Research Article

Psychological Science
1–15

DOI: 10.1177/0956797618799300
www.psychologicalscience.org/PS
SAGE

First Impressions of Personality Traits From Body Shapes

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Abstract
People infer the personalities of others from their facial appearance. Whether they do so from body shapes is less studied. We explored personality inferences made from body shapes. Participants rated personality traits for male and female bodies generated with a three-dimensional body model. Multivariate spaces created from these ratings indicated that people evaluate bodies on valence and agency in ways that directly contrast positive and negative traits from the Big Five domains. Body-trait stereotypes based on the trait ratings revealed a myriad of diverse body shapes that typify individual traits. Personality-trait profiles were predicted reliably from a subset of the body-shape features used to specify the three-dimensional bodies. Body features related to extraversion and conscientiousness were predicted with the highest consensus, followed by openness traits. This study provides the first comprehensive look at the range, diversity, and reliability of personality inferences that people make from body shapes.

Keywords
Big Five personality domains, first impressions, human body perception, correspondence analysis, open data

Received 10/11/17; Revision accepted 7/21/18

Personality inferences made from appearance are important because they affect job status, perceived culpability for crimes, suitability for political office, governance, and more (Efran, 1974; Todorov, Mandisodza, Goren, & Hall, 2005). These inferences are made involuntarily, consistently, and with brief exposure times, and they emerge in children by 3 years of age (Cogsdill, Todorov, Spelke, & Banaji, 2014; Oosterhof & Todorov, 2008; Todorov, Pakrashi, & Oosterhof, 2009; Todorov, Said, Engell, & Oosterhof, 2008; Willis & Todorov, 2006). Further, the physical information in the face underlying these inferences can be modeled and manipulated with predictable effects on trait perception (Oosterhof & Todorov, 2008; Walker & Vetter, 2009).

In most real-world situations, however, we see faces along with bodies. This raises the question of whether we form personality impressions from body shapes as readily as we form them from faces. Body shape is a salient feature of a person's appearance that can be perceived from a distance (Yovel & O'Toole, 2016). Anecdotal evidence for the human tendency to make social judgments from body shapes can be seen in both Western and Eastern cultures with the popularity of weight-loss programs, fitness training, body-toning activities, and elective surgeries aimed at making specific alterations of body parts.

The study of the relationship between body form and personality became popular many years ago following early work by several research groups (e.g., Brodsky, 1954; Kretschmer, 1951; Lerner, 1969; Sheldon, 1954; Sheldon, Stevens, & Tucker, 1940; Strongman & Hart, 1968; W. D. Wells & Siegel, 1961). Sheldon (1954) proposed that human bodies could be categorized along three fundamental dimensions: mesomorph (e.g., heavily muscled, broad shoulders, small waist), ectomorph (e.g., tall and thin, fragile), and endomorph (e.g., round body, short neck). This early work was aimed at

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establishing a biological genetic relationship between body type and personality. In subsequent research, however, Sheldon's body models were used to study trait inferences from body shapes (Brodsky, 1954; Lerner, 1969; Strongman & Hart, 1968; W. D. Wells & Siegel, 1961). These studies suggested that mesomorphs are viewed as energetic and desirable; ectomorphs are seen as neurotic and quiet; and endomorphs are judged as lazy, dependent, and undesirable (e.g., Brodsky, 1954).

More recently, studies of body perception have focused on the role the body plays in emotion recognition (Aviezer et al., 2012; de Gelder, de Borst, & Watson, 2015; de Gelder & Hadjikhani, 2006; Sinke, Kret, & de Gelder, 2013), person identification (Rice, Phillips, Natu, An, & O'Toole, 2013; Robbins & Coltheart, 2012), attractiveness (Currie & Little, 2009; Fallon & Rozin, 1985), self-esteem (Furnham, Badmin, & Sneade, 2002; Puhl & Heuer, 2009), and eating disorders (e.g., anorexia, bulimia; Farrell, Lee, & Shafran, 2005). There has also been a return to understanding the role of body shape in social inferences, although this line of work has focused primarily on obesity. Obese people are judged to be lazy and incompetent (for a review, see Carr & Friedman, 2005). The obesity measures employed, however, have been limited to body mass index (Carr & Friedman, 2005; Puhl & Heuer, 2009) and waist-to-hip ratio (Singh, 2002), which miss salient variations in body features that are perceived readily in three-dimensional body shapes (J. C. Wells, Treleaven, & Cole, 2007). Here, we return to a more complete representation of body shape. This approach mirrors that of Sheldon's full-scale body models but offers a more complete and quantifiable account of body shape. This enabled us to create a broader range of stimuli for evaluating the diversity of the social judgments that people make from bodies.

From another perspective, language can be used as a powerful medium for representing the physical structure of complex body shapes. Recent studies showed that descriptive ratings of global and local body features (e.g., pear-shaped body, long legs) provide sufficient information to reconstruct highly accurate three-dimensional shape models of people (Hill, Streuber, Hahn, Black, & O'Toole, 2016; Streuber et al., 2016). In these studies, reconstructions were made using simple linear regression methods that learned example mappings from physical descriptor terms to three-dimensional body parameters. The question of whether (and how) body shapes are related to the more abstract language-based descriptions of personality traits (e.g., shy, extraverted, quarrelsome) is not known.

The goal of this study was to explore personality inferences made from human body shapes. We focused on visualizing and quantifying these inferences. To this end, participants rated the applicability of personality/social traits to three-dimensional models of female and male bodies. First, to probe the structure of the social-trait evaluations on body shapes, we created multivariate spaces separately for male and female bodies along with their associated traits, using correspondence analysis (CA). The resulting spaces suggest that personality inferences are based on quantifiable physical features of body shapes. Second, to specifically visualize the stereotypes of bodies and traits, we showed female and male bodies that typify a subset of traits. Third, to provide a more concrete quantification of the personality inferences made from body shapes, we applied multiple linear regression analysis to map body-shape features from three-dimensional bodies to their human-assigned trait ratings. Prediction accuracy was measured at both a global level (trait profile) and a local level (individual trait).

Method

Participants

Undergraduate students ($N = 76$; 17 men; age: $M = 20.40$ years, $SD = 2.89$) from the School of Behavioral and Brain Sciences at The University of Texas at Dallas rated body shapes for personality traits in exchange for research credit in a psychology course. In this study, sample size was selected to be adequate to obtain stable ratings. The sample size was determined as follows. We used the study by Hill et al. (2016) as a reference. We doubled their sample size, given the anticipated difference between the reliability of applying physical description words to bodies (Hill et al., 2016) and the reliability of applying traits describing body shapes in the present study. The adequacy of the sample size was tested using bootstrap simulations (see the CA Results section) to evaluate the stability of the trait ratings in the multivariate analysis. Ratings that were not stable in the bootstrapping tests were omitted from further analyses and interpretations. As will be seen, no traits failed the bootstrapping test for female bodies, and only 3 of the 30 traits failed for male bodies, indicating an adequate sample size for stable ratings. We also conducted a correlation-based analysis to ensure that rating patterns were consistent across subsets of raters (for details, see Table S1 in the Supplemental Material available online).

