Part I. Demographics

Table 1. Basic demographic description of the sample of the participants (raters)

Culture	Number part's	Of it females/males	Age [yrs]	Height [cm]	Weight [kg]
Australia + New Zeal.	53	28 / 24	34.51 ± 12.62	169.57 ± 8.94	73.81 ± 20.77
Colombia	16	8 / 8	30.12 ± 12.95	164.2 ± 9.54	61.81 ± 10.26
Czech Republic	152	119 / 32	35.94 ± 10.13	170.3 ± 8.23	72.24 ± 16.97
South Africa	47	32 /15	25.62 ± 4.28	165.66 ± 10.11	80.18 ± 24.86
Turkey	79	63 / 15	22.15 ± 3.03	168.79 ± 7.88	63.24 ± 14.88
Vietnam	72	42 / 28	26.36 ± 7.46	163.78 ± 9.4	60.26 ± 11.35

Part II. YUFE – rating study, results:

From this point onwards GMM = Geometric Morphometrics. It denotes models in which we use facial distinctiveness, asymmetry, and sexual shape dimorphism.

Part 1: ATTR/TRUSTW/NO-GMM

"Zero stage": Predictions based on the models with just one response variable: Either attractiveness or trustworthiness. Model transcriptions:

(a) Model with varying term for faces (corresponding tems/parts in bold)

```
CZRSAUS_A_WAIC_long <- ulam(alist(
  AtrRating ~ normal(muA, sigma_Scale),

  muA <- a_A + a_group_A[FSMUi] + f_per_group_A[face,FSMUi] + z_A[rater]*sigma_rater_A,

  # Big intercept for Country_1_orig
  a_A ~ dnorm(0, 0.5),

  # intercept change per country
  a_group_A[FSMUi] ~ dnorm(0, 0.5),

  z_A[rater] ~ normal(0,1),
  sigma_rater_A ~ dexp(1),

  gq > vector[rater]:a_rater_A <<- a_A + z_A*sigma_rater_A,

  # Group-level increases per face in attractiveness (here the correlation matrix shall be
inspected to see similarities in ratings)
  transpars> matrix[face,13]:f_per_group_A <-
compose_noncentered(sigma_FSMUi_A,L_Rho_FSMUi_A,z_FSMUi_A),

  # Priors for multivariate normal distribution parameters - Face/FSMUi
  cholesky_factor_corr[13]:L_Rho_FSMUi_A ~ lkj_corr_cholesky(2),
  matrix[13,face]:z_FSMUi_A ~ normal(0, 1),
  vector[13]:sigma_FSMUi_A ~ dexp(1),

  # Face and rater varying effects
  gq> matrix[13,13]:Rho_FSMUi_A <<- Chol_to_Corr(L_Rho_FSMUi_A),

  # Uppermost
  sigma_Scale ~ dexp(1)

), data=D_AT, iter=300, sample=T, cores=14, chains=14, log_lik=T)
```

We also run the same model with the parts in bold deleted. The two models were compared using WAIC.

The same models were also fitted for trustworthiness.

WAIC - attractiveness:

```
                            WAIC     SE   dWAIC    dSE  pWAIC weight
CZRSAUS_A_WAIC_long  237068.7 561.03     0.0     NA 2415.0      1
CZRSAUS_A_WAIC_short 279031.8 520.53 41963.1 389.85 1166.3      0
# The larger model = model with correlations estimated across samples
(CZRSAUS_A_WAIC_long)
```

WAIC – trustworthiness:

```
                            WAIC     SE   dWAIC    dSE  pWAIC weight
CZRSAUS_T_WAIC_long  261717.5 514.84     0.0     NA 2340.6      1
CZRSAUS_T_WAIC_short 285553.0 483.57 23835.5 296.93 1161.3      0
# The larger model = model with correlations estimated across samples
(CZRSAUS_T_WAIC_long)
```

In both cases, the models with varying terms for each face (estimating also the correlation between different groups' ratings) had better out-of-sample predictive accuracy. Results of these models are reported below. Please compare the models' predictions with the predictions based on the full models that entered attractiveness and trustworthiness simultaneously, and that considered morphometric predictors (facial distinctiveness, sexual shape dimorphism and asymmetry), age, and skin lightness.

Part 1.2. Models with attractiveness or trustworthiness as the sole response variable

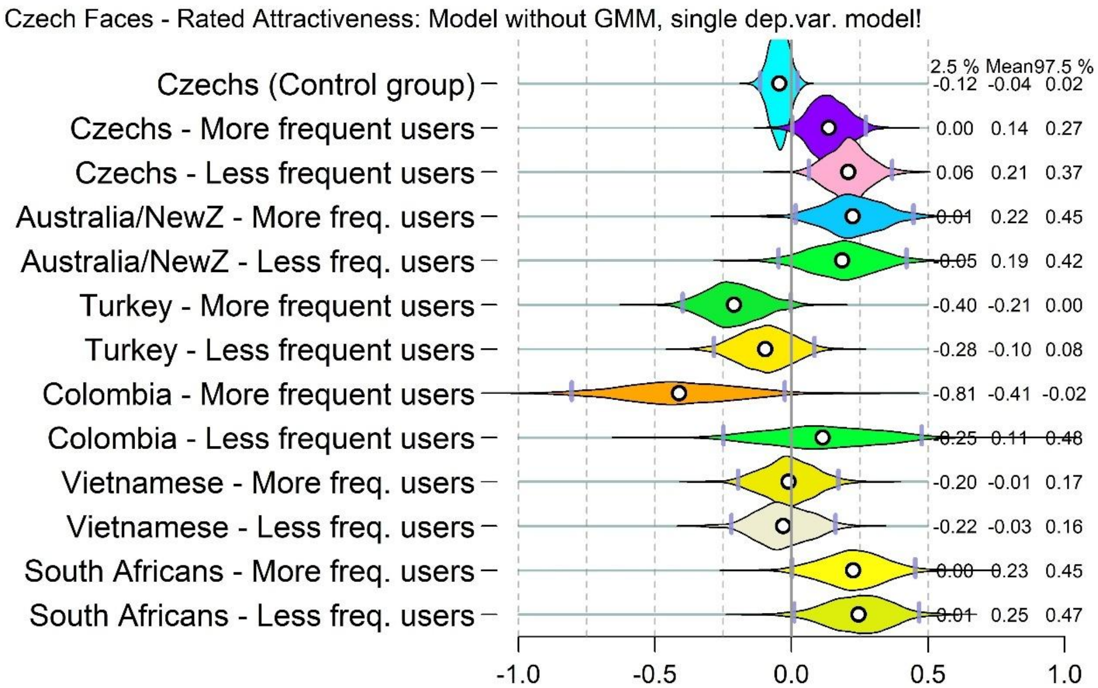


Figure S1: How assigned attractiveness differs (relatively) between the samples, model without GMM, L, and Age. Attractiveness is the sole response variable in this model.

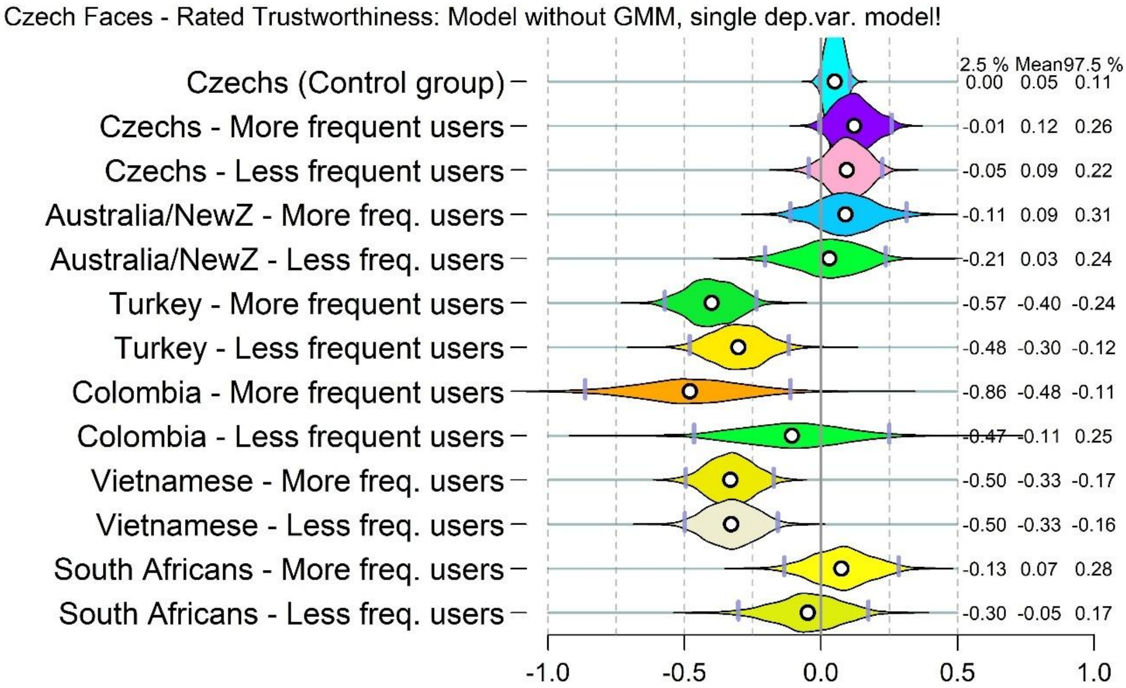


Figure S2: How assigned <u>trustworthiness</u> differs (relatively) between the samples, model without GMM, L, and Age. Trustworthiness is the sole response variable in this model.

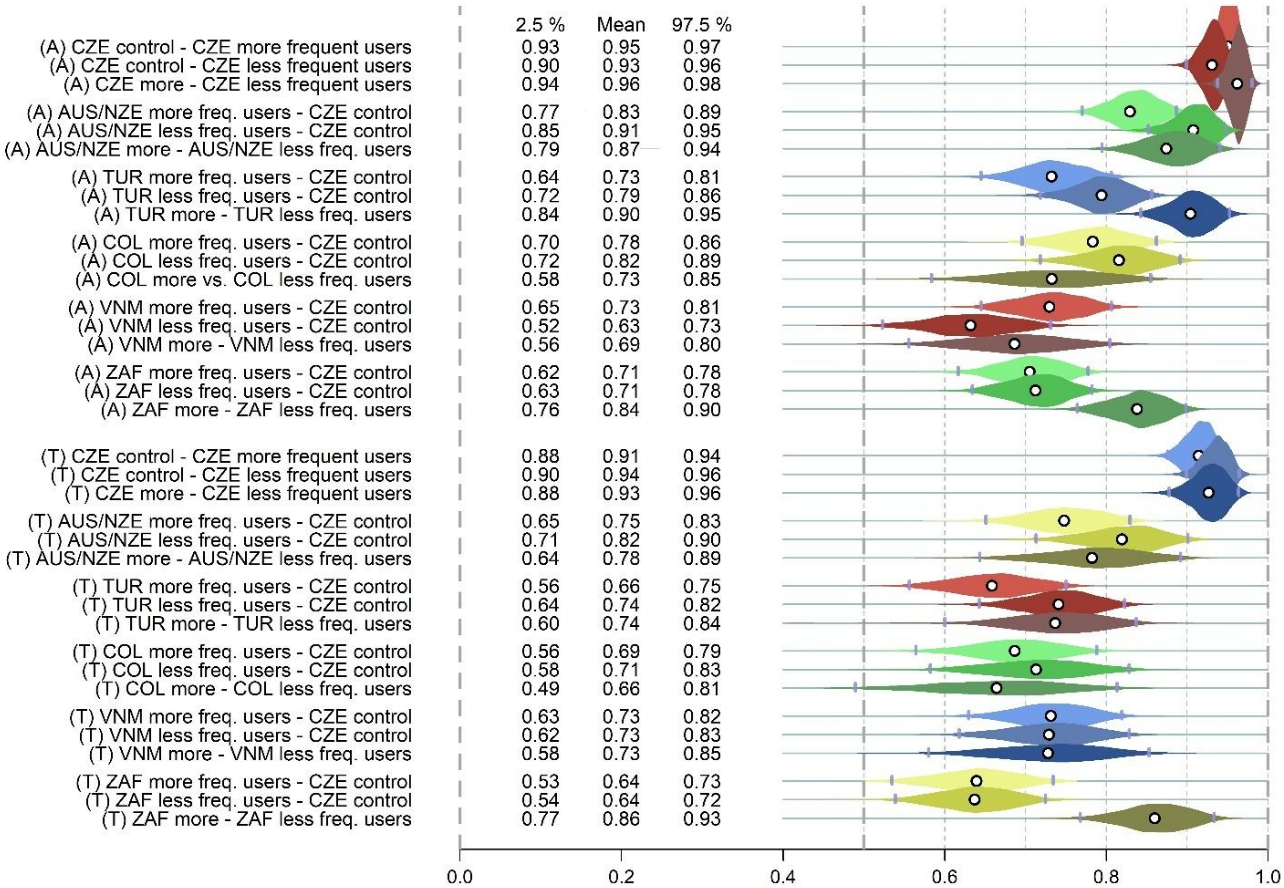


Figure S3: Correlations between <u>attractiveness (upper half)</u>, respectively, <u>trustworthiness (lower half)</u>, ratings in different groups. **Please note that the two series of coefficients are from two separate models!**

Part 1.3. Models without GMM, but with both the attractiveness and trustworthiness

Model 1: Full-length dataset, no GMM included, Attractiveness and Trustworthiness considered simultaneously.

Model transcription:

```
CZRSAUS_AT_TW_5 <- ulam(alist(
  c(TrustwRating, AtrRating) ~ multi_normal(c(muA,muT), Rho_Scales, sigma_Scales),

  muA <- a_A + a_group_A[FSMUi] + f_per_group_A[face,FSMUi] + z_A[rater]*sigma_rater_A,
  muT <- a_T + a_group_T[FSMUi] + f_per_group_T[face,FSMUi] + z_T[rater]*sigma_rater_T,


  # Big intercept for Country_1_orig
  a_A ~ dnorm(0, 0.5),
  a_T ~ dnorm(0, 0.5),

  # intercept change per country
  a_group_A[FSMUi] ~ dnorm(0, 0.5),
  a_group_T[FSMUi] ~ dnorm(0, 0.5),

  z_A[rater] ~ normal(0,1),
  sigma_rater_A ~ dexp(1),

  gq > vector[rater]:a_rater_A <<- a_A + z_A*sigma_rater_A,

  z_T[rater] ~ normal(0,1),
  sigma_rater_T ~ dexp(1),

  gq > vector[rater]:a_rater_T <<- a_T + z_T*sigma_rater_T,

  # Group-level increases per face in attractiveness (here the correlation matrix shall be
inspected to see similarities in ratings)
  transpars> matrix[face,13]:f_per_group_A <-
compose_noncentered(sigma_FSMUi_A,L_Rho_FSMUi_A,z_FSMUi_A),

  # Priors for multivariate normal distribution parameters - Face/FSMUi
  cholesky_factor_corr[13]:L_Rho_FSMUi_A ~ lkj_corr_cholesky(2),
  matrix[13,face]:z_FSMUi_A ~ normal(0, 1),
  vector[13]:sigma_FSMUi_A ~ dexp(1),

  # Face and rater varying effects
  gq> matrix[13,13]:Rho_FSMUi_A <<- Chol_to_Corr(L_Rho_FSMUi_A),

  # Group-level increases per face in attractiveness (here the correlation matrix shall be
inspected to see similarities in ratings)
  transpars> matrix[face,13]:f_per_group_T <-
compose_noncentered(sigma_FSMUi_T,L_Rho_FSMUi_T,z_FSMUi_T),

  # Priors for multivariate normal distribution parameters - Face/FSMUi
  cholesky_factor_corr[13]:L_Rho_FSMUi_T ~ lkj_corr_cholesky(2),
  matrix[13,face]:z_FSMUi_T ~ normal(0, 1),
  vector[13]:sigma_FSMUi_T ~ dexp(1),

  # Face and rater varying effects
  gq> matrix[13,13]:Rho_FSMUi_T <<- Chol_to_Corr(L_Rho_FSMUi_T),

  # Uppermost
  sigma_Scales ~ dexp(1),
  Rho_Scales ~ lkj_corr(2)

), data=D_AT, iter=500, sample=T, cores=20, chains=20)
```

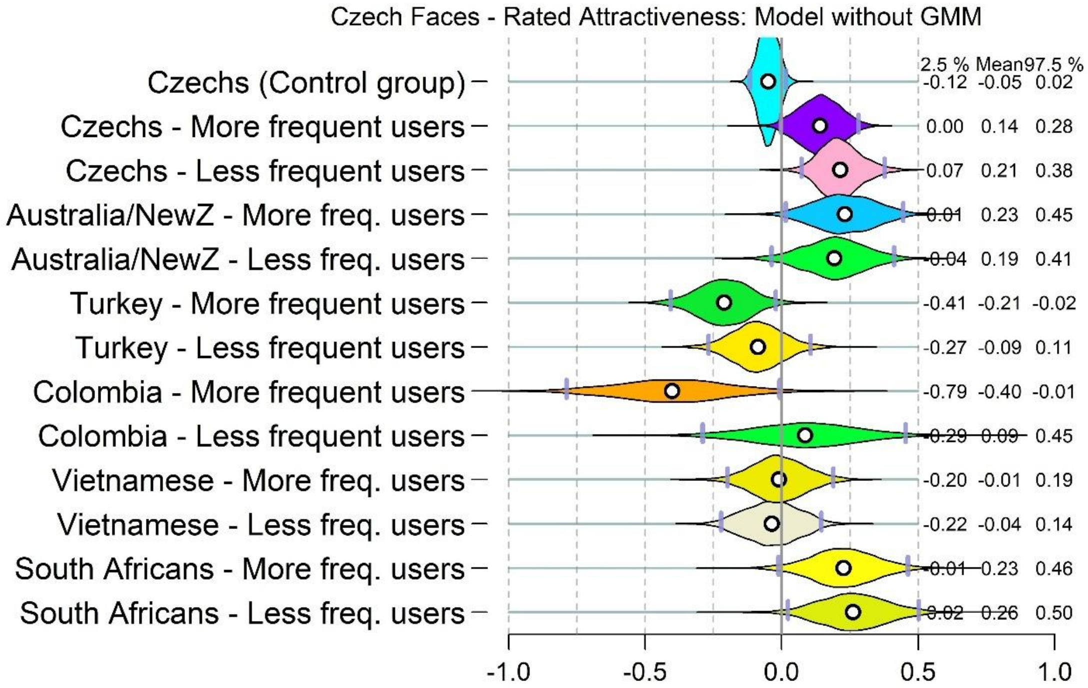


Figure S4: How assigned <u>attractiveness</u> differs (relatively) between the samples.

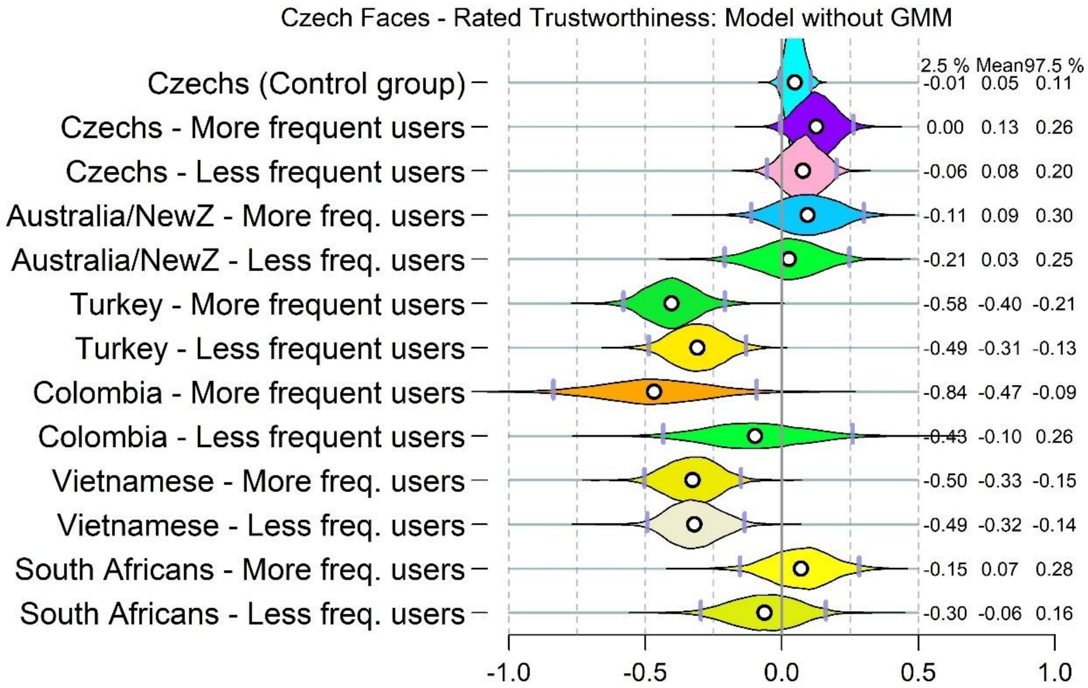


Figure S5: How assigned <u>trustworthiness</u> differs (relatively) between the samples.

