Supplemental Material

Person knowledge shapes face identity perception

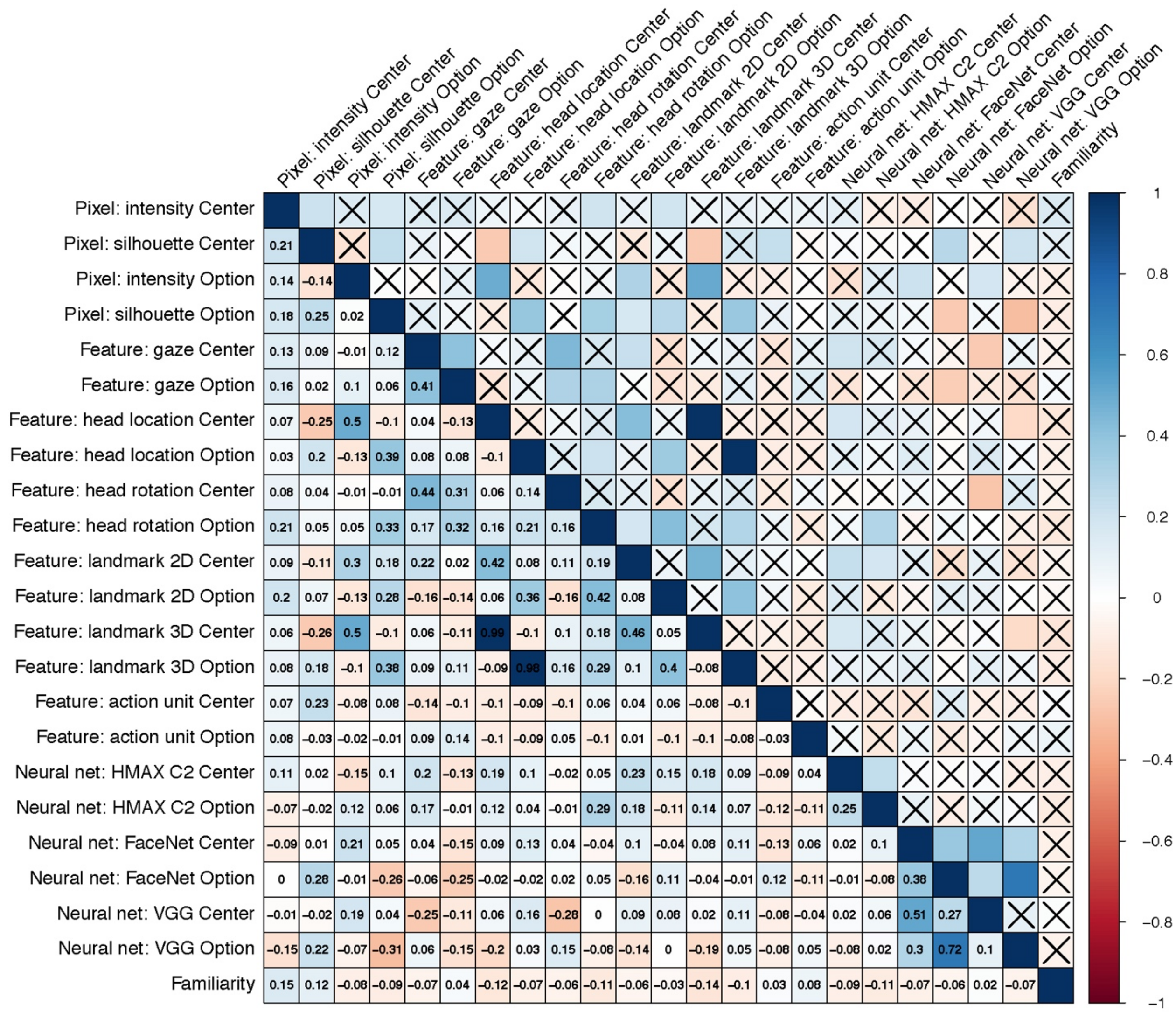
DongWon Oh
New York University

Mirella Walker
University of Basel

Jonathan B. Freeman
New York University

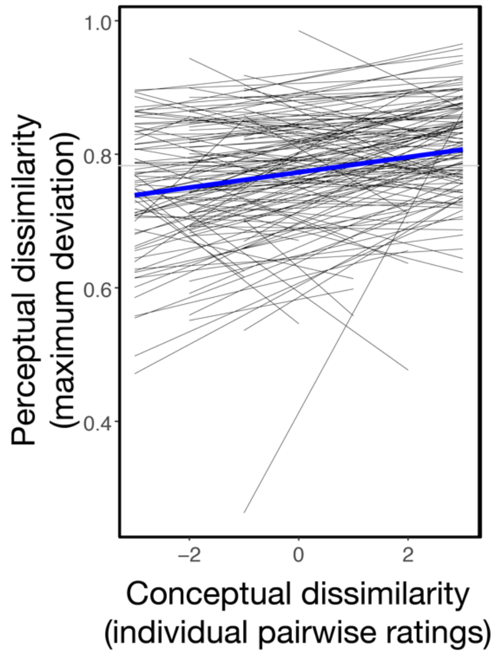
Table of Content

Corresponding author:
DongWon Oh
6 Washington Place
New York, NY 10003
orcid.org/0000-0002-2105-3756
Email: dongwon.oh@nyu.edu