Stimuli

The stimuli were 140 (70 female, 70 male) bodies generated randomly using the skinned multiperson linear (SMPL) model (Loper, Mahmood, Romero, Pons-moll, & Black, 2015), a vertex-based model that accurately represents a wide variety of body shapes in natural

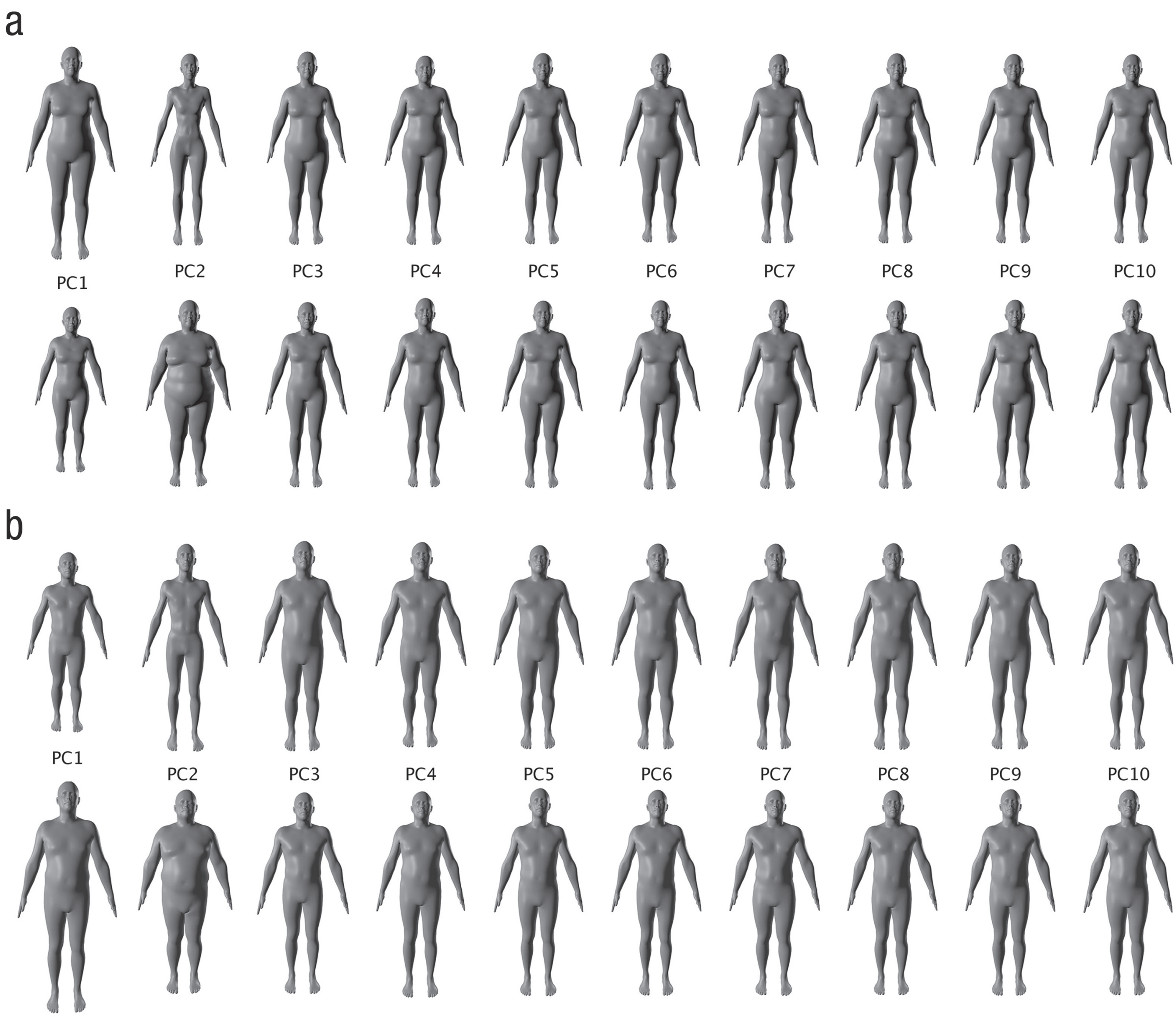

Fig. 1. Renderings of the contrasts captured by the first 10 principal components (PCs) in the principal component analysis body-shape space for (a) female bodies and (b) male bodies. For each component, the figure shows a body with values 3 standard deviations above the origin (upper row) and 3 standard deviations below the origin (lower row).

human poses. In the SMPL model, a body is represented by a three-dimensional template mesh with 6,890 vertices. The template mesh is registered to individual high-resolution laser scans of 1,700 male and 2,100 female bodies in the Civilian American and European Surface Anthropometry Resource (CAESAR) data set (Robinette et al., 2002; Robinette, Daanen, & Paquet, 1999). The CAESAR data set is composed of full-body laser scans of American and European volunteers (age: minimum = 18 years, maximum = 65 years; for both men and women, the ages of people were roughly equally distributed across this range). For the scans, male subjects wore bicycle-style shorts and women wore bicycle shorts with a tank top. Male and female bodies in this model were analyzed in principal component analysis (PCA) separately. In the body space U, a body shape S^j is represented as $S^j = \sum_i^{|\beta|} U_i \, \beta_i^j + u$, where u is the mean (template) mesh, β^j represents the shape coefficients corresponding to this specific body shape, and $|\beta|$ is the number of principal components (PCs) used to represent the shape space. The resulting female and male body spaces are based on a Mahalanobis (i.e., z-score space) distance metric. See Figure 1 for an illustration of the body-shape variations captured by each of the components.

Stimuli for the present study were synthesized on the basis of a weighted linear combination of the first 10 PCs of the space. We limited ourselves to these axes because they were sufficient to create a wide variety of realistic bodies. Among these PCs, several were interpretable in terms of body descriptor terms. For example, for both men and women, PCs 1 and 2 relate to height and weight. Other PCs were not easily interpretable. For the present purposes, the PCs were used as a tool for precise quantification of body shapes, and so it is not important that they be interpretable or psychologically meaningful in isolation. Where interpretations are obvious, we note them, but we are cautious in the visual interpretations of these shapes without direct empirical data. To generate each body stimulus, we sampled randomly from a Gaussian standard normal distribution to obtain body space coordinates for each of the 10 PCs (for the distribution of the coordinates, see Fig. S1 in the Supplemental Material). Next, each body was synthesized as a weighted linear combination of the 10 PCs, for which the weights (noted as βs) corresponded to the randomly sampled PC coefficients. For the purpose of displaying the body, the pose was set to a natural standing position. The generated body geometry was imported to Blender (Version 2.78; https://www.blender.org) and rendered in a frontal view and 45° profile view. All bodies were rendered under controlled illumination conditions and with the same surface material. Illumination and surface material were chosen to create images of bodies that made it easy to see the three-dimensional shapes (for an example of the rating screen, see Fig. 2). All stimuli are available on the Open Science Framework (http://osf.io/64nzg).

Personality-trait list

The list of personality traits was created on the basis of a short version of the Big Five factors of personality (Gosling, Rentfrow, & Swann, 2003). We began with 20 traits from the Gosling et al. study. These traits have proven to be highly representative of individual personalities (Gosling et al., 2003). We amended the list by replacing and adding traits within each of the Big Five domains, according to the Big Five inventory (John & Srivastava, 1999). The final list included 30 words that could be categorized within one of the five domains (see Table S2 in the Supplemental Material). Within each domain, we chose 3 positive and 3 negative traits. For example, the extraversion domain was represented with 6 words: The positive words were *enthusiastic, extraverted*, and *dominant*; the negative words were *quiet, reserved*, and *shy*.

