CHAPTER 12

Using Data-Driven Methods to Advance Knowledge of Social Face Perception

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Understanding Social Face Perception: The Challenge – Human Faces Represent Myriad Complex Social Information

The human face is as ubiquitous as it is complex, which makes it a powerful tool for social communication. To illustrate this complexity, consider the many ways in which human faces can vary. First, they vary in 3D shape – for example, overall size, height and width, lip fullness, nose width, eye position, and forehead height. Second, they come in a wide variety of complexions – that is, skin color and texture – from very dark to very light tones, from smoother to more wrinkled, and dewier to drier. Finally, human faces can move in many different ways via the activation of facial muscles – for example, broad smiles, eye widening, mouth gaping, eyebrow flashing, lip stretching, snarling, frowning, pouting, and wincing. By virtue of these multiple complex variations, the human face can display a commensurately broad range of information about a person, including their sex (e.g., Little et al., 2008; Thornhill & Gangestad, 2006), ethnicity (e.g., O'Toole et al., 1994; Tanaka et al., 2004), age (e.g., Hummert, 2014; van Rijsbergen et al., 2014), health (e.g., Jones et al., 2012; Rhodes et al., 2001), individual identity (e.g., Haxby et al., 2000; McKone et al., 2009), and their emotional (e.g., Ekman et al., 1969; but see also Barrett et al., 2019), cognitive (e.g., Back et al., 2009; Chen et al., 2015), and physiological states (e.g., Craig et al., 1992; Fernández-Dols et al., 2011; Thorstenson et al., 2021). Further, faces are spontaneously judged as more or less attractive (e.g., Rhodes, 2006; Zhan et al., 2021), trustworthy and competent (e.g., Oosterhof & Todorov, 2008; Sutherland et al., 2018), and even betray one's social class (e.g., Bjornsdottir & Rule, 2019) or political affiliation (e.g., Wilson & Rule, 2014).

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To clearly fix ideas about the important relationship between the complexity of the face and the myriad information it can provide, consider a scenario in which human faces comprise only two components – face length and eyebrow movement, each of which has only two states – long versus short face and raised versus lowered eyebrows. In this case, human faces could only ever display four distinct patterns (2 elements ^ 2 states) – for example, a long face plus raised eyebrows – and thus only four distinct messages across all people. In contrast, the human face comprises a much greater number of components and states that enable it to display a much broader range of information about the owner. Thus, it is this complexity that makes the human face a powerful tool for social communication.

Social Face Perception Is Part of a Dynamic System of Communication

Unlocking this wealth of information – a person's sex, age, ethnicity, and emotional state – critically relies on an observer extracting this information from their facial features. For example, determining that a person is happy or of advanced age relies on the observer seeing specific facial features, such as a broad smile or wrinkled skin texture (e.g., see Schyns et al., 1998 for further discussion). Thus, social face perception is part of a dynamic system of communication where information about a person is transferred to others around them via the perception of certain facial features. Understanding the basic principles of such a system is therefore important to understand social face perception. Figure 12.1 outlines this general system using one illustrative example.

Broadly defined, communication is the act of successfully transferring information between two individuals (e.g., see Dukas, 1998; Scott-Phillips, 2008; Shannon, 1948). Specifically, as shown in Figure 12.1, communication starts with a sender who, in this case, encodes the message "I am happy" into a visible signal – here, a smiling facial movement displayed at a social distance – and transmits that signal to others. Simultaneously, other features of the sender's face can provide further information about them – for example, their face shape and complexion could indicate their sex, age, or ethnicity (e.g., see Hill et al., 1995; Rhodes, 2009). On viewing these facial features, observers use their prior knowledge of them – represented here as letters in their brain – to extract information about the sender, thus resulting in a perception of that person. For example, this observer perceived the sender as "male" based on their large face shape, "old" from their heavy jowls and wrinkled skin, "White" from their light skin tone, and "happy" from their broad smile. In this case, communication is successful because the sender is indeed male, White, older, and feeling happy.