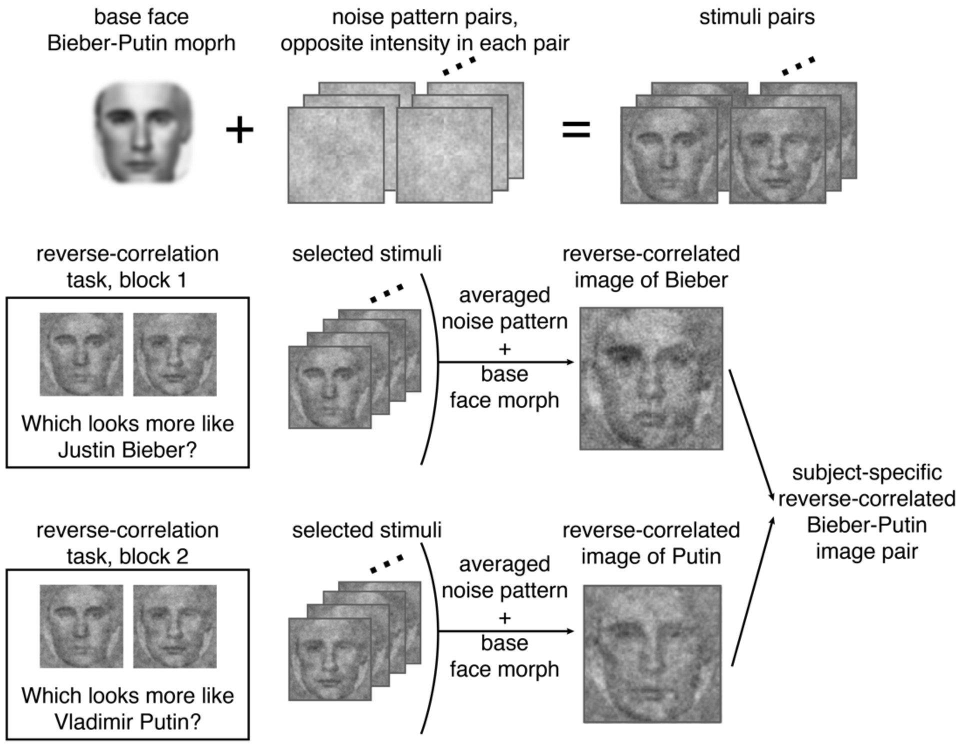


Supplementary Figure 1. Correlations between control covariates in Study 1. To account for the contribution of overlap in physical features and other potential confounds between face images, we included four types of similarity measures across all pairs of face images in our regression models: Pixel-based, facial-feature-based, and neural-net-based visual similarity measures, and familiarity measure (see Study 1 Method for details). The lower triangle of the matrix displays pairwise Pearson correlation coefficients. The upper triangle indicates the statistical significance of each correlation at α=.05 as a rough reference. The number of cases in the correlational analyses was 120=C(16,2) (16 total identities).

