Supplementary Materials

Supplementary Simulation 1

Our theoretical hypothesis rests on the premise that individuals within groups will look alike because candidates resembling group members are more likely to be accepted by the group. Such a process of group acceptance would lead to greater homogeneity in facial appearance within a group over time. Because this theorized process is at the foundation of our hypotheses, supporting the statistical framework for the subsequent studies, we first demonstrate this in a simulation. For those with an understanding of sampling and probability the results of this simulation may be forthright, however we intend this simulation as an accessible illustration showing that accepting similar-looking members will *necessarily*, over time, decrease the variability in appearance of individuals within the group.

Methods

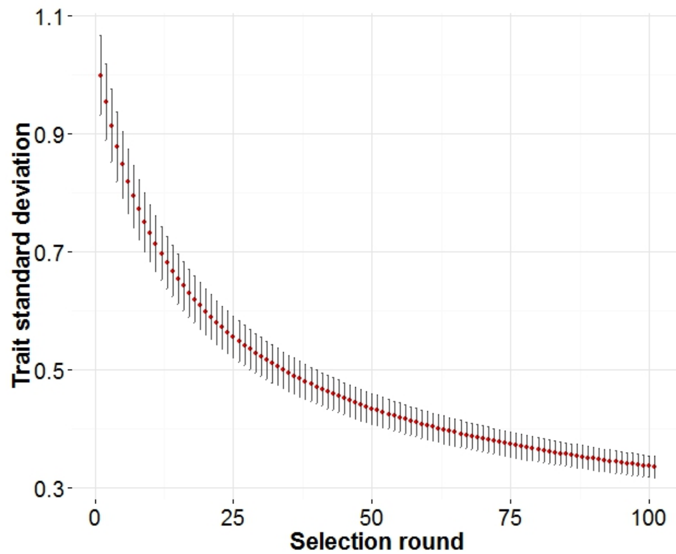
Groups were created as random samples of 100 members (i.e., 100 values corresponding to a hypothetical facial appearance value of each member) drawn from a distribution with a mean of 0 and a standard deviation of 1. Candidate pools were generated each round in a similar manner, a pool of 50 members was randomly drawn from a distribution with a mean of 0 and a standard deviation of 1. To operationalize groups accepting the most similar-looking candidates, each round the 10 candidates from the candidate pool with values closest to the group mean in facial appearance were "accepted" by the group.

Five hundred simulations were run in R, and each simulation consisted of 100 rounds. While real-world groups rarely have the opportunity to select members for 100 rounds, doing so allows us to examine the distribution of the "group's" variance over a long period of time. Each round following candidate selection (e.g., following round 1, the group consisted of the original 100 members plus the new 10 selected candidates), group variance was estimated to assess their overall variance in appearance over time due to acceptance criteria differences. In this context, standard deviation represented overall group variance in facial appearance.

Results

While Supplementary Figure 1 makes clear that the average variance of the group decreased across selection rounds, for illustration purposes a two-tailed independent samples *t*-test indicated that standard deviation was already significantly lower in round 2 than round 1, $t(198)=4.59$, $p<.001$, 95% CI [.026, .065]. Whereas the standard deviation of the group started at 1, after 100 rounds of selecting the most similar-looking candidates into the group, the overall group standard deviation approached .3. Mathematically, this decrease in group variance would eventually asymptote right above zero, as the candidate pool maintains some amount of variability.

Of course, this outcome was mathematically inevitable, yet this demonstration provides an important proof of concept for the base of our theoretical argument. If groups accept similar looking others, the overall variance in facial appearance of the group decreases over time. Thus, the variability in facial appearance across people will be shifted more so to *between* groups, relative to within groups, making it possible to accurately classify individuals into their group from facial appearance alone.



Supplementary Figure 1. Mean standard deviations across groups over simulation rounds. Error bars represent the standard deviation of the standard deviations over the 500 simulations in each round.

Supplementary Simulation 2

In the present research several studies classify targets using measurements derived from computer-generated face models (Study 4 and 5B in the main text, and many of the Supplementary Analyses below). In these studies, the classification process has available a large number of variables, and one concern is that the high degree of accurate classification may be an artifact of this large number of parameters. We explored this concern with another small simulation, testing whether classification accuracy would be possible even from meaningless, randomly generated variables. Should accurate classification be an artifact of the approach, or inevitable, we would expect high classification accuracy even with these meaningless, randomly generated data.

Methods

We generated 10 random datasets, identical in size to Study 4 of the primary manuscript. Specifically, these datasets had the same number of observations (e.g., fraternity members) within each cluster (e.g., fraternities), and the same number of parameters (*n* = 62) as that reported in the manuscript. The values for these 62 variables, however, varied randomly between 0 and 1. We tested classification accuracy using leave-one-out cross-validation, then calculated the average classification accuracy and variability of accuracy across replications.

Results and Discussion

Because there were 6 clusters, chance classification would be ~16.67%. Average classification accuracy in the training set was 55.74% (*SD* = 3.26%). More importantly, average classification accuracy in the test set was 20.54% (*SD* = 4.06%), generally what we would expect from chance alone. In contrast, classification accuracy of the groups in the primary manuscript were at least 49%. This result makes it clear that our results are not an artifact of our methodology or the large number of variables available. Instead, the parameters from the computer-generated faces are capturing something that separates these groups in meaningful ways.

Syntax to Perform Analyses in SPSS

```
*[Group] represents the clustering variable
*[Variable1] – [Variable5] represents the variables by which [Group] will be classified

*The below syntax performs hold-out cross-validation
*This would be performed after creating [HoldOutVariable] which randomly assigns
*each observation to the training (0) or test sample (1)

  DISCRIMINANT
  /GROUPS=Group(1 99)
  /VARIABLES=Variable1 Variable2 Variable3 Variable4 Variable5
  /SELECT=HoldOutVariable(1)
  /ANALYSIS ALL
  /PRIORS SIZE
  /STATISTICS=TABLE
  /PLOT=COMBINED MAP
  /CLASSIFY=NONMISSING POOLED.

*The below syntax performs leave-one-out cross-validation
```

```
DISCRIMINANT
  /GROUPS=Group (1 99)
  /VARIABLES= Variable1 Variable2 Variable3 Variable4 Variable5
  /ANALYSIS ALL
  /PRIORS SIZE
  /STATISTICS=CROSSVALID
  /PLOT=COMBINED MAP
  /CLASSIFY=NONMISSING POOLED.
```

Supplementary Analyses to Study 1

Within-Gender Analyses. Because friendship groups in Study 1 varied by gender, even though gender was not a variable made available to the discriminant function analyses, it is possible that the gender of the targets influenced the ratings. To test that our results were independent of gender, we conducted two additional discriminant function analyses *within* male and female categories, meaning one for female friendship groups only, and one for male friendship groups only.