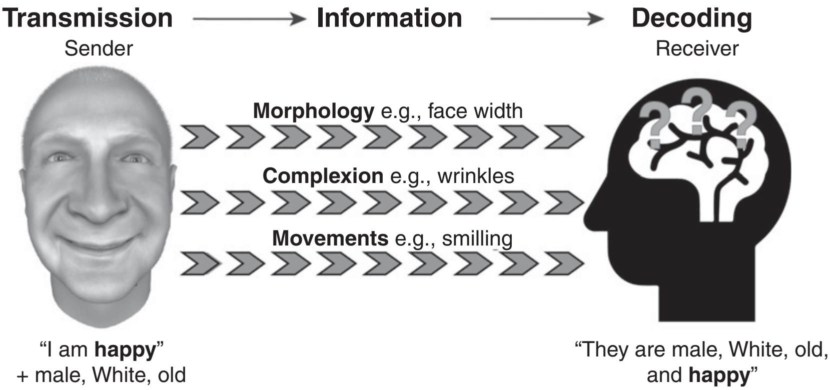

Figure 12.1. Illustrative example of the general system of communication. To communicate an emotion, a person displays the message "I am happy" as a visible signal, such as a smiling facial movement at social distance (e.g., Hall, 1966). The sender's face shape and complexion provide additional information such as their age, sex, and ethnicity. On viewing these facial features, observers use their prior knowledge of them (represented as S-C-M letters in their brain) to extract this information – here, "they are male, White, old, and happy." For example, this observer used the sender's large face shape to determine their sex, their light complexion to determine their ethnicity, their wrinkles and heavy jowls to determine their age, and their smiling facial movement to determine their emotion.

In contrast, communication can fail if such features are not visible – for example, fine detailed wrinkles are not visible at longer viewing distances (e.g., see Smith & Schyns, 2009) – or if the observer misinterprets the features – for example, an American smiling broadly would be interpreted accurately as socially acceptable in the USA but misinterpreted as socially unacceptable in Eastern cultures based on culture-specific preferences and expectations (e.g., Krys et al., 2016; Tsai et al., 2016). Thus, as illustrated here, social face perception is part of a complex, dynamic system of information exchange that critically relies on a mutual understanding between sender and observer.

Navigating the Complex Space of the Human Face: What Facial Features Drive Perception?

As illustrated earlier, extracting information about a person from their facial appearance involves interpreting a range of specific features, such as a smile or the color and texture of their skin. Remarkably, humans

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perform this complex perceptual task frequently and effortlessly across their lifetime. However, understanding what specific facial features observers use to derive these perceptions – that is, the stimulus-response relationship that is critical to understanding the causal mechanisms of social perception – is empirically challenging. One main reason for this is that the human face is highly complex, composed of many different features that could drive perception in different ways. For example, perceiving that someone is "happy" might rely on the observer seeing a specific combination of facial movements, such as broad smiling and eye squeezing with an intense and sustained activation (e.g., Ambadar et al., 2009; Ekman & Friesen, 1982; Korb et al., 2014; Niedenthal et al., 2010; Rychlowska et al., 2017). In contrast, perceiving that someone is of advanced age might rely on seeing a specific combination of shape and complexion features, such as heavy jowls and dry, wrinkled skin (e.g., Rhodes, 2009). Further, all faces comprise an inextricable combination of face shape, complexion, and often movements, that could produce complex interactions – for example, the wrinkles and folds of aging skin could distort the appearance of certain facial movements that could in turn impact emotion perception (e.g., see Hess et al., 2012; Malatesta et al., 1987). In addition, as illustrated in Figure 12.1, the observer's prior knowledge, including stereotypes, prejudice, biases, and cultural norms, could influence these interactions – for example, a smile displayed by an older White male could be interpreted differently depending on the observer's internal representations of older White men (e.g., van Rijsbergen et al., 2014; see also Hess et al., Chapter 1, this volume). Therefore, the facial features that drive social perception are likely complex, multivariate, multi-component, often dynamic (e.g., see Hebets & Papaj, 2005; Patricelli & Hebets, 2016; Rowe, 1999) and shaped by the observer's prior knowledge (e.g., Hehman et al., 2017; see also Guilford & Dawkins, 1991 for broader discussion). Consequently, finding these features is akin to finding the proverbial needle in the proverbial haystack. How then do we navigate this complex task?