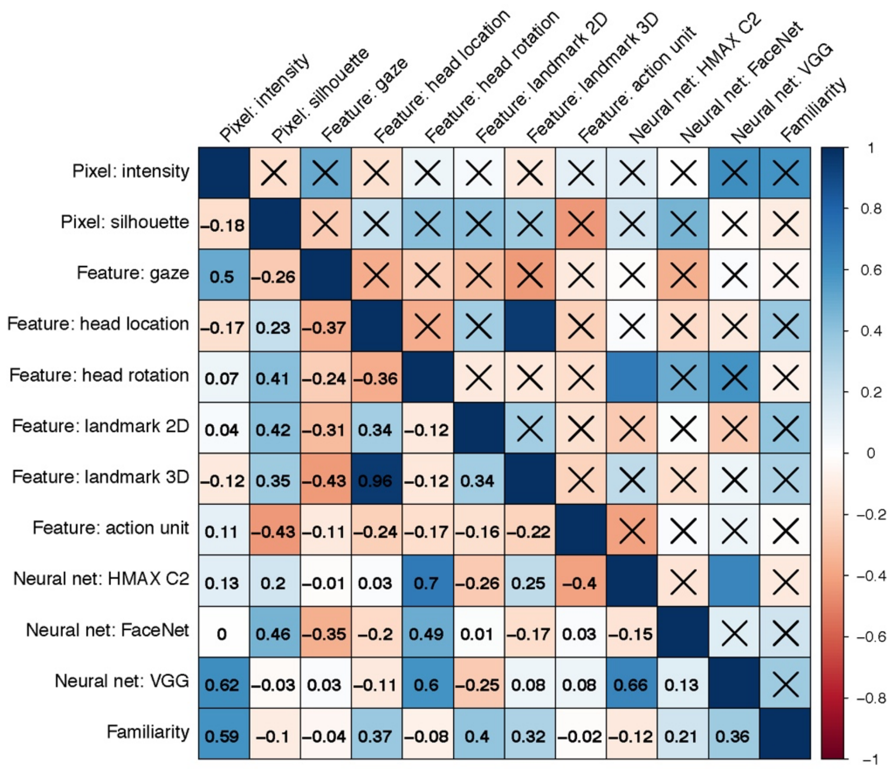
Note. 'Center': measures of face images that were presented at center in the perceptual matching mousetracking task, 'Option': measures of the same target individuals' different face images that were presented at top as binary options in the mousetracking task. HMAX=Hierarchical Max-pooling model (Riesenhuber & Poggio, 1999; Serre, Wolf, Bileschi, Riesenhuber, & Poggio, 2007), FaceNet=FaceNet deep neural network (Schroff, Kalenichenko, & Philbin, 2015), VGG=VGG-Face deep neural network (Parkhi, Vedaldi, & Zisserman, 2015).
.



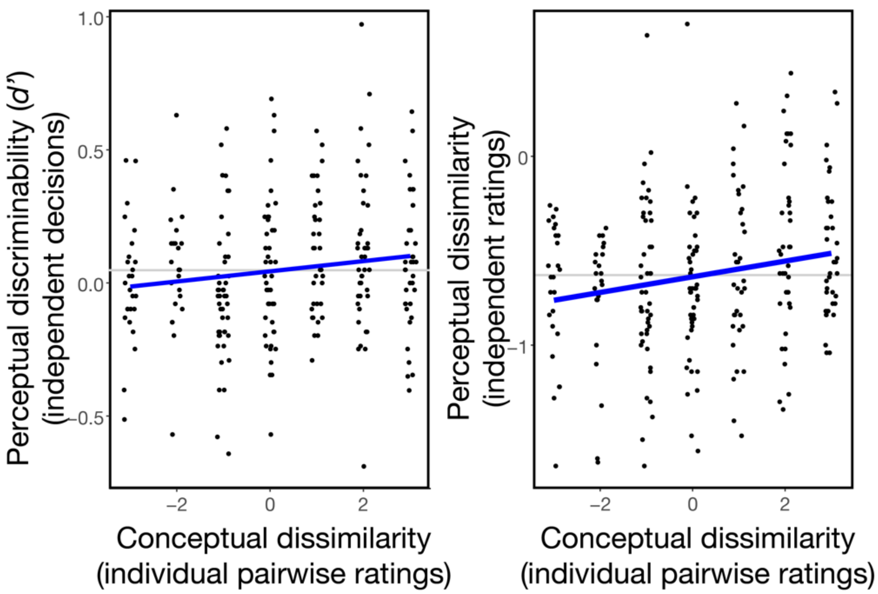
Supplementary Figure 2. Multi-level regression results for Study 1: Conceptual dissimilarity predicts perceptual similarity. In Study 1 (n=193), in addition to the euclidean distance derived from specific personality trait ratings (see main text and Figures 1 & 2), conducted an analysis using a complementary measure of conceptual dissimilarity – explicit dissimilarity ratings between identities for each of all 120 identity pairs recorded by each mousetracking task participant (see main text for details). As in the results in Figure 2 (Study 1), each black line represents a participant and the blue line denotes the least-squares linear fit of all data points. The plot is displayed for illustrative purposes. The actual analysis was conducted using GEE multilevel regression.



