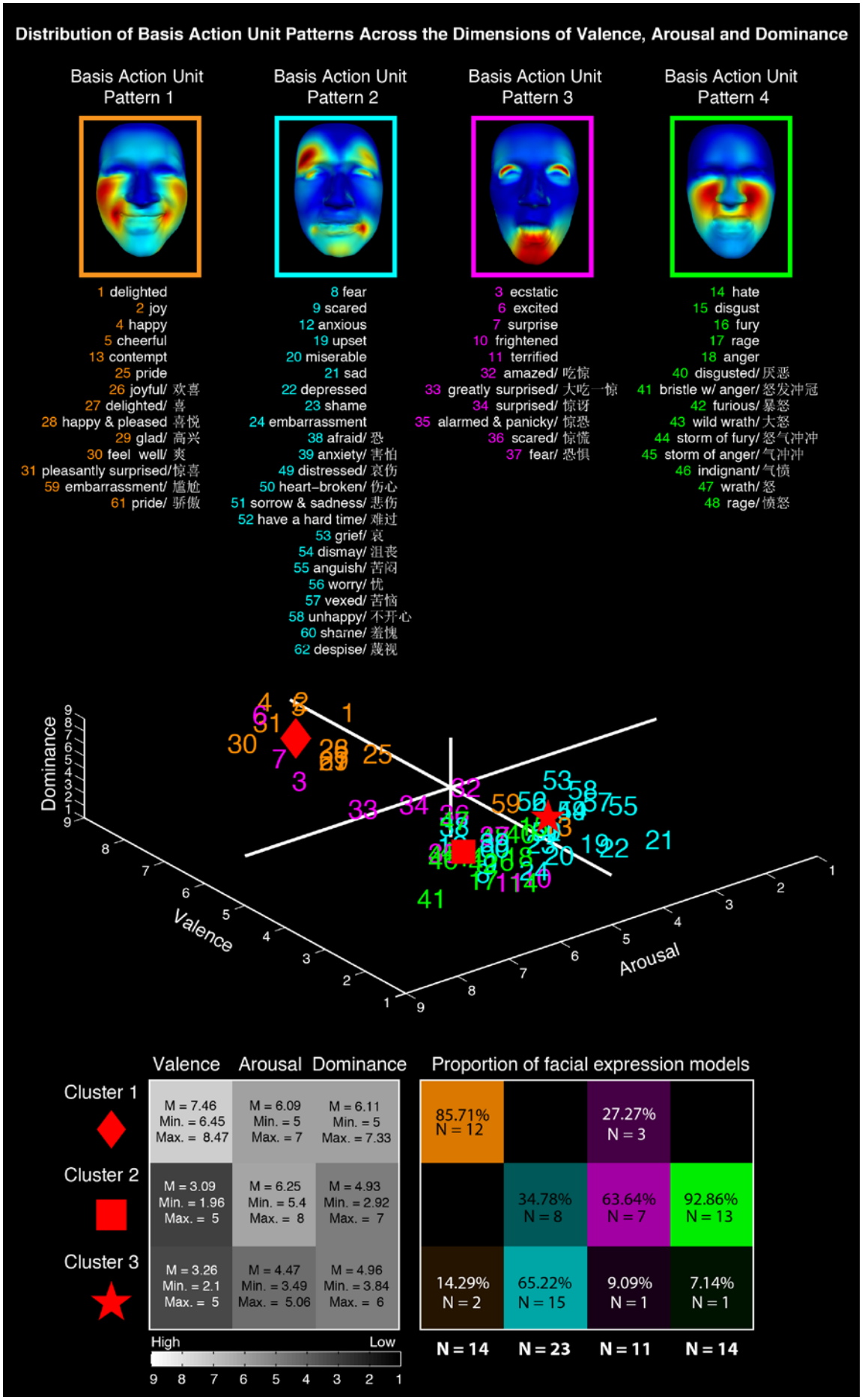
Distribution of Basis Action Unit Patterns Across the Dimensions of Valence, Arousal and Dominance
Basis Action Unit Pattern 1
Basis Action Unit Pattern 2
Basis Action Unit Pattern 3
Basis Action Unit Pattern 4
1 delighted
2 joy
4 happy
5 cheerful
13 contempt
25 pride
26 joyful/ 欢喜
27 delighted/ 喜
28 happy & pleased 喜悦
29 glad/ 高兴
30 feel well/ 爽
31 pleasantly surprised/惊喜
59 embarrassment/ 尴尬
61 pride/ 骄傲
8 fear
9 scared
12 anxious
19 upset
20 miserable
21 sad
22 depressed
23 shame
24 embarrassment
38 afraid/ 恐
39 anxiety/ 害怕
49 distressed/ 哀伤
50 heart-broken/ 伤心
51 sorrow & sadness/ 悲伤
52 have a hard time/ 难过
53 grief/ 哀
54 dismay/ 沮丧
55 anguish/ 苦闷
56 worry/ 忧
57 vexed/ 苦恼
58 unhappy/ 不开心
60 shame/ 羞愧
62 despise/ 蔑视
3 ecstatic
6 excited
7 surprise
10 frightened
11 terrified
32 amazed/ 吃惊