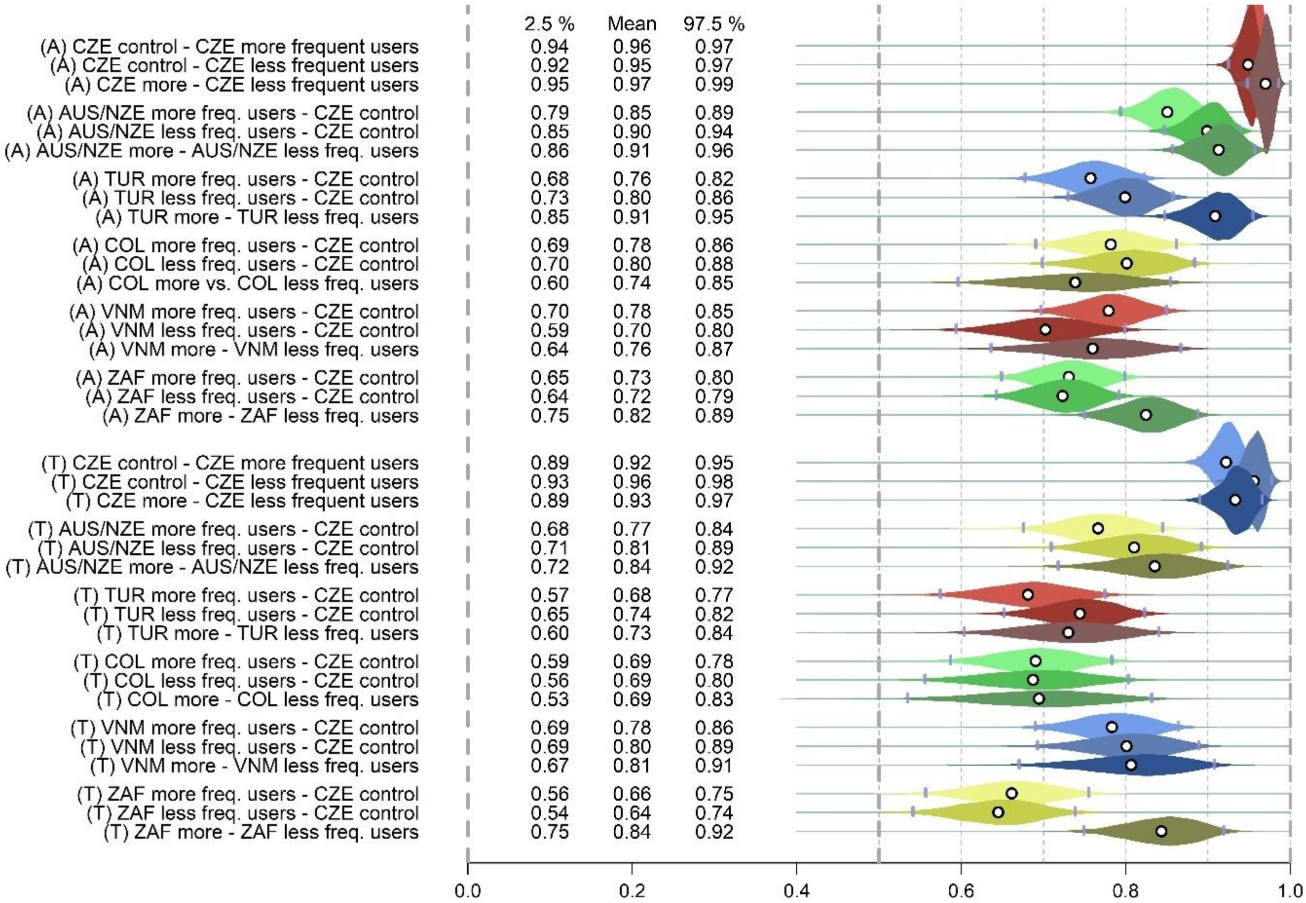


Figure S6: Correlations between attractiveness (upper half), respectively, trustworthiness (lower half), ratings in different groups. Why comparison with Czech raters from control sample: There is no reason to suspect the Czech raters from any sample to outperform other Czechs as the knowledge of Czech faces is expected to be very high in the group.

Note for VF: The erroneous figures with A and T swapped were corrected.

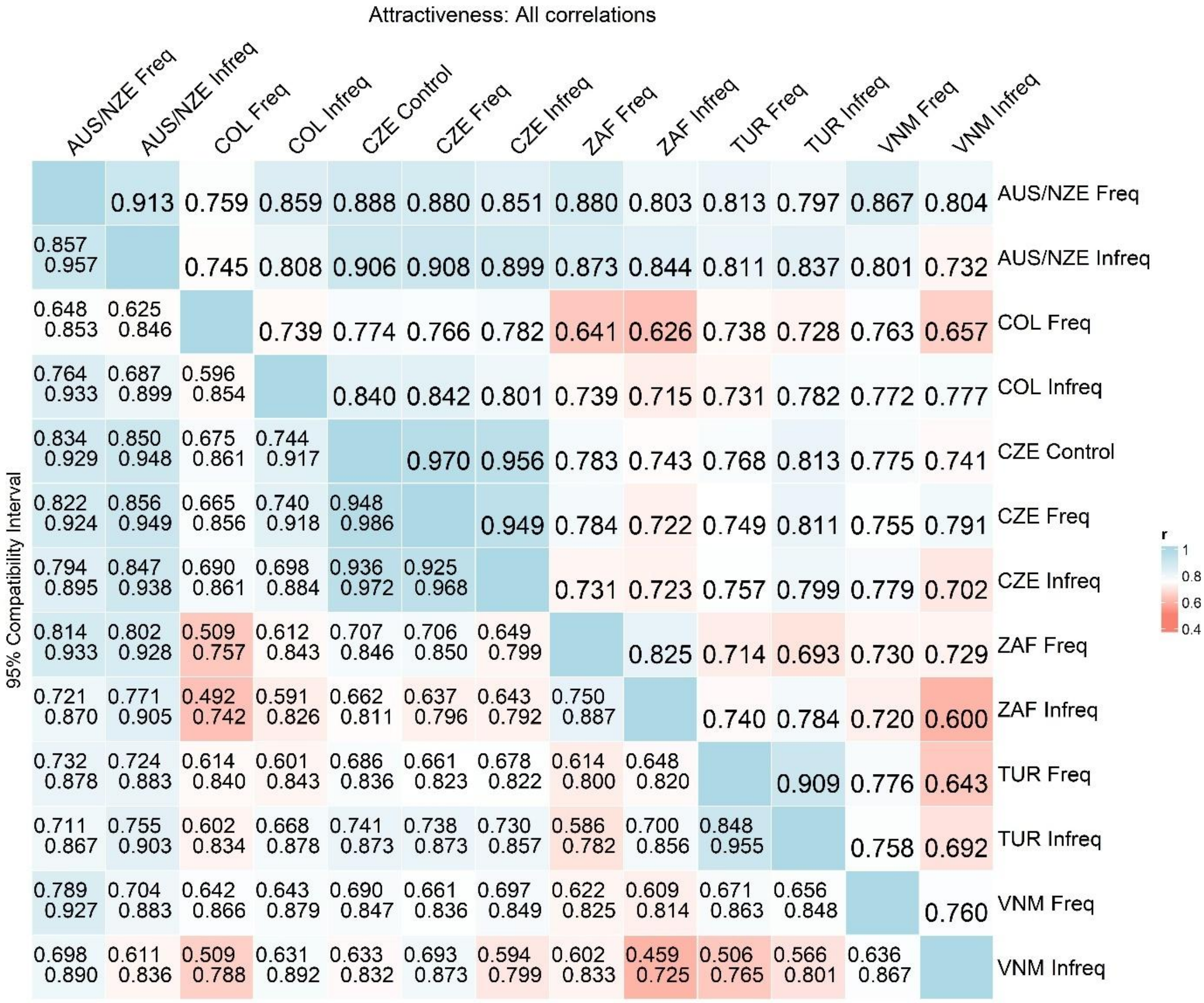


Figure S7. Correlation heatmap for <u>Attractiveness</u>. Above diagonal are means of the estimates, below diagonal, 95% percentile-based Compatibility Intervals are drawn.

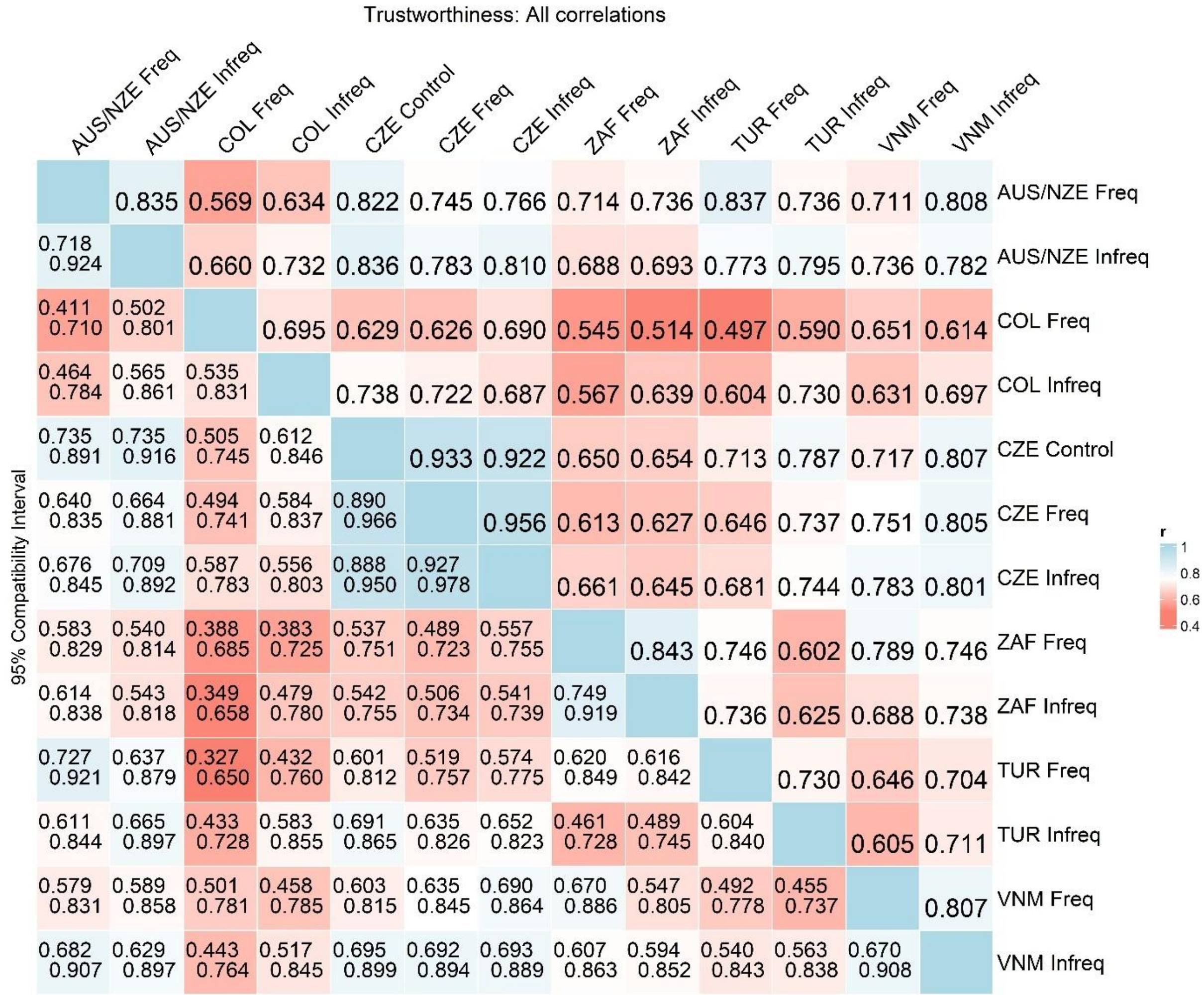


Figure S8. Correlation heatmap for Trustworthiness. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn.

Part 2: ATTR/TRUSTW/WITH-GMM

Principially the same model, including GMM, skin L*, and Age (run for exploratory purposes):

From this point onwards GMM = Geometric Morphometrics. It denotes models in which we use facial distinctiveness, asymmetry, and sexual shape dimorphism.

Model transcription:

```
CZRSAUS_TW_4 <- ulam(alist(

  # Multivariate normal for Trustworthiness and Attractiveness
  c(TrustwRating, AtrRating) ~ multi_normal(c(muT, muA), Rho_Scales, sigma_Scales),

  # Mean structure for Trustworthiness and Attractiveness
  muT <- aT + a_group_T[FSMUi]
  + z_rNV_T[rater] * sigma_rater_T
  + f_per_group_T[face,FSMUi]
  + (b_age_T + f_per_group_pr_T[FSMUi, 1]) * Age
  + (b_dist_T + f_per_group_pr_T[FSMUi, 2]) * dist
  + (b_FA_T + f_per_group_pr_T[FSMUi, 3]) * FA
  + (b_sshd_T + f_per_group_pr_T[FSMUi, 4]) * sshd
  + (b_L_T + f_per_group_pr_T[FSMUi,5]) * L,

  muA <- aA + a_group_A[FSMUi]
  + z_rNV_A[rater] * sigma_rater_A
  + f_per_group_A[face,FSMUi]
```

```
  + (b_age_A + f_per_group_pr_A[FSMUi, 1]) * Age
  + (b_dist_A + f_per_group_pr_A[FSMUi, 2]) * dist
  + (b_FA_A + f_per_group_pr_A[FSMUi, 3]) * FA
  + (b_sshd_A + f_per_group_pr_A[FSMUi, 4]) * sshd
  + (b_L_A + f_per_group_pr_A[FSMUi,5]) * L,

  # Priors for Attractiveness and Trustworthiness intercepts
  aT ~ dnorm(0, 0.5),  # Trustworthiness
  aA ~ dnorm(0, 0.5),  # Attractiveness

  # Priors for Attractiveness and Trustworthiness slopes
  b_age_T ~ dnorm(0, 0.3),
  b_dist_T ~ dnorm(0, 0.3),
  b_FA_T ~ dnorm(0, 0.3),
  b_sshd_T ~ dnorm(0, 0.3),
  b_L_T ~ dnorm(0, 0.3),

  b_age_A ~ dnorm(0, 0.3),
  b_dist_A ~ dnorm(0, 0.3),
  b_FA_A ~ dnorm(0, 0.3),
  b_sshd_A ~ dnorm(0, 0.3),
  b_L_A ~ dnorm(0, 0.3),

  # Intercept change per country for both Trustworthiness and Attractiveness
  a_group_T[FSMUi] ~ dnorm(0, 0.5),  # Trustworthiness
  a_group_A[FSMUi] ~ dnorm(0, 0.5),  # Attractiveness

  # Non-centered parameterization for rater effects
  z_rNV_T[rater] ~ dnorm(0, 1),  # Trustworthiness latent variable
  z_rNV_A[rater] ~ dnorm(0, 1),  # Attractiveness latent variable

  sigma_rater_T ~ dexp(1),  # Trustworthiness
  sigma_rater_A ~ dexp(1),  # Attractiveness

  gq> vector[rater]:a_rNV_T <<- aT + z_rNV_T * sigma_rater_T,  # Generate rater effects for
Trustworthiness
  gq> vector[rater]:a_rNV_A <<- aA + z_rNV_A * sigma_rater_A,  # Generate rater effects for
Attractiveness

  # Varying effects for Trustworthiness morpho-predictors
  transpars> matrix[FSMUi, 5]:f_per_group_pr_T <- compose_noncentered(sigma_pr_T, L_Rho_pr_T,
z_pr_T),
  cholesky_factor_corr[5]:L_Rho_pr_T ~ lkj_corr_cholesky(2),
  matrix[5, FSMUi]:z_pr_T ~ normal(0, 1),
  vector[5]:sigma_pr_T ~ dexp(1),

  gq> matrix[5, 5]:Rho_pr_T <<- Chol_to_Corr(L_Rho_pr_T),

  # Varying effects for Attractiveness morpho-predictors
  transpars> matrix[FSMUi, 5]:f_per_group_pr_A <- compose_noncentered(sigma_pr_A, L_Rho_pr_A,
z_pr_A),
  cholesky_factor_corr[5]:L_Rho_pr_A ~ lkj_corr_cholesky(2),
  matrix[5, FSMUi]:z_pr_A ~ normal(0, 1),
  vector[5]:sigma_pr_A ~ dexp(1),

  gq> matrix[5, 5]:Rho_pr_A <<- Chol_to_Corr(L_Rho_pr_A),

  # Priors for the multivariate normal distribution for face intercepts across groups
  transpars> matrix[face, 9]:f_per_group_T <- compose_noncentered(sigma_FSMUi_T,
L_Rho_FSMUi_T, z_FSMUi_T),
  cholesky_factor_corr[9]:L_Rho_FSMUi_T ~ lkj_corr_cholesky(2),
  matrix[9, face]:z_FSMUi_T ~ normal(0, 1),
  vector[9]:sigma_FSMUi_T ~ dexp(1),

  transpars> matrix[face, 9]:f_per_group_A <- compose_noncentered(sigma_FSMUi_A,
L_Rho_FSMUi_A, z_FSMUi_A),
  cholesky_factor_corr[9]:L_Rho_FSMUi_A ~ lkj_corr_cholesky(2),
  matrix[9, face]:z_FSMUi_A ~ normal(0, 1),
  vector[9]:sigma_FSMUi_A ~ dexp(1),

  gq> matrix[9, 9]:Rho_FSMUi_T <<- Chol_to_Corr(L_Rho_FSMUi_T),
  gq> matrix[9, 9]:Rho_FSMUi_A <<- Chol_to_Corr(L_Rho_FSMUi_A),

  # Covariance between Attractiveness and Trustworthiness
  sigma_Scales ~ dexp(1),
  Rho_Scales ~ lkj_corr(2)

), data=D_AT, iter=500, sample=T, cores=20, chains=20)
```

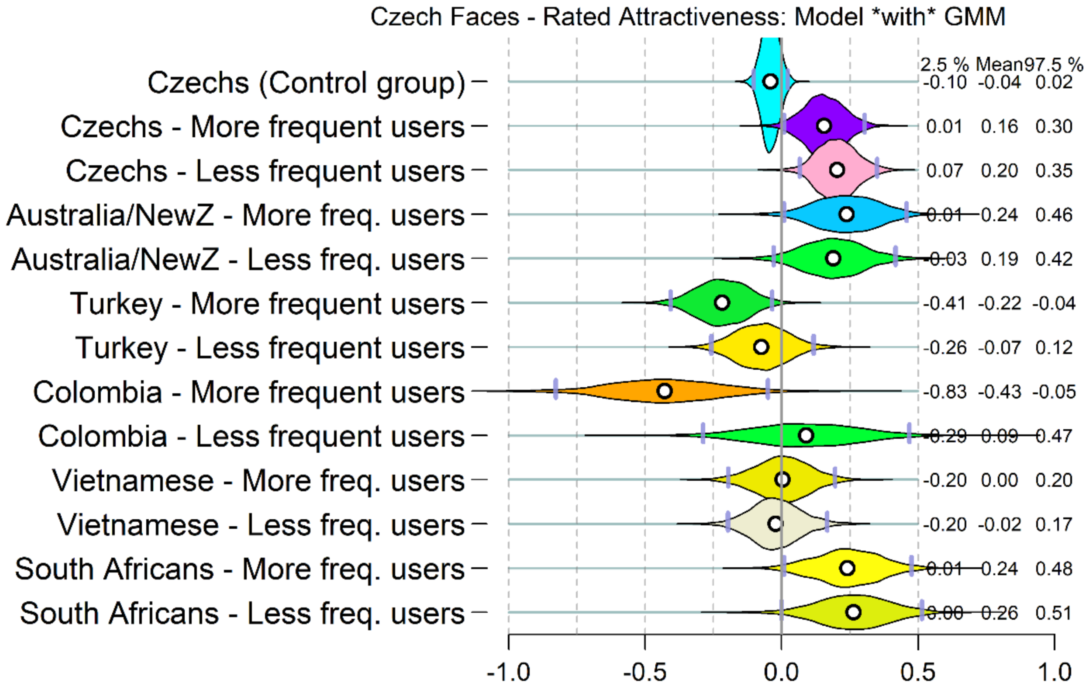


Figure S9: How assigned <u>attractiveness</u> differs (relatively) between the samples – model with GMM, Skin L* and Age… Predictions are, at this point, stable and similar to Model with GMM.

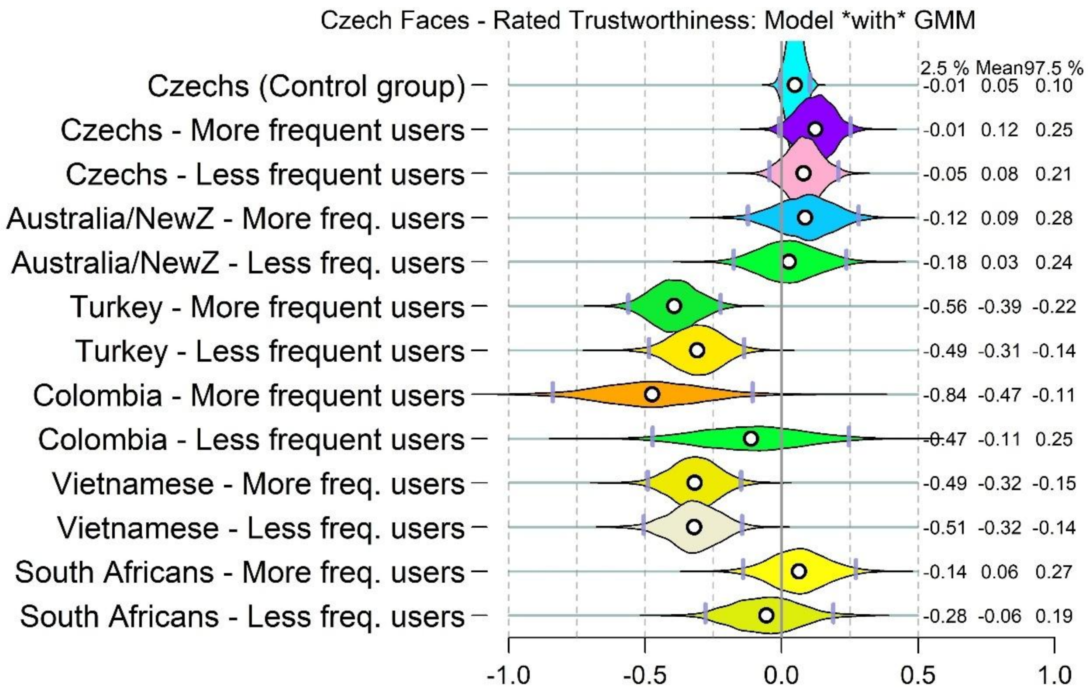


Figure S10: How assigned <u>trustworthiness</u> differs (relatively) between the samples; model with GMM.