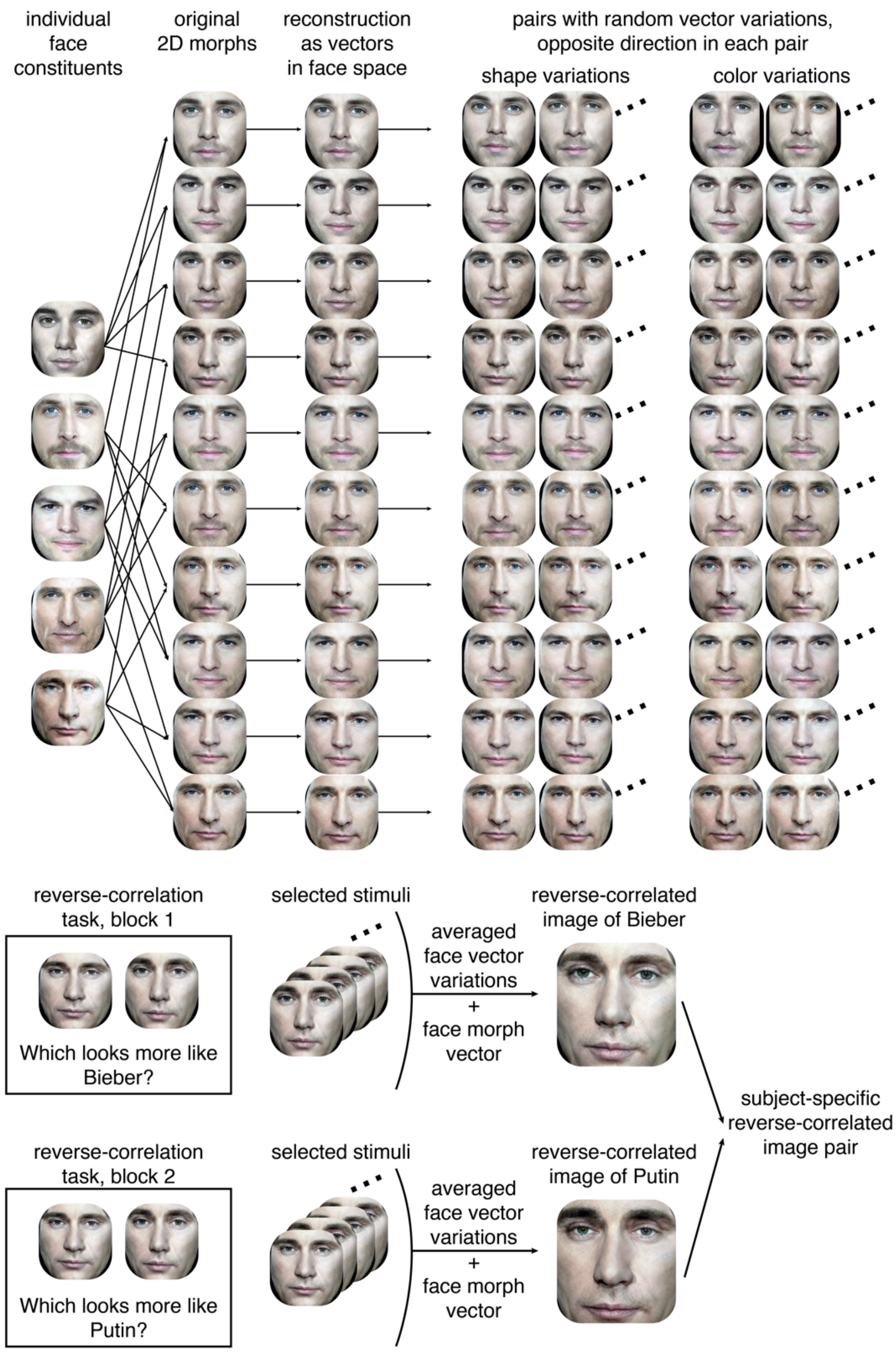
Supplementary Figure 3. Stimulus preparation and reverse-correlation procedures in Study 2. To visualize a participant's mental representation of celebrities using a noise-imposed reverse correlation approach, we generated two image pairs for each identity pair (e.g., Bieber-Putin pair). We chose 5 individuals that are famous in the US with a range of conceptual dissimilarity. We then created the base face image of each pairwise identity combination by morphing the two faces to a 50/50 blend of each identity using PsychoMorph (Tiddeman, Burt, & Perrett, 2001). We applied to each base image a Gaussian blur with 3-pixel radius, removing high spatial frequency information. We then imposed five layers of sinusoid noise patterns varying in spatial scale and their negative versions using the *rcicr* R library (Dotsch, 2015). From the base image of each identity pair, we created 400 images comprising of 200 side-by-side face images. Each participant in the reverse-correlation task was assigned one of the 10 pairwise combinations of the 5 target identities (e.g., Bieber and Putin). On each trial, participants were presented with two side-by-side noise-imposed face images. Participants were asked to choose the face that appeared more like one of the two identities in the pair. In the next block, participants were asked to choose the face that appeared more like the other identity (shown here at the bottom is an example of one pair). The noise patterns on the faces selected in the reverse-correlation task were averaged and superimposed on the base face to generate that particular participant's reverse-correlated image of the identity. The whole procedure resulted in two images for each reverse-correlation participant. Later, these resulting reverse-correlated images (n=500, 2 identities × 10 identity pair conditions × 25 reverse-correlation-task participants per condition) were employed as stimuli in a categorization task (to calculate perceptual discriminability, d') and a similarity rating task (to calculate the perceptual similarity rating). Independent groups of participants participated in these two tasks.