To do so we collected entirely new ratings from new participants, as the gender of target may have influenced usage of the scales when rating each trait. Data was collected and processed in an identical fashion to that reported in the main text. Different groups of participants rated both female targets (n = 92, M_{Age} = 36.37, SD = 11.04, 55.6% female) and male targets (n = 109, M_{Age} = 38.49, SD = 13.34, 71.3% female). Ratings were again averaged across participants such that target was the unit of analyses.

First examining classification accuracy within female friendship groups, 81.8% of the individuals in the training set were accurately classified into their friendship groups. Applying this model to the test set, 28.6% of the individuals in the test set were accurately categorized into their friendship groups. Because 9 different female friendship groups were involved, expected accuracy due to chance would be approximately 11.1% accuracy. To determine that 28.6% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .286 > MCC critical .171), and because the Q statistic was significant (Q = 6.81, *p* =.0091), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 23.3%. See Supplementary Table 1 for discriminant function loadings for this analysis

Supplementary Table 1. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

	Discriminant Functions			
Traits	1	2	3	4
Attractive	.392	1.252	-1.298	-.724
Intelligent	-.628	-.114	1.332	-.227
Strong	-.192	.355	.670	.934
Youthful	.958	-.883	.536	.188
% Variance	47.5	31.4	13.0	8.0

Turning to the male friendship groups, 50.0% of the individuals in the training set were accurately classified into their friendship groups. Applying this model to the test set, 12.5% of the individuals in the test set were accurately categorized into their friendship groups. Because 18 different male friendship groups were involved, expected accuracy due to chance would be approximately 5.6% accuracy. To determine whether 12.5% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .125 > MCC critical .089), and because the Q statistic was significant (Q = 3.86, *p* =.0495), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 12.2%. See Supplementary Table 2 for discriminant function loadings for this analysis.

Supplementary Table 2. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

Traits	Discriminant Functions			
	1	2	3	4
Attractive	-1.095	-1.397	-.076	-.683
Intelligent	.718	.205	.062	1.215
Strong	.046	.855	.860	.577
Youthful	1.337	.392	.621	.214
% Variance	72.4	12.4	11.2	4.0

Thus, within-gender analyses were consistent with the cross-gender analyses presented in the primary manuscript, in that individuals could be successfully classified into their friendship groups from trait ratings alone, even when gender could not contribute to these ratings.

Supplementary Analyses to Study 2

Within-Gender Analyses. Identical to Supplementary Analysis 1, we sought to examine whether classification accuracy was still above chance when performed within gender friendship groups. Again, we collected new ratings of both female (n = 88, M_{Age} = 38.38, SD = 12.17, 60.3% female) and male targets (n = 95, M_{Age} = 38.20, SD = 13.93, 72.8% female) to examine this question.

For female friendship groups, 48.8% of the individuals in the training set were accurately classified into their friendship groups. Applying this model to the test set, 23.3% of the individuals in the test set were accurately categorized into their friendship groups. Because 9 different female friendship groups were involved, expected accuracy due to chance would be approximately 11.1% accuracy. To examine whether 23.3% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .233 > MCC critical .179) though the Q statistic was only marginally significant (Q = 3.16, p =.0755). Thus, the tests conflicted in whether the model built on the training sample generalized to the test sample. Leave-one-out results indicated that it did, with averaged accuracy at 23.3%. Together there was conflicting evidence as to whether this solution generalized, though 2 of the 3 tests indicated targets could still be accurately classified to some extent. But certainly, in this context classification accuracy was weakest relative to male and female friendship groups in Study 1 and 2. See Supplementary Table 3 for discriminant function loadings for this analysis.

Supplementary Table 3. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

	Discriminant Functions			
Traits	1	2	3	4
Attractive	-.211	-.931	.745	-.791
Intelligent	-.122	.984	.552	-.075
Strong	-.346	-.347	.015	1.086
Youthful	1.165	.419	-.209	.384
% Variance	56.9	26.8	13.7	2.6

Turning to the male friendship groups, 32.9% of the individuals in the training set were accurately classified into their friendship groups. Applying this model to the test set, 19.5% of the individuals in the test set were accurately categorized into their friendship groups. Because 18 different male friendship groups were involved, expected accuracy due to chance would be approximately 5.6% accuracy. To determine whether 19.5% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .195 > MCC critical .092), and because the Q statistic was significant (Q = 15.19, $p <$ .0001), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 9.8%. See Supplementary Table 4 for discriminant function loadings for this analysis.

Supplementary Table 4. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

Traits	Discriminant Functions			
	1	2	3	4
Attractive	.489	-.799	.595	-1.515
Intelligent	.288	-.211	.460	.944
Strong	-.921	.974	.279	.752
Youthful	.649	.894	-.210	.540
% Variance	64.8	17.2	11.2	6.8

All together, results generally converged with those reported in the main text. Most tests indicated that accurate classification of individuals into their friendship groups was possible, even when removing gender as a potential explanatory factor.

Supplementary Analyses to Study 3

White-Only Analyses. In the analyses reported in the main text, while fraternities were primarily White, 14 (4.4%) of fraternity members were non-White. These individuals were accepted into these groups, so to maximize ecological validity have included them in the primary analyses. We considered it important, however, to firmly rule out the possibility that race might be contributing to classification accuracy within fraternities. We therefore conducted new analyses when these targets were removed from the dataset.

In these analyses, 52.0% of the individuals in the training set were accurately classified into their fraternity. Applying this model to the test set, 39.6% of the individuals in the test set were accurately categorized into their fraternities. Because 6 different fraternities were involved, expected accuracy due to chance would be approximately 16.7% accuracy. To determine whether 39.6% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .396 > MCC critical .370), and because the Q statistic was significant (Q = 57.56, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 41.2%. See Supplementary Table 5 for discriminant function loadings for this analysis.

Supplementary Table 5. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

	Discriminant Functions			
Traits	1	2	3	4
Attractive	1.549	.273	-.365	.382
Intelligent	.092	.388	.680	1.202
Strong	-.616	-.762	.653	.389
Warm	-.189	.485	-.369	-.156
Competent	-.407	.039	.425	-1.561
% Variance	71.5	17.0	9.0	2.5

Thus, classification accuracy was still high when removing the possibility that race might have contributed.

Supplementary Analyses to Study 4

White-Only Analyses. Identical to Supplementary Analyses 3, we wished to demonstrate classification accuracy with computer-generated face models was above chance when race could not be an explanatory factor. We therefore conducted new analyses when these targets were removed from the dataset.