Procedure

On each trial, participants were shown a body rendered from two views (frontal and 45° profile) with the trait list displayed at its right side (see Fig. 2). The task was

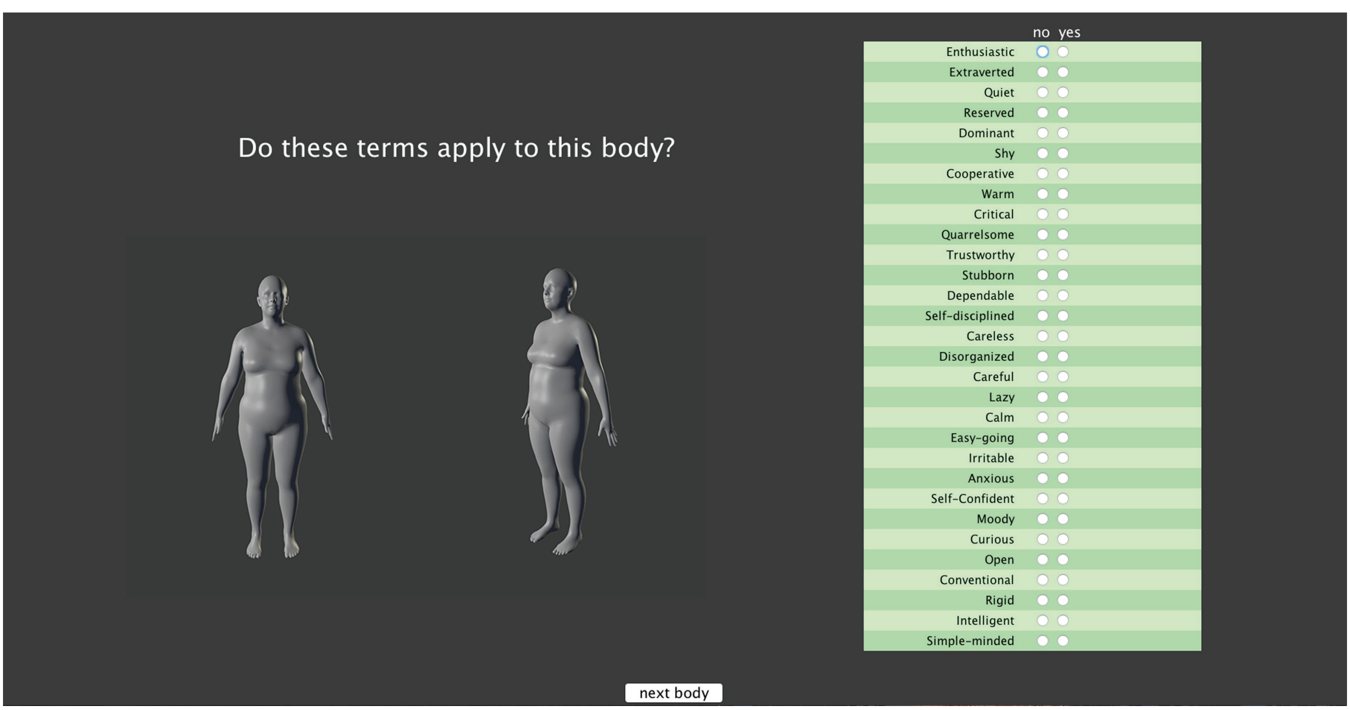

Fig. 2. An example screen used for collecting body ratings. For each stimulus, participants simultaneously viewed one frontal image and one 45° profile image. They then clicked one of two radio buttons for each of 30 traits to indicate whether that trait applied or did not apply to the body.

to judge whether each of the 30 words on the trait list "applied to the body" by clicking on the radio buttons labeled "yes" and "no."[1] There was no default setting for the radio buttons. When all ratings were entered for the displayed body and the participant clicked the "next body" button, the next body appeared. The procedure was repeated until all of the bodies were rated. The experiment was self-paced.

To reduce the workload of the participants, we divided the generated bodies into two sets, with each body randomly assigned to one of the two sets. Each set was composed of a female block of 35 bodies and a male block of 35 bodies. Each participant was randomly assigned to rate one of the two sets of bodies. The female/male blocks were presented to each participant in random order, and the stimulus was presented in random order within each block.

Analysis and Results

All results and analysis scripts are available on the Open Science Framework (http://osf.io/64nzg).

Visualization: CA

To explore the structure of the relationship between bodies and the personality traits we infer from them, we created a multidimensional space that enabled us to simultaneously visualize the body shapes and the trait labels. For this exploratory analysis, CA was conducted to analyze the application of the traits to the bodies (Benzécri, 1973; Greenacre, 2017). CA is a multivariate statistical method, similar to PCA but developed for categorical data. CA uses generalized singular value decomposition to convert a contingency table into two new sets of factor scores, which can be plotted visually or evaluated numerically (Abdi & Béra, 2014). CA is particularly useful for this application because it allows simultaneous (i.e., biplot) visualization of the observations (bodies) and variables (traits) in a unitary multivariate space. In an analogy to PCA, the dimensions of the space are referred to as components. A component is interpreted, generally, by looking at the observations/variables that most strongly contribute to it. The contribution score of a trait to a component is defined by the squared cosine of the trait factor score divided by the component eigenvalue (Abdi & Béra, 2014; Greenacre, 2017).

To implement the CA, we tallied body and trait variables in a contingency table: bodies along the rows and traits along the columns. The *i*th row and *j*th column of the contingency matrix contained the count of participants who judged that the *j*th trait applied to the *i*th body. CA was used to decompose and transform the body and trait variables into two new sets of factor scores—one for the bodies and one for the traits. With these factor scores as coordinates, two-dimensional maps were formed to visualize the similarity structure of the traits and bodies.

Figure 3 shows the first two dimensions of the body-trait space for female stimuli (Fig. 3a) and male stimuli (Fig. 3b; for the complete loadings, see Table S3 in the Supplemental Material). For visual clarity in Figure 3, we do not label terms that had less-than-average contributions on both axes. To facilitate interpretation, we have color-coded the traits by the Big Five personality domains they represent. The first two axes explained 74.22% of the variance (64.85% by Axis 1, 9.37% by Axis 2) for female bodies and 68.67% (57.7% by Axis 1, 10.97% by Axis 2) for male bodies. We interpret only the first two axes from each CA because these axes survived a permutation test for stability (Greenacre, 2017). It is worth noting that the third axis explained 5.94% and 5.78% of the variance for the female and the male spaces, respectively. Although the third axis did not survive a permutation analysis for either the female space or the male space, several of the traits contrasted on this axis were reliably predicted from body shape in the regression analysis. We return to this point in the Shape-to-Trait Regression Results section.

CA results

Before interpreting the CA results, we performed a bootstrap test on the stability of the traits in the space. We did this by resampling observations (bodies) with replacement and projecting the traits into the space as supplementary points, using the scatter as an index of stability (Greenacre, 2017). On the basis of this method, no traits were omitted from the female space. For the male space, we omitted the traits *critical, warm*, and *easygoing*. Therefore, we conclude that the traits retained were applied consistently and reliably to the body shapes.