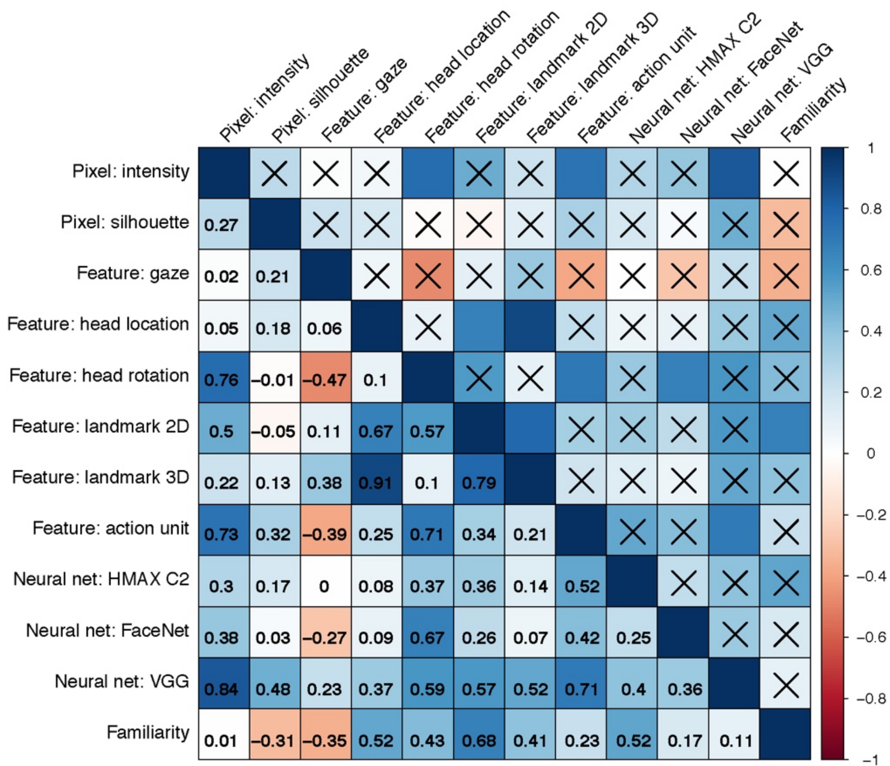
Supplementary Figure 4. Correlations between control covariates in Study 2. To account for the contribution of overlap in physical features and other potential confounds between face images and other potential confounds, we included various similarity measures across all pairs of face images in our regression models. To avoid the multicollinearity issues, we excluded four variables with the strongest correlations with other variables from our final model (Pixel: silhouette, Feature: head location, Feature: head rotation, Neural net: VGG). For the detailed description of the exclusion rule, see the main text. The lower triangle of the matrix displays pairwise Pearson correlation coefficients. The upper triangle indicates the statistical significance of each correlation at α=.05 as a reference. The number of cases in the correlations was only 10=C(5,2) (5 total identities).



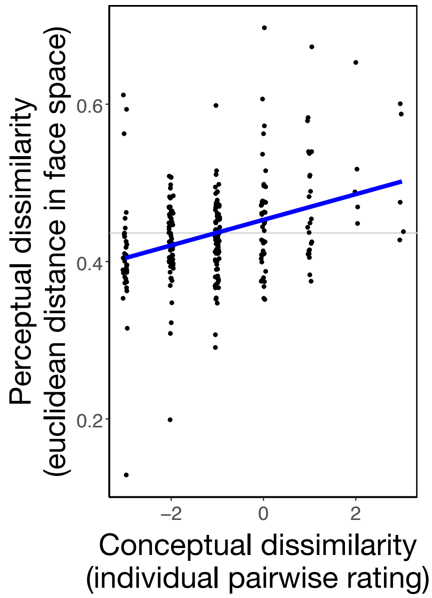
Supplementary Figure 5. Multi-level regression results for Study 2: Conceptual dissimilarity predicts perceptual similarity. In Study 2 (n=250), in addition to the euclidean distance derived from specific personality trait ratings (see main text and Figures 1 & 2), we conducted analyses using a complementary measure of conceptual similarity: explicit dissimilarity ratings between identities generated from the reverse-correlation task (see main text for details). Horizontal values of all data points are integer ([–3,3]) and are jittered for better visibility. As in the results in Figures 2 & 3, each data point represents a participant and the blue line denotes the least-squares linear regression line of all data points. The plots are displayed for illustrative purposes. The actual analysis was conducted using GEE multilevel regression.