To address this question, most studies have used a theory-driven approach that selects specific facial features – such as facial width, skin color, or smiling – as plausible candidates to drive a given perception – such as dominance, attractiveness, or positive affect (e.g., de Lurdes Carrito et al., 2016; Ekman, 1972; Jones et al., 2012; Oosterhof & Todorov, 2008). One well-known example is the seminal work of Ekman and colleagues who hypothesized that a specific set of facial movements universally represent six basic emotions – happy, surprise, fear, disgust, anger, and sad (e.g., Darwin, 1999/1872; Ekman, 1972; Ekman et al., 1969; Matsumoto & Ekman, 1989). People across the world recognized these hand-selected facial expressions, leading to the conclusion that they are universal signals of basic emotions. Studies using this approach made considerable strides in understanding how facial expressions communicate emotions (see Fernández-Dols, 2013 for a review). However, this approach only examines a small subset of hand-selected facial features and is therefore not well suited to objectively exploring the broad range of facial features that could drive perception, plus their interactions, particularly in different cultures (see Jack et al., 2018 for a review). In addition, such approaches typically use standard photographs or videos of faces which cannot readily be used to identify the specific features that drive perception. Instead, they can typically only identify which *labels* assigned to the photograph or video by the experimenter, such as "happy," "old," or "White," are associated with perception – that is, a non-causal response–response relationship. Similarly, such approaches often measure agreement across observers – for example, how many observers across two cultures interpret a particular facial expression as "happy" – which cannot determine whether the observers used the same or different features to arrive at the same perception (see Medin et al., 1993; Schyns et al., 2002). Therefore, navigating the complex space of the human face to objectively identify the facial features that drive social perception requires a further degree of sophistication than traditional methods.

Data-Driven Methods to Model the Facial Features That Drive Social Perception

A fruitful alternative is the use of data-driven methods from the field of psychophysics, because they are specifically designed to identify the stimulus features that drive perceptual responses and derive law-like models of the stimulus–response relationship (e.g., Fechner, 1860; Stevens, 1957; see also Sutherland and Young, Chapter 7, this volume; Albohn et al., Chapter 11, this volume). Importantly, this approach makes few a priori assumptions about what stimulus features will drive perception. For example, rather than hand-selecting specific facial features based on an existing hypothesis, all plausible features would be experimentally controlled and tested. Thus, by adopting this more agnostic approach, data-driven psychophysical methods can overcome the limitations of traditional methods by objectively characterizing the critical stimulus–response relationship that is foundational to understanding causal mechanisms (e.g., see Jack et al., 2018; Jack & Schyns, 2017 for recent reviews). Consequently, such approaches have been used to understand a variety of behavioral (e.g., Mangini & Biederman, 2004; Mareschal et al., 2006) and neural responses (Hubel & Wiesel, 1959; Ringach & Shapley, 2004; Smith et al., 2012) in humans and other animals (e.g., Gibson et al., 2005; Nielsen et al., 2006). Here, we present one such approach that can model the facial features that drive human social perception by combining the psychophysical method of reverse correlation (e.g., Ahumada & Lovell, 1971; Lee & Schetzen, 1965; Volterra, 1930) with a generative model of the human face (Yu et al., 2012; Zhan, Garrod, et al., 2019). Figure 12.2 outlines each step of an illustrative experimental trial to model the facial features driving the perception of age and basic emotions.