In these analyses, 97.2% of the individuals in the training set were accurately classified into their fraternity. Applying this model to the test set, 80.0% of the individuals in the test set were accurately categorized into their fraternities. Because 6 different fraternities were involved, expected accuracy due to chance would be approximately 16.7% accuracy. To determine whether 80.0% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .800 > MCC critical .399), and because the Q statistic was significant ($Q = 407.21$, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 81.4%. See Supplementary Table 6 for discriminant function loadings for this analysis.

Supplementary Table 6. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5
BrowRidgehighlow	3.340	.159	-.140	4.062	-1.217
BrowRidgeInnerdownup	2.285	-1.406	.466	.975	-.047
BrowRidgeOuterupdown	-.248	-.029	-.008	-.579	.646
Cheekboneslowhigh	-.573	.214	.470	.792	-1.039
Cheekbonesshallowpronounced	1.072	-1.220	-.416	-1.132	.726
Cheekbonesthinwide	.128	-.880	-.003	.198	.700
Cheeksconcaveconvex	-.085	.376	-.060	.842	.676
Cheeksroundgaunt	-.310	.104	.256	-.044	-.069
Chinforwardbackward	-3.339	2.216	1.218	-.569	-.921
Chinpronouncedrecessed	9.545	-2.835	.258	4.362	4.269
Chinretractedjutting	8.034	-2.721	1.092	1.486	4.378
Chinshallowdeep	.648	.303	-.594	.359	-.129
Chinsmalllarge	-.094	2.309	1.073	5.629	-.216
Chintallshort	-9.964	2.963	.408	-4.036	-3.426

Chinwidethin	-1.032	1.867	.515	2.551	-.663
Eyesdownup	-1.405	-2.204	-.905	-3.708	1.518
Eyessmalllarge	-.024	.083	.331	.401	.588
Eyestiltinwardoutward	-1.034	.228	.597	-.515	-1.223
Eyesaparttogether	-1.422	.070	-.125	-1.313	-.290
Facebrownosechinratio	.934	.002	.769	-.995	.682
Faceforeheadsellionnoseratio	-.945	-.452	.443	-2.094	-.793
Faceheavylight	-.060	-.161	-.546	.196	.104
Faceroundgaunt	1.435	-1.884	.049	-1.942	1.153
Facetallshort	-1.308	.246	1.015	-1.820	-.339
Faceupdown	1.840	-3.152	-.885	-1.431	1.988
Facewidethin	.302	.149	.381	-.404	-.589
Foreheadsmalllarge	.305	.467	-.042	-.361	-.157
Foreheadtallshort	.372	-.224	1.036	-.098	-1.421
Foreheadtiltforwardback	-.148	.151	.248	-.019	-.560
Headthinwide	-.199	-.477	-.024	.185	-.257
Jawwidethin	.086	-.275	.480	.602	.482
JawNeckslopehighlow	-.290	-.172	.426	.414	.174
Jawlineconcaveconvex	-.465	1.054	-.048	1.328	-.827
Mouthdrawnpursed	-5.635	3.417	3.003	2.731	-.332
Mouthhappysad	1.092	1.377	-.523	.581	.770
MouthLipsdeflatedinflated	-2.094	1.950	1.540	2.171	1.079
MouthLipspuckeredretracted	2.178	1.595	.782	1.003	-.046
MouthLipsthinthick	4.498	-.808	-1.091	.024	.765
Mouthprotrudingretracted	.996	-2.559	.249	-2.170	1.195
Mouthtiltupdown	-3.607	2.937	1.176	1.752	.250
Mouthupdown	.994	-.864	1.130	-2.885	.113
Mouthwidethin	.093	-.234	-.230	1.811	.595
Nosebridgeshallowdeep	-1.296	.021	-.346	-.029	-.390
Nosebridgeshortlong	-.042	.822	1.005	.136	-.873
Noseflatpointed	.862	-.321	.249	-.275	-.086
Nosenostrilswidethin	-.211	-.358	-.155	-.905	-.201
Noseselliondownup	2.084	.102	.370	-.179	-.201
% Variance	44.3	25.4	14.8	9.6	5.9

Thus, it is clear that racial group membership was not a significant contributor to classification accuracy from either social perception ratings or from morphological measurement.

No Mouth Component Analyses. In addition, in the majority of photographs in the fraternity composites the individuals were smiling. The Photofit tool technique used to create the computer-generated face models was designed to be used on target faces with neutral expressions. It was therefore important to demonstrate the obtained classification accuracy was not an artifact of importing smiling faces. To this end, we performed additional discriminant function analyses in which we removed the parameters of the computer-generated face models for the mouth, chin, and jaw, which would be influenced by smiling. To see the full list of parameters included in these analyses see "Face Gen Parameters in Analyses Removing Mouth-Related Parameters" listed further in the Supplementary Materials.

In these analyses, 95.3% of the individuals in the training set were accurately classified into their fraternity. Applying this model to the test set, 76.4% of the individuals in the test set were accurately categorized into their fraternities. Because 6 different fraternities were involved, expected accuracy due to chance would be approximately 16.7% accuracy. To determine whether 76.4% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .764 > MCC critical .310), and because the Q statistic was significant ($Q = 382.78$, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 78.7%. See Supplementary Table 7 for discriminant function loadings for this analysis.

Supplementary Table 7. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5
BrowRidgehighlow	4.375	-.196	-1.434	10.330	4.312
BrowRidgeInnerdownup	1.823	-.123	-.420	5.698	3.496
BrowRidgeOuterupdown	-.062	.569	.049	-1.354	-.696
Cheekboneslowhigh	.310	-.642	-.531	-.167	-.667
Cheekbonesshallowpronounced	-.439	-.399	.499	-.128	-.169
Cheekbonesthinwide	-.244	-.608	-.213	.284	.816
Cheeksconcaveconvex	-.541	.425	-.176	-.152	.708
Cheeksroundgaunt	-.670	-.271	-.350	-.118	.070
Eyesdownup	-3.949	-.774	1.706	-4.619	-.870
Eyessmalllarge	-1.201	-.540	-.180	-.138	-.006
Eyestiltinwardoutward	-1.003	-.131	.267	-1.573	-1.174
Eyesaparttogether	-2.056	1.075	.923	-2.849	-2.034
Facebrownosechinratio	.474	.287	-.264	.127	-.147
Faceforeheadsellionnoseratio	.023	2.078	.290	-2.874	-2.884
Faceheavylight	-.466	-.076	.697	.063	.231
Faceroundgaunt	.073	.025	-.196	.070	-.040
Facetallshort	-3.075	-.600	1.234	-1.250	.498
Faceupdown	.690	-1.886	.261	-.286	.357
Facewidethin	-.449	-.130	-.417	-.012	-.285
Foreheadsmalllarge	.073	.319	.200	-.239	.134
Foreheadtallshort	.266	-.312	-.300	.319	-.878
Foreheadtiltforwardback	-.292	.085	-.287	.037	-.616
Headthinwide	-.217	-.189	.331	.394	-.354
Nosebridgeshallowdeep	-4.111	-2.367	.232	-2.909	4.469
Nosebridgeshortlong	4.915	.193	-.575	1.460	1.351
Nosedownup	4.037	.861	.758	1.636	.238
Noseflatpointed	5.585	3.794	1.217	4.498	-5.200
Nosenostriltiltdownup	1.307	-.895	-1.303	.014	3.319
Nosenostrilssmalllarge	-3.273	-1.494	-1.301	-2.232	-.156
Nosenostrilswidethin	-.359	.252	-.385	-.974	-.284
Noseregionconcaveconvex	-2.002	-.991	.633	-.885	-.559