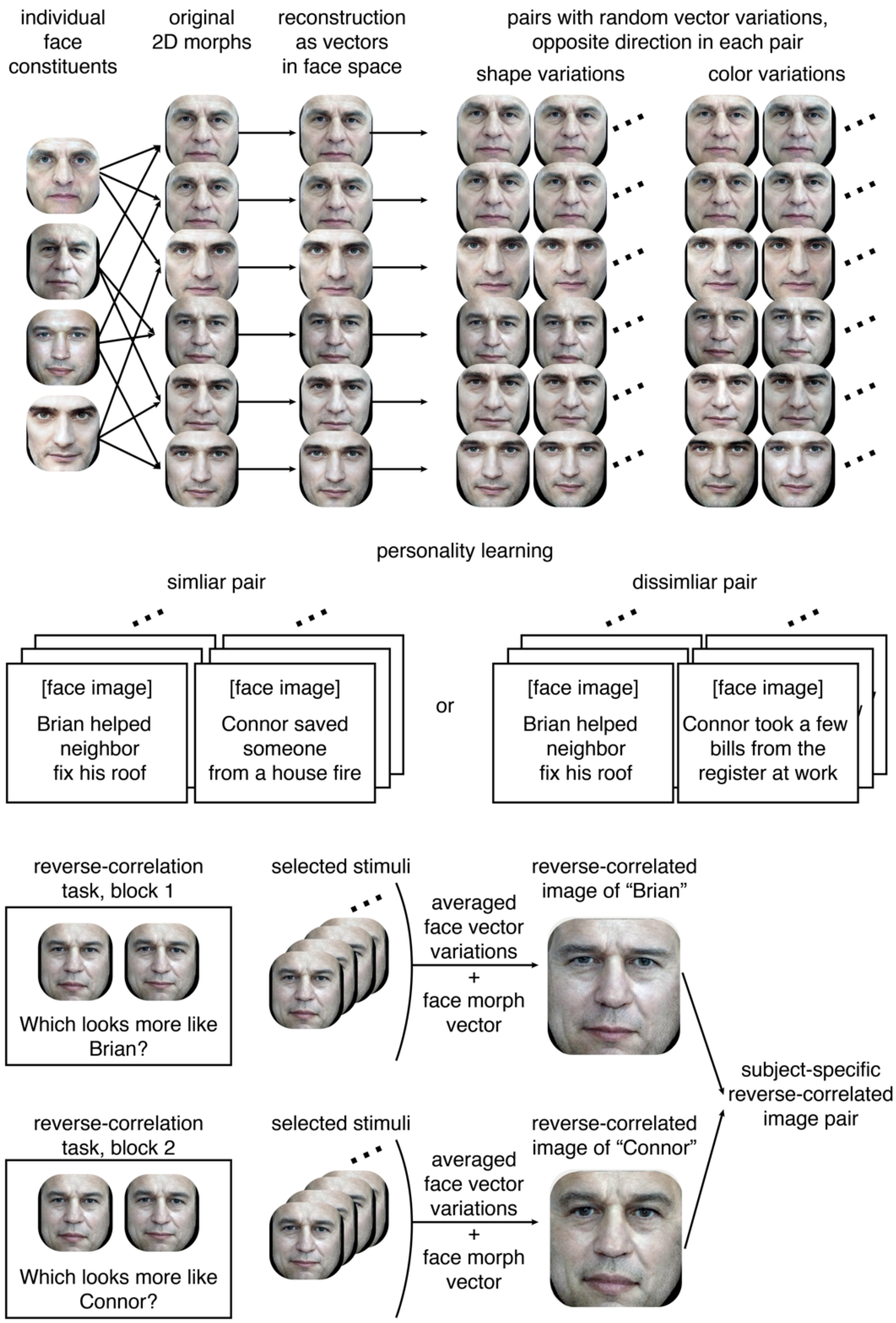
Supplementary Figure 6. Stimulus preparation and reverse-correlation procedures in Study 3. To visualize a participant's mental representation of celebrities using a face-space reverse correlation approach, we first selected five identities that are well known to people in the US (the same identities as Study 2; see the main text and Supplementary Figure 3). We created each of the five individuals' faces by averaging multiple different images of the person using WebMorph (DeBruine, 2018). We then created a 2D 50/50-blend morph between two identities for each of the ten pairs. We transformed the ten morphs into ten respective vectors in the face space, in which the shape and color of a face is determined by numeric values, i.e., shape and color parameters (Paysan, Knothe, Amberg, Romdhani, & Vetter, 2009). We then created random variations of each of the morphed faces (i.e., 100 face pairs varied only on shape and 100 varied only on color) (Walker & Keller, 2019), creating 200 image pairs for each identity pair (e.g., Bieber-Putin pair). In each image pair, two faces were randomly varied either only in shape or only in color. Two faces in each pair were shifted in the opposite direction in the face space, from the original morph face, which rendered the two images subtly distinctive. Here, for each identity pair, an example of a shape-variation pair and a color-variation pair used in the reverse correlation task are displayed. In the reverse-correlation task, on each trial participants were presented with two side-by-side random-variation face images. Participants were asked to choose the face that appeared more like one of the two identities in the pair. In the next block, participants were asked to choose the face that appeared more like the other identity (shown here at the bottom is an example of one pair). The face vectors underlying the faces that were selected in the reverse-correlation task were averaged and combined with the vector of the face morph of the pair to generate the reverse-correlated image of the identity. The whole procedure resulted in two face vectors for each reverse-correlation participant. Here, two such face vectors are visualized as two faces. Later, these resulting face vectors (n=500, 2 identities × 10 identity pair conditions × 25 reverse-correlation-task participants per condition) were subjected to calculating the euclidean distance of each pair in the face space. The distance represented how similar the two faces were between two identities at the level of their objective features.