Stimulus Generation

To objectively explore how different facial features influence perception, a large number of face stimuli are generated that represent the naturalistic variations of face shape, complexion, and movements. To do so, stimuli are generated from a 3D model of the human face that is built from the 3D capture of faces of real people varying in age, ethnicity, and sex, and represents face shape, complexion, and movements as objectively measurable features (see Yu et al., 2012; Zhan, Garrod, et al., 2019 for details). Figure 12.2's first panel shows an example. Specifically, 3D face shape is represented as x, y, and z coordinates where the main dimensions of variance across individuals are represented as principal components (PCs), called identity components. To generate a novel face shape, the model generates random identity components and adds them to a base face shape – here, an older White male. The resulting face stimulus, shown on the right, is an older White male who, by virtue of these random identity components, has a longer nose, heavier jowls, and thinner lips than the average older White male. Next, complexion, which captures skin color, reflectance, and texture, is represented as color space coordinates (i.e., L*a*b – lightness, red-green, blue-yellow) with the main dimensions of variance across individuals also represented as PCs. As before, to generate a novel face complexion, the model generates random identity components and adds them to a base face complexion. Here, the resulting face stimulus is an older White male who has deeper cheek folds, a lighter skin tone, and a more wrinkled texture than the average older White male. Next, facial movement is represented as a set of individual facial movements called Action Units (AUs; Ekman & Friesen, 1978) and several movement parameters that control, for example, how quickly each AU is activated, the specific order of the AUs, and how long the activation of each AU is sustained for. As before, to generate a facial expression, the model randomly generates a set of dynamic AUs. Here, the resulting facial expression comprises the Lip Corner Puller (AU12), Cheek Raiser (AU6) and Dimpler (AU14), each with specific dynamics. Finally, these three components – shape,