Noseselliondownup	5.692	4.223	.140	1.439	2.020
Nosesellionshallowdeep	-3.288	-3.366	-.876	1.510	-6.895
Nosesellionshallowdeep_A	3.923	3.993	.224	-.039	2.737
Templesthinwide	.604	.271	-.170	-.527	-.247
% Variance	40.9	29.1	16.5	7.4	6.1

Orthogonal Components Analyses. In addition, the analyses of the computer-generated models used as input the linear combinations of the underlying orthogonal parameters in the face models. To ensure our results were not an artifact of these linear combinations, we additionally performed discriminant function analyses on the orthogonal components themselves. Like the analyses with linear combinations, we used shape parameters only (i.e., no texture parameters).

In these analyses, 98.8% of the individuals in the training set were accurately classified into their fraternity. Applying this model to the test set, 93.9% of the individuals in the test set were accurately categorized into their fraternities. Because 6 different fraternities were involved, expected accuracy due to chance would be approximately 16.7% accuracy. To determine whether 93.9% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .939 > MCC critical .355), and because the Q statistic was significant (Q = 635.63, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 95.2%. See Supplementary Table 8 for discriminant function loadings for this analysis.

Supplementary Table 8. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function

	1	2	3	4	5
symmetric_shape_000	.441	.310	-.267	.037	-.116
symmetric_shape_001	.292	.131	-.112	.125	-.150
symmetric_shape_002	.501	.156	-.107	-.019	-.104
symmetric_shape_003	.204	.035	-.126	.429	.352
symmetric_shape_004	-.371	-.402	.073	.173	-.016
symmetric_shape_005	-.179	-.127	-.169	-.044	-.180
symmetric_shape_006	-.918	-.031	.388	-.349	-.538
symmetric_shape_007	-.085	.273	.400	.066	.202
symmetric_shape_008	.266	.034	.070	.004	.202
symmetric_shape_009	.151	.451	.093	.027	-.091
symmetric_shape_010	.152	-.116	-.124	.424	.273
symmetric_shape_011	-.250	-.116	.154	-.036	-.383
symmetric_shape_012	-.155	.012	.340	.316	-.006
symmetric_shape_013	.259	.428	.036	-.044	.040
symmetric_shape_014	.204	.147	-.096	-.148	.215
symmetric_shape_015	.426	-.057	-.254	.284	.142
symmetric_shape_016	.006	.140	.189	-.186	.096
symmetric_shape_017	.236	.075	.060	.091	-.176
symmetric_shape_018	-.044	-.189	.267	.120	-.077
symmetric_shape_019	-.168	-.031	.015	.038	-.259
symmetric_shape_020	-.165	.040	-.004	-.019	-.033
symmetric_shape_021	.011	-.008	-.256	-.144	-.032
symmetric_shape_022	-.070	.097	.114	-.109	-.127
symmetric_shape_023	.018	-.130	.032	-.083	.175
symmetric_shape_024	.259	-.114	-.089	.015	.123
symmetric_shape_025	.176	.207	.109	-.223	-.041
symmetric_shape_026	-.223	-.330	.010	-.198	-.256
symmetric_shape_027	-.116	-.072	.079	-.047	.003
symmetric_shape_028	.080	-.176	-.093	-.055	-.140
symmetric_shape_029	-.085	-.207	.174	-.270	-.074
symmetric_shape_030	.077	-.201	-.762	-.878	-.228
symmetric_shape_031	.527	-.595	.295	-.285	.047
symmetric_shape_032	-.733	.849	.114	1.180	.609
symmetric_shape_033	.174	.446	-.095	-.154	-.108
symmetric_shape_034	-.505	.808	.045	.833	.149
symmetric_shape_035	.448	-.306	-.112	.407	-.232
symmetric_shape_036	-.165	.039	-.057	.179	.208
symmetric_shape_037	-.103	.277	.122	-.199	.146
symmetric_shape_038	-.039	.154	-.189	.172	-.196

symmetric_shape_039	.244	.023	-.242	.358	.015
symmetric_shape_040	.189	-.152	-.115	.230	.123
symmetric_shape_041	-.113	.509	.091	.348	-.107
symmetric_shape_042	-.298	.502	.487	.008	.097
symmetric_shape_043	.087	-.003	-.279	.340	.002
symmetric_shape_044	.625	-.336	.296	.068	-.055
symmetric_shape_045	.266	-.194	.029	.107	-.457
symmetric_shape_046	-.239	.199	-.028	-.028	-.044
symmetric_shape_047	.032	-.127	-.184	.047	.151
symmetric_shape_048	.015	-.161	.273	-.035	-.067
symmetric_shape_049	-.207	.276	.295	-.101	.100
asymmetric_shape_050	-.113	-.059	-.010	-.217	.314
asymmetric_shape_051	.068	.089	.491	.085	-.042
asymmetric_shape_052	.000	-.220	.187	-.049	.232
asymmetric_shape_053	.054	-.096	.182	-.077	.036
asymmetric_shape_054	.258	-.283	-.021	.140	.444
asymmetric_shape_055	.337	.196	-.022	.265	-.056
asymmetric_shape_056	.052	-.142	.119	-.193	.084
asymmetric_shape_057	-.221	-.025	.107	-.083	.049
asymmetric_shape_058	.194	.111	-.234	.260	-.114
asymmetric_shape_059	-.151	-.040	.186	.090	-.252
asymmetric_shape_060	-.115	-.023	-.198	-.072	-.039
asymmetric_shape_061	-.175	-.232	-.364	-.145	.091
asymmetric_shape_062	-.133	-.326	-.168	-.400	-.208
asymmetric_shape_063	.125	.137	.315	-.221	.191
asymmetric_shape_064	.103	.010	.310	-.286	.112
asymmetric_shape_065	-.004	-.090	.069	-.095	-.084
asymmetric_shape_066	-.272	.037	.056	.374	-.116
asymmetric_shape_067	-.144	-.242	-.177	-.129	.142
asymmetric_shape_068	.170	.002	-.412	.124	.078
asymmetric_shape_069	.112	.096	.022	.068	-.159
asymmetric_shape_070	.316	-.010	-.611	-.212	.081
asymmetric_shape_071	-.024	-.007	.167	.046	-.083
asymmetric_shape_072	-.128	-.067	-.252	.077	.325
asymmetric_shape_073	.141	.154	-.452	.037	.299
asymmetric_shape_074	-.250	-.285	.277	.035	-.072
asymmetric_shape_075	-.271	.006	.170	-.031	-.138
asymmetric_shape_076	.300	.095	.224	-.345	-.042
asymmetric_shape_077	.035	-.445	.328	-.067	.355
asymmetric_shape_078	-.079	-.003	-.015	.132	.221