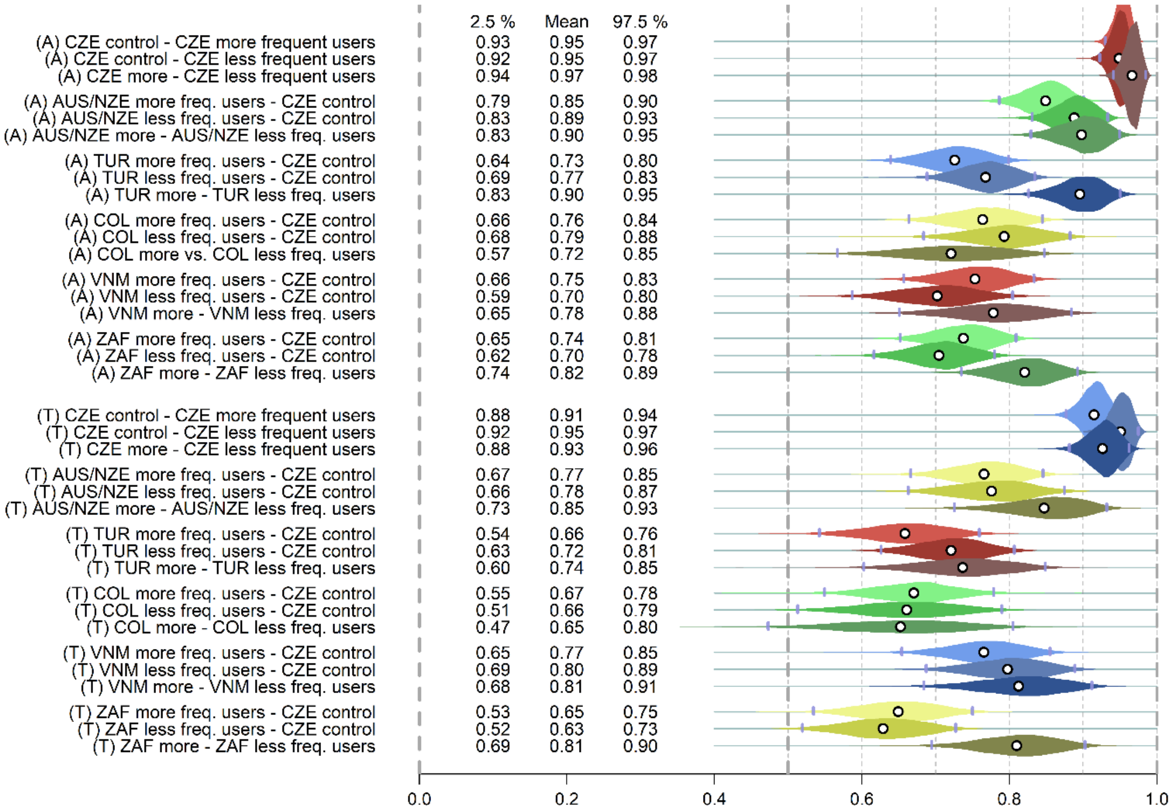


Figure S11: Correlations between attractiveness (upper panel), respectively, trustworthiness (lower panel), ratings in different groups; Model with GMM.

Table S2. Selected correlation comparison (see the manuscript)			
Comparison	CI_2_5	Mean	CI_97_5
ATTR: Turkey Freq/Infreq vs CZ & Turkey_Freq	0,08	0,17	0,26
ATTR: Turkey Freq/Infreq vs CZ & Turkey_Infreq	0,04	0,13	0,22
ATTR: SouthAf Freq/Infreq vs CZ & SouthAf_Freq	-0,01	0,08	0,18
ATTR: SouthAf Freq/Infreq vs CZ & SouthAf_Infreq	0,02	0,12	0,21
TRUSTW: Austr/NZ Freq/Infreq vs CZ & Turkey_Freq	-0,04	0,08	0,2
TRUSTW: Austr/NZ Freq/Infreq vs CZ & Turkey_Infreq	-0,07	0,07	0,19
TRUSTW: SouthAf Freq/Infreq vs CZ & SouthAf_Freq	0,02	0,16	0,29
TRUSTW: SouthAf Freq/Infreq vs CZ & SouthAf_Infreq	0,05	0,18	0,31

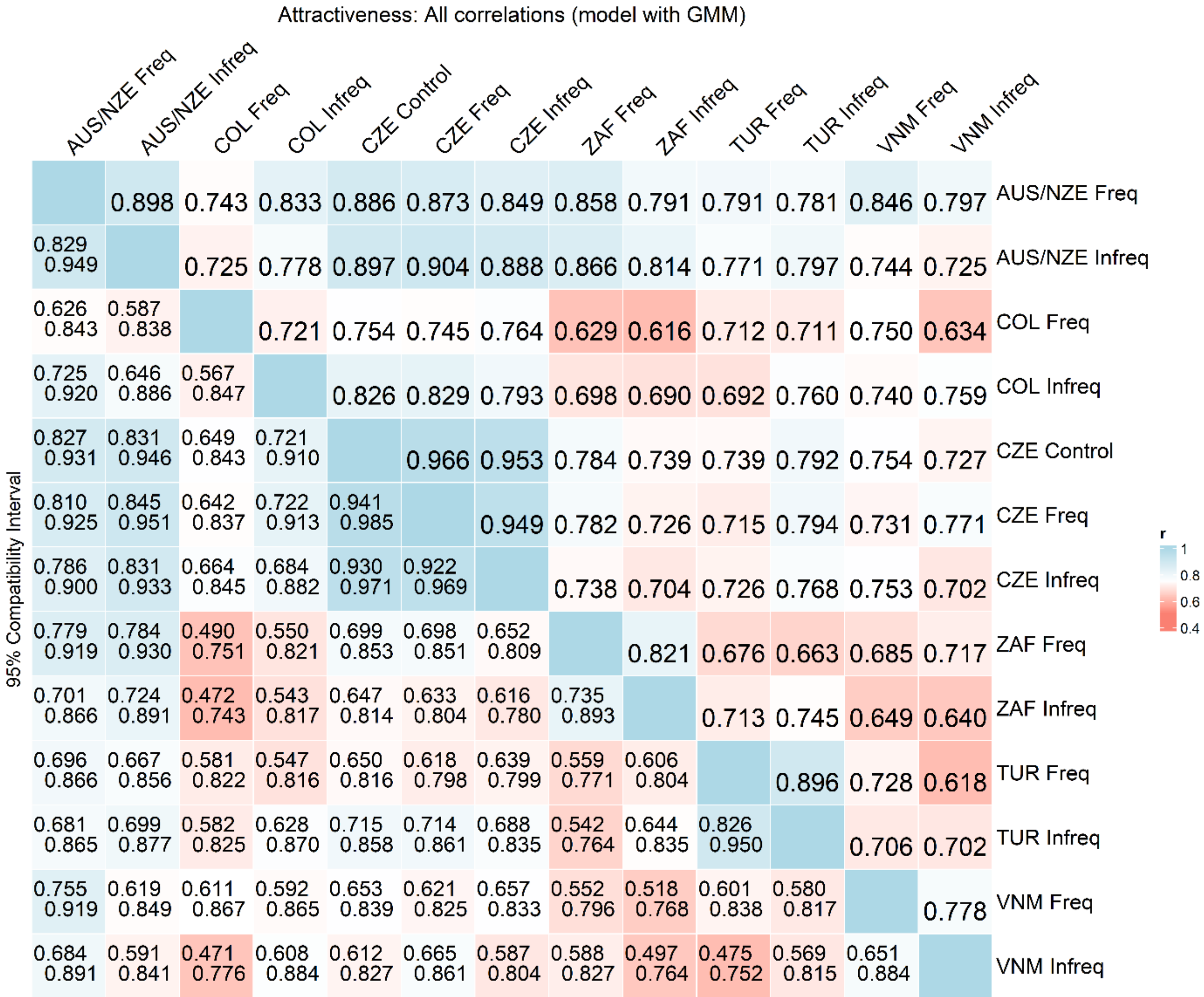


Figure S12. Correlation heatmap for Attractiveness. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn. Model with GMM.

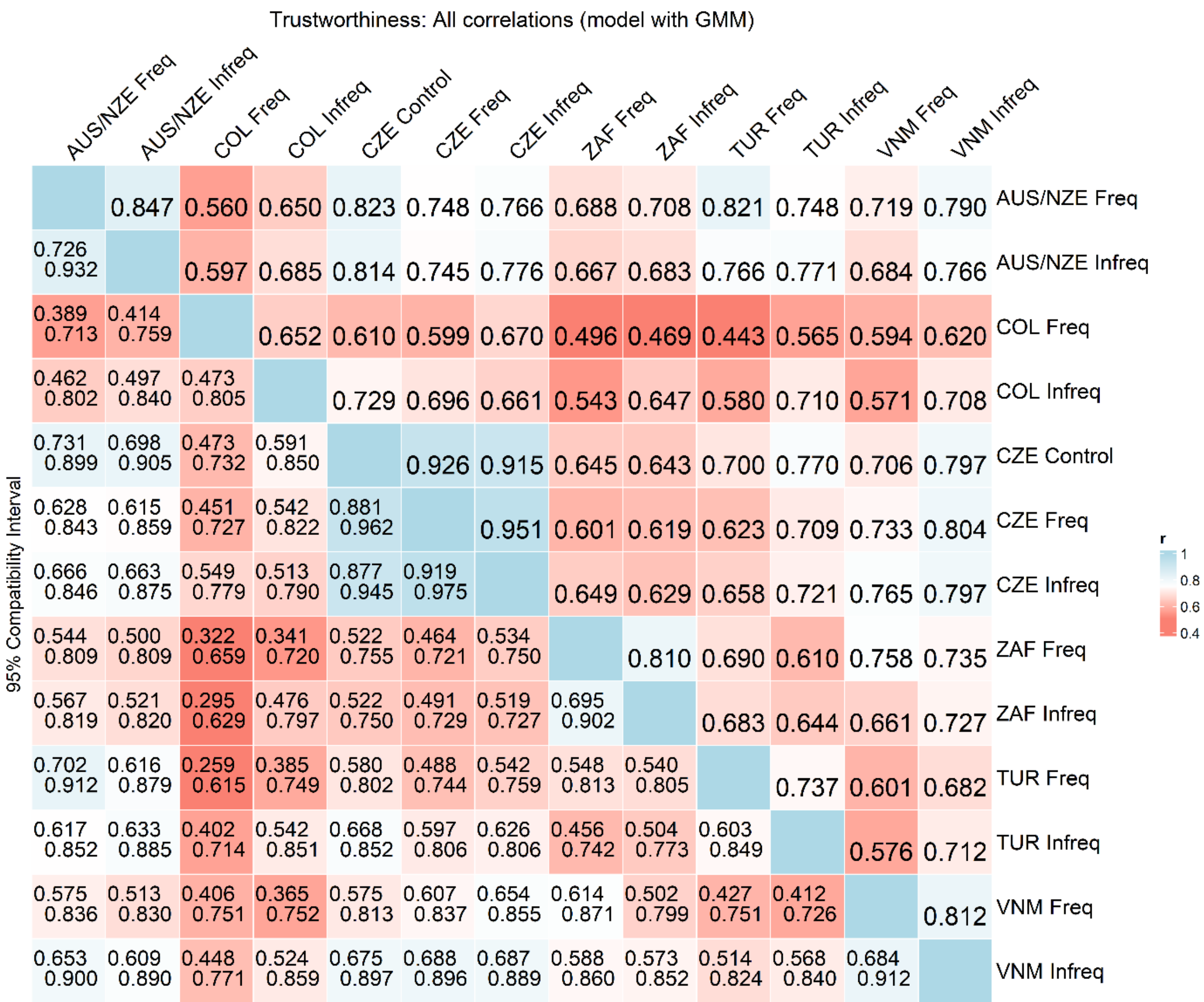


Figure S13. Correlation heatmap for Trustworthiness. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn. Model with GMM.

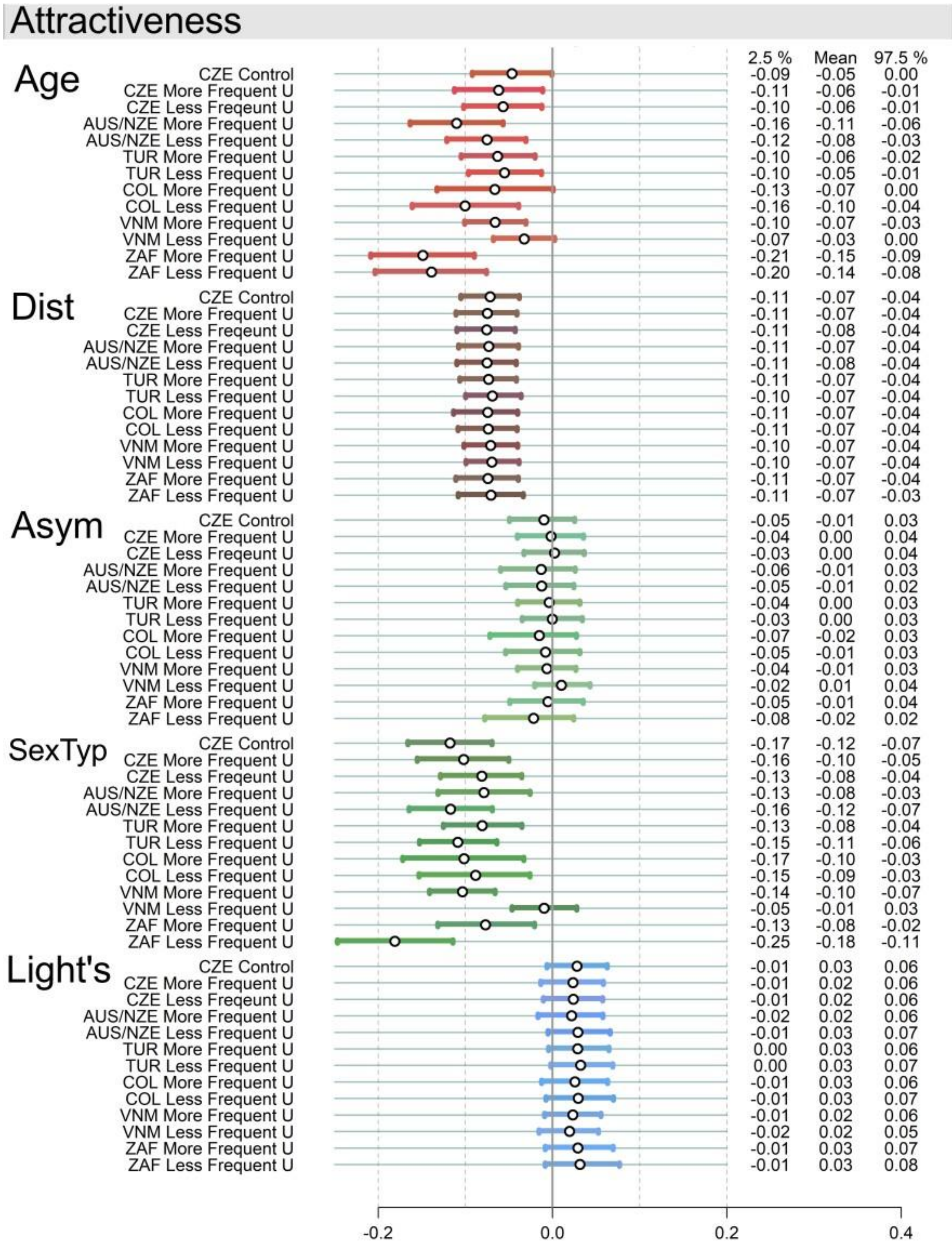
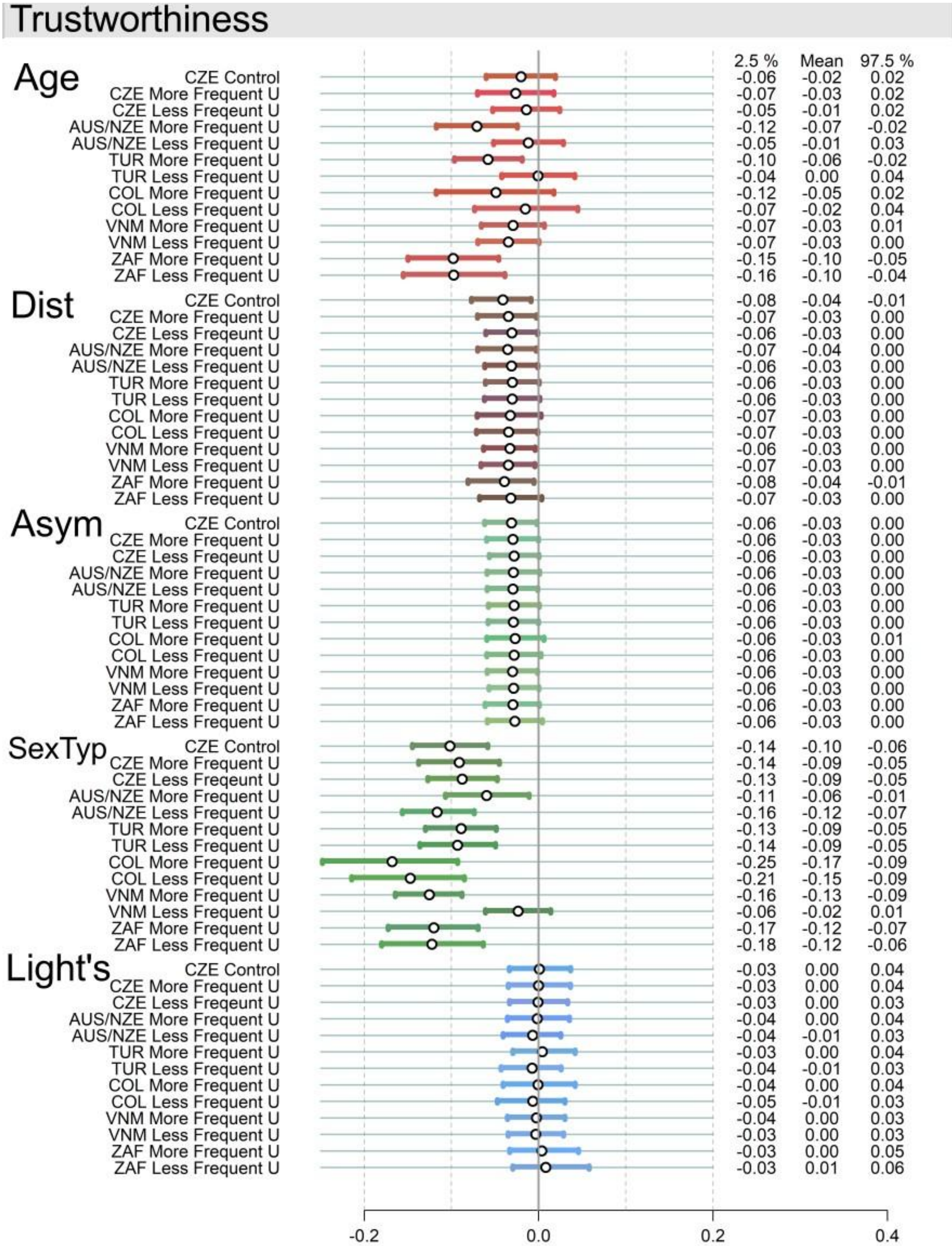


Figure S14. Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived attractiveness, rated by different groups. Age = self-reported age of the stimuli; Dist = position of an individual stimuli faces among all the same-sex faces; Asym = facial asymmetry; SexTyp = measured sexual shape dimorphism; Light's = measured skin lightness (CIELab L*)



	2.5 %	Mean	97.5 %
Age			
CZE Control	-0.06	-0.02	0.02
CZE More Frequent U	-0.07	-0.03	0.02
CZE Less Freqeunt U	-0.05	-0.01	0.02
AUS/NZE More Frequent U	-0.12	-0.07	-0.02
AUS/NZE Less Frequent U	-0.05	-0.01	0.03
TUR More Frequent U	-0.10	-0.06	-0.02
TUR Less Frequent U	-0.04	0.00	0.04
COL More Frequent U	-0.12	-0.05	0.02
COL Less Frequent U	-0.07	-0.02	0.04
VNM More Frequent U	-0.07	-0.03	0.01
VNM Less Frequent U	-0.07	-0.03	0.00
ZAF More Frequent U	-0.15	-0.10	-0.05
ZAF Less Frequent U	-0.16	-0.10	-0.04
Dist			
CZE Control	-0.08	-0.04	-0.01
CZE More Frequent U	-0.07	-0.03	0.00
CZE Less Freqeunt U	-0.06	-0.03	0.00
AUS/NZE More Frequent U	-0.07	-0.04	0.00
AUS/NZE Less Frequent U	-0.06	-0.03	0.00
TUR More Frequent U	-0.06	-0.03	0.00
TUR Less Frequent U	-0.06	-0.03	0.00
COL More Frequent U	-0.07	-0.03	0.00
COL Less Frequent U	-0.07	-0.03	0.00
VNM More Frequent U	-0.06	-0.03	0.00
VNM Less Frequent U	-0.07	-0.03	0.00
ZAF More Frequent U	-0.08	-0.04	-0.01
ZAF Less Frequent U	-0.07	-0.03	0.00
Asym			
CZE Control	-0.06	-0.03	0.00
CZE More Frequent U	-0.06	-0.03	0.00
CZE Less Freqeunt U	-0.06	-0.03	0.00
AUS/NZE More Frequent U	-0.06	-0.03	0.00
AUS/NZE Less Frequent U	-0.06	-0.03	0.00
TUR More Frequent U	-0.06	-0.03	0.00
TUR Less Frequent U	-0.06	-0.03	0.00
COL More Frequent U	-0.06	-0.03	0.01
COL Less Frequent U	-0.06	-0.03	0.00
VNM More Frequent U	-0.06	-0.03	0.00
VNM Less Frequent U	-0.06	-0.03	0.00
ZAF More Frequent U	-0.06	-0.03	0.00
ZAF Less Frequent U	-0.06	-0.03	0.00
SexTyp			
CZE Control	-0.14	-0.10	-0.06
CZE More Frequent U	-0.14	-0.09	-0.05
CZE Less Freqeunt U	-0.13	-0.09	-0.05
AUS/NZE More Frequent U	-0.11	-0.06	-0.01
AUS/NZE Less Frequent U	-0.16	-0.12	-0.07
TUR More Frequent U	-0.13	-0.09	-0.05
TUR Less Frequent U	-0.14	-0.09	-0.05
COL More Frequent U	-0.25	-0.17	-0.09
COL Less Frequent U	-0.21	-0.15	-0.09
VNM More Frequent U	-0.16	-0.13	-0.09
VNM Less Frequent U	-0.06	-0.02	0.01
ZAF More Frequent U	-0.17	-0.12	-0.07
ZAF Less Frequent U	-0.18	-0.12	-0.06
Light's			
CZE Control	-0.03	0.00	0.04
CZE More Frequent U	-0.03	0.00	0.04
CZE Less Freqeunt U	-0.03	0.00	0.03
AUS/NZE More Frequent U	-0.04	0.00	0.04
AUS/NZE Less Frequent U	-0.04	-0.01	0.03
TUR More Frequent U	-0.03	0.00	0.04
TUR Less Frequent U	-0.04	-0.01	0.03
COL More Frequent U	-0.04	0.00	0.04
COL Less Frequent U	-0.05	-0.01	0.03
VNM More Frequent U	-0.04	0.00	0.03
VNM Less Frequent U	-0.03	0.00	0.03
ZAF More Frequent U	-0.03	0.00	0.05
ZAF Less Frequent U	-0.03	0.01	0.06

Figure S15. Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived trustworthiness, rated by different groups.