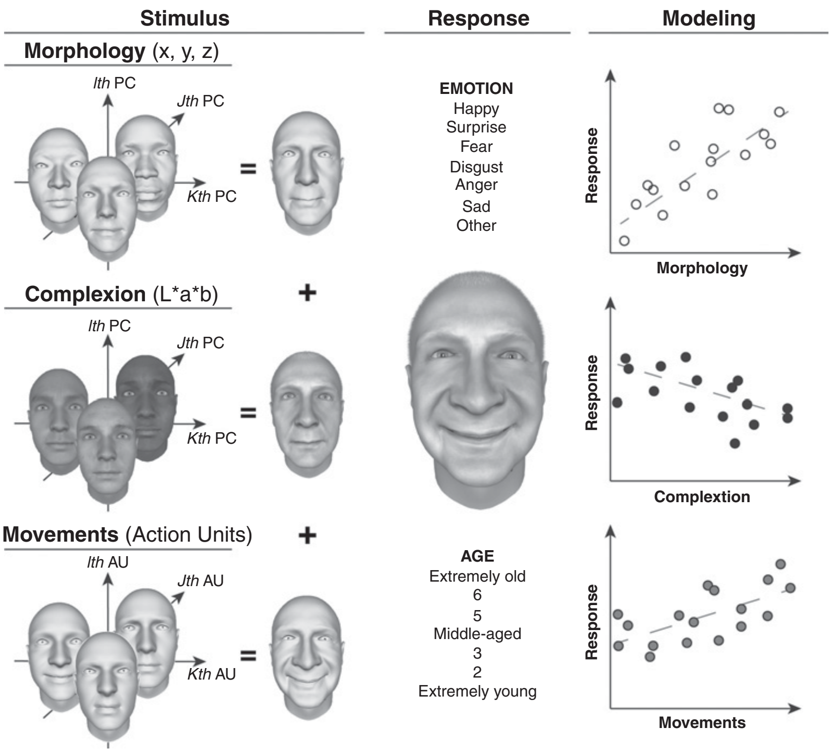

Figure 12.2. Modeling facial features that drive social perception using a generative model of the human face and reverse correlation. *Stimulus.* Generative model of the human face. Shape (represented as x, y, z coordinates): the model generates a 3D face shape by randomly varying the shape identity features (represented as principal components, PCs) and adding them to a base face – here, an average older White male. Example on right. Complexion (represented in L*a*b color space): same as above – the model generates a complexion by randomly varying the complexion identity features (also represented as PCs) and adding them to a base face. Example on right. Movements (represented as Action Units, AUs): same as above – the model generates a dynamic facial expression by randomly varying the facial movements (represented as individual AUs) and adding them to a face identity. Example on right. The randomly generated shape, complexion, and movement features are combined to create the face stimulus, shown to right. *Response.* Observers select a label that accurately describes the face – for example, "very old" and "happy" – otherwise, choosing "other/none of the above." Each observer completes many such trials. *Stimulus-response relationship.* Following the experiment, statistical analyses measure the relationship between the feature variations presented on each trial (e.g., 3D shape) and the observer's responses (e.g., age). *Facial features.* This procedure thus identifies the specific facial features that drive perception – for example, this observer used the heavy jowls and deep cheek folds for "very old" and the smile for "happy" (see highlighted face areas).

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complexion, and movements – are combined to create a complete face stimulus, shown in the second panel of Figure 12.2.

Perceptual Task

Next, as illustrated in the second panel of Figure 12.2, the observer views the randomly generated face stimulus and selects a label that they believe accurately describes it – for example, "very old" and "happy." Importantly, if the observer thinks that none of the emotion labels accurately describes the facial expression, they select "other/none of the above." Therefore, on each trial where the observer does select a label, we capture the specific facial features that caused the observer to perceive the person as "very old" or "happy," for example. Across the experiment, each observer completes many such trials to expose them to a sufficiently broad range of naturalistic variations of the face in an agnostic manner. Following the experiment, each of the observer's responses are then typically associated with many face stimuli, each comprised of objectively measurable facial features – for example, PC values that represent specific face shape or complexion features.

Modeling the Facial Features That Drive Perception

Next, to derive the facial features the observer used to perceive each emotion and different ages, statistical analyses are used to measure the relationship between the facial features presented on each trial and the observer's responses, as schematized in next panel of Figure 12.2. For example, if the observer frequently responds "happy" when a smile – represented as the Lip Corner Puller (AU12) – is present, this suggests that they are using this facial movement to perceive that someone is "happy." In other words, the presence of AU12 predicts this observer's "happy" responses. In contrast, if the observer rarely responds "middle aged" when the face has heavy jowls – represented as shape PC values – this suggests that they did not use this face shape to perceive that someone is "middle aged." Here, as shown by the shaded faces in the last panel of Figure 12.2, this observer used a combination of heavy jowls and deep cheek folds to perceive the age "very old," and a smile to perceive the emotion "happy."

Main Advantages: Moving Beyond Traditional Methods

As illustrated, this data-driven method provides a fruitful alternative to understanding what facial features drive social perception, with several advantages that overcome the limitations of traditional theory-driven methods. First, this approach makes few a priori assumptions about which features will elicit which responses in whom, and instead agnostically tests a wider range of plausible candidates – for example, generating biologically plausible combinations of facial movements to identify which ones represent basic emotions such as "happy," "sad," or "anger" in different cultures (e.g., see Jack et al., 2018 for further discussion). Second, this approach can inform understanding of the causal mechanisms of social face perception – that is, what drives social perception – because it characterizes the critical stimulus–response relationship, rather than the non-causal, correlational response–response relationships measured by traditional approaches (see Jack & Schyns, 2017 for further discussion). Third, by delivering an objective, quantitative model of the facial features that drive perception, this approach enables formal comparisons – for example, to determine whether thin lips are exclusively associated with advanced age or also associated with masculinity, or whether the emotion "happy" is represented by the same combination of facial movements depending on the age of the sender. Importantly, such comparisons can show exactly *how* they are similar or different (see Medin et al., 1993) which goes beyond coarser global or subjective measures (e.g., Barranti et al., 2017; Edwards, 1994). Fourth, such approaches typically derive individual observer models using a high number of trials to produce highly powered, statistically robust results per observer with several advantages – for example, demonstrating replication of effects across observers, estimating the prevalence of these effects in the broader population, and characterizing individual variance within a population that would otherwise be erased by averaging (see also discussion by Elfenbein et al., 2002 for erasing of cultural accents in facial expressions). Finally, this approach is generic and can thus be applied to almost any objectively measurable stimulus space, including voices and other sounds (e.g., Ponsot et al., 2018; Wollman et al., 2020), and other response types, including neural activity (e.g., Schyns et al., 2011; Smith et al., 2004).