asymmetric_shape_079	-.155	.071	.021	.031	-.172
% Variance	55.0	27.1	8.6	5.5	3.8

Supplementary Analyses to Study 5

White-Only Analyses. Again, we were interested in confirming whether race played a role in classification accuracy with baseball teams. Racial minorities were a larger percentage of the baseball team data, comprising 15.0% of the targets. We therefore conducted new analyses when these targets were removed from the dataset (n = 125).

First focusing on the ratings of social perceptions in Study 5A, 45.8% of the individuals in the training set were accurately classified into their baseball teams. Applying this model to the test set, 39.4% of the individuals in the test set were accurately categorized into their team. Because 6 different baseball teams were involved, expected accuracy due to chance would be approximately 16.7%. To determine whether 39.4% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .394 > MCC critical .275), and because the Q statistic was significant (Q = 21.95, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 30.4%. See Supplementary Table 9 for discriminant function loadings for this analysis.

Supplementary Table 9. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

Traits	Discriminant Functions			
	1	2	3	4

Attractive	-.674	.368	-.335	-.643
Competent	-.021	-.715	1.391	.831
Strong	-.587	.734	-.339	.736
Warm	1.054	.387	-.804	.196
Dominant	1.272	.286	.663	-.427
% Variance	63.4	24.5	8.2	3.9

Recognition. As reported in the primary manuscript, we assessed the role of familiarity in classification accuracy by including it in analyses and examining its weighting in the created discriminant functions. Evidence that recognition played a large role would have been if it was given a large weighting in the discriminant functions responsible for a larger percentage of variance. As evident in Supplementary Table 10, however, it only featured prominently in discriminant functions 4 and 5, which were responsible for a small percentage of variance overall.

Supplementary Table 10. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Traits	Discriminant Functions				
	1	2	3	4	5
Attractive	-.484	.713	.807	.219	.327
Competent	.020	-1.519	-.670	.064	.580
Strong	-1.122	.131	-.231	.147	-.403
Warm	1.147	.852	1.063	-.189	.051
Dominant	1.611	.397	.212	.650	.401
Familiarity	.053	-.323	.450	.443	-.698
% Variance	69.1	15.4	9.1	5.9	.4

Next turning to the computer-generated face models of Study 5B, 100% of the individuals in the training set were accurately classified into their baseball teams. Applying this model to the test set, 38.3% of the individuals in the test set were accurately categorized into their team. Because 6 different baseball teams were involved, expected accuracy due to chance would be approximately 16.7%. To determine whether 38.3% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .383 > MCC critical .275), and because the Q statistic was significant (Q = 19.88, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 53.8%. See Supplementary Table 11 for discriminant function loadings for this analysis.

Supplementary Table 11. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5
BrowRidgehighlow	12.392	1.841	.773	-2.568	8.833
BrowRidgeInnerdownup	5.246	1.288	1.791	-1.447	4.822
BrowRidgeOuterupdown	-2.405	.260	-.814	.818	-2.030
Cheekboneslowhigh	-2.746	-.060	-.811	1.051	-.507
Cheekbonesshallowpronounced	1.487	.711	-.466	1.070	-.499
Cheekbonesthinwide	-.078	.453	-.165	-.338	.807
Cheeksconcaveconvex	.541	.602	.123	.511	.077
Cheeksroundgaunt	-1.648	-.676	.551	.009	.244
Chinforwardbackward	-4.133	.412	-1.756	1.037	4.051
Chinpronouncedrecessed	8.222	5.043	2.101	2.984	-4.447
Chinretractedjutting	10.346	4.752	.414	1.297	-1.388
Chinshallowdeep	-2.436	-.547	-1.244	.095	-1.418
Chinsmalllarge	-1.007	4.649	1.836	5.614	.268
Chintallshort	-11.098	-4.614	-2.834	-2.949	7.355
Chinwidethin	-3.541	1.687	2.344	2.779	-.224
Eyesdownup	-3.315	-.245	-.357	1.048	-2.437
Eyessmalllarge	.666	.260	.293	.393	.581
Eyestiltinwardoutward	-1.709	-1.704	2.432	-1.207	-.543

Eyesaparttogether	-2.947	-1.770	2.008	-.971	-.642
Facebrownosechinratio	1.967	.632	-1.406	-.842	-.657
Faceforeheadsellionnoseratio	-3.113	-1.303	-1.522	-1.030	-3.703
Faceheavylight	1.766	.922	-.132	.290	.741
Faceroundgaunt	2.286	-1.201	-2.317	-1.971	-1.033
Facetallshort	-4.766	-.819	4.479	.374	1.912
Faceupdown	2.664	1.982	-3.768	.498	-2.512
Facewidethin	.987	1.822	-2.266	1.650	-2.192
Foreheadsmalllarge	.758	.030	-.386	.731	-.287
Foreheadtallshort	-.642	-.863	.281	-.903	-.120
Foreheadtiltforwardback	-.355	.082	-.667	.568	-.136
Headthinwide	-.752	.950	-.091	1.090	.086
Jawwidethin	-1.150	1.007	.654	.552	-1.106
JawNeckslopehighlow	1.552	.723	-.960	.260	-.380
Jawlineconcaveconvex	-1.007	1.399	-.423	2.726	.324
Mouthdrawnpursed	3.122	1.403	1.286	.854	2.768
Mouthtiltupdown	8.996	2.038	-.897	-1.233	-.901
Mouthunderbiteoverbite	-6.246	.921	-.712	2.155	3.454
Mouthwidethin	-2.338	.289	2.291	.207	-.985
Nosebridgeshallowdeep	.539	.408	.659	-.797	-1.088
% Variance	53.3	23.0	11.3	7.9	4.5

Results indicate that racial group membership was not a significant contributor to classification accuracy from either social perception ratings or from morphological measurement.