33 greatly surprised/ 大吃一惊
34 surprised/ 惊讶
35 alarmed & panicky/ 惊恐
36 scared/ 惊慌
37 fear/ 恐惧
14 hate
15 disgust
16 fury
17 rage
18 anger
40 disgusted/ 厌恶
41 bristle w/ anger/ 怒发冲冠
42 furious/ 暴怒
43 wild wrath/ 大怒
44 storm of fury/ 怒气冲冲
45 storm of anger/ 气冲冲
46 indignant/ 气愤
47 wrath/ 怒
48 rage/ 愤怒
Dominance
Valence
Arousal
Valence Arousal Dominance
Cluster 1
M = 7.46 Min. = 6.45 Max. = 8.47
M = 6.09 Min. = 5 Max. = 7
M = 6.11 Min. = 5 Max. = 7.33
Cluster 2
M = 3.09 Min. = 1.96 Max. = 5
M = 6.25 Min. = 5.4 Max. = 8
M = 4.93 Min. = 2.92 Max. = 7
Cluster 3
M = 3.26 Min. = 2.1 Max. = 5
M = 4.47 Min. = 3.49 Max. = 5.06
M = 4.96 Min. = 3.84 Max. = 6
High
Low
Proportion of facial expression models
85.71% N = 12
27.27% N = 3
34.78% N = 8
63.64% N = 7
92.86% N = 13
14.29% N = 2
65.22% N = 15
9.09% N = 1
7.14% N = 1
N = 14
N = 23
N = 11
N = 14