Recent Advances in Social Face Perception Using Data-Driven Methods

Given these advantages, data-driven methods have considerable potential to advance fundamental knowledge of social face perception. For example, this approach has been used to make new discoveries about how facial expressions vary across cultures, including emotions (Jack et al., 2012; Jack et al., 2016), pain and pleasure (Chen et al., 2018), and cognitive states such as bored and confused (Chen et al., 2015), how facial expressions dynamically transmit complex messages (Jack et al., 2014; Liu et al., 2022), including different smiles (Rychlowska et al., 2017), and how facial expressions can override social trait impressions made from static facial appearance (Gill et al., 2014). Similarly, this approach has been used to examine how familiar and unfamiliar faces are encoded in memory (Zhan, Garrod, et al., 2019), how perceptions of beauty differ across cultures (Zhan et al., 2021), and has uncovered the main facial features that underlie social trait perception (Hensel et al., 2020). Further, this approach has bridged the traditionally adjacent fields of linguistics and face perception to examine how facial movements augment the meaning of spoken words (Nölle et al., 2022). To illustrate this potential, we present two recent studies that have advanced understanding of social face perception using this method. Figure 12.3 summarizes the results.

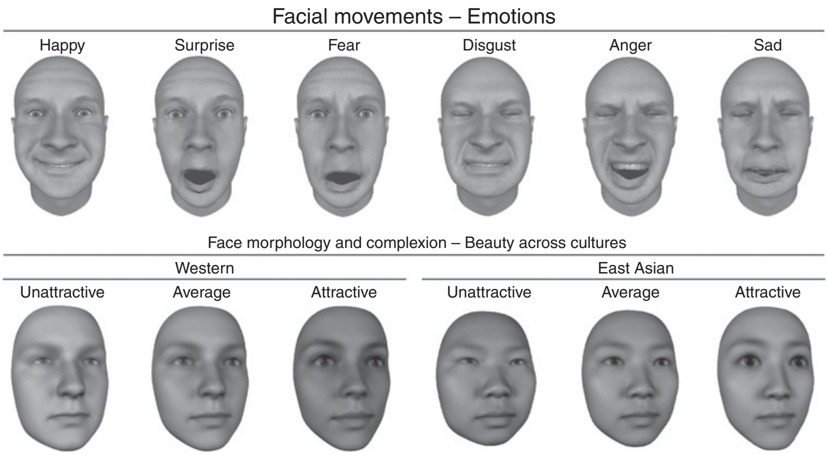

Figure 12.3. Modeling the facial features of emotion and beauty perception across cultures. *Facial movements – emotions across cultures.* Facial expressions of emotion composed of cross-cultural and cultural accents, extracted from Jack et al., (2016). Facial expressions of anxiety in two cultures – Western and East Asian. Each are composed of a cross-cultural facial movement (center) plus a culture-specific accent (left/right). Western accents include unilateral lip pulling while East Asian accents include mouth gaping. *Face shape and complexion – beauty across cultures.* Attractive and unattractive faces in each culture, extracted from Zhan et al., (2021). Westerners consider poutier lips and darker skin tones as more beautiful, whereas East Asians consider higher nose bridges and lighter skin tones as more beautiful; both cultures prefer larger eyes and darker eyelids.