No Mouth Component Analyses. As discussed in Supplementary Analyses to Study 4, in many of the photographs in Study 5B the baseball players were smiling. The Photofit tool technique used to create the computer-generated face models was designed to be used on target faces with neutral expressions. It was therefore important to demonstrate the obtained classification accuracy was not an artifact of sometimes importing smiling faces. To this end, we performed additional discriminant function analyses in which we removed the parameters of the computer-generated face models for the mouth, chin, and jaw, which would be influenced by smiling to some extent. To see the full list of parameters included in these analyses see “Face Gen Parameters in Analyses Removing Mouth-Related Parameters” listed further in the Supplementary Materials.

With analyses using only these parameters, 95.8% of the individuals in the training set were accurately classified into their baseball teams. Applying this model to the test set, 47.8% of the individuals in the test set were accurately categorized into their team. Because 6 different baseball teams were involved, expected accuracy due to chance would be approximately 16.7%. To determine whether 47.8% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .478 > MCC critical .295), and because the Q statistic was significant (Q = 50.25, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 53.2%. See Supplementary Table 12 for discriminant function loadings for this analysis.

Supplementary Table 12. Composition of the five functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5
BrowRidgehighlow	12.786	8.619	2.690	5.014	-.839
BrowRidgeInnerdownup	6.015	4.797	1.221	2.980	-.767
BrowRidgeOuterupdown	-2.112	-2.083	-.156	-.769	-.032
Cheekboneslowhigh	.241	-.272	1.147	.436	.157
Cheekbonesshallowpronounced	-.850	.494	.344	.562	-.142
Cheekbonesthinwide	1.148	-.203	.100	-.463	.162
Cheeksconcaveconvex	.643	-.050	.108	-.513	-.171
Cheeksroundgaunt	.404	-.039	.378	-.229	-.824
Eyesdownup	-4.957	-2.036	-.630	-1.767	.934

Eyessmalllarge	-1.405	-1.356	-1.617	-1.504	-.281
Eyestiltinwardoutward	-1.808	-.690	-1.587	-.495	.035
Eyesaparttogether	-2.969	-3.500	-1.610	-1.374	.806
Facebrownosechinratio	.009	-.534	-.944	-.396	.113
Faceforeheadsellionnoseratio	-3.662	-2.248	-.111	.126	.980
Faceheavylight	.206	1.075	-.009	-.158	.485
Faceroundgaunt	-.589	-.616	.295	.000	1.032
Facetallshort	-.804	.638	-.152	-1.773	-.354
Faceupdown	-2.282	-.246	-.288	-.277	.660
Facewidethin	.256	.533	-.273	1.484	-.702
Foreheadsmalllarge	.118	.227	-.239	1.222	-.003
Foreheadtallshort	.706	.061	.487	1.243	.267
Foreheadtiltforwardback	.092	-.217	.454	.140	-.416
Headthinwide	.041	.407	.919	.426	-.034
Nosebridgeshallowdeep	.390	-1.212	-1.858	-.525	-.626
Nosebridgeshortlong	.862	4.368	1.600	.966	1.377
Nosedownup	-2.123	1.331	.325	.558	.485
Noseflatpointed	-4.245	-2.412	-2.641	1.348	-.473
Nosenostriltiltdownup	3.890	5.285	3.326	1.902	.903
Nosenostrilssmalllarge	2.599	2.503	1.757	-1.595	1.014
Nosenostrilswidethin	.252	.072	.577	-.605	.571
Noseregionconcaveconvex	-1.204	-2.507	-1.156	-1.049	-.508
Noseselliondownup	1.639	2.549	1.837	.403	-.078
Nosesellionthinwide	.371	-1.097	-.937	-1.107	-.041
asymmetry	-.428	.895	.592	.064	.206
% Variance	43.5	23.9	21.0	6.2	5.3

Orthogonal Components Analyses. In addition, the analyses of the computer-generated models used as input the linear combinations of the underlying orthogonal parameters in the face models. To ensure our results were not an artifact of these linear combinations, we additionally performed discriminant function analyses on the orthogonal components themselves.

In these analyses, 100% of the individuals in the training set were accurately classified into their baseball team. Applying this model to the test set, 45.7% of the individuals in the test set were accurately categorized. Because 6 different baseball teams were involved, expected accuracy due to chance would be approximately 16.7% accuracy. To determine whether 45.7% was significantly better than chance, both MCC and Q approaches were examined. Accuracy did exceed the MCC critical value (accuracy .457 > MCC critical .308), and because the Q statistic was significant (Q = 41.88, $p < .0001$), both tests of the hold-out approach indicated that the model built on the training sample did generalize to the test sample. Leave-one-out results converged with this conclusion, with averaged accuracy at 56.1%. See Supplementary Table 13 for discriminant function loadings for this analysis.

Supplementary Table 13. Composition of the four functions created by the discriminant function analysis using the hold-out approach.

Standardized Canonical Discriminant Function Coefficients

	Function			
	1	2	3	4
symmetric_shape_000	4.472	.135	-8.146	-4.272
symmetric_shape_001	2.358	2.929	.395	1.273
symmetric_shape_002	6.079	.404	.839	-1.233
symmetric_shape_003	-.256	.899	5.328	3.232
symmetric_shape_004	-.982	1.420	-2.668	-1.124
symmetric_shape_005	5.683	2.464	4.688	1.626
symmetric_shape_006	-1.955	-2.884	-3.178	-.474
symmetric_shape_007	2.284	-.018	1.605	2.231
symmetric_shape_008	-1.454	1.476	1.139	-2.794
symmetric_shape_009	-5.162	.536	-1.893	-4.520
symmetric_shape_010	3.104	.191	.920	2.055
symmetric_shape_011	-1.084	2.219	3.248	1.835
symmetric_shape_012	1.296	1.943	-.375	-2.775
symmetric_shape_013	.476	3.561	-1.154	-3.152
symmetric_shape_014	-7.185	.784	-3.376	-2.839
symmetric_shape_015	7.370	3.034	-9.501	-2.651
symmetric_shape_016	-4.317	2.630	4.141	1.186
symmetric_shape_017	-3.919	-2.916	2.427	-.150
symmetric_shape_018	-3.932	-3.129	4.679	2.549
symmetric_shape_019	-1.471	-1.667	-7.829	.709