Part 3: ATTR/TRUSTW – With GMM, L*, and Age: sampled separately for men and women

<u>Purpose</u>: Two characteristics of the models above are obvious even from the model transcription: (I) The formula is complex, and the interpretation requires subsequent addition and subtraction of the posterior samples for different terms. (II) They use predictors from geometric morphometrics (distinctiveness, sexual shape dimorphism, facial asymmetry) that may differ systematically between men and women. Moreover, distinctiveness and facial asymmetry were calculated separately for men and women. Sexual shape dimorphism, on the contrary, use the pooled sample. However, as the computation of sexual shape dimorphism is a regression of sex on facial shape, one sex is coded as 1 and the other as -1. Therefore, mean of one sex lies below zero, the other being true for the 2nd sex (with the points representing individual configurations being projected on an axis crossing both the means). Then, the positive and negative values have no meaning outside the equation. Even though, the prediction of the equation may be still correct, when using such a scale. Previous evidence shows that while more male-like facial shape is not attractive in either sex, more feminine facial configuration may be slightly preferred in men and more strongly preferred in women. Then, we would get a constant negative slope.

However, this is just an anticipation, and the model predictions may be misleading in the pooled sample. Potential solution would be to add another layer in the model (or double the number of the existing groups, see Kleisner et al. 2024 for an instance of this solution). The current model took around 60 hours to sample on a machine with cutting-edge Intel Xeon processor using as many cores and sampling parallelisation as possible. Adding another layer here would impose simplifying the model elsewhere to make it sampled in a reasonable time. To account for potentially different effect of the predictor in the two sexes, we instead run the analysis separately for men and women. This is also an explanation, why no separate model was run as an analogue of Model 1 (model without GMM, Age, and L*).

Model on females' subsample – the predictions:

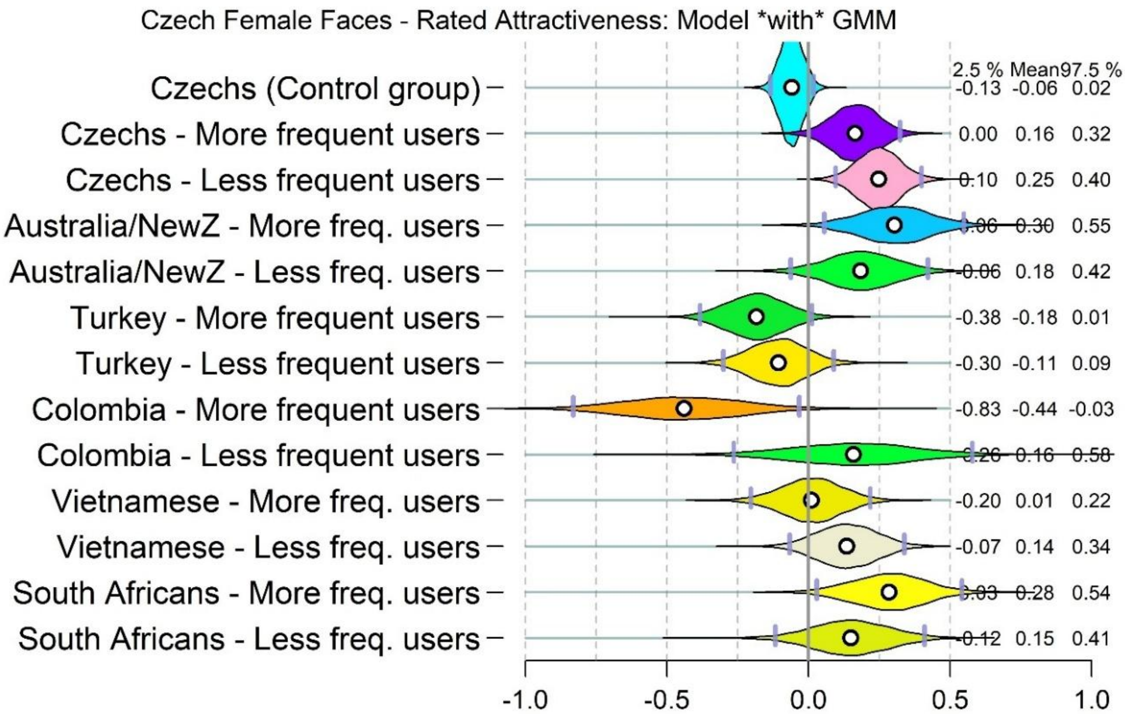


Figure S16: Female subsample: How assigned attractiveness differs (relatively) between the samples – model with GMM, Skin L*, and Age.

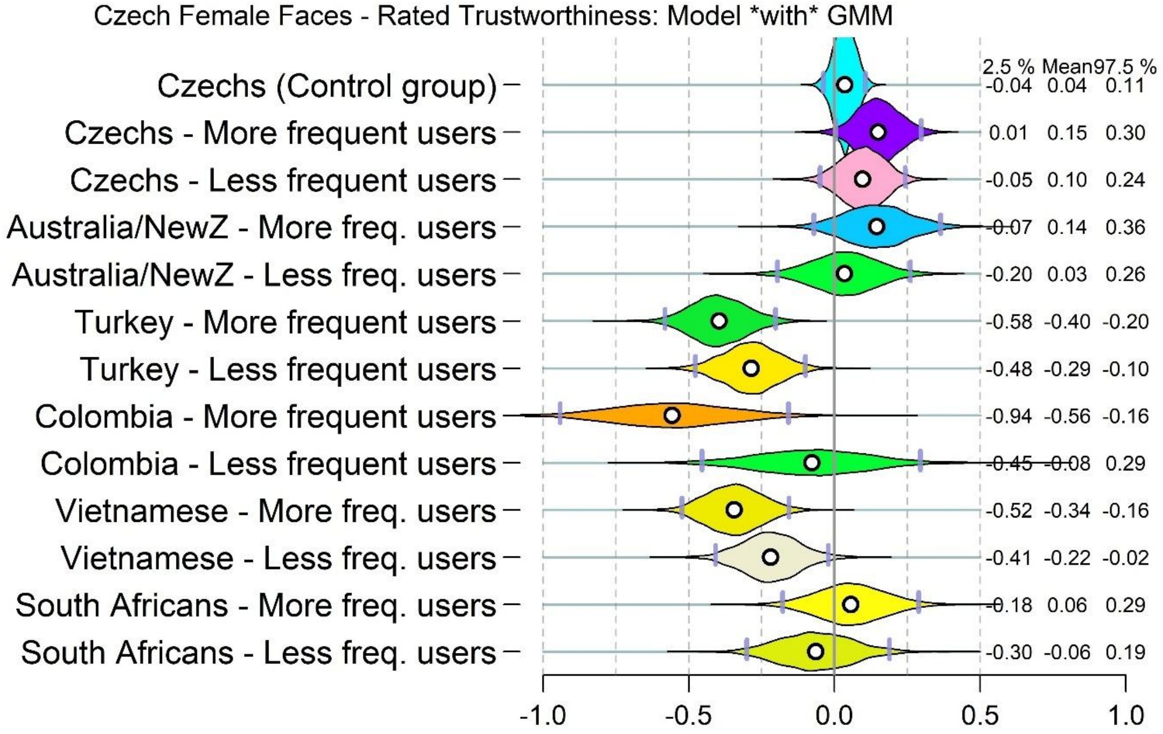


Figure S17: Female subsample: How assigned trustworthiness differs (relatively) between the samples; model with GMM, Skin L*, and Age.

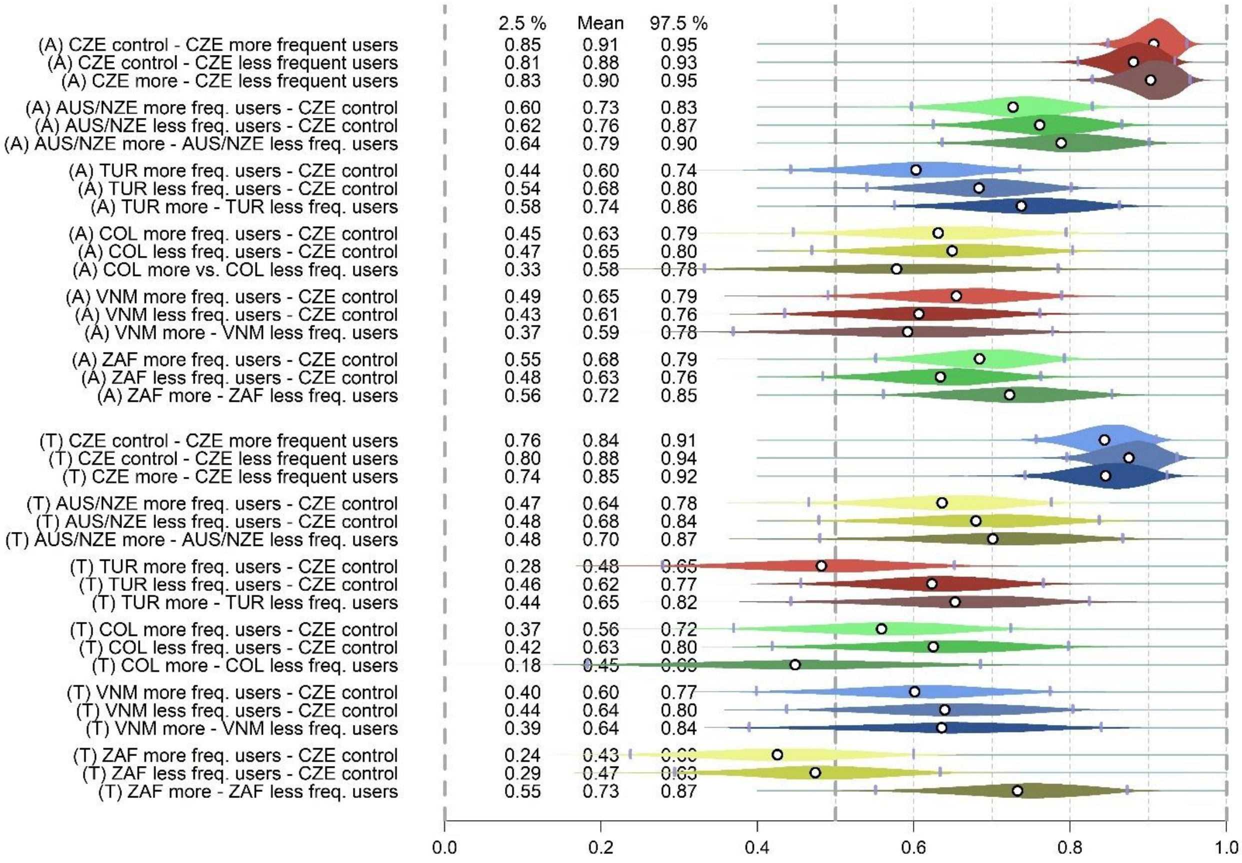


Figure S18: Female subsample: Correlations between attractiveness (upper panel), respectively, trustworthiness (lower panel), ratings in different groups; Model with GMM.

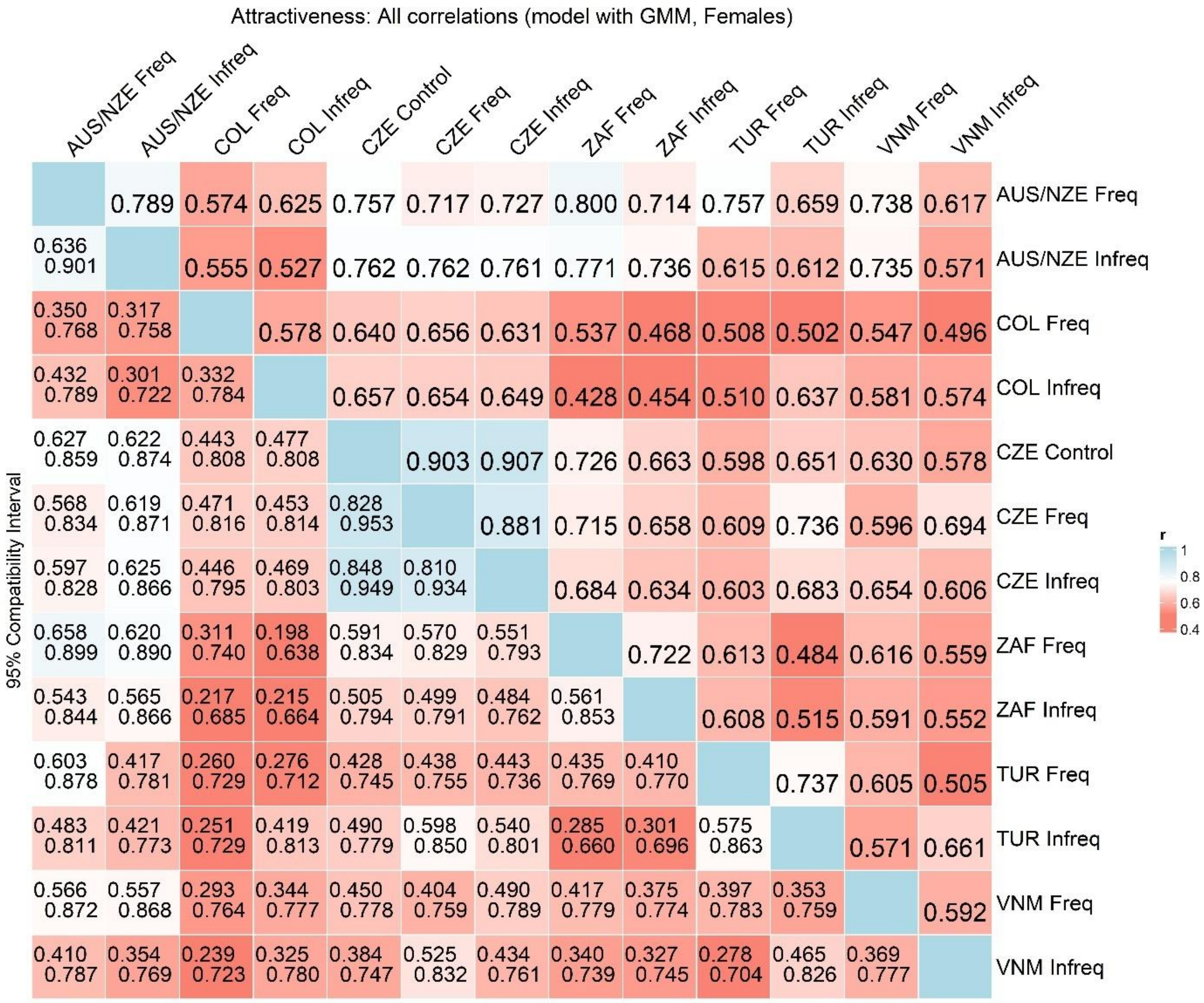


Figure S19. Female subsample: Correlation heatmap for Attractiveness. Above diagonal are means of the estimates, below diagonal, 95% percentile-based Compatibility Intervals are reported. Model with GMM.

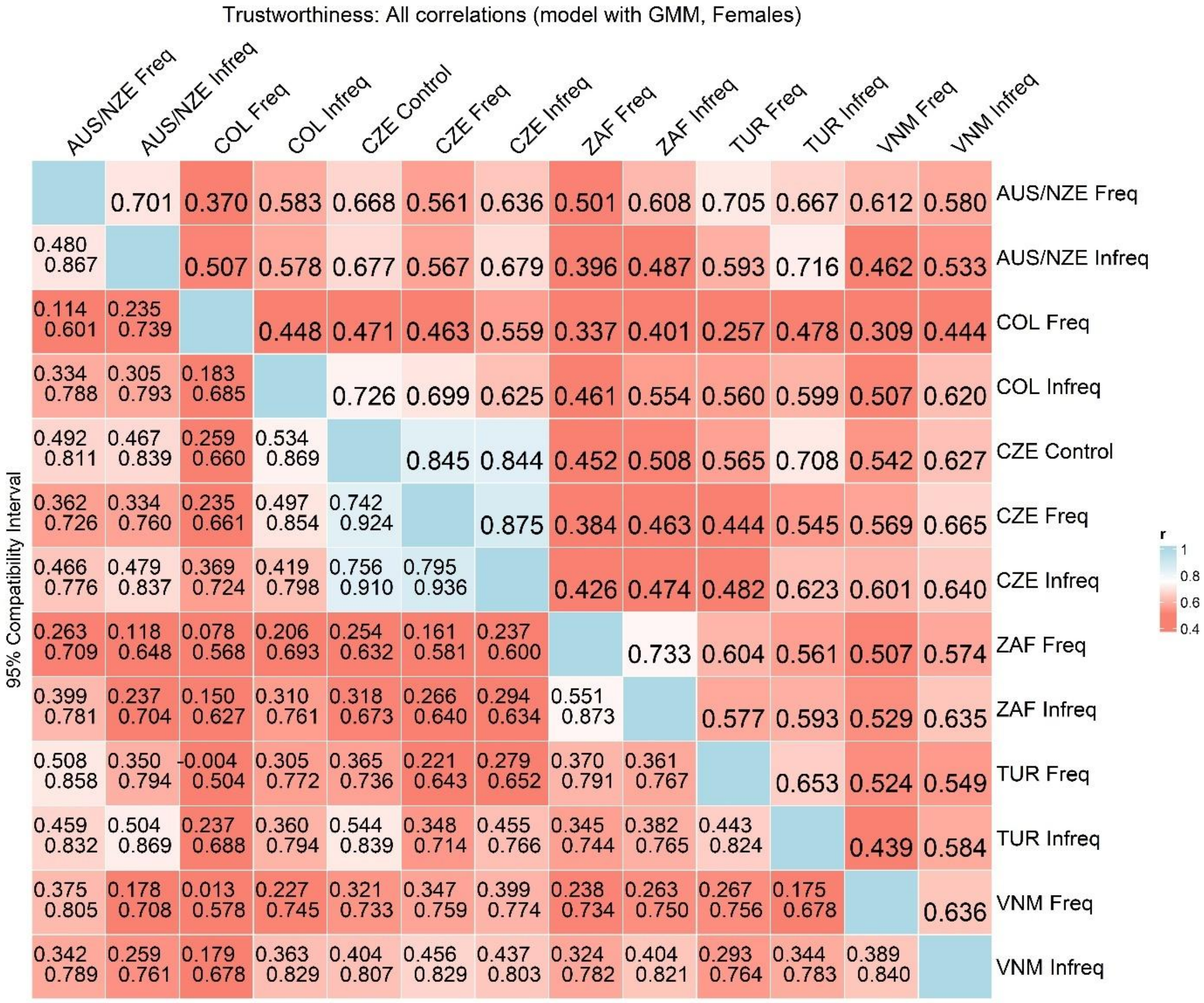


Figure S20. Female subsample: Correlation heatmap for Trustworthiness. Above diagonal are means of the estimates, below diagonal, 95% percentile-based Compatibility Intervals are drawn. Model with GMM.