The CA spaces were interpreted using two approaches. The first was to consider each axis in isolation. This produced a simple interpretation for both the female and the male spaces. The first axis separated traits by valence, for both women and men, with the traits considered positive (e.g., enthusiastic, self-disciplined) on the right side and the traits considered negative (e.g., lazy, careless) on the left side. We can interpret body shapes with descriptor terms only by eye, and so we make these interpretations cautiously, limiting ourselves to variations that are self-evident. Along the valence axis, body shapes vary in the feature of weight, with skinnier bodies on the positive side and heavier bodies on the negative side. The second axis separated traits

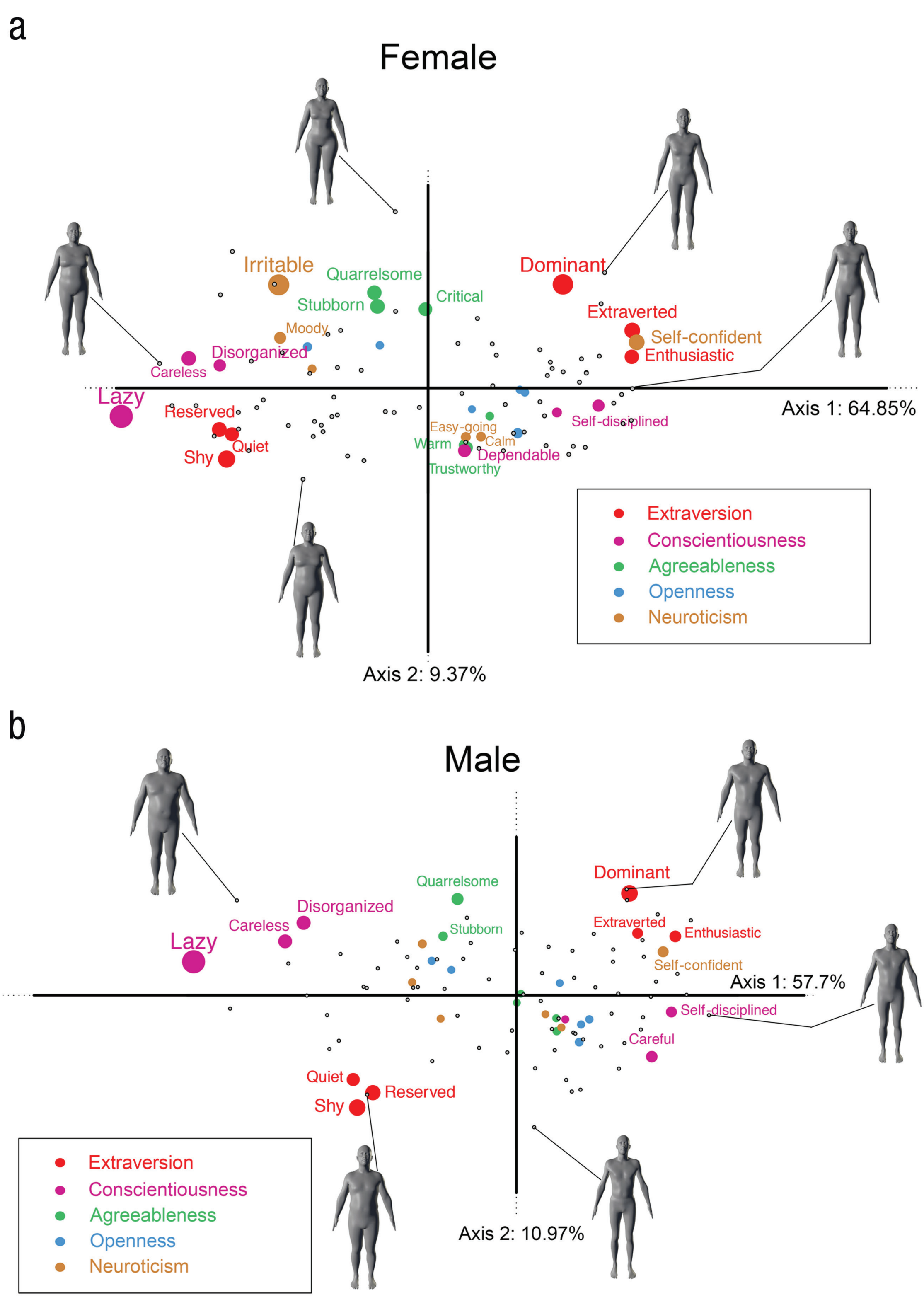

Fig. 3. Biplots of the correspondence analyses that show the space of personality-trait ratings of (a) female bodies and (b) male bodies. Axis 1 and Axis 2 represent valence and agency, respectively. Correspondence-analysis plots illustrate the relationship between body images (gray circles) and participant-assigned personality traits (colored circles) in the Big Five domains. Example body models are shown. Axis labels show the percentage of variance explained by the axis. The size of the colored circles reflects the relative magnitude of their contribution scores.

by agency, with active traits (e.g., quarrelsome, dominant) in the top half of the space and passive traits (e.g., shy, trustworthy) in the bottom half. Along the agency axis, the body shapes vary in different features for female and male bodies. For female bodies, the most salient variation appears to be between pear-shaped bodies and rectangular bodies, with pear-shaped bodies in the active half of the space and rectangular bodies in the passive half of the space. For male bodies, the most salient feature appears to be shoulder width, with wide-shouldered bodies in the active half of the space and narrow-shouldered bodies in the passive half of the space.

A second, more theoretical approach to interpretation is to consider the structure of the Big Five domains in the space. Beginning with the female bodies and traits, the structure of the space is well described by oppositions within four of the five Big Five personality domains. This pattern applies to all traits other than the traits from the openness domain, which did not systematically dissociate in any part of the CA space that survived permutation analysis. These body/trait oppositions separate positive from negative domain stereotypes. To begin, we see the positive extraversion traits (extraverted, enthusiastic, dominant) contrasted against the negative extraversion traits (reserved, shy, quiet) in the top-right versus bottom-left quadrants, respectively. Notably, the term *self-confident* grouped with the positive extraversion terms. Conscientiousness traits are divided along the first axis with positive terms (dependable, self-disciplined) at one end and negative terms (lazy, careless, disorganized) at the other end. Agreeableness is divided along the second axis, which separates positive (warm, trustworthy) and negative (stubborn, quarrelsome, critical). Neuroticism terms are also opposed in the space with positive terms (easygoing, calm) in the bottom-right quadrant and negative terms (irritable, moody) in the top-left quadrant.

The male space mirrored the female space in the oppositional structure described by the Big Five personality domains but for only three domains: extraversion, conscientiousness, and, more tentatively, agreeableness. As in the female space, male body/trait oppositions separated stereotypes into positive and negative domains. Positive extraversion traits (extraverted, enthusiastic, dominant) and negative extraversion traits (reserved, shy, quiet) are contrasted in the top-right versus bottom-left quadrants. Conscientious traits are again separated along the first axis with positive terms (careful, self-disciplined) at one end and negative terms (lazy, careless, disorganized) at the other end. Agreeableness is contrasted along the second axis with positive and negative (stubborn, quarrelsome) terms on opposing sides. Again, the term *self-confident* grouped with the positive extraversion terms.