symmetric_shape_020	2.926	2.674	1.869	1.007
symmetric_shape_021	-3.006	1.424	-3.395	1.964
symmetric_shape_022	1.150	.345	3.638	-1.287
symmetric_shape_023	4.749	1.948	-5.404	-.978
symmetric_shape_024	-3.277	-1.351	1.698	.608
symmetric_shape_025	-2.351	-3.122	-4.042	-1.251
symmetric_shape_026	4.928	-2.501	-2.569	-1.121
symmetric_shape_027	-1.041	.963	2.633	1.043
symmetric_shape_028	4.907	-.296	.534	.055
symmetric_shape_029	-1.014	2.508	-3.455	-3.009
symmetric_shape_030	4.910	4.699	2.106	4.137
symmetric_shape_031	3.304	.063	-2.555	-2.349
symmetric_shape_032	7.303	2.854	-3.761	.211
symmetric_shape_033	-5.118	-5.575	.338	-.991
symmetric_shape_034	-.110	1.746	10.949	2.949
symmetric_shape_035	2.726	1.626	-4.405	1.192
symmetric_shape_036	2.925	.786	-2.246	-2.043
symmetric_shape_037	-5.400	.566	-.682	.895
symmetric_shape_038	-1.118	1.045	-4.934	-1.044
symmetric_shape_039	1.444	-1.814	-1.469	-1.133
symmetric_shape_040	5.325	2.846	-3.921	1.622
symmetric_shape_041	-6.255	-.480	4.989	4.903
symmetric_shape_042	-2.826	-2.220	-3.683	.375
symmetric_shape_043	.044	1.027	3.816	.836
symmetric_shape_044	-6.220	1.505	4.584	2.911
symmetric_shape_045	-1.984	-3.032	9.702	4.995
symmetric_shape_046	.699	-.352	-.645	1.862
symmetric_shape_047	2.378	1.771	2.800	.485
symmetric_shape_048	-.696	-.725	2.828	1.869
symmetric_shape_049	3.932	-.633	-6.076	-2.842
asymmetric_shape_050	-.252	2.723	-2.632	.374
asymmetric_shape_051	3.368	-2.106	-5.382	-4.151
asymmetric_shape_052	.722	-.950	2.856	.239
asymmetric_shape_053	-.445	3.882	.865	2.055
asymmetric_shape_054	1.746	.636	.551	.897
asymmetric_shape_055	-.970	-.023	8.264	3.554
asymmetric_shape_056	1.914	-1.083	.837	.030
asymmetric_shape_057	.605	-.135	-4.344	-.850
asymmetric_shape_058	4.031	-.864	4.245	-.428
asymmetric_shape_059	.636	1.012	-3.837	-3.138

asymmetric_shape_060	-1.602	-1.869	5.408	.213
asymmetric_shape_061	-.127	1.045	4.736	2.995
asymmetric_shape_062	-1.035	-1.572	-1.616	-.761
% Variance	46.7	30.7	18.4	3.3

Supplementary Discriminant Function Tables for Analyses Reported in Main Text

Supplementary Table 14. Composition of the four functions created by the discriminant function analysis in Study 2.

Traits	Discriminant Functions			
	1	2	3	4
Attractive	-1.235	0.614	-0.35	0.876
Intelligent	0.311	0.557	0.899	-0.249
Strong	0.422	-1.078	0.379	0.285
Youthful	1.442	0.067	-0.006	0.015
% Variance	64.7	17.1	9.9	8.2

Supplementary Table 15. Composition of the five functions created by the discriminant function analysis in Study 4.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5
BrowRidgehighlow	3.830	-1.428	1.180	5.260	3.862
BrowRidgeInnerdownup	2.456	.311	.868	1.964	1.693
BrowRidgeOuterupdown	-.446	.124	.024	-.785	-.749
Cheekboneslowhigh	-.699	.239	.656	.551	1.393
Cheekbonesshallowpronounced	1.133	.466	-.883	-.944	-1.590
Cheekbonesthinwide	.194	.675	.005	.289	-.538
Cheeksconcaveconvex	-.180	-.175	.082	.928	-.671
Cheeksroundgaunt	-.224	.014	.250	.100	.482
Chinforwardbackward	-3.476	-.083	.735	-.640	1.622
Chinpronouncedrecessed	8.531	.822	1.308	3.045	-7.409
Chinretractedjutting	7.245	1.726	1.500	.076	-7.599
Chinshallowdeep	.671	-.422	-.384	.731	.742
Chinsmalllarge	-.238	-.824	2.137	4.723	-.338
Chintallshort	-9.548	-.350	-.906	-3.152	6.300
Chinwidethin	-1.086	-.865	1.108	2.240	.906
Eyesdownup	-1.386	1.641	-1.778	-3.645	-2.219
Eyessmalllarge	.075	-.316	.463	.452	-.707
Eyestiltinwardoutward	-1.216	.193	-.140	-.809	-.270

Eyesaparttogether	-1.916	.637	-.725	-1.817	-1.074
Facebrownosechinratio	.783	.203	.499	-1.150	-1.014
Faceforeheadsellionnoseratio	-1.499	1.348	-.280	-2.616	-.025
Faceheavylight	-.109	.168	-.570	.374	-.112
Faceroundgaunt	1.420	1.111	-.467	-1.928	-1.750
Facetallshort	-1.103	.534	.334	-1.782	.384
Faceupdown	1.856	1.499	-.769	-.926	-1.485
Facewidethin	.449	-.665	-.044	-.136	-.116
Foreheadsmalllarge	.201	-.448	-.161	-.343	-.021
Foreheadtallshort	.122	.730	.622	-.218	1.152
Foreheadtiltforwardback	-.258	.069	.250	-.094	.680
Headthinwide	-.105	.417	-.151	.242	.108
Jawwidethin	.094	.582	.325	.528	-.661
JawNeckslopehighlow	-.310	.330	.330	.274	-.527
Jawlineconcaveconvex	-.355	-.515	.427	1.191	1.462
Mouthdrawnpursed	-5.907	.597	3.507	1.370	1.443
Mouthhappysad	1.379	-1.354	.694	.481	1.160
MouthLipsdeflatedinflated	-1.710	.571	2.984	1.743	3.171
MouthLipspuckeredretracted	1.635	-1.963	1.279	.473	-1.655
MouthLipsthinthick	4.068	-1.258	-.857	.086	-2.691
Mouthprotrudingretracted	1.167	2.660	-.499	-1.720	-.130
Mouthtiltupdown	-3.280	-.026	2.329	1.011	2.991
Mouthupdown	1.586	1.862	.304	-2.747	1.630
Mouthwidethin	.343	.917	.973	1.938	2.581
Nosebridgeshallowdeep	-1.153	-.514	-.099	.141	.672
Nosebridgeshortlong	.080	-.065	1.017	-.340	.979
Noseflatpointed	.569	.654	-.515	-.512	-1.465
Nosenostrilswidethin	-.352	.277	-.479	-.991	-.425
Noseselliondownup	1.770	.411	.128	-.225	.164
Nosetiltdownup	.329	-.066	.403	.131	1.264
% Variance	44.6	23.9	14.5	10.3	6.7

Supplementary Table 16. Composition of the five functions created by the discriminant function analysis in Study 5B.