Supplementary Figure 7. Correlations between control covariates in Study 3. To account for the contribution of overlap in physical features and other potential confounds between face images, we included various similarity measures across all pairs of face images in our regression models. To avoid the multicollinearity issues, we excluded four variables with the strongest correlations with other variables from our final model (Feature: head rotation, Feature: landmark 2D, Feature: action unit, Neural net: VGG). For the detailed description of the exclusion rule, see the main text. The lower triangle of the matrix displays pairwise Pearson correlation coefficients. The upper triangle indicates the statistical significance of each correlation at α=.05 as a reference. The number of cases in the correlations was only 10=C(5,2) (5 total identities).

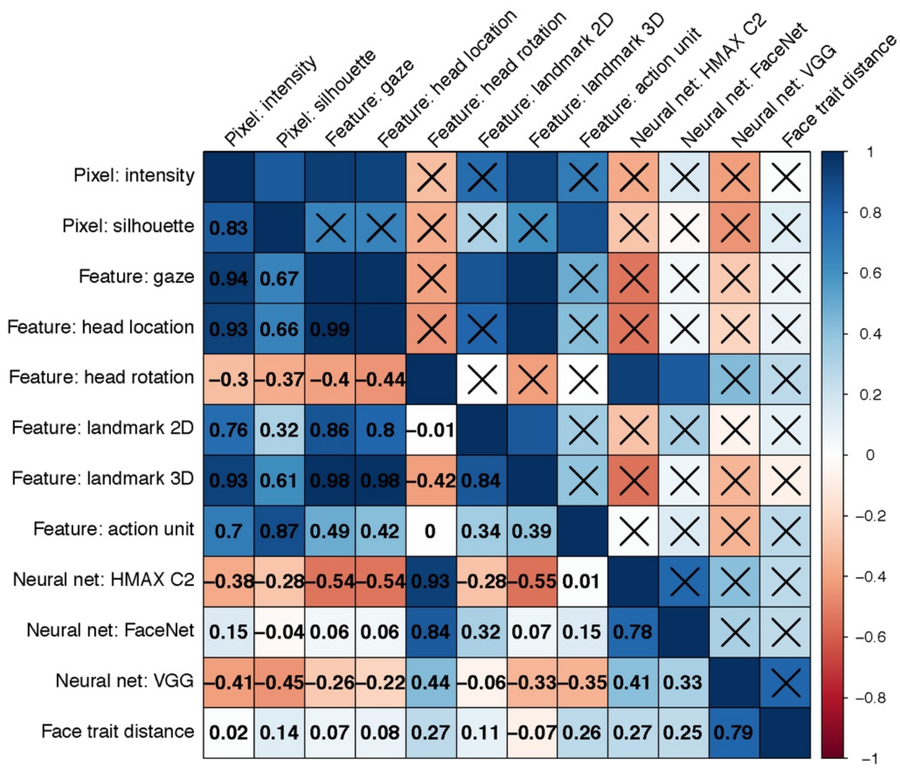


Supplementary Figure 8. Multi-level regression results for Study 3: Conceptual dissimilarity predicts perceptual similarity. In Study 3 (n=250), in addition to the euclidean distance derived from specific personality trait ratings (see main text and Figures 1 & 2), we conducted analyses using a complementary measure of conceptual similarity: explicit dissimilarity ratings between identities generated from the reverse-correlation task (see main text for details). Horizontal values of all data points are integer ([–3,3]) and are jittered for better visibility. As in the results in Figures 2 & 3, each data point represents a participant and the blue line denotes the least-squares linear regression line of all data points. The plots are displayed for illustrative purposes. The actual analysis was conducted using GEE multilevel regression.