Figure 5. Distribution of Basis Action Unit Patterns Across Valence, Arousal and Dominance. In the top row, each basis AU pattern is displayed as a color-coded face map and outlined with a color-coding. Below each face map, we list and number all associated emotion words with a culturally validated facial expression model that comprises that basis AU pattern as main contributor. In the 3-dimensional plot below the face maps, all listed facial expression models (represented by a color-coded number according to its basis AU pattern) are plotted according to the average valence, arousal and dominance rating of the associated emotion word (see also Figures 1 and 2). Clustering analysis revealed that the distribution of facial expression models comprise three clusters, where red shapes (diamond, square, star) indicate the centroid of each cluster. Below the 3-dimensional plot, the gray-scale matrix shows each cluster's average valence, arousal and dominance rating with lighter to darker squares indicating high to low average ratings, respectively (see colorbar below). The color-coded matrix to the right shows for each cluster, the proportion of facial expression models associated with each basis AU pattern (see color-coding above), where color brightness indicates a higher proportion of facial expression models. See *Supplemental Materials – Figure S3* for corresponding 2 dimensional plots.

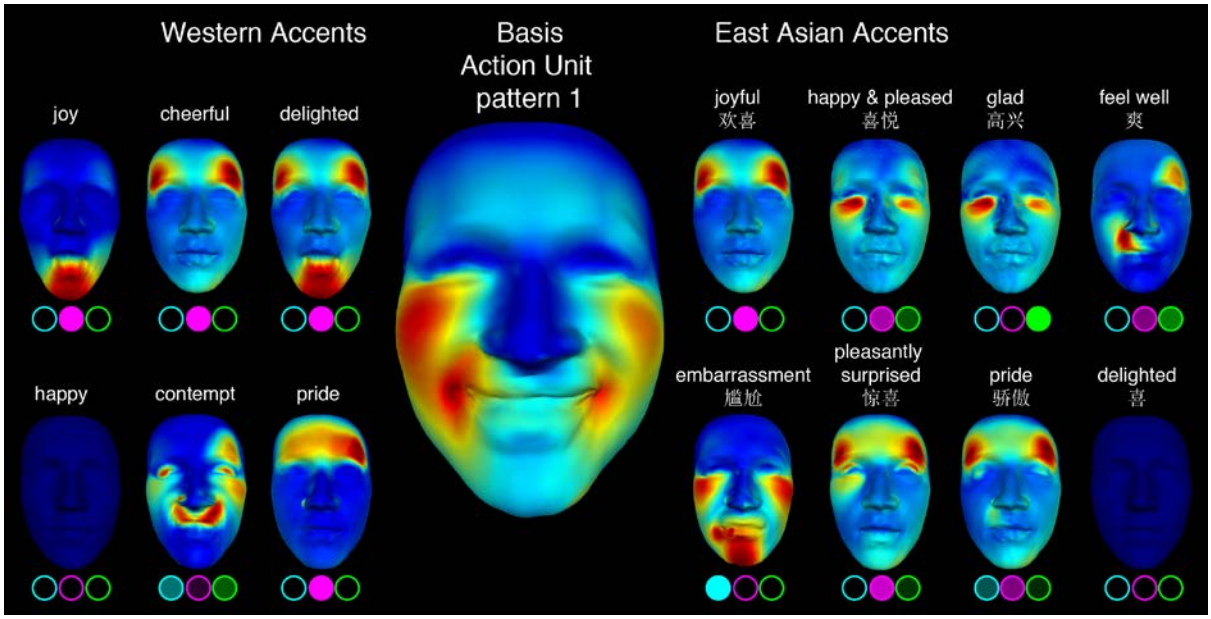

Figure 6. Basis Action Unit Pattern 1 with Western and East Asian Accents. The central face map represents basis AU pattern 1 (e.g., Lip Corner Puller – AU12, Cheek Raiser – AU6, Dimpler – AU14, Sharp Lip Puller – AU13), which contributes most to the facial expressions of 6 Western and 8 East Asian emotions (see emotion words). Below each emotion word, smaller face maps show the corresponding accent AU patterns (values normalized per face map). Color-coded circles below each face show the proportion of accent AUs that correspond to each of the other three basis AU patterns (see color key in Figure 5), where brighter colors indicate higher proportions. For example, the Western accent AU pattern in 'delighted' comprises Outer Brow Raiser (AU2), Upper Lid Raiser (AU5) and Jaw Drop (AU26) – i.e., aspects of basis AU pattern 3 (color-coded in magenta). The East Asian accent AU pattern in 'embarrassment'/尴尬 includes Cheek Raiser (AU6), Chin Raiser (AU17) and Lip Stretcher Right (AU20R) – i.e., aspects of basis AU pattern 2 (color-coded in cyan).