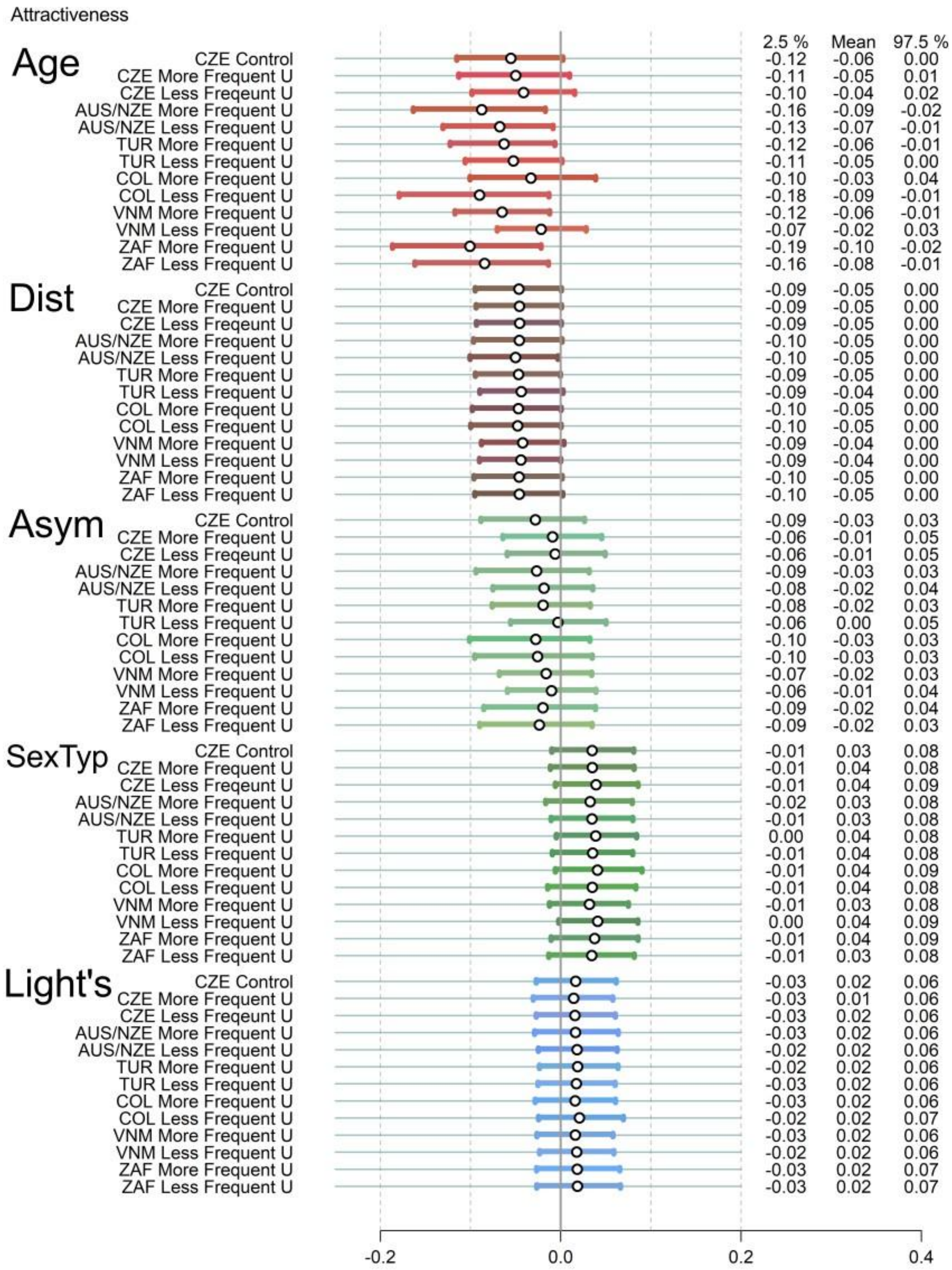


Figure S21. Female subsample: Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived attractiveness, rated by different groups. Age = self-reported age of the stimuli; Dist = position of an individual stimuli faces among all the same-sex faces; Asym = facial asymmetry; SexTyp = measured sexual shape dimorphism; Light's = measured skin lightness (CIELab L*)

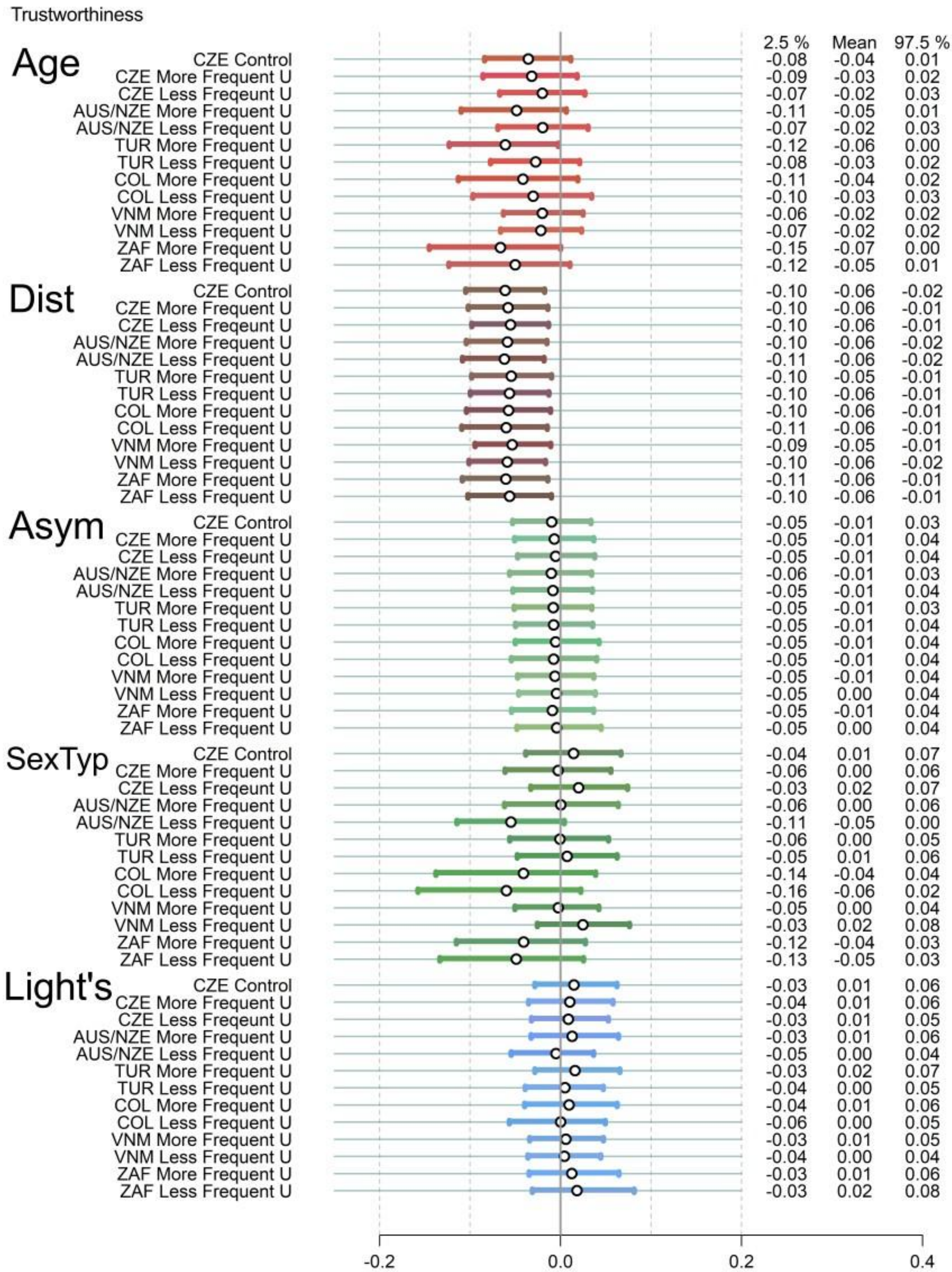


Figure S22. Female subsample: Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived trustworthiness, rated by different groups.

Model on males' subsample – the predictions:

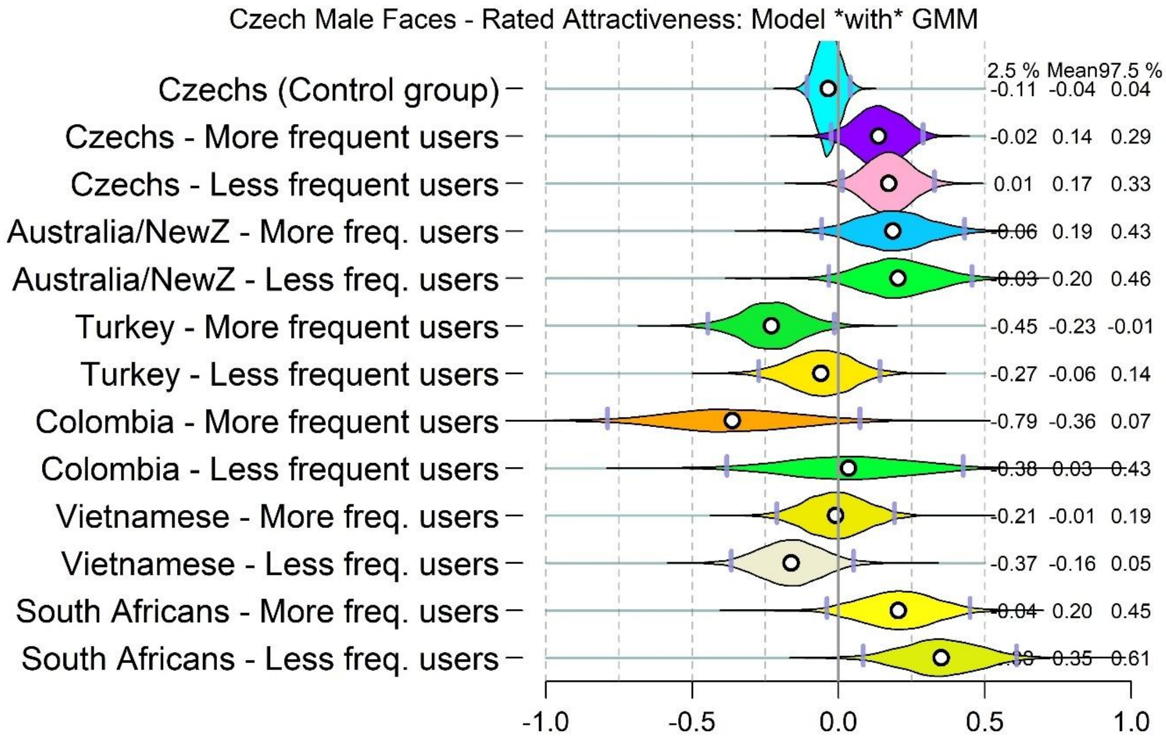


Figure S23: Male subsample: How assigned attractiveness differs (relatively) between the samples – model with GMM, Skin L*, and Age.

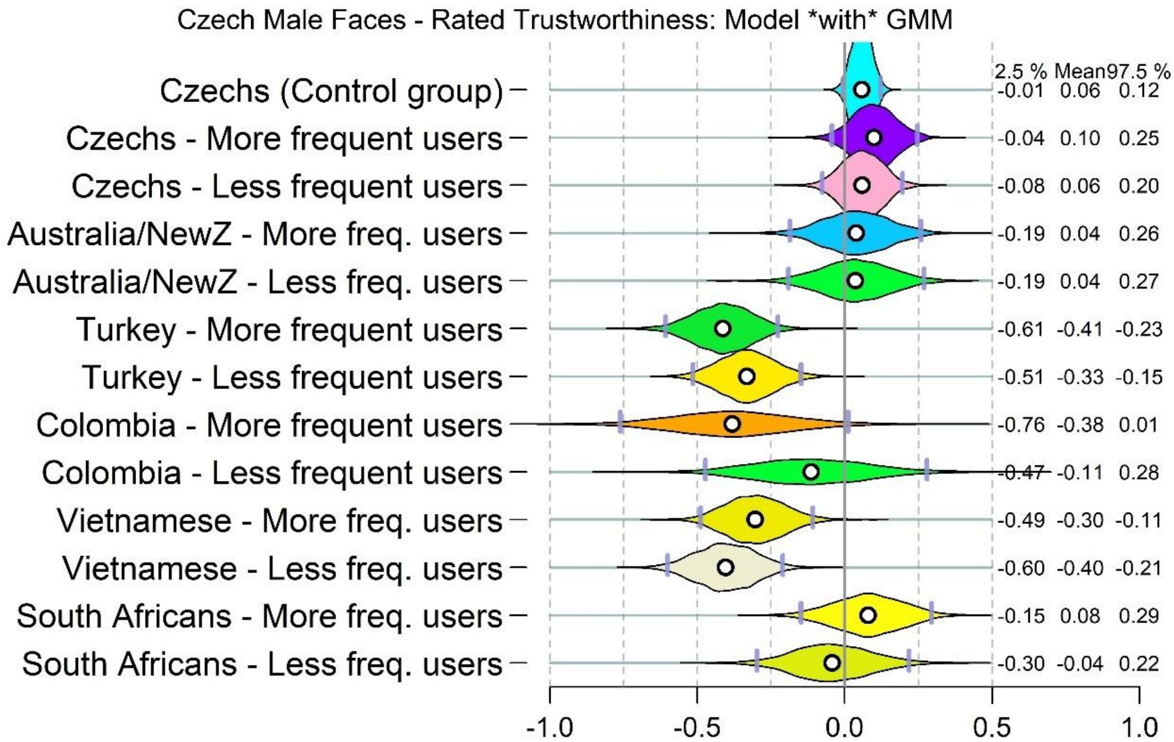


Figure S24: Male subsample: How assigned trustworthiness differs (relatively) between the samples; model with GMM, Skin L*, and Age.

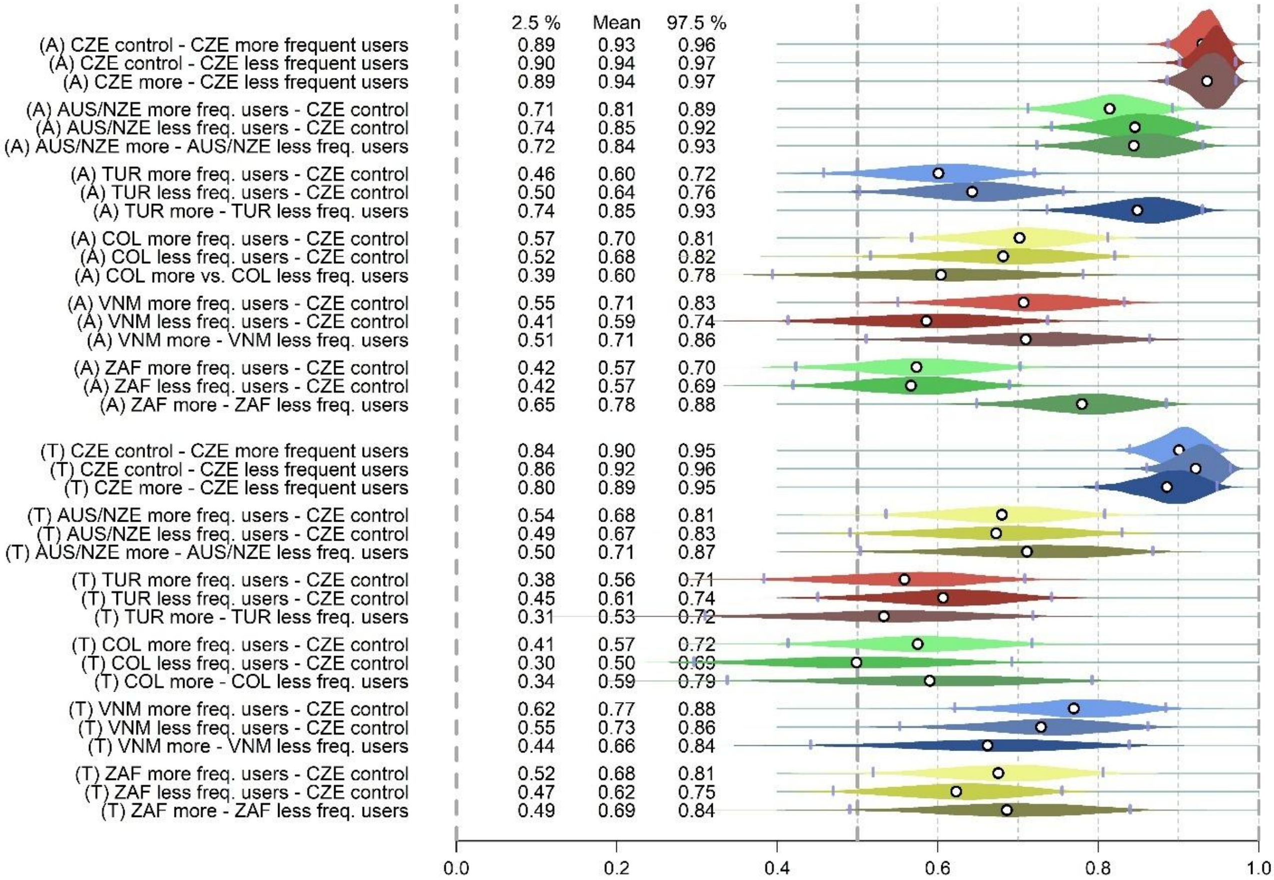


Figure S25: Male subsample: Correlations between attractiveness (upper panel), respectively, trustworthiness (lower panel), ratings in different groups; Model with GMM.

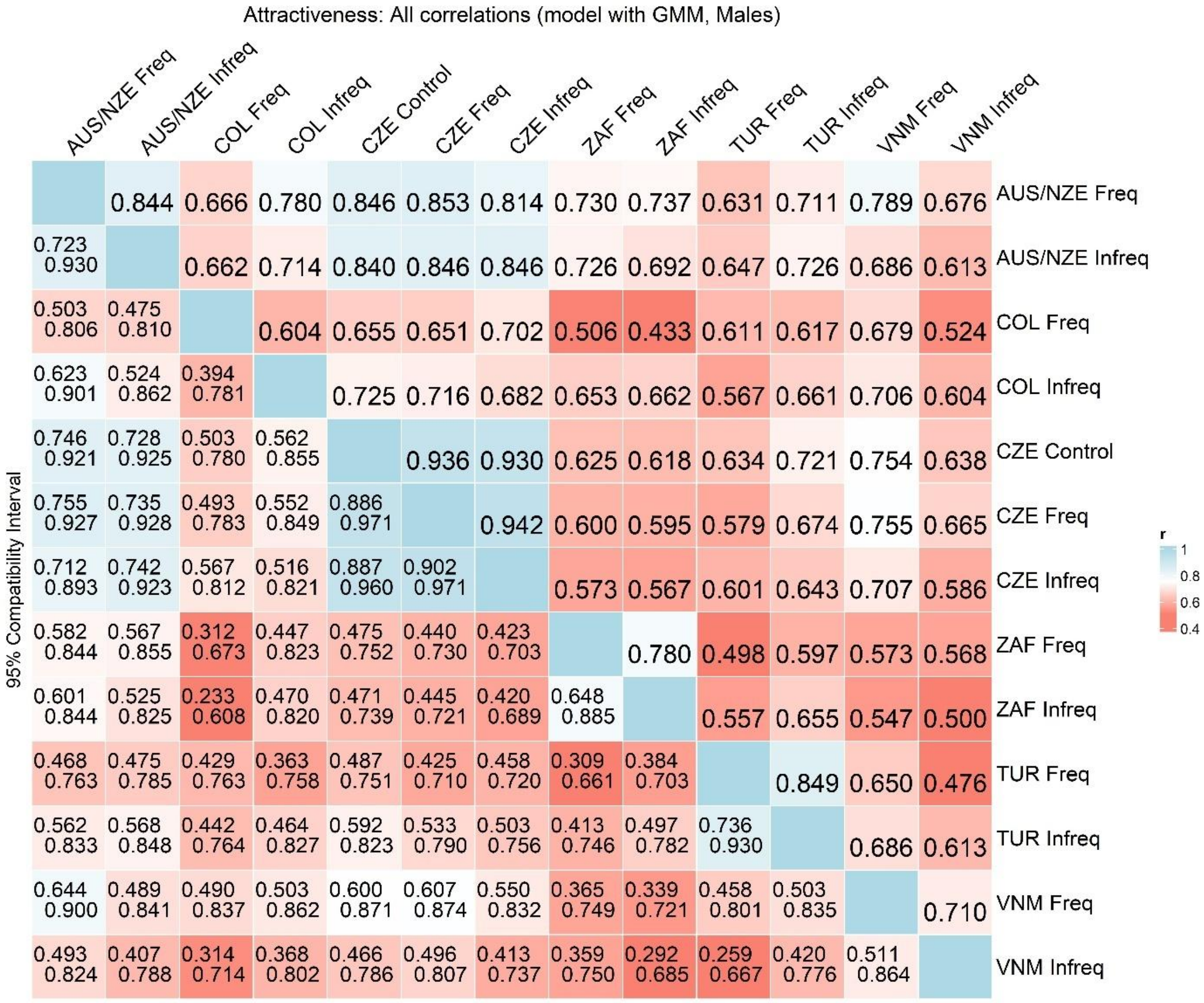


Figure S26. Male subsample: Correlation heatmap for Attractiveness. Above diagonal are means of the estimates, below diagonal, 95% percentile-based Compatibility Intervals are drawn. Model with GMM.