Interim Discussion

In answer to the first question, we found a consistent and reliable structure of the trait inferences from body shapes. This conclusion is supported by the stability and the structure of the CA spaces. The structure of the spaces suggests agreement across participants in making body-trait inferences for all but three (male body) traits. We found stability for the first two axes (valence and agency) of both the male and the female spaces.

We also found that the male and female spaces were related but were not identical. In both cases, the spaces revealed oppositions between positive and negative stereotypes within the Big Five domains. The spaces differed in the number of oppositions that were expressed, with women showing this opposition for all but the openness domain and men showing opposition only for the conscientiousness, extraversion, and agreeableness domains. Note that the common structural elements of the male and female body-trait spaces are somewhat surprising given that the body shapes on which they are based (i.e., male/female shapes) are categorically different. This further suggests the existence of shared trait stereotypes of human bodies that are flexible enough to be applied to different categories of bodies.

CA revealed that certain body shapes are associated with certain traits. For example, the body type associated with *extraverted* differs visually from the body type associated with *shy*. This indicates an internal stereotyping of body features and traits. Next, we consider physical correlates of the Big Five traits as well as the contrast between valence and agency, with visualization of stereotypes in the next section.

Stereotyping of body-trait inferences

The goal of this analysis was to visualize the stereotypes of bodies associated with individual traits. We began with bodies in the stimulus set that received highly consistent ratings on individual traits. We manipulated these bodies using their underlying three-dimensional model parameters to produce trait stereotypes, which would typify body shapes that correspond to individual traits. Specifically, we standardized (z scored) the trait rating columns in the body-trait contingency table so that each rating was represented with reference to the average body. For each trait rating, positive values indicated bodies rated higher on that trait than the average rating, and negative values indicated bodies rated lower on that trait than the average rating. For female bodies, we set the cutoff z value at 2 and found 18 female bodies that typified 18 of the traits. For male bodies, we set the cutoff z value at 2.13 and found 18 male bodies that typified 21 of the traits (3 bodies typified multiple

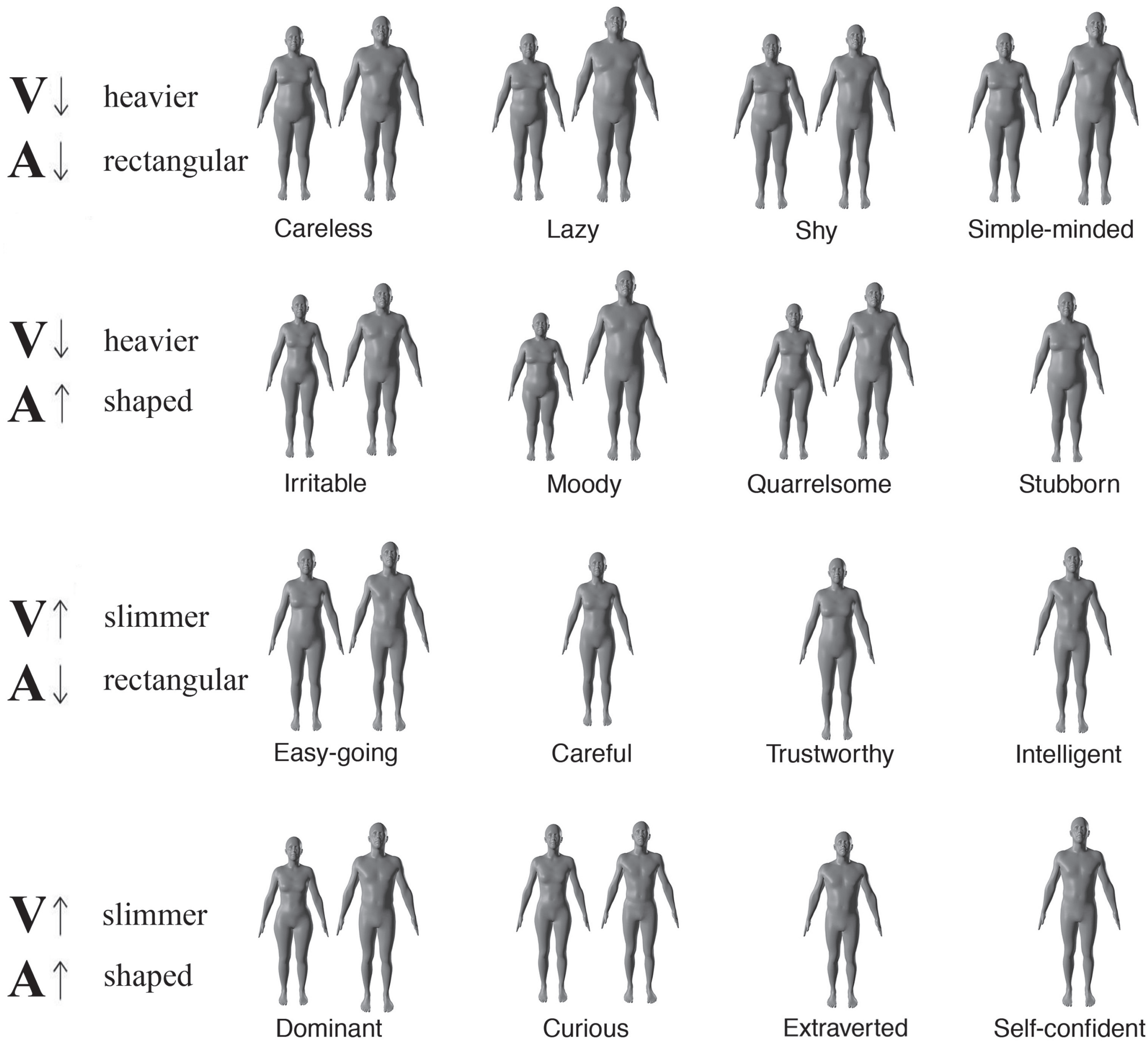

Fig. 4. A subset of body stereotypes we created from single or multiple bodies that received extreme ratings on individual traits (for the entire set, see Fig. S2 in the Supplemental Material available online). The figure is organized to show sample traits with positive and negative combinations of valence (V) and agency (A). For example, Row 1 shows bodies that have negative valence (heavier) and negative agency (less shaped, more rectangular).

traits). For some traits, there were no bodies that exceeded the cutoff. In those cases, we did not present a stereotype. For some traits, if more than one body received ratings that exceeded the cutoff value, we averaged the feature values (i.e., body parameters) of those bodies to create a composite body. In a small number of cases, a single body typified more than one trait. In these cases, the body represents more than one trait (e.g., the same male body represented dominance and self-confidence).

Figure 4 shows a subset of the stereotypes. The figure is organized to illustrate the body shapes associated with valence and agency from the CA trait space. The figure shows example traits in four categories (low/high valence, low/high agency). These align well with the interpretation that weight is related to valence and that shapeliness (shaped or rectangular) is related to agency. For example, the top row shows bodies that have negative valence as heavy and negative agency as less shapely and more rectangular. The full set of stereotypes (27 traits for both men and women) appears in Figure S2 in the Supplemental Material. That figure is organized to show positive and negative personality factors for each Big Five domain.