Standardized Canonical Discriminant Function Coefficients

	Function				
	1	2	3	4	5

BrowRidgehighlow	-14.112	1.570	-1.795	-.678	-1.349
BrowRidgeInnerdownup	-11.383	.299	-3.542	.050	.001
BrowRidgeOuterupdown	1.717	-.110	.769	.154	1.385
Cheekboneslowhigh	3.091	.282	.185	-1.057	-.959
Cheekbonesshallowpronounced	-3.856	-1.680	-.280	.020	.681
Cheekbonesthinwide	.353	.523	.671	.521	-.348
Cheeksconcaveconvex	.860	.519	.432	.118	.011
Cheeksroundgaunt	.494	.669	.183	.092	.623
Chinforwardbackward	3.351	4.646	.843	2.279	-.647
Chinpronouncedrecessed	2.419	-.268	4.010	-1.729	.590
Chinretractedjutting	.684	2.137	3.663	1.386	1.354
Chinshallowdeep	.632	-2.196	-.019	-.934	-.559
Chinsmalllarge	8.682	5.181	4.475	-.013	-.842
Chintallshort	-1.001	3.341	-4.180	3.354	-1.799
Chinwidethin	6.093	2.842	1.714	-.792	-.609
Eyesdownup	-1.039	-3.066	-1.512	2.011	1.556
Eyessmalllarge	.913	-.023	2.752	1.773	.978
Eyestiltinwardoutward	2.053	.659	-3.150	-1.342	-1.530
Eyesaparttogether	4.432	3.134	-3.043	-1.878	-2.363
Facebrownosechinratio	-1.112	-.847	.562	1.080	.689
Faceforeheadsellionnoseratio	.082	-.025	-4.015	-.993	.308
Faceheavylight	-.287	-.062	.815	.746	.110
Faceroundgaunt	-2.504	-1.876	-1.525	-.301	.295
Facetallshort	-.410	.476	-.372	4.032	.248
Faceupdown	-2.774	-4.819	1.257	.400	2.838
Facewidethin	-2.534	-2.345	.076	-.772	1.218
Foreheadsmalllarge	-.305	-.142	-.684	-1.123	-.214
Foreheadtallshort	-.120	1.209	-2.781	-.738	-.479
Foreheadtiltforwardback	-.087	.088	-.532	-.583	.051
Headthinwide	.055	.169	-.053	.789	.532
Jawwidethin	.466	.063	-.126	-.289	.601
JawNeckslopehighlow	-.474	.651	.101	-.347	-.431
Jawlineconcaveconvex	2.416	1.710	1.893	-.166	.046
Mouthdrawnpursed	9.309	6.913	3.528	1.604	1.150
Mouthhappysad	1.490	-.390	2.921	.697	.593
MouthLipsdeflatedinflated	-.634	-1.453	-.104	-.038	2.903
MouthLipspuckeredretracted	.094	.657	-.352	-.271	2.467
MouthLipsthinthick	-.933	.585	.855	.640	.725

Mouthprotrudingretracted	-8.096	-3.938	-4.581	-.139	.738
Mouthtiltupdown	7.666	7.784	7.652	4.461	1.194
Mouthupdown	-4.537	-2.846	-.919	2.380	-.907
Nosebridgeshallowdeep	-.876	1.607	.937	-.803	-.709
Nosedownup	-.617	-2.799	-.695	-.151	.444
Nosesellionthinwide	1.378	.820	2.708	.870	.940
% Variance	51.2	26.8	10.0	8.4	3.6

Face Gen Parameters.
List of FaceGen parameters included in discriminant function analysis in Study 4 and 5B:

BrowRidgehighlow
BrowRidgeInnerdownup
BrowRidgeOuterupdown
Cheekboneslowhigh
Cheekbonesshallowpronounced
Cheekbonesthinwide
Cheeksconcaveconvex
Cheeksroundgaunt
Chinforwardbackward
Chinpronouncedrecessed
Chinretractedjutting
Chinshallowdeep
Chinsmalllarge
Chintallshort
Chinwidethin
Eyesdownup
Eyessmalllarge
Eyestiltinwardoutward
Eyesaparttogether
Facebrownosechinratio
Faceforeheadsellionnoseratio
Faceheavylight
Faceroundgaunt
Facetallshort
Faceupdown
Facewidethin
Foreheadsmalllarge
Foreheadtallshort
Foreheadtiltforwardback
Headthinwide
Jawretractedjutting
Jawwidethin
JawNeckslopehighlow
Jawlineconcaveconvex

Mouthdrawnpursed
Mouthhappysad
MouthLipsdeflatedinflated
MouthLipslargesmall
MouthLipspuckeredretracted
MouthLipsthinthick
Mouthprotrudingretracted
Mouthtiltupdown
Mouthunderbiteoverbite
Mouthupdown
Mouthwidethin
MouthChindistanceshortlong
Nosebridgeshallowdeep
Nosebridgeshortlong
Nosedownup
Noseflatpointed
Nosenostriltiltdownup
Nosenostrilssmalllarge
Nosenostrilswidethin
Noseregionconcaveconvex
Noseselliondownup
Nosesellionshallowdeep
Nosesellionshallowdeep_A
Nosesellionthinwide
Noseshortlong
Nosetiltdownup
Templesthinwide
Asymmetry

Face Gen Parameters in Analyses Removing Mouth-Related Parameters.
List of FaceGen parameters included in supplementary discriminant function analysis for Study 4 and 5B:

BrowRidgehighlow
BrowRidgeInnerdownup
BrowRidgeOuterupdown
Cheekboneslowhigh
Cheekbonesshallowpronounced
Cheekbonesthinwide
Cheeksconcaveconvex
Cheeksroundgaunt
Eyesdownup
Eyessmalllarge
Eyestiltinwardoutward
Eyesaparttogether
Facebrownosechinratio

Faceforeheadsellionnoseratio
Faceheavylight
Faceroundgaunt
Facetallshort
Faceupdown
Facewidethin
Foreheadsmalllarge
Foreheadtallshort
Foreheadtiltforwardback
Headthinwide
Nosebridgeshallowdeep
Nosebridgeshortlong
Nosedownup
Noseflatpointed
Nosenostriltiltdownup
Nosenostrilssmalllarge
Nosenostrilswidethin
Noseregionconcaveconvex
Noseselliondownup
Nosesellionshallowdeep
Nosesellionshallowdeep_A
Nosesellionthinwide
Noseshortlong
Nosetiltdownup
Templesthinwide
Asymmetry