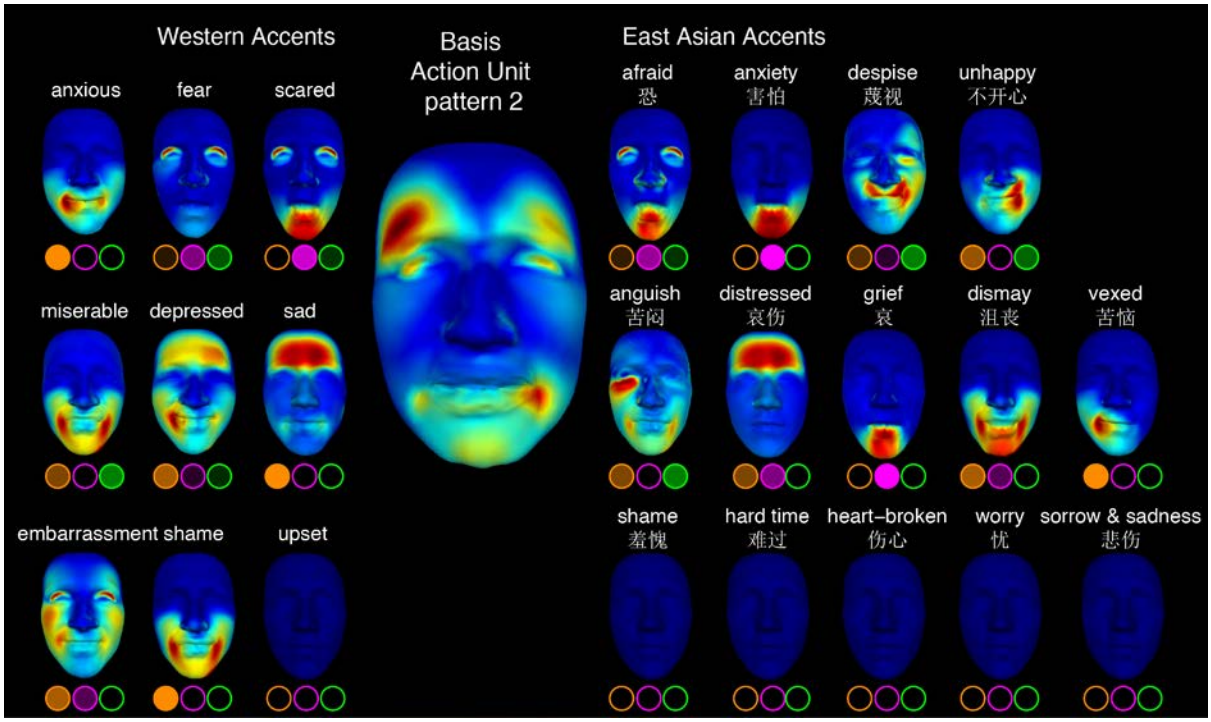

Figure 7. Basis Action Unit Pattern 2 with Western and East Asian Accents. The central face map represents basis AU pattern 2 (e.g., Brow Lowerer – AU4, Lip Stretcher – AU20, Eyes Closed – AU43, Lip Pressor – AU24), which contributes most to the facial expressions of 9 Western and 14 East Asian emotions. Below each emotion word, smaller face maps show the corresponding accent AU pattern (values normalized per face map). Color-coded circles below each face show the proportion of accent AUs that correspond to each of the other three basis AU patterns (see color key in Figure 5), where brighter colors indicate higher proportions. For example, Western accent AU pattern in 'anxious' comprises Lip Corner Puller Left (AU12L) and Dimpler Left and Right (AU14L/R) – i.e. aspects of basis AU pattern 1 (color-coded in orange).