The stereotypes we found show diverse and complex body shapes that typify individual traits. These reinforce obesity stereotypes previously found (for a review, see Carr & Friedman, 2005) and substantially expand the range of body-trait inferences to encompass a larger and more general range of shapes and traits. Next, we investigated whether this stereotyping could be generalized to new bodies through systematic quantification of the body features that give rise to shape inferences.

Quantification: shape-to-trait regression

The goal of this analysis was to test the consistency of body-trait inferences. To accomplish this goal, we used multiple linear regression analysis to create a predictive mapping from body shapes to personality-trait ratings. The prediction accuracy indicates the consistency of the trait ratings for bodies across participants. Specifically, we predicted the traits that people associated with the bodies from parameters controlling body shape in the three-dimensional body-shape model. For each gender, a body $i \in 1, \ldots, 70$ was represented in the regression as a vector containing the set of coefficients needed to synthesize it, $x_i = [\beta_1, \beta_2, \ldots, \beta_{10}]^T$, where the βs are the linear coefficients for the PCs in the SMPL model. The personality traits associated with each body were coded in a trait vector $y_i = [t_1, t_2, \ldots, t_{30}]^T$ that contained the sum of raters who judged each trait to be applicable to the body. For preprocessing, the trait values for each body were expressed in standard scores, normalizing the trait value with respect to its average across the set of bodies. For modeling, we used the basic equation $Y = XB + E$, where X contained the body-shape vectors,

$$X = \begin{bmatrix} 1 & x_1^T \\ \vdots & \vdots \\ 1 & x_{70}^T \end{bmatrix},$$

and Y contained the trait vectors, $Y = [y_1, \ldots, y_{70}]^T$. The system was solved for B using least squares.[2]

The generalizability of the model predictions was tested using cross-validation. Specifically, for each gender, we trained the model with 69 bodies, reserving 1 body for test. Using the calculated B as the weight for the shape vector, we predicted the trait vector of the test body from its shape vector. We iterated through this procedure 70 times until each body had served as the test body.

Shape-to-trait regression results

At a global level, we measured the extent to which trait-rating profiles could be predicted from body shapes. At a local level, we measured the extent to which individual trait ratings could be predicted from body shapes. It is worth noting that the global predictions encompass accuracy for both predictive and nonpredictive traits.

Global prediction accuracy. For each body, we computed the cosine similarity between the participant-assigned trait vector and the trait vector predicted by the model. Perfect alignment of the two vectors yields a cosine similarity of 1, orthogonal vectors yield a similarity of 0, and two vectors with opposite directions have a similarity of −1. To test model significance, we conducted an inferential test. First, we generated random bodies by permuting the body-shape coefficients. Next, we predicted the traits using the random bodies (n = 70 for each gender), iterating 1,000 times. We measured the average cosine similarity between the actual trait vectors (participant assigned) and predicted trait vectors for the permuted bodies. This served as the null distribution against which we evaluated the trait vector predictions. We inferentially tested whether the mean cosines obtained from the actual model (true cosines) differed statistically from the null distribution. For both the female and the male bodies, the trait vectors were predicted at levels significantly better than chance. In fact, there was no overlap between the actual mean of the predicted traits and the null distribution for either male bodies (true cosines: M = .39; null distribution cosines: M = −.03, SE = .07) or female bodies (true cosines: M = .36; null distribution cosines: M = −.04, SE = .08). This indicates that there is enough information in the body-shape parameters to predict the profile of personality traits assigned by the human raters. Thus, we concluded that there is a consistent relationship between body shapes and the personality inferences that people make from bodies.

Trait-prediction accuracy. Here, we consider the extent to which predictions for the individual traits were accurate. Prediction accuracy was measured as the magnitude of the prediction error (E) for each individual trait. E was calculated as the absolute value of the difference between the participant-assigned trait and the predicted trait value. A lower E indicates higher accuracy. The results are summarized in Figure 5. For each trait, the mean E obtained from the actual model was tested against the distribution of mean Es obtained from the permuted models. To counteract the problem of multiple comparisons, we applied a Bonferroni correction for the 30 comparisons, which reduced the alpha level for significance to .002 (.05/30).