Supplementary Figure 9. Stimulus preparation and reverse-correlation procedures in Study 4. We first selected four identities that are not well known to people in the US but are well known in another White-majority, industrialized country (i.e., Switzerland). We created each of the four individuals' faces by averaging three different images of the person using WebMorph (DeBruine, 2018). We then created a 2D 50/50-blend morph between two identities for each of the six pairs. We transformed the six morphs into six respective vectors in the face space (Paysan et al., 2009). We then created random variations of each of the morphed faces (i.e., 100 face pairs varied only on shape and 100 varied only on color), creating 200 image pairs for each identity pair. In each face pair, two faces were shifted in the opposite direction in the face space.

Here, for each identity pair, an example of a shape-variation pair and a color-variation pair used in the reverse correlation task are displayed. Participants that were naïve to all four identities in real life completed the learning stage and the reverse-correlation task. Each participant learned about either two individuals that are similar (both trustworthy or both untrustworthy) or dissimilar to each other in personality. Each participant was assigned one of the six pairwise combinations of the 4 target faces. Personalities and names were randomly linked with two faces. Participants were presented with a series of 20 slides (10 trials per identity), one at a time, with the face and a sentence describing the person's behavior below a naturalistic face photo of the corresponding identity (not shown here to avoid copyright infringement). A total of four naturalistic face photos were displayed for each identity, and were randomly paired with 10 sentences. In the reverse-correlation task, which followed the learning stage, on each trial participants were presented with two side-by-side random-variation face images. Participants were asked to choose the face that appeared more like one of the two identities in the pair. In the next block, participants were asked to choose the face that appeared more like the other identity (shown here at the bottom is an example of one pair). The face vectors underlying the faces that were selected in the reverse-correlation task were averaged and combined with the vector of the face morph of the pair to generate the reverse-correlated image of the identity. The whole procedure resulted in two face vectors for each reverse-correlation participant. Here, two such face vectors are visualized as two faces. Later, these resulting face vectors (n=312, 2 identities × 6 identity pair conditions × 2 similar/dissimilar personality conditions × 13 reverse-correlation-task participants per condition) were subjected to calculating the euclidean distance of each pair in the face space, as in Study 3. The distance represented how similar the two faces were between two identities at the level of their objective features.



Supplementary Figure 10. Correlations between control covariates in Study 4. To account for the contribution of overlap in physical features and other potential confounds between face images, we included various similarity measures across all pairs of face images in our regression models. To avoid the multicollinearity issues, we excluded eight variables with the strongest correlations with other variables from our final model (Pixel: intensity, Pixel: silhouette, Feature: gaze, Feature: head location, Feature: landmark 3D, Neural net: HMAX C2, Neural net: FaceNet, Neural net: VGG). For the detailed description of the exclusion rule, see the main text. The lower triangle of the matrix displays pairwise Pearson correlation coefficients. The upper triangle indicates the statistical significance of each correlation at α=.05 as a reference. The number of cases in the correlations was only 6=C(4,2) (4 identities).

References

DeBruine, L. (2018). debruine/webmorph: Beta release 2 (Version v0.0.0.9001). Retrieved from https://webmorph.org/

Dotsch, R. (2015). rcicr: Reverse correlation image classification toolbox (Version 0.3.2) [R package].

Parkhi, O. M., Vedaldi, A., & Zisserman, A. (2015). *Deep face recognition.* Paper presented at the Proceedings of the British Machine Vision Conference (BMVC).

Paysan, P., Knothe, R., Amberg, B., Romdhani, S., & Vetter, T. (2009). *A 3D face model for pose and illumination invariant face recognition.* Paper presented at the Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS).

Riesenhuber, M., & Poggio, T. (1999). Hierarchical models of object recognition in cortex. *Nature Neuroscience, 2*(11), 1019-1025.

Schroff, F., Kalenichenko, D., & Philbin, J. (2015). *FaceNet: A unified embedding for face recognition and clustering.* Paper presented at the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Serre, T., Wolf, L., Bileschi, S., Riesenhuber, M., & Poggio, T. (2007). Robust object recognition with cortex-like mechanisms. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 29*(3), 411-426. doi:10.1109/TPAMI.2007.56

Tiddeman, B., Burt, D., & Perrett, D. (2001). Computer graphics in facial perception research. *IEEE Computer Graphics and Applications, 21*(5), 42-50.

Walker, M., & Keller, M. (2019). Beyond attractiveness: A multimethod approach to study enhancement in self-recognition on the Big Two personality dimensions. *Journal of Personality and Social Psychology, 117*, 483-499. doi:10.1037/pspa0000157