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Modeling Facial Expressions of Emotion Across Cultures

A longstanding debate is whether facial expressions are culturally universal or culture-specific (see Fernández-Dols, 2013; Hwang & Matsumoto, 2015 for reviews). One influential theory posits that six basic emotions – happy, surprise, fear, disgust, anger, and sad – each have a distinct facial expression that form the building blocks of all other facial expressions, including those which are culture-specific (e.g., Darwin, 1999/1872; Ekman & Cordaro, 2011; Ekman et al., 1969; Izard, 1971; Tomkins, 1962; see Keltner et al., 2019 for a recent review). To test this, Jack and colleagues (2016) used the above method to model the facial expressions of more than sixty emotions across two cultures – East Asian and Western – and examined how they are structured. In contrast to existing theories, they found that facial expressions of emotion are structured by four, not six, underlying facial expressions. Thus, all facial expressions are a combination of these four expressions and typically comprises a core, cross-cultural expression plus a culture-specific expression (referred to in the literature as accents, see e.g., Elfenbein & Ambady, 2002b). Figure 12.3, top panel, shows two such examples of this composition – the facial expression of anxiety in Western and East Asian culture, respectively. Together, this work revealed that facial expressions of emotion are structured in an algebraic manner by four main building blocks, thus challenging existing theories that six facial expressions are fundamental and culturally universal.

Modeling the Facial Features of Beauty Across Cultures

Beauty has a powerful influence on many aspects of life (e.g., see Langlois et al., 2000 for a review) – for example, attractive people are more likely to be seen as healthier, more competent, and more intelligent than less attractive individuals (e.g., Rhodes et al., 2001; Zebrowitz et al., 2002; Zebrowitz & Rhodes, 2004, see also Sutherland and Young, Chapter 7, this volume). Two longstanding theories propose that attractive faces are universally close to the average face (Langlois & Roggman, 1990) and have exaggerated sexually dimorphic features (Perrett et al., 1998). However, recent work now shows that attractiveness judgments vary considerably across individuals and cultures (e.g., Hönekopp, 2006; Tanaka et al., 2020), thus questioning these theories. To examine this further, Zhan and colleagues (2021) used the above method to model attractive faces in two cultures – East Asian and Western. Figure 12.3's bottom panel shows the results – for example, both cultures preferred smaller faces with larger, darker eyes with Westerners preferring poutier lips and darker skin and East Asians preferring higher nose bridges, pointier chins, and lighter skin tones. In both cultures, attractive faces are neither close to the average nor comprise exaggerated sexually dimorphic features, thus challenging existing theories. Rather, they showed clear cultural and individual diversity in beauty preferences that align with existing accounts of genetic selection.

These two examples show how the data-driven method described here can make new discoveries in understanding social face perception, by enabling deeper testing of central theories and debates, including the cultural universality of facial expressions of emotion (e.g., see Fernández-Dols, 2013 for a review), whether facial expressions represent emotion categories or dimensions (e.g., see Barrett & Bliss-Moreau, 2009; Izard, 1977 for contrasting sides of the debate), how social trait impressions are derived from facial appearance (e.g., Oosterhof & Todorov, 2008; Sutherland et al., 2013), and whether beauty is really in the eye of the beholder. In the final section of this chapter, we now illuminate new research directions using this method to deepen understanding of age and emotion perception – a topic that has gained increasing attention with progressively aging societies.

Future Directions

Communicating Emotions across the Ages: Do Aging Faces Affect Emotion Perception?

As has been illustrated in this book, facial expressions are particularly powerful signals that are designed to optimize communication success (e.g., see Arak & Enquist, 1993; Guilford & Dawkins, 1991; Hasson, 1997, 2000). However, facial expression recognition can vary depending on the age of the sender and the observer. For example, both younger and older observers are less accurate at recognizing facial expressions of emotion displayed by people of other age groups (e.g., Malatesta et al., 1987; Riediger et al., 2011). This well-documented effect – known as the Other Age Bias (OAB; e.g., see Rhodes & Anastasi, 2012 for a review) – thus highlights the importance of understanding social face perception in the context of a complex, dynamic system of communication between sender and observer, as outlined in Figure 12.1 (e.g., see Hess & Hareli, 2015 for a discussion). Further, given that ineffective emotion communication can have substantial negative consequences (e.g., see Hawkley & Cacioppo, 2007), understanding why these age-related differences occur is critical to improving social communication across age groups. Consequently, three main lines of inquiry have developed to understand the basis of these age-related differences in recognizing facial expressions of emotion. First, one line of research posits that lower recognition accuracy with aging faces could be because wrinkles and deep folds distort the appearance of facial expressions (Freudenberg et al., 2015; Hess et al., 2012; Malatesta