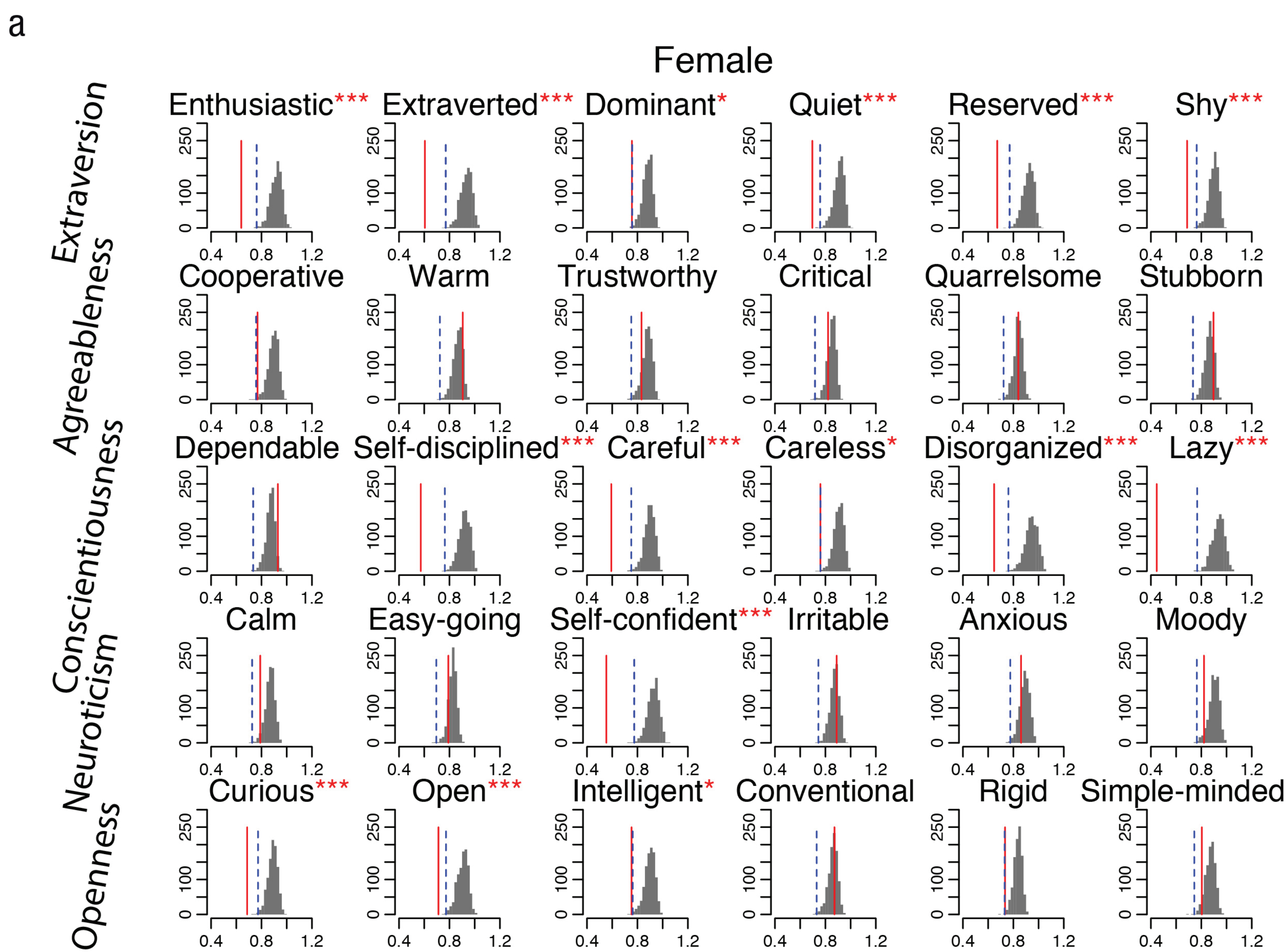

Fig. 5. *(continued on next page)*

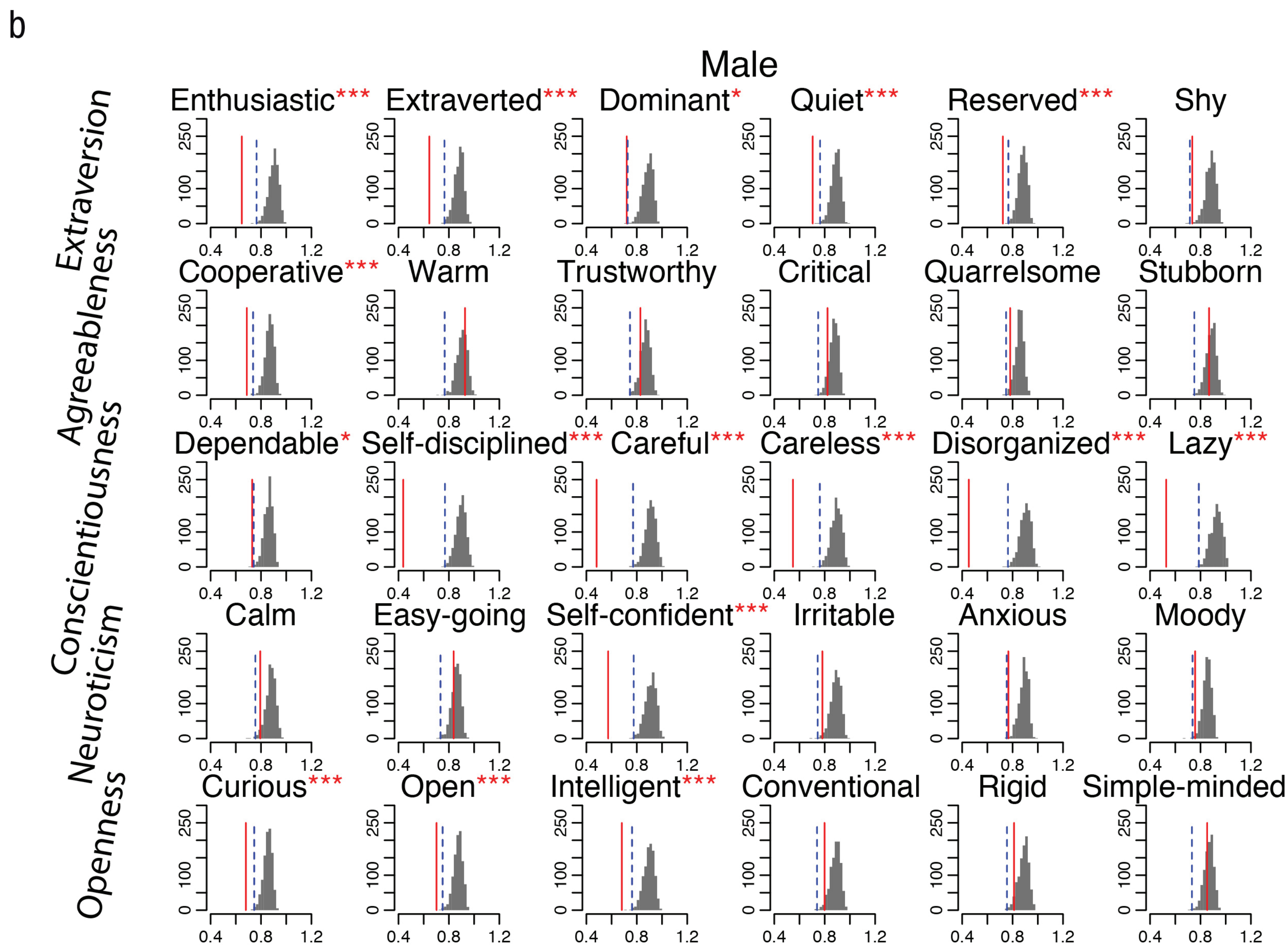

Fig. 5. Prediction accuracy of individual traits from body-shape parameters. Plots show the permuted distribution of the mean error magnitude for (a) female bodies and (b) male bodies. Red solid lines indicate the mean error magnitude of the trait-rating prediction. Gray bars show the mean error magnitude from the 1,000 permuted bodies. The blue dashed lines indicate the cutoff p value after Bonferroni correction (*$p < .05/30$, ***$p < .001/30$).

For both female and male bodies, the traits from the extraversion and conscientiousness domains of the Big Five were predicted with the highest accuracy. For the extraversion domain, six traits were predicted for women and five traits were predicted for men. For the conscientiousness domain, five traits were predicted for women and six traits were predicted for men. For the openness domain, three traits (curious, open, intelligent) were predicted for both women and men. For agreeableness, only one trait (cooperative) was predicted for men and none were predicted for women. For the neuroticism domain, only one trait (self-confidence) was predicted, but it was predicted for both women and men.[3]

In summary, a subset of traits (16 for men and 15 for women) was predicted reliably by the body-shape parameters. The most consistent trait predictions for both male and female bodies came from the extraversion and conscientiousness domains, followed by traits from the openness domain.

Discussion

The findings of this study are as follows. First, people infer a wide range of diverse personality traits from body shapes. Second, these personality inferences are grounded firmly in physical features of body shapes. Third, shape-to-trait inferences from bodies reflect the valence and agency of traits as well as nuanced personality features related to the Big Five domains of extraversion, conscientiousness, and agreeableness. To interpret the role of body shape in trait inferences, we consider the body-trait multivariate space, the stereotypes, and the trait predictions we made from body parameters. The combination of these three approaches gives insight from multiple perspectives into how a perceiver uses body shape to infer personality.

Beginning with valence, for both men and women, the first axis of the multivariate body-trait space was determined by body weight. Body weight aligned with conscientiousness traits, including self-disciplined and careful, on the slimmer side of the axis, and careless, disorganized, and lazy, on the heavier side of the axis. The valence link to conscientiousness traits is likely to reflect evaluative judgments about lifestyle choices that contribute to the maintenance of a healthy body weight (e.g., self-disciplined people may exercise more than lazy people).

Agency was contrasted on the second axis of the body-trait space. High agency personality traits such as quarrelsome, extraverted, and critical opposed low agency traits such as trustworthy, shy, and dependable. High agency body features for both men and women were associated with less rectangular, gender-specific "shaping" (e.g., pear-shaped women, masculine men). More nuanced interpretations emerge, however, in considering the Big Five domains that drive this axis.