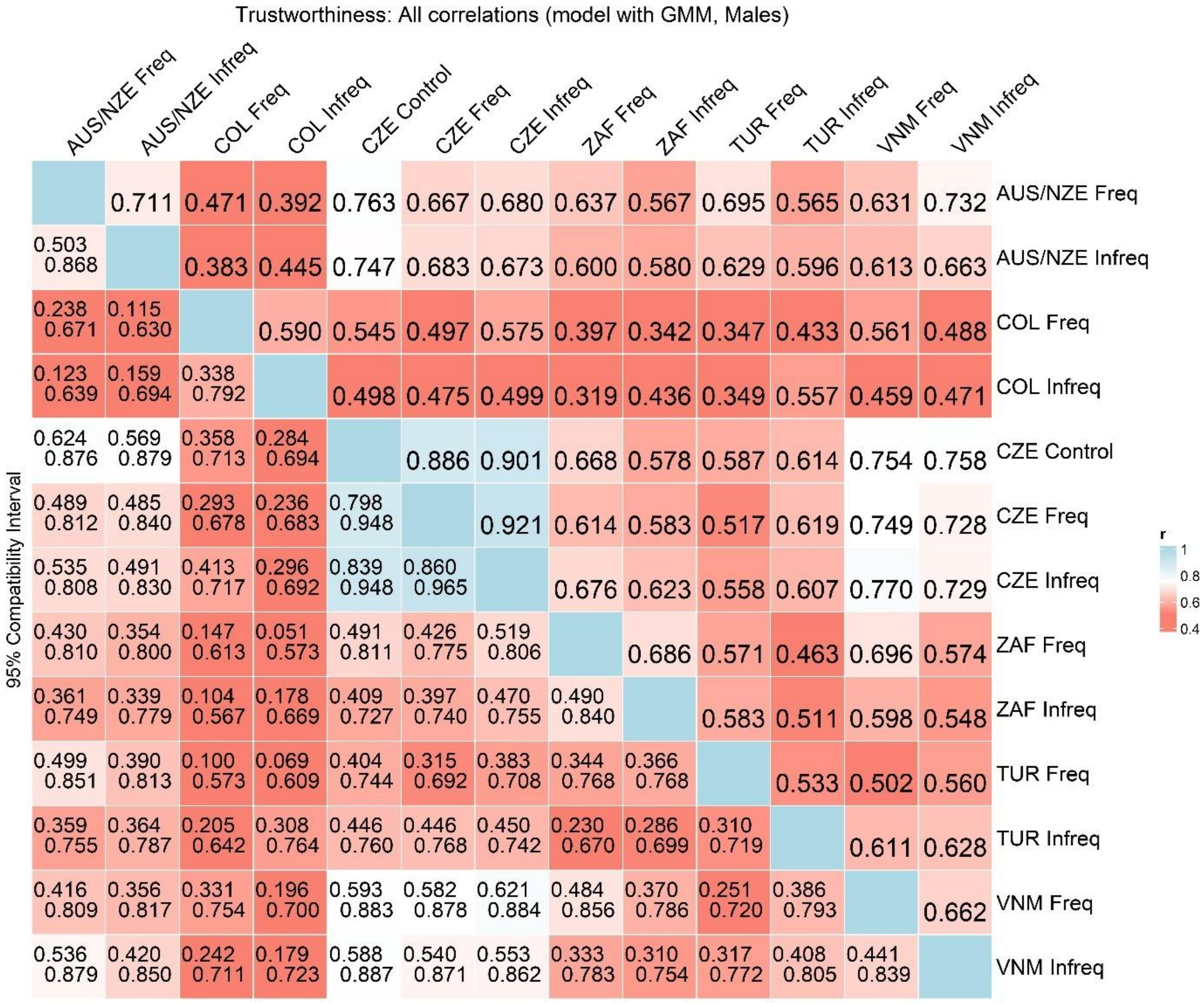
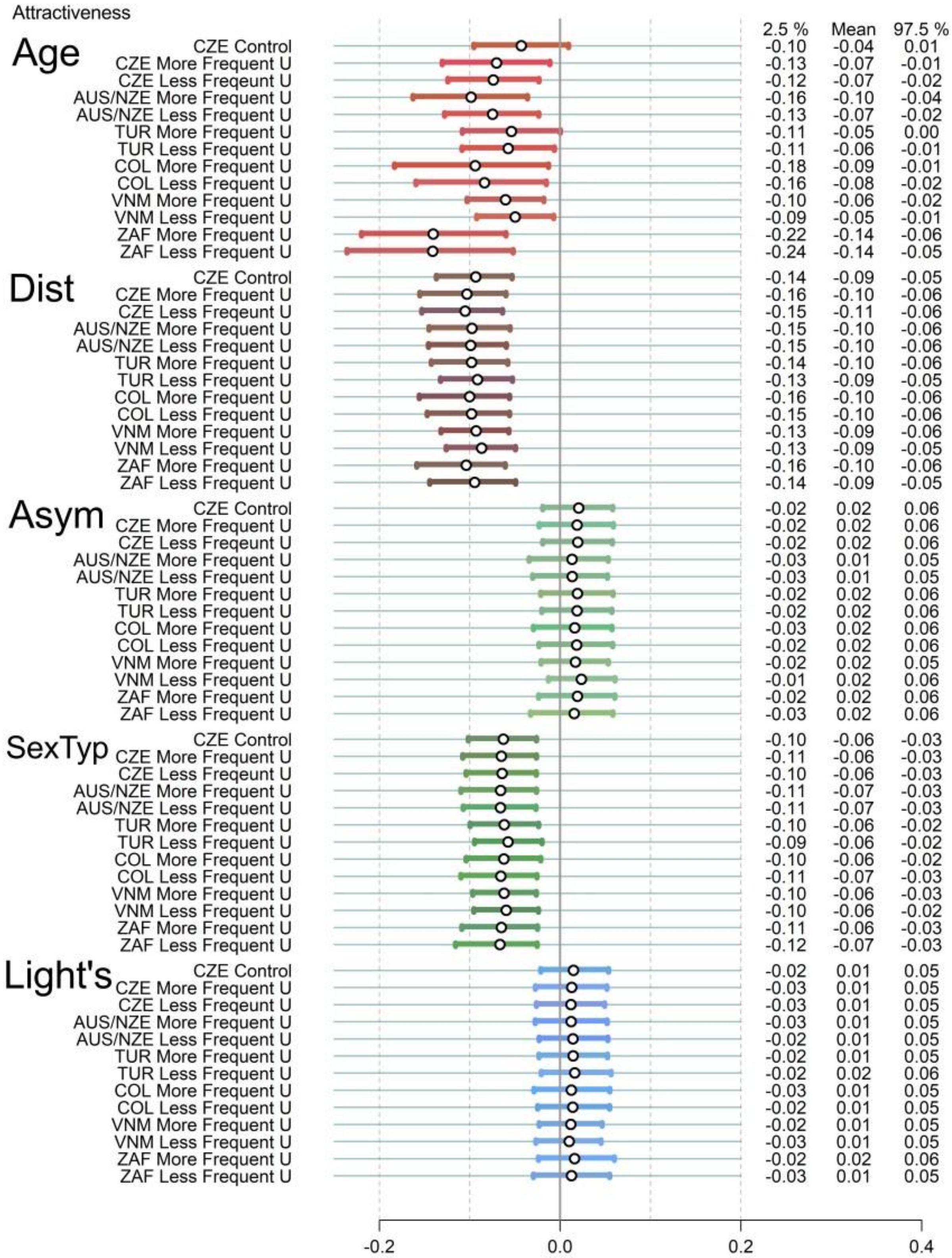
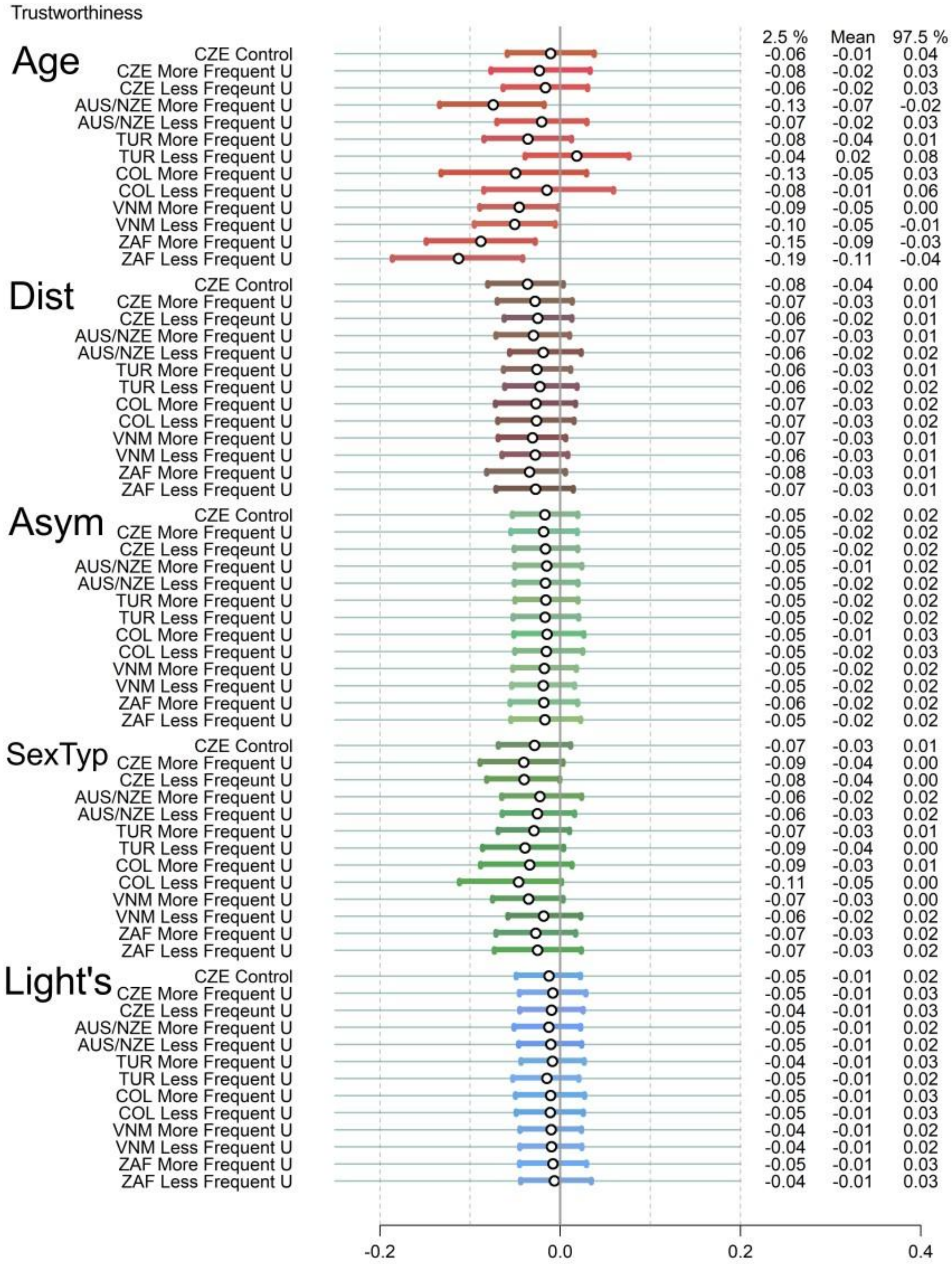


Figure S27. Male subsample: Correlation heatmap for Trustworthiness. Above diagonal are means of the estimates, below diagonal, 95% percentile-based Compatibility Intervals are drawn. Model with GMM.



	2.5 %	Mean	97.5 %
Age CZE Control	-0.10	-0.04	0.01
CZE More Frequent U	-0.13	-0.07	-0.01
CZE Less Freqeunt U	-0.12	-0.07	-0.02
AUS/NZE More Frequent U	-0.16	-0.10	-0.04
AUS/NZE Less Frequent U	-0.13	-0.07	-0.02
TUR More Frequent U	-0.11	-0.05	0.00
TUR Less Frequent U	-0.11	-0.06	-0.01
COL More Frequent U	-0.18	-0.09	-0.01
COL Less Frequent U	-0.16	-0.08	-0.02
VNM More Frequent U	-0.10	-0.06	-0.02
VNM Less Frequent U	-0.09	-0.05	-0.01
ZAF More Frequent U	-0.22	-0.14	-0.06
ZAF Less Frequent U	-0.24	-0.14	-0.05
Dist CZE Control	-0.14	-0.09	-0.05
CZE More Frequent U	-0.16	-0.10	-0.06
CZE Less Freqeunt U	-0.15	-0.11	-0.06
AUS/NZE More Frequent U	-0.15	-0.10	-0.06
AUS/NZE Less Frequent U	-0.15	-0.10	-0.06
TUR More Frequent U	-0.14	-0.10	-0.06
TUR Less Frequent U	-0.13	-0.09	-0.05
COL More Frequent U	-0.16	-0.10	-0.06
COL Less Frequent U	-0.15	-0.10	-0.06
VNM More Frequent U	-0.13	-0.09	-0.06
VNM Less Frequent U	-0.13	-0.09	-0.05
ZAF More Frequent U	-0.16	-0.10	-0.06
ZAF Less Frequent U	-0.14	-0.09	-0.05
Asym CZE Control	-0.02	0.02	0.06
CZE More Frequent U	-0.02	0.02	0.06
CZE Less Freqeunt U	-0.02	0.02	0.06
AUS/NZE More Frequent U	-0.03	0.01	0.05
AUS/NZE Less Frequent U	-0.03	0.01	0.05
TUR More Frequent U	-0.02	0.02	0.06
TUR Less Frequent U	-0.02	0.02	0.06
COL More Frequent U	-0.03	0.02	0.06
COL Less Frequent U	-0.02	0.02	0.06
VNM More Frequent U	-0.02	0.02	0.05
VNM Less Frequent U	-0.01	0.02	0.06
ZAF More Frequent U	-0.02	0.02	0.06
ZAF Less Frequent U	-0.03	0.02	0.06
SexTyp CZE Control	-0.10	-0.06	-0.03
CZE More Frequent U	-0.11	-0.06	-0.03
CZE Less Freqeunt U	-0.10	-0.06	-0.03
AUS/NZE More Frequent U	-0.11	-0.07	-0.03
AUS/NZE Less Frequent U	-0.11	-0.07	-0.03
TUR More Frequent U	-0.10	-0.06	-0.02
TUR Less Frequent U	-0.09	-0.06	-0.02
COL More Frequent U	-0.10	-0.06	-0.02
COL Less Frequent U	-0.11	-0.07	-0.03
VNM More Frequent U	-0.10	-0.06	-0.03
VNM Less Frequent U	-0.10	-0.06	-0.02
ZAF More Frequent U	-0.11	-0.06	-0.03
ZAF Less Frequent U	-0.12	-0.07	-0.03
Light's CZE Control	-0.02	0.01	0.05
CZE More Frequent U	-0.03	0.01	0.05
CZE Less Freqeunt U	-0.03	0.01	0.05
AUS/NZE More Frequent U	-0.03	0.01	0.05
AUS/NZE Less Frequent U	-0.02	0.01	0.05
TUR More Frequent U	-0.02	0.01	0.05
TUR Less Frequent U	-0.02	0.02	0.06
COL More Frequent U	-0.03	0.01	0.05
COL Less Frequent U	-0.02	0.01	0.05
VNM More Frequent U	-0.02	0.01	0.05
VNM Less Frequent U	-0.03	0.01	0.05
ZAF More Frequent U	-0.02	0.02	0.06
ZAF Less Frequent U	-0.03	0.01	0.05

Figure S28. Male subsample: Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived <u>attractiveness</u>, rated by different groups. Age = self-reported age of the stimuli; Dist = position of an individual stimuli faces among all the same-sex faces; Asym = facial asymmetry; SexTyp = measured sexual shape dimorphism; Light's = measured skin lightness (CIELab L*)



	2.5 %	Mean	97.5 %
Age CZE Control	-0.06	-0.01	0.04
CZE More Frequent U	-0.08	-0.02	0.03
CZE Less Freqeunt U	-0.06	-0.02	0.03
AUS/NZE More Frequent U	-0.13	-0.07	-0.02
AUS/NZE Less Frequent U	-0.07	-0.02	0.03
TUR More Frequent U	-0.08	-0.04	0.01
TUR Less Frequent U	-0.04	0.02	0.08
COL More Frequent U	-0.13	-0.05	0.03
COL Less Frequent U	-0.08	-0.01	0.06
VNM More Frequent U	-0.09	-0.05	0.00
VNM Less Frequent U	-0.10	-0.05	-0.01
ZAF More Frequent U	-0.15	-0.09	-0.03
ZAF Less Frequent U	-0.19	-0.11	-0.04
Dist CZE Control	-0.08	-0.04	0.00
CZE More Frequent U	-0.07	-0.03	0.01
CZE Less Freqeunt U	-0.06	-0.02	0.01
AUS/NZE More Frequent U	-0.07	-0.03	0.01
AUS/NZE Less Frequent U	-0.06	-0.02	0.02
TUR More Frequent U	-0.06	-0.03	0.01
TUR Less Frequent U	-0.06	-0.02	0.02
COL More Frequent U	-0.07	-0.03	0.02
COL Less Frequent U	-0.07	-0.03	0.02
VNM More Frequent U	-0.07	-0.03	0.01
VNM Less Frequent U	-0.06	-0.03	0.01
ZAF More Frequent U	-0.08	-0.03	0.01
ZAF Less Frequent U	-0.07	-0.03	0.01
Asym CZE Control	-0.05	-0.02	0.02
CZE More Frequent U	-0.05	-0.02	0.02
CZE Less Freqeunt U	-0.05	-0.02	0.02
AUS/NZE More Frequent U	-0.05	-0.01	0.02
AUS/NZE Less Frequent U	-0.05	-0.02	0.02
TUR More Frequent U	-0.05	-0.02	0.02
TUR Less Frequent U	-0.05	-0.02	0.02
COL More Frequent U	-0.05	-0.01	0.03
COL Less Frequent U	-0.05	-0.02	0.03
VNM More Frequent U	-0.05	-0.02	0.02
VNM Less Frequent U	-0.05	-0.02	0.02
ZAF More Frequent U	-0.06	-0.02	0.02
ZAF Less Frequent U	-0.05	-0.02	0.02
SexTyp CZE Control	-0.07	-0.03	0.01
CZE More Frequent U	-0.09	-0.04	0.00
CZE Less Freqeunt U	-0.08	-0.04	0.00
AUS/NZE More Frequent U	-0.06	-0.02	0.02
AUS/NZE Less Frequent U	-0.06	-0.03	0.02
TUR More Frequent U	-0.07	-0.03	0.01
TUR Less Frequent U	-0.09	-0.04	0.00
COL More Frequent U	-0.09	-0.03	0.01
COL Less Frequent U	-0.11	-0.05	0.00
VNM More Frequent U	-0.07	-0.03	0.00
VNM Less Frequent U	-0.06	-0.02	0.02
ZAF More Frequent U	-0.07	-0.03	0.02
ZAF Less Frequent U	-0.07	-0.03	0.02
Light's CZE Control	-0.05	-0.01	0.02
CZE More Frequent U	-0.05	-0.01	0.03
CZE Less Freqeunt U	-0.04	-0.01	0.03
AUS/NZE More Frequent U	-0.05	-0.01	0.02
AUS/NZE Less Frequent U	-0.05	-0.01	0.02
TUR More Frequent U	-0.04	-0.01	0.03
TUR Less Frequent U	-0.05	-0.01	0.02
COL More Frequent U	-0.05	-0.01	0.03
COL Less Frequent U	-0.05	-0.01	0.03
VNM More Frequent U	-0.04	-0.01	0.02
VNM Less Frequent U	-0.04	-0.01	0.02
ZAF More Frequent U	-0.05	-0.01	0.03
ZAF Less Frequent U	-0.04	-0.01	0.03

Figure S29. Male subsample: Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived <u>trustworthiness</u>, rated by different groups.

Part 4: ATTR/TRUSTW/WITHOUT-GMM; 25 median ppl out

Participants standing too close to the median are excluded. Exclusion criteria:

- Mark participants who were in a 25% band around median for each of the scales ("Centre") or not ("Sides").
- As a result, there will be three vectors of "Centres" and "Sides".
- Combine them.
- Cut out those who have at least two "Centres".
- Rerun selected models with this reduced dataset

Note: We run only the models without GMM.

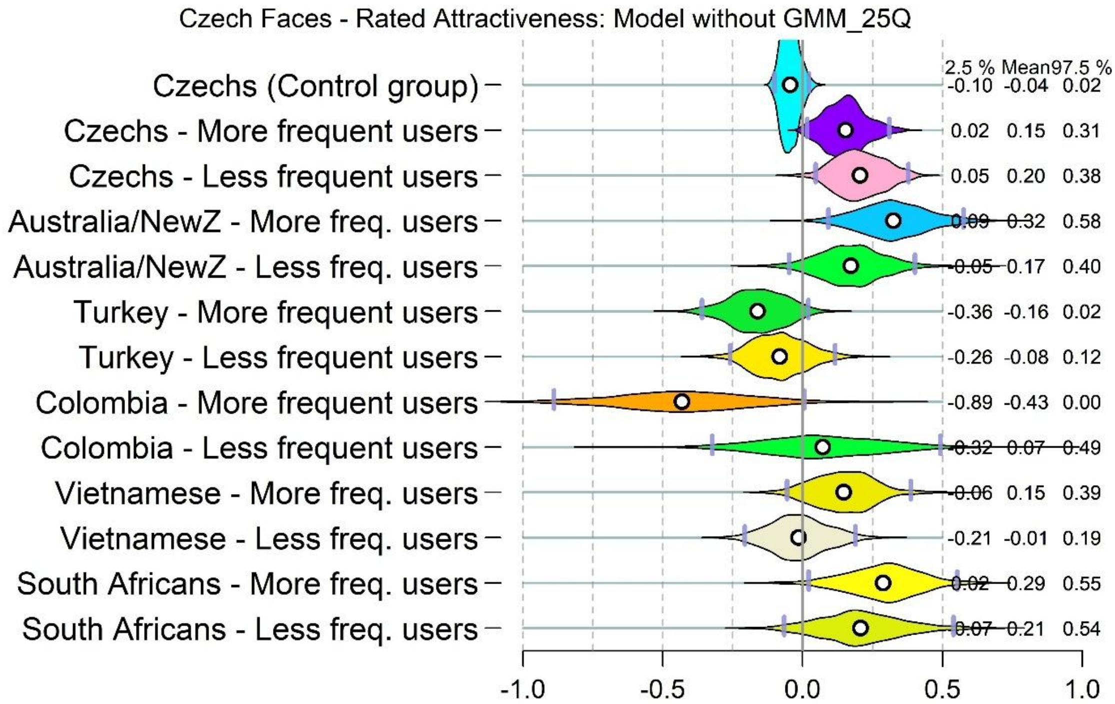


Figure S30: How assigned attractiveness differs (relatively) between the samples – model without GMM, Skin L* and Age, centre-scoring raters excluded.