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et al., 1987) – for example, pronounced crow's feet and deep cheek folds could etch signs of smiling on the face and bias observers to perceive happiness. Second, age-related facial features could bias emotion perception by activating age-related stereotypes (e.g., Freudenberg et al., 2020; Hummert, 2014) – for example, smiling faces are often perceived as younger than faces displaying angry (Voelkle et al., 2012) or sad facial expressions (Hass et al., 2016), suggesting that age is negatively associated with affect. Third, younger and older people might display facial expressions differently (e.g., Magai et al., 2006) due to age-related changes in muscle tone and flexibility (e.g., Ebner et al., 2011), which could result in lower cross-age emotion recognition due to less experience interacting with other age groups (i.e., in-group advantage; e.g., see Elfenbein & Ambady, 2002a; Thibault et al., 2006; but see also, e.g., Tanaka & Gauthier, 1997; Tanaka & Taylor, 1991).

Investigating these different lines of inquiry would thus contribute both to advancing current theories of social perception (e.g., Adams & Kveraga, 2015; Hess et al., 2009) and informing interventions to improve cross-age social communication. As we have illustrated, the data-driven approach described is particularly well suited to this task because it can disentangle the different facial features that affect recognition accuracy. For example, to examine whether certain age-related features distort the appearance of facial expressions, this data-driven method could be used to objectively isolate the specific complexion features that enhance or diminish emotion recognition, including specific misclassifications. Results could therefore reveal whether higher and lower recognition accuracy is driven by emotion resembling cues, such as crow's feet and deep cheek folds, as predicted by current accounts. In contrast, if age-related features impact emotion recognition by activating stereotype knowledge, we might instead expect a broader range of age-related features to impact performance and a higher contribution of these features in predicting observer behavior, particularly among those endorsing age-related stereotypes. Finally, to examine whether observers expect people of different ages to express emotions differently, the above method could be used to model the facial expressions that drive emotion perception when displayed on younger and older faces in younger and older observers. In line with work on age-related mental representations (e.g., van Rijsbergen et al., 2014), we might expect the resulting facial expression models to differ according to both the age of the sender's face and the age of the observer. Analysis of the models could further reveal whether observers from different age groups perceive emotions using certain facial movements to compensate for signal distortions imposed by age-related features, for example.

In sum, using three main examples of how age-related facial features could influence the perception of facial expressions of emotion, we have demonstrated how the data-driven method described in this chapter could be used to address outstanding questions in the field with the potential to impact existing theories.

Conclusions

In this chapter, we have extended the discussion on data-driven methods introduced in Chapter 11 by demonstrating an approach that combines the power of generative models akin to those used in ethology (e.g., Tinbergen, 1948) and neuroscience (e.g., Hubel & Wiesel, 1959; Ringach & Shapley, 2004; Zhan, Ince, et al., 2019) with the classic psychophysical method of reverse correlation used in vision science (e.g., Mangini & Biederman, 2004; Scarfe & Hibbard, 2013), engineering (e.g., Kraft et al., 2006; Thompson et al., 1999) and more recently social psychology (e.g., Dotsch et al., 2008; Zhan, Garrod, et al., 2019; see Jack & Schyns, 2017 for a review). By showcasing recent work using this method, we demonstrate its main advantages over traditional methods and its potential to illuminate new research directions and unearth new discoveries. Consequently, we anticipate that this approach will continue to inform existing theories in social perception and support the development of adjacent fields, including social neuroscience to understand what facial features drive neural responses (e.g., Schyns et al., 2011; Smith et al., 2004) and in assessing the utility of machine learning techniques such as deep neural networks as models of human cognition (e.g., see Daube et al., 2021). Finally, we anticipate that results arising from this approach will have several real-world applications, including improving the social signaling capabilities and repertoire of socially interactive artificial agents and companion robots (e.g., Chen et al., 2020; Chen et al., 2019), particularly for the elderly.

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