Among the Big Five domains, extraversion traits were formed as a combination of valence and agency, with high-agency, high-valence traits (dominant, extraverted, enthusiastic) opposing low-agency, low-valence traits (shy, reserved, quiet). Extraverted male bodies are trim with wide shoulders and an inverted-triangle shape. Shy male bodies are heavier and more rectangular. For women, extraverted bodies are trim and pear shaped. They oppose shy bodies that are heavier, noncurvy, and rectangular.

Agreeableness and neuroticism were also formed as a combination of valence and agency. However, this combination was formed as the inverse of that found for extraversion. High-agency, low-valence traits (quarrelsome, stubborn, and irritable) opposed low-agency, high-valence traits (trustworthy, easygoing, and calm). Neuroticism did not differ strongly from agreeableness in that it separated rectangular bodies from more shapely bodies. On the associated body features, it is worth noting that weight variation (as it aligns with the valence axis) was less variable for neuroticism than for agreeableness. For both agreeableness and neuroticism, the negative traits are characterized for women by bottom-heavy, powerful-looking figures with short legs. For men, although the negative trait stereotypes for these domains vary substantially, these stereotypes all had broad shoulders. This contrast is demonstrated most clearly by the contrast of irritable and moody versus easygoing bodies for both women and men (see Fig. 4).

By comparison with the other domains, the body features associated with openness were more challenging to interpret. The positive openness traits (curious, open, intelligent) were predicted for both men and women. In the multivariate space, openness traits did not contribute strongly to either the valence or the agency axes. As noted previously, openness traits were contrasted on the third axis of the CA space, which did not survive the permutation test. One possibility is that these traits are associated with average-looking bodies, which may be easy to predict but difficult to stereotype. Averages, by definition, are not amenable to caricaturing. In this regard, openness may be special as a trait domain because it mixes cognitive and emotional elements of personality. Whereas the former may be linked to body shape, the latter emotional elements may be conveyed more by body gesture than by body shape.

More broadly, the structure of personality inferences made to bodies can be compared with established findings for faces. Facial personality can be captured largely by valence and dominance (Oosterhof & Todorov, 2008), which are perceived from facial cues that reflect approachability (e.g., emotional expressions) and physical strength, respectively. Social evaluations of bodies, on the other hand, reflect a similar structure, but with different diagnostic features: Valence is inferred from body weight rather than emotional expressions. This could be because emotional expression is typically reflected by body pose, which was controlled in this study, so expression has only a limited effect on trait judgments. However, we also note that an absolutely neutral body pose does not exist, and so the pose used in the present research could be biased toward certain traits. Thus, for faces, valence taps information that relates to whether someone is perceived as a good or bad person (approachableness). For bodies, valence contrasts appearance associated with a good versus bad work ethic (conscientious)—a quite different metric. For bodies, inferences about whether someone is a good person (high valence, low agency) or bad person (low valence, high agency) are based on agreeableness and neuroticism.

In a broader historical context, the valence axis might be related to Sheldon's contrast between endomorph and ectomorph, and the agency dimension might be related to the mesomorph shape. Although it would be of interest to compare our findings with approaches used in earlier studies (e.g., Brodsky, 1954; Kretschmer, 1951; Lerner, 1969; Sheldon, 1954; Sheldon et al., 1940; Strongman & Hart, 1968; W. D. Wells & Siegel, 1961), this is challenging and would require additional experiments to align the older body-type models with the quantification approach used here.

It is worth mentioning that we did not present stereotypes for all of the traits that were predicted reliably from body-shape parameters. This is because stereotypes were visualized for traits only when there were bodies in the original stimulus set that had a large number of participants agree on the presence of these traits. This may simply reflect a sampling issue. Concomitantly, we provided stereotypes for some traits (e.g., agreeableness traits) that were not predicted reliably in the regression. There are several possible reasons that we found bodies rated with strong consensus on traits that were not reliably predicted in the regression. One possibility is that the body-model parameters are related to body features in ways too complex to capture with simple linear regression (e.g., there might be a nonlinear mapping from shape features to some traits). A deeper understanding of this will require additional research.

The findings open the door to addressing a range of questions that can expand our perspective of how we form first impressions of people from their bodies. Here, we list three possible future directions. First, we have established an empirical link between personality/trait words and the parameters of a body-shape model. Previously, Hill et al. (2016) established an empirical link between body descriptions and the body model. A next logical empirical step is to bridge the gap between trait words (e.g., dominant) and descriptor words (e.g., pear shaped). Second, we report the major trait axes (valence, agency) but do not model them directly. This modeling could be done by manipulating the body cues and testing new samples of participants. Third, it is well worth exploring other factors, including the effects of attractiveness, age, and gender, to determine their role in driving these trait inferences.

In summary, people infer personality traits from body shapes in systematic and reliable ways. The present study takes an important first step toward understanding how these inferences can be understood in the context of body-shape parameters from three-dimensional bodies. There is, however, an important caveat to these findings. Although we believe that all humans infer personality traits from body shape, we expect that these inferences will differ substantially across ethnicity, culture, and possibly age. Moreover, the body-shape model is limited to the demographic characteristics of the people scanned. The consistency of ratings, across different samples of individuals, both within and across cultures, is well worthy of future study, as is the exploration of real-world experiences with bodies rather than with computer presentations of them. These differences may be useful for understanding how we form first impressions of other people when we have nothing but appearance to rely on.

Action Editor

D. Stephen Lindsay served as action editor for this article.

Author Contributions

Y. Hu and A. J. O'Toole contributed to the study design. Y. Hu and C. J. Parde programmed the experiment. Y. Hu, M. Q. Hill, and C. J. Parde analyzed and interpreted the data under the supervision of A. J. O'Toole. N. Mahmood assisted with computations related to stimulus quantification from the skinned multiperson linear body model. Y. Hu drafted the manuscript, and A. J. O'Toole provided critical revisions. All the authors approved the final manuscript for submission.

Acknowledgments

We thank Robert Ackerman, Michael Kriegsman, and Ju-Chi Yu for their suggestions in the data analysis.

Declaration of Conflicting Interests

N. Mahmood is a founder and the CEO at Meshcapade, which is commercializing body-modeling technology. Her research was performed solely at, and funded solely by, the Max Planck Institute for Intelligent Systems, Tübingen, Germany.

The other author(s) declared that there were no potential conflicts of interest with respect to the authorship or the publication of this article.

Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797618799300

Open Practices

All stimuli, data, and analysis scripts have been made publicly available via the Open Science Framework and can be accessed at http://osf.io/64nzg. The design and analysis plans for this study were not preregistered. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797618799300. This article has received the badge for Open Data. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

Notes

1. We decided to use a categorical rather than continuous scale because we were uncertain about whether a more standard Likert-type scale would translate consistently onto body-trait ratings. The categorical ratings also present the rater with a less complex task.
2. In this atypical regression form, human subjects, rather than the observations, contribute to the dependent variable. Instead, bodies are the observations.
3. The fact that self-confidence was the only trait predicted for neuroticism could be an artifact because it loaded on extraversion in the CA presentation (see Fig. 3).

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