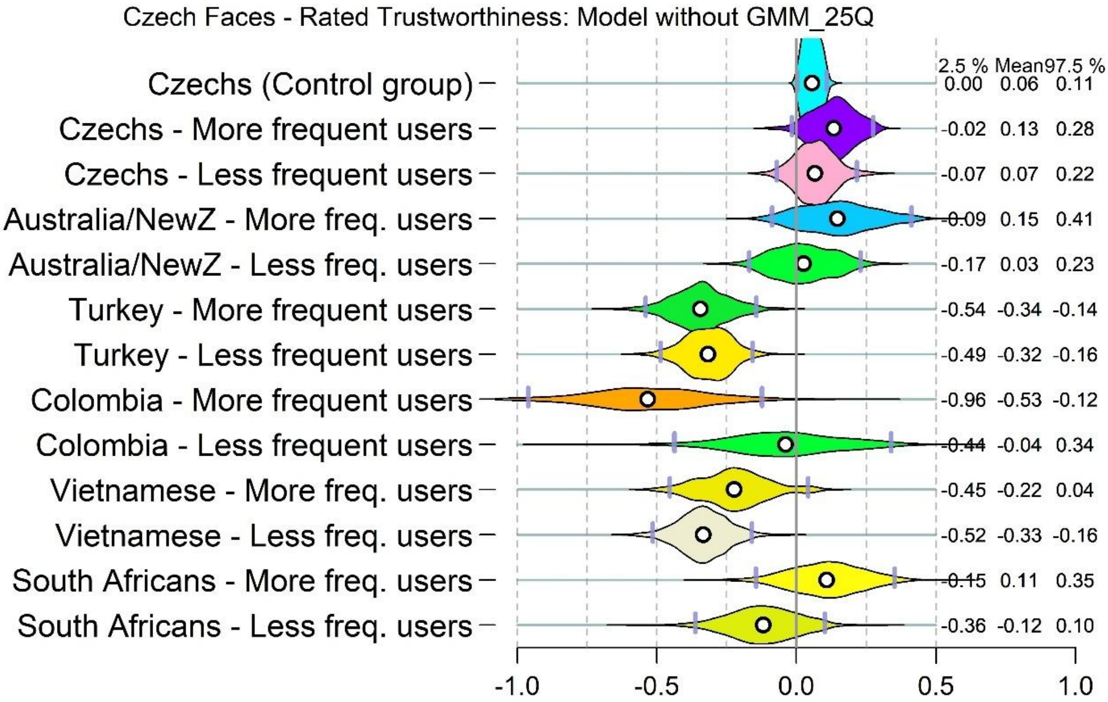


Figure S31: How assigned <u>trustworthiness</u> differs (relatively) between the samples; model without GMM, centre-scoring raters excluded.

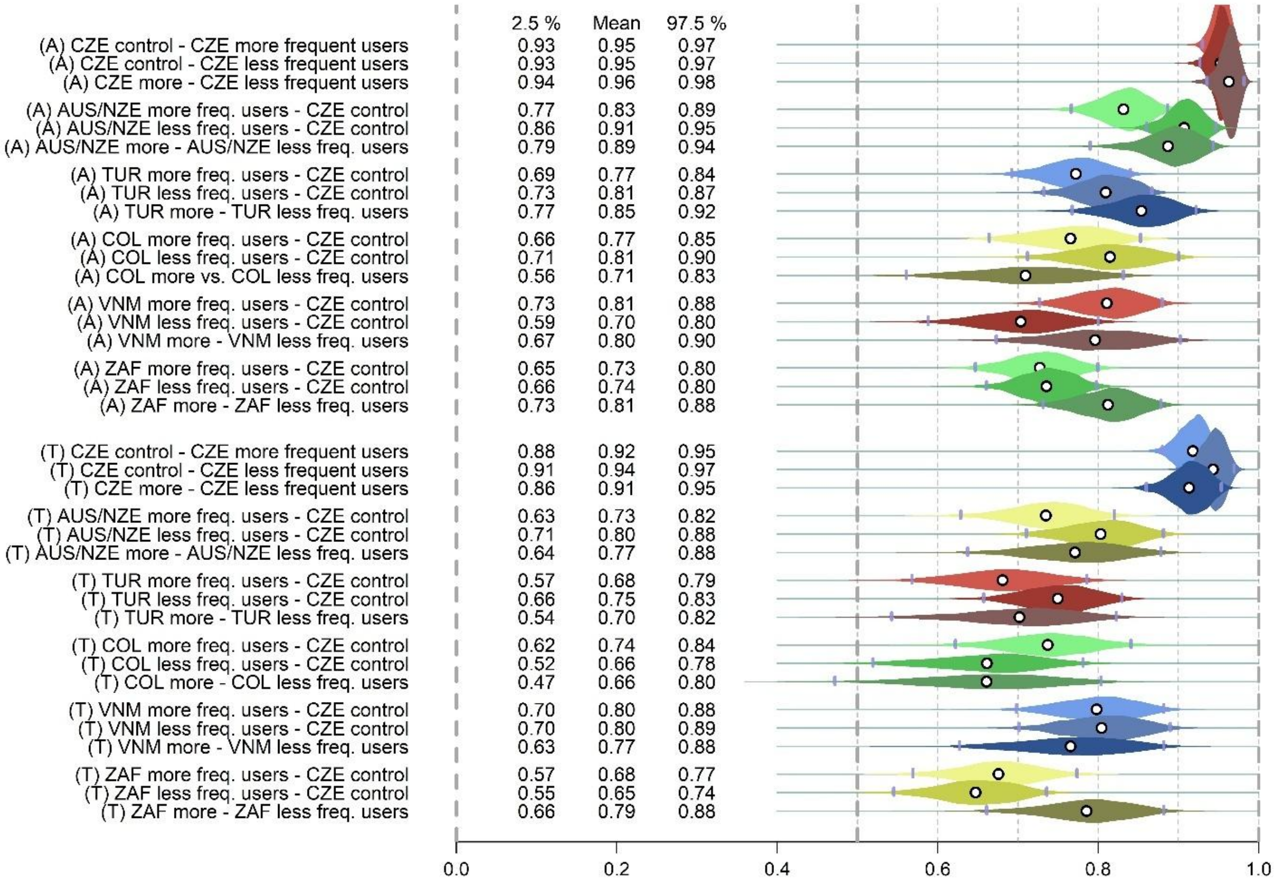


Figure S32: Correlations between <u>attractiveness (upper panel, marked with [A])</u>, respectively, <u>trustworthiness (lower panel, marked with [T])</u>, ratings in different groups; Model without GMM, centre-scoring raters excluded.

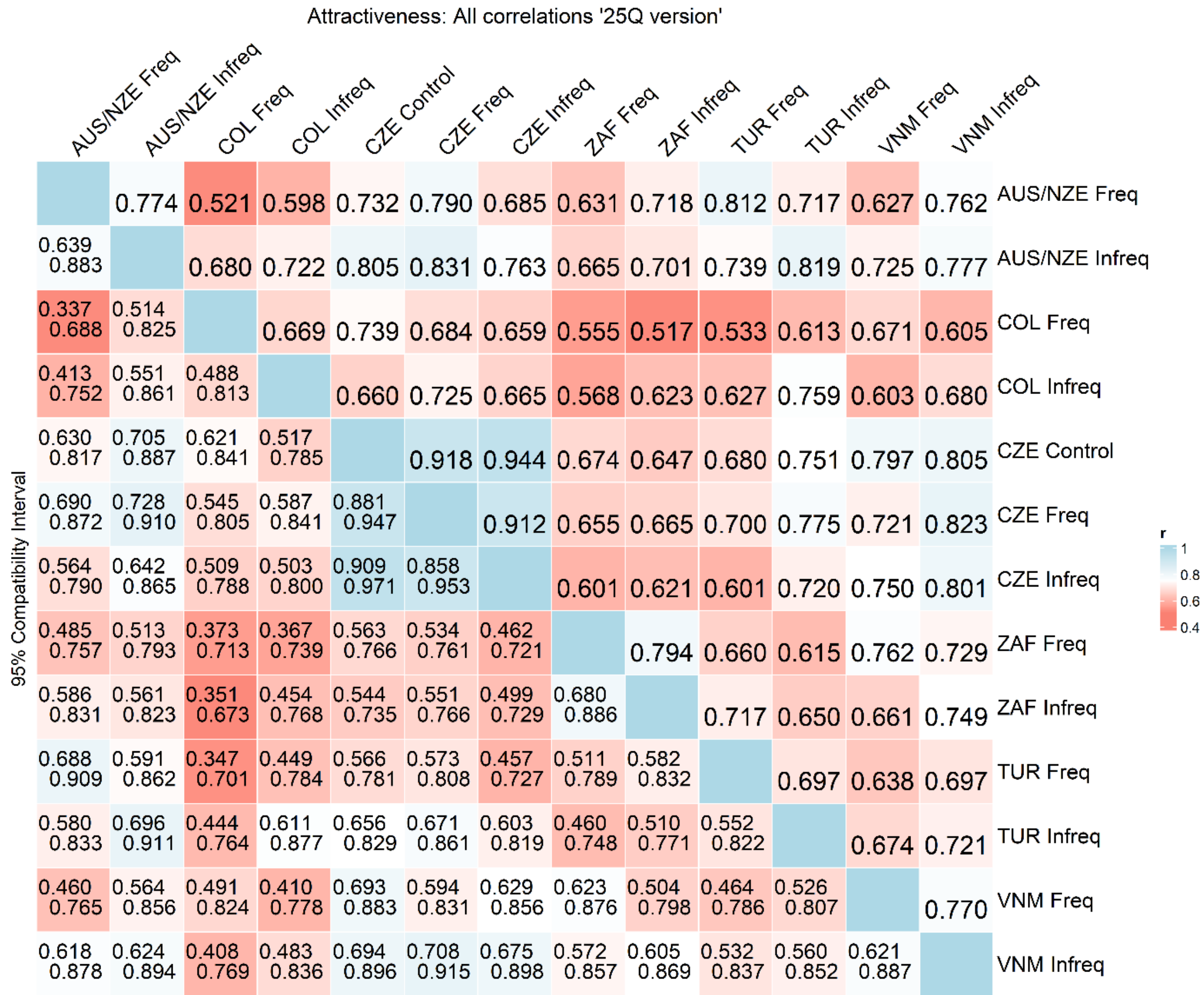


Figure S33. Correlation heatmap for Attractiveness. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn. Model without GMM, centre-scoring raters excluded.

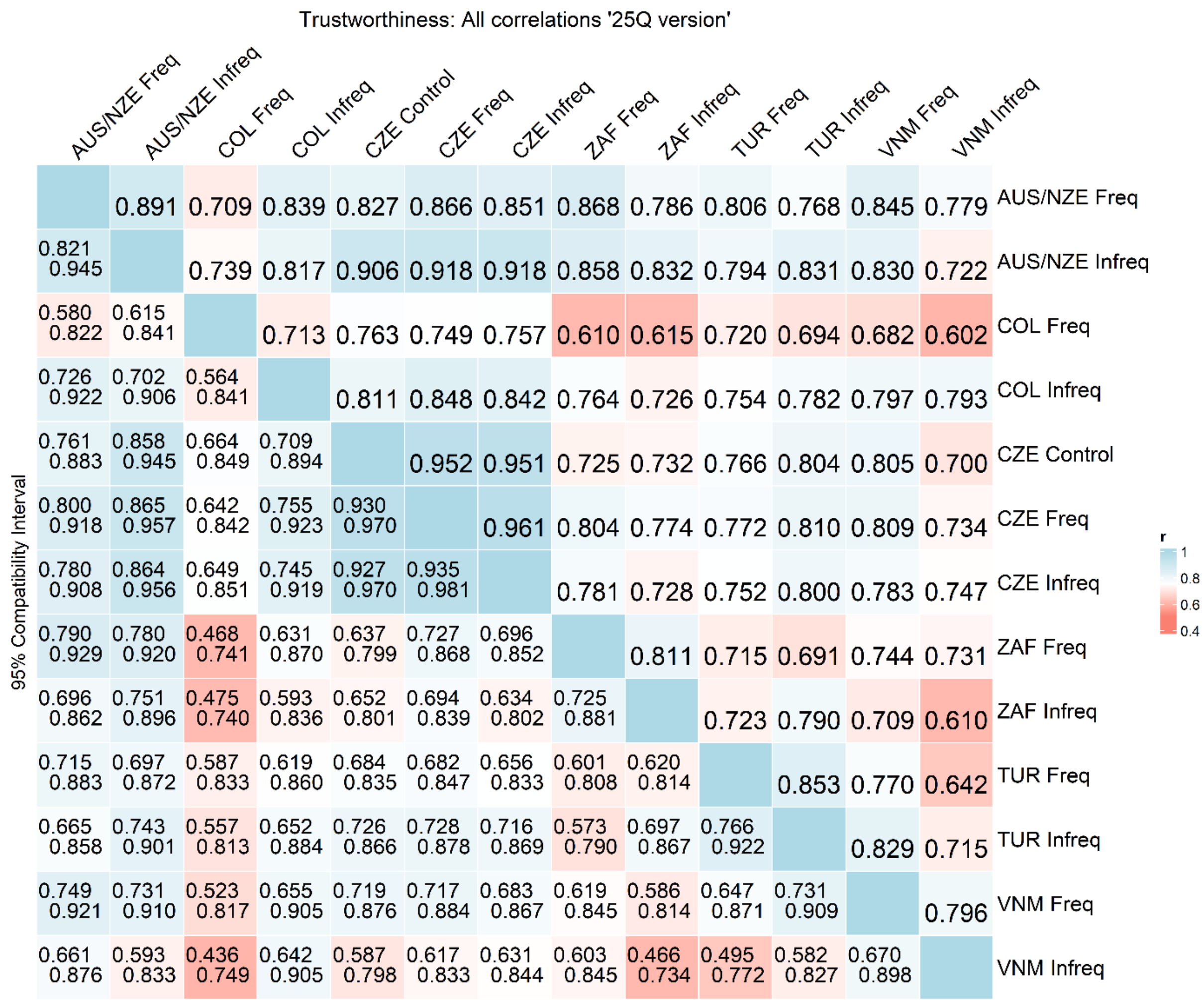


Figure S34. Correlation heatmap for Trustworthiness. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn. Model without GMM, centre-scoring raters excluded.

NOTE for VF: Also here were the swapped scales corrected.

Part 5: Dominance

5.1. Dominance: model without morphometric predictors (preregistered analysis)

Note: we also run a model without the varying terms for faces. As before, this model was found to perform worse according to out-of-sample predictive accuracy.

```
                WAIC     SE  dWAIC    dSE  pWAIC weight
M_lik_1_DOM 159053.2 354.34    0.0     NA 1627.3      1
M_lik_2_DOM 169023.0 329.23 9969.8 201.81  603.0      0
# this is how it looks like when the first ("larger") model is supported.
# The larger model = model with correlations estimated across samples (M_lik_1_DOM)
---------
```

```
M_lik_1_DOM <- ulam(alist(

  # Multivariate normal for Trustworthiness and Attractiveness
  DomRating ~ normal(muD, sigmaD),

  # Mean structure for Trustworthiness and Attractiveness
  muD <- aD + a_group_D[FSMUi]
  + z_rNV_D[rater] * sigma_rater_D
  + f_per_group_D[face,FSMUi],

  # Priors for Attractiveness and Trustworthiness intercepts
  aD ~ dnorm(0, 0.5),  # Trustworthiness

  a_group_D[FSMUi] ~ dnorm(0, 0.5),

  # Non-centered parameterization for rater effects
  z_rNV_D[rater] ~ dnorm(0, 1),  # Trustworthiness latent variable

  sigma_rater_D ~ dexp(1),  # Trustworthiness

  gq> vector[rater]:a_rNV_D <<- aD + z_rNV_D * sigma_rater_D,  # Generate rater effects for
Trustworthiness

  # Priors for the multivariate normal distribution for face intercepts across groups
  transpars> matrix[face, 13]:f_per_group_D <- compose_noncentered(sigma_FSMUi_D,
L_Rho_FSMUi_D, z_FSMUi_D),
  cholesky_factor_corr[13]:L_Rho_FSMUi_D ~ lkj_corr_cholesky(2),
  matrix[13, face]:z_FSMUi_D ~ normal(0, 1),
  vector[13]:sigma_FSMUi_D ~ dexp(1),

  gq> matrix[13, 13]:Rho_FSMUi_D <<- Chol_to_Corr(L_Rho_FSMUi_D),

  # Covariance between Attractiveness and Trustworthiness
  sigmaD ~ dexp(1)

), data=D_DOM, iter=500, sample=T, cores=14, chains=14, log_lik = T)
```

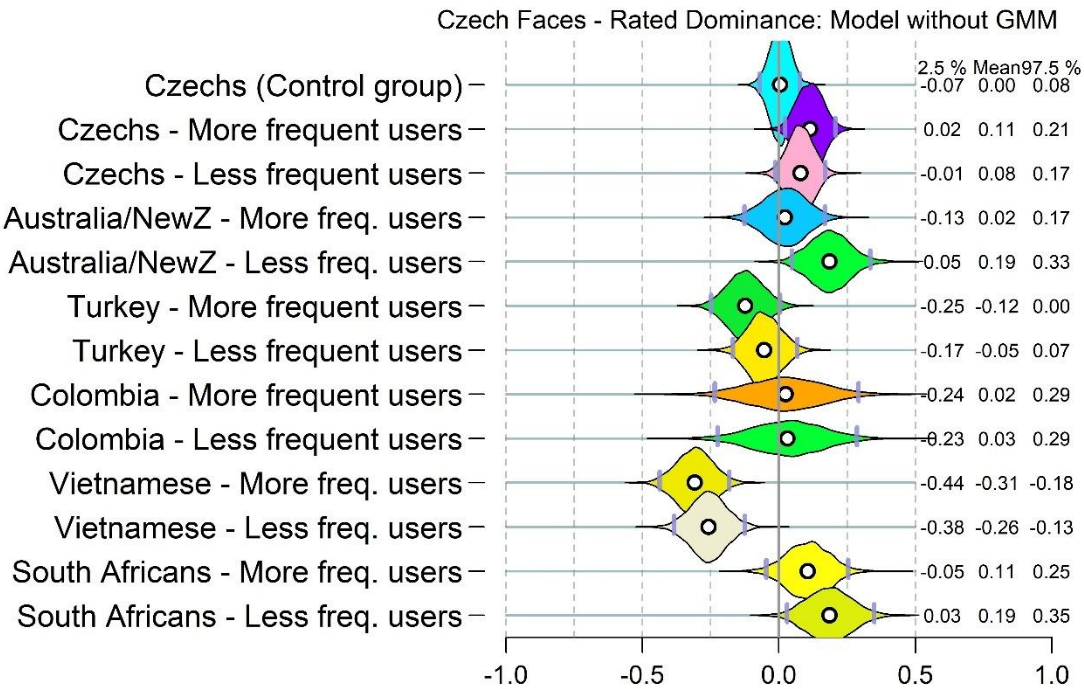


Figure S35: How assigned <u>dominance</u> differs (relatively) between the samples – model without GMM, L*, and Age.

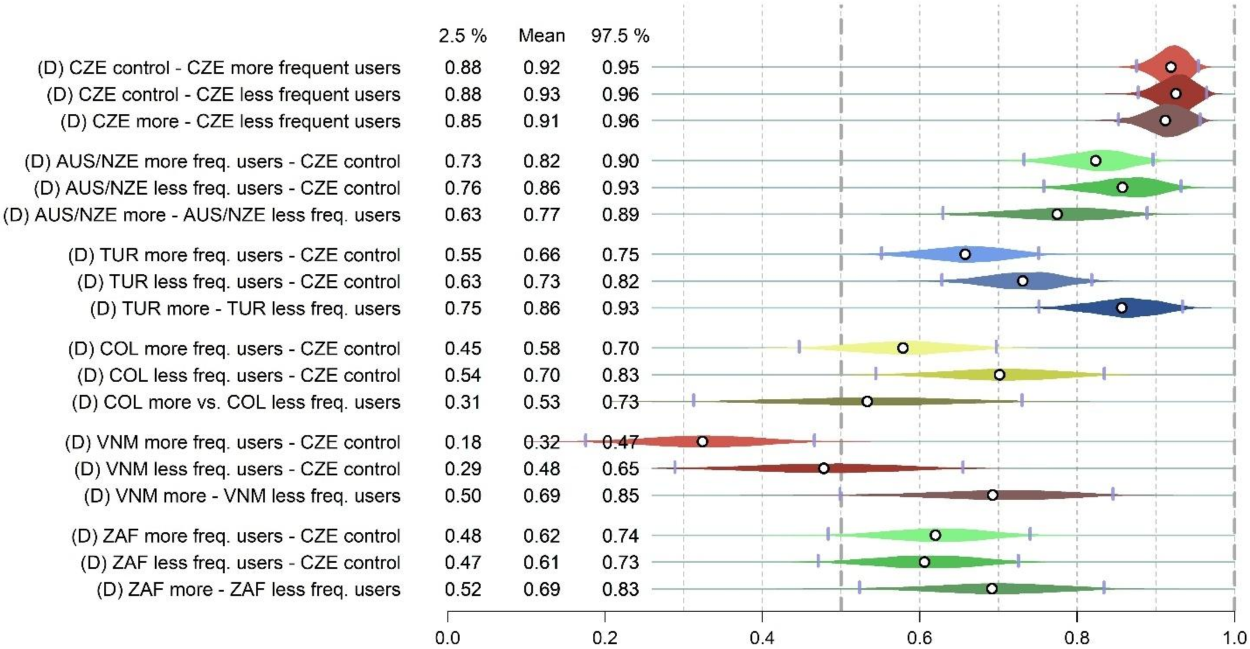


Figure S36: Correlations between dominance ratings by different raters' samples. Model without GMM.