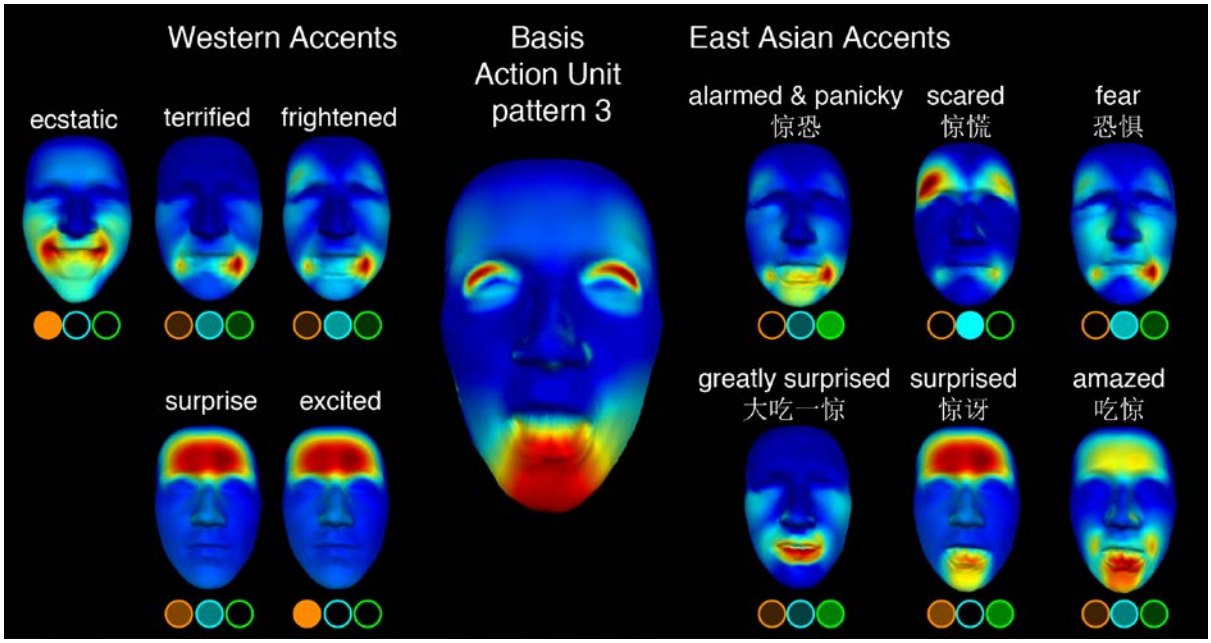

Figure 8. Basis Action Unit Pattern 3 with Western and East Asian Accents. The central face map represents basis AU pattern 3 (e.g., Upper Lid Raiser – AU5, Mouth Stretch – AU27, Jaw Drop – AU26 and Outer Brow Raiser – AU2), which contributes most to the facial expressions of 5 Western and 6 East Asian emotions. Below each emotion word, smaller face map show the corresponding accent AU pattern (values normalized per face map). Color-coded circles below each face show the proportion of accent AUs that correspond to each of the other three basis AU patterns (see color key in Figure 5), where brighter colors indicate higher proportions. For example, the Western accent AU pattern of 'ecstatic' comprises Lip Corner Puller (AU12) and Cheek Raiser (AU6) – i.e. aspects of basis AU pattern 1 (color-coded in orange).

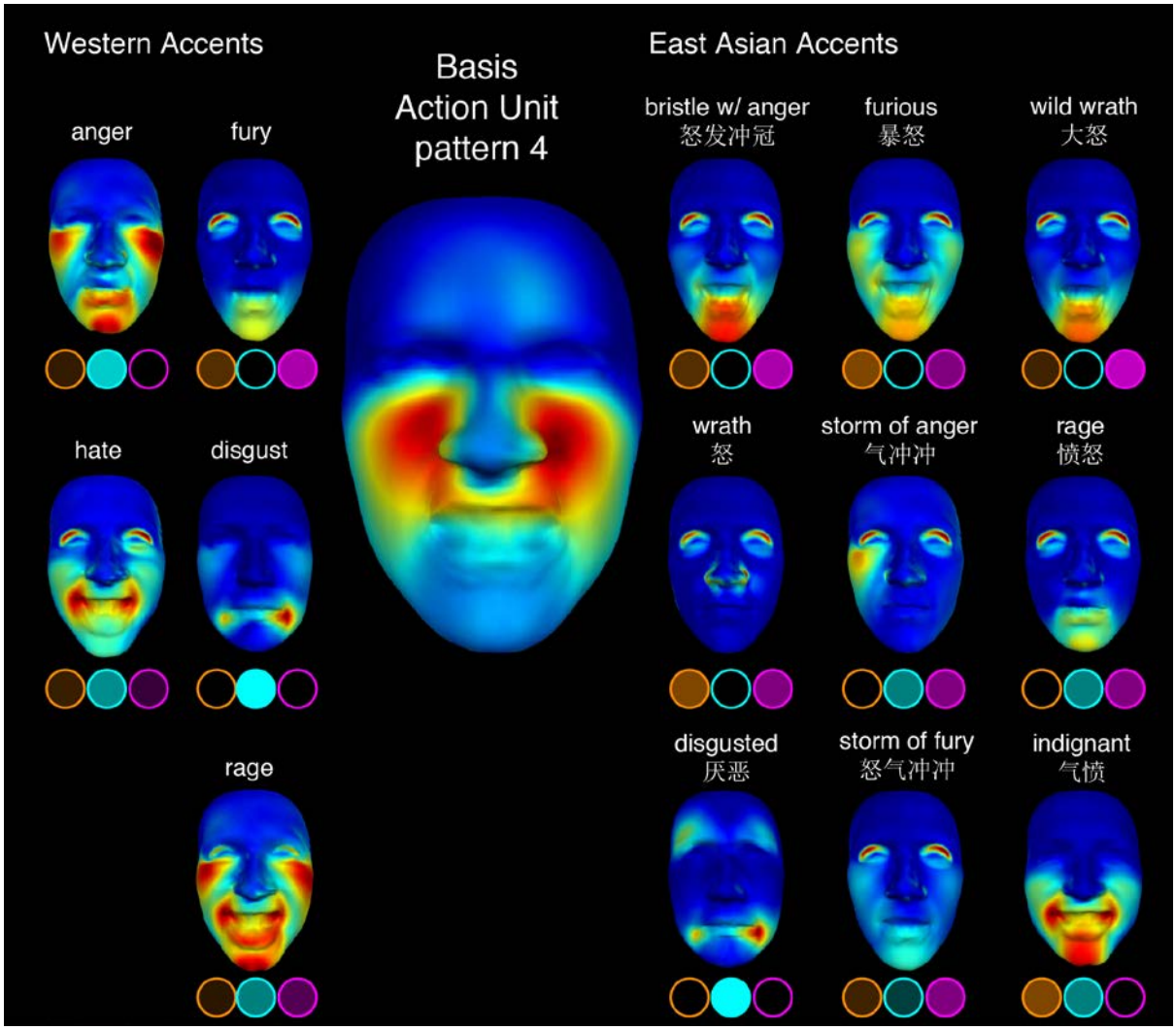

Figure 9. Basis Action Unit Pattern 4 with Western and East Asian Accents. The central face map represents basis AU pattern 4 (e.g., Nose Wrinkler – AU9, Upper Lip Raiser – AU10, Lower Lip Depressor – AU16 and Lip Funneler – AU22), which contributes most to the facial expressions of 5 Western and 9 East Asian emotions (see emotion words). Below each word, smaller face maps show the corresponding accent AU pattern (values normalized per face map). Color-coded circles below each face show the proportion of accent AUs that correspond to each of the other three basis AU patterns (see color key in Figure 5), where brighter colors indicate higher proportions. For example, the Western accent AU pattern of 'anger' comprises Cheek Raiser (AU6) and Lip Pressor (AU24) – i.e., aspects of basis AU pattern 2 (color-coded in cyan). The East Asian accent AU pattern of 'wrath'/怒 includes

Upper Lid Raiser (AU5) – i.e., aspects of basis AU pattern 3 (color-coded in magenta) – and Nostril Dilator (AU38) – i.e., aspects of basis AU pattern 1 (color-coded in orange).

Supplemental Material

Screening Questionnaire. Each potential observer completed the following (culture appropriate) questionnaire. We selected only those answering 'no' to all questions for participation.

Western white Caucasian Observers

Have you ever:

a) lived in a non-Western* country before (e.g., on a gap year, summer work, move due to parental employment)?

b) visited a non-Western country (e.g., vacation)?

c) dated or had a very close friendship with a non-Westerner person?

d) been involved with any non-Western culture societies/groups?

*By Western groups/countries we are referring to Europe (Eastern and Western), North America, United Kingdom and Australia.

East Asian Observers

Have you ever:

a) lived in a non-East Asian* country before (e.g., on a gap year, summer work, move due to parental employment)?

b) visited a non-East Asian country (e.g., vacation)?

c) dated or had a very close friendship with a non-East Asian person?

d) been involved with any non-Eastern culture societies/groups?

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