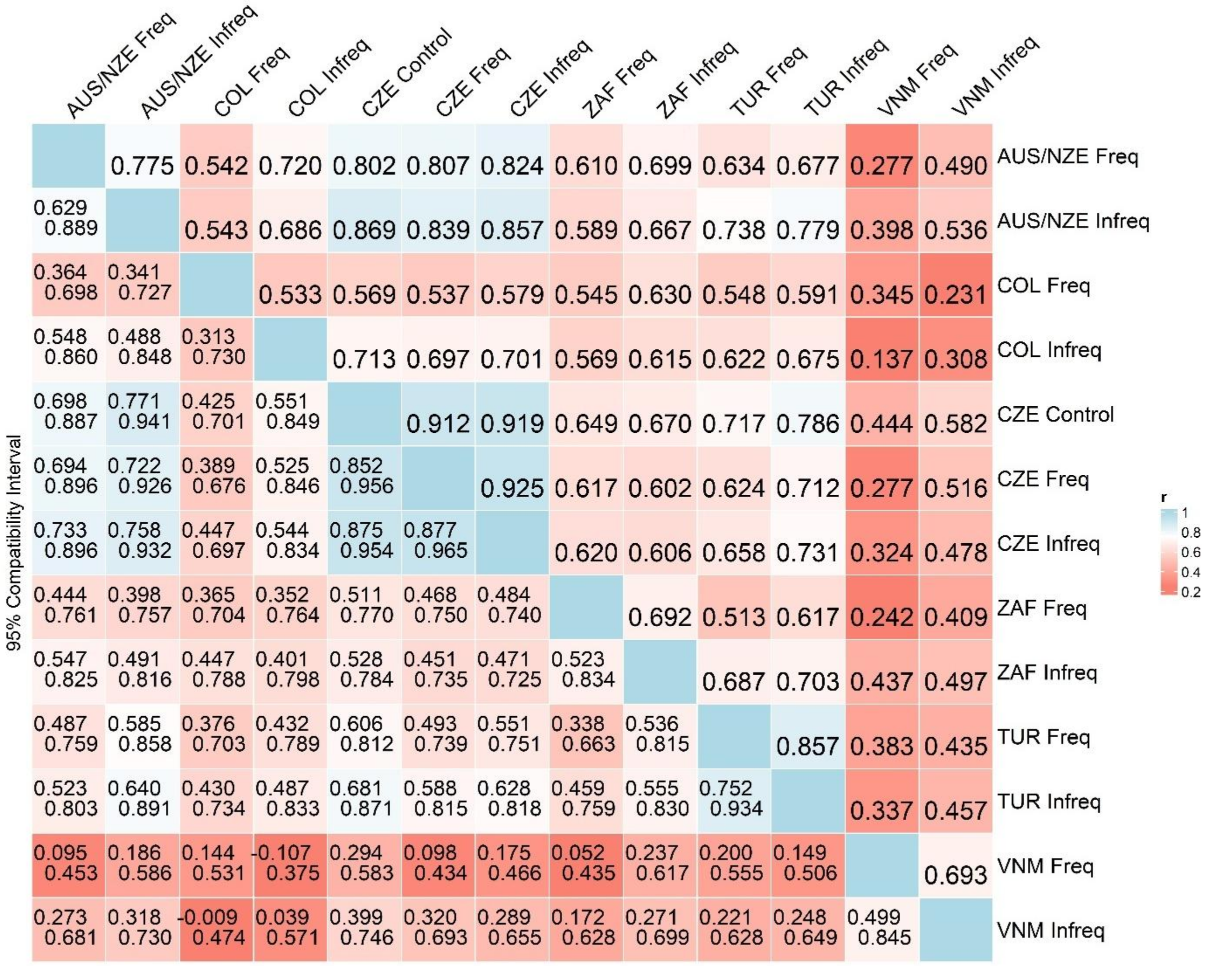


Figure S37: Correlation heatmap for dominance. Above diagonal are means of the estimates, below diagonal, 95 % percentile-based Compatibility Intervals are drawn. Model without GMM.

5.2. Dominance: model with morphometric predictors, L*, and Age

```
M3_DOM <- ulam(alist(

  # Multivariate normal for Trustworthiness and Attractiveness
  DomRating ~ normal(muD, sigmaD),

  # Mean structure for Trustworthiness and Attractiveness
  muD <- aD + a_group_D[FSMUi]
  + z_rNV_D[rater] * sigma_rater_D
  + f_per_group_D[face,FSMUi]
  + (b_age_D + f_per_group_pr_D[FSMUi, 1]) * Age
  + (b_dist_D + f_per_group_pr_D[FSMUi, 2]) * dist
  + (b_FA_D + f_per_group_pr_D[FSMUi, 3]) * FA
  + (b_sshd_D + f_per_group_pr_D[FSMUi, 4]) * sshd
  + (b_L_D + f_per_group_pr_D[FSMUi,5]) * L,

  # Priors for Attractiveness and Trustworthiness intercepts
  aD ~ dnorm(0, 0.5),  # Trustworthiness

  # Priors for Attractiveness and Trustworthiness slopes
  b_age_D ~ dnorm(0, 0.3),
  b_dist_D ~ dnorm(0, 0.3),
  b_FA_D ~ dnorm(0, 0.3),
  b_sshd_D ~ dnorm(0, 0.3),
  b_L_D ~ dnorm(0, 0.3),

  a_group_D[FSMUi] ~ dnorm(0, 0.5),

  # Non-centered parameterization for rater effects
  z_rNV_D[rater] ~ dnorm(0, 1),  # Trustworthiness latent variable

  sigma_rater_D ~ dexp(1),  # Trustworthiness

  gq> vector[rater]:a_rNV_D <<- aD + z_rNV_D * sigma_rater_D,  # Generate rater effects for
Trustworthiness

  # Varying effects for Dominance morpho-predictors
  transpars> matrix[FSMUi, 5]:f_per_group_pr_D <- compose_noncentered(sigma_pr_D, L_Rho_pr_D, z_pr_D),
  cholesky_factor_corr[5]:L_Rho_pr_D ~ lkj_corr_cholesky(2),
  matrix[5, FSMUi]:z_pr_D ~ normal(0, 1),
  vector[5]:sigma_pr_D ~ dexp(1),

  gq> matrix[5, 5]:Rho_pr_D <<- Chol_to_Corr(L_Rho_pr_D),

  # Priors for the multivariate normal distribution for face intercepts across groups
  transpars> matrix[face, 13]:f_per_group_D <- compose_noncentered(sigma_FSMUi_D,
L_Rho_FSMUi_D, z_FSMUi_D),
  cholesky_factor_corr[13]:L_Rho_FSMUi_D ~ lkj_corr_cholesky(2),
  matrix[13, face]:z_FSMUi_D ~ normal(0, 1),
  vector[13]:sigma_FSMUi_D ~ dexp(1),

  gq> matrix[13, 13]:Rho_FSMUi_D <<- Chol_to_Corr(L_Rho_FSMUi_D),

  # Covariance between Attractiveness and Trustworthiness
  sigmaD ~ dexp(1)

), data=D_DOM, iter=750, sample=T, cores=14, chains=14)
```

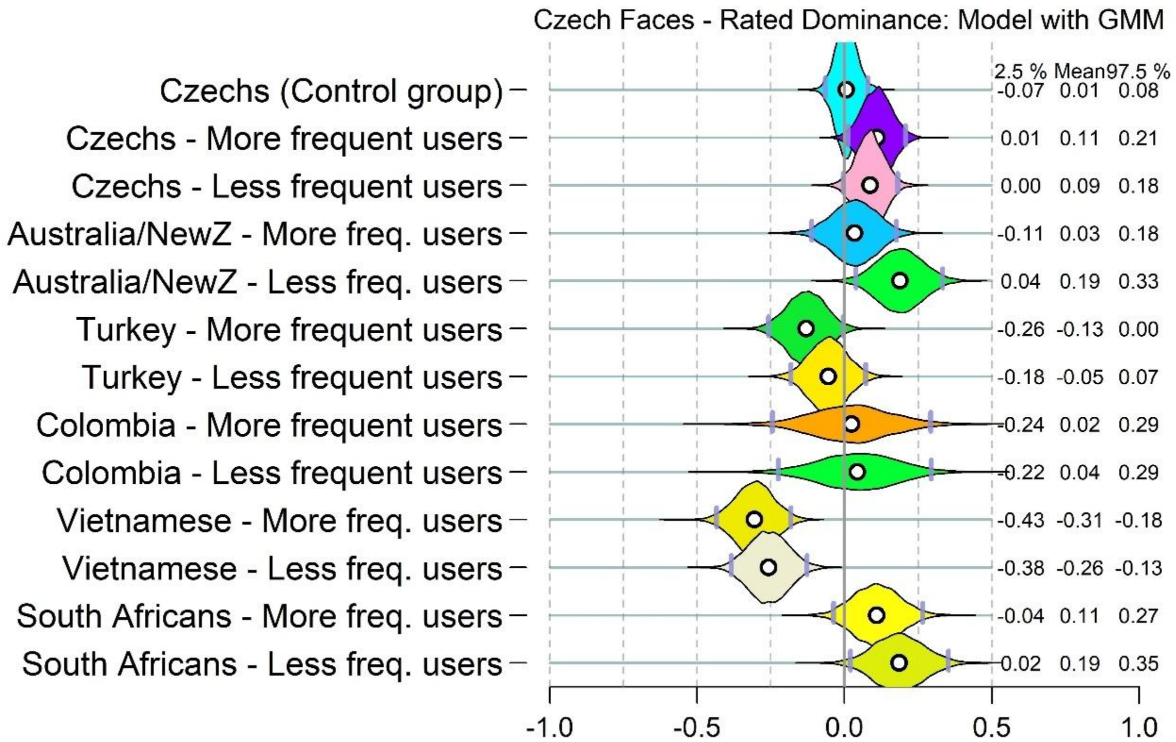


Figure S38: How assigned dominance differs (relatively) between the samples – model with GMM, L*, and Age.

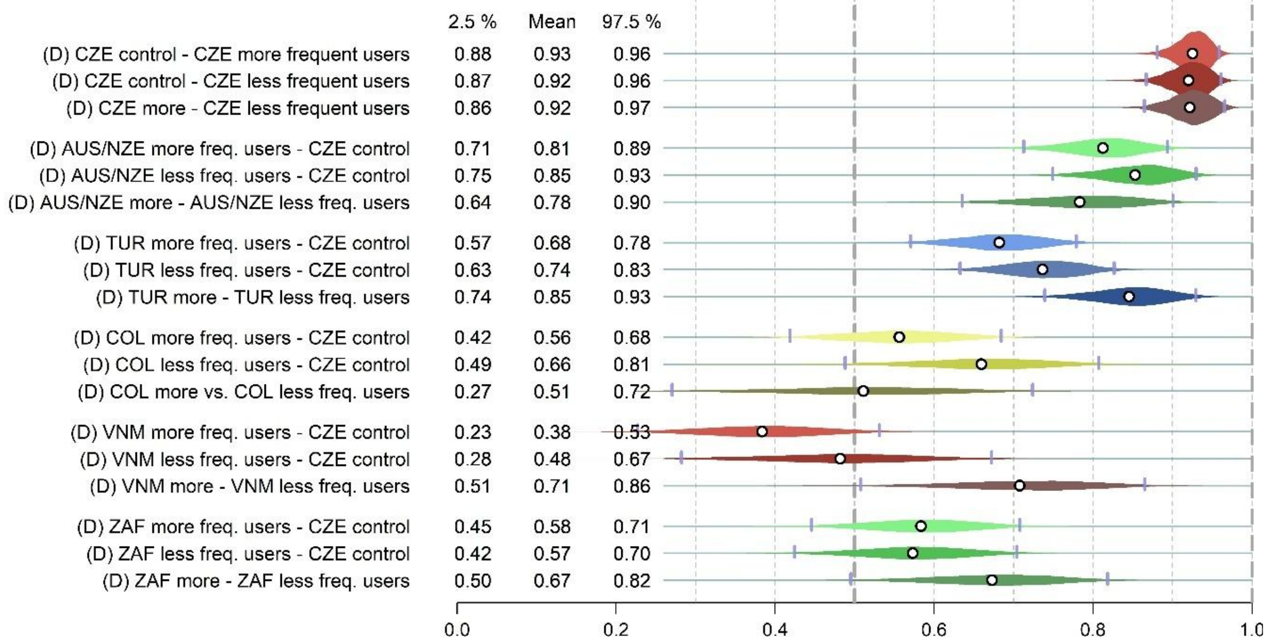


Figure S39: Correlations between dominance ratings by different raters' samples. Model with GMM.

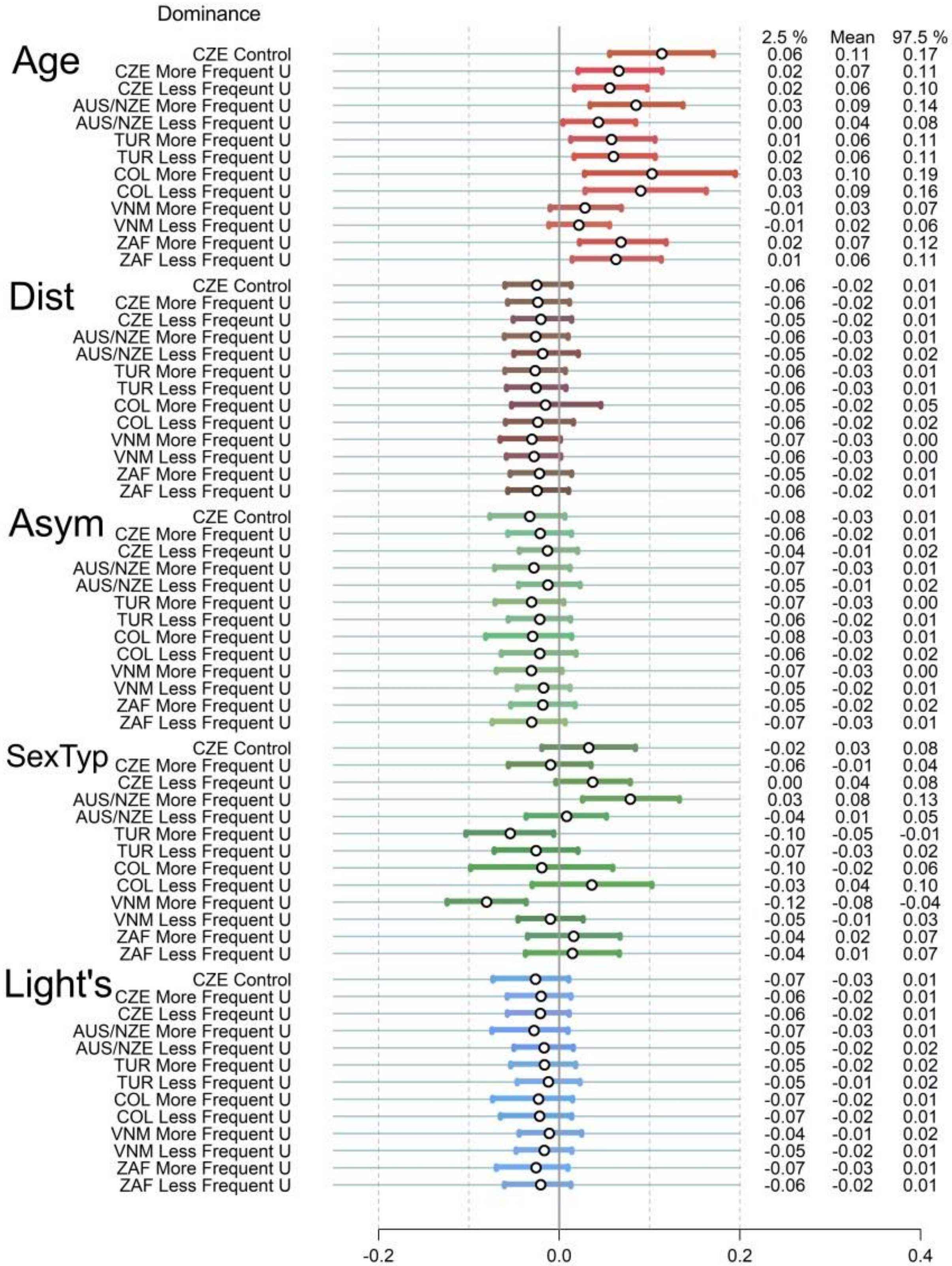


Figure S40. Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived <u>dominance</u>, rated by different groups.

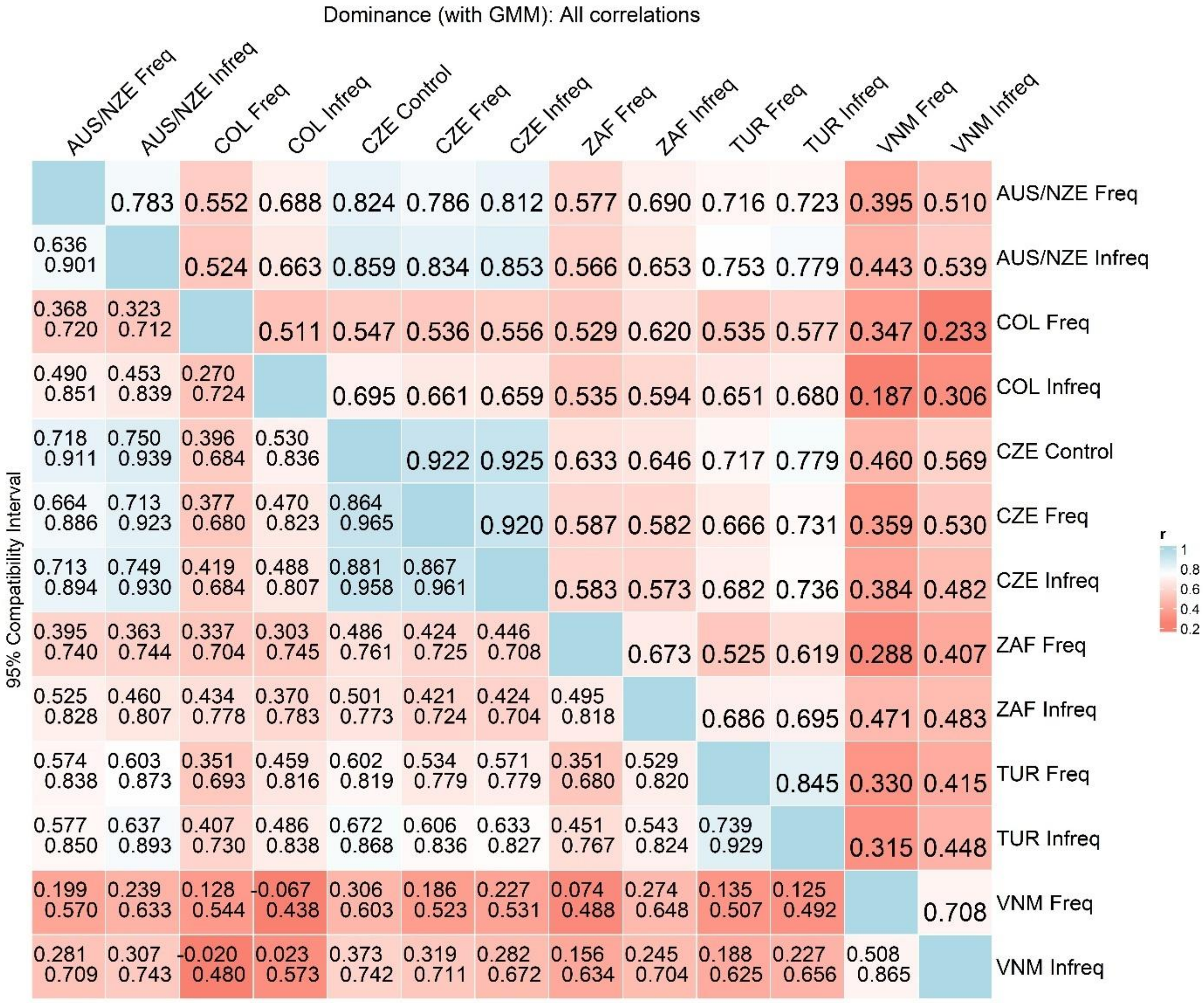


Figure S41. Correlations' heatmap, Dominance, model with GMM, L*, and Age.

5.3. Dominance – model for male and female subsample

5.3.1. Males

[The model is the same as above, but it only uses male or female subsample]

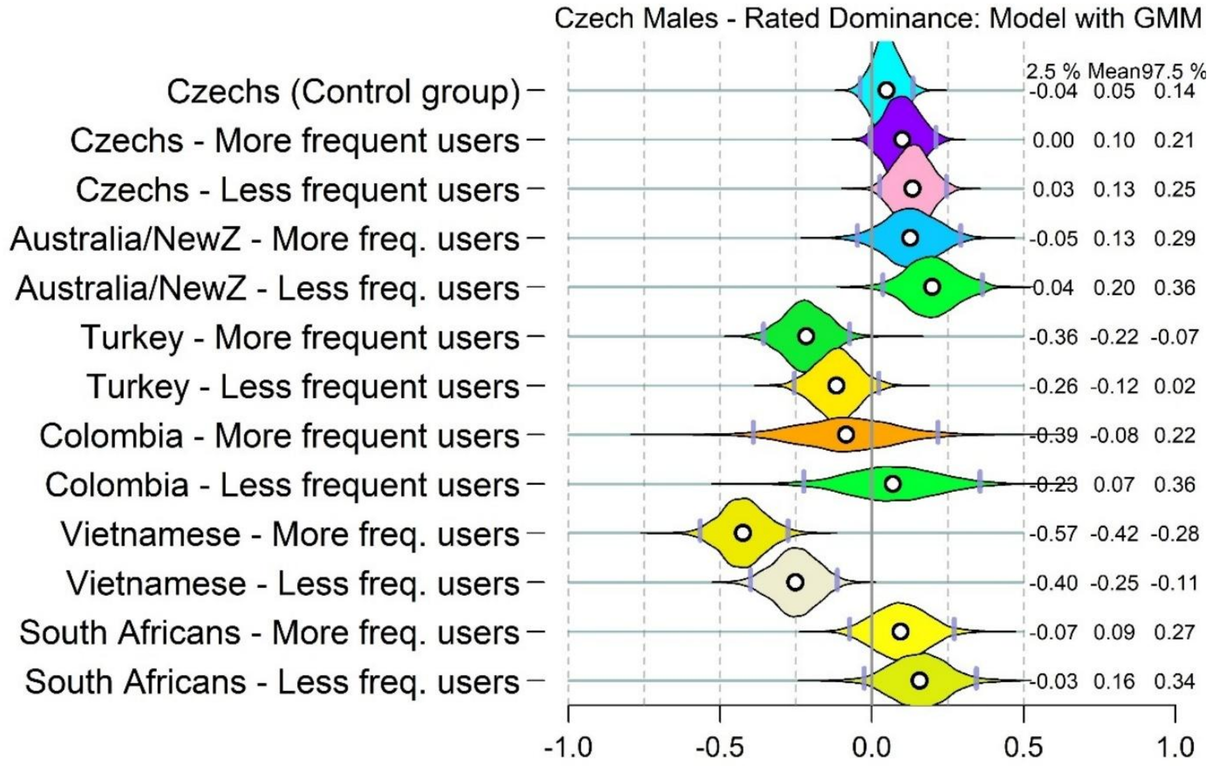


Figure 42. How assigned <u>dominance</u> differs (relatively) between the samples – model with GMM, L*, and Age, male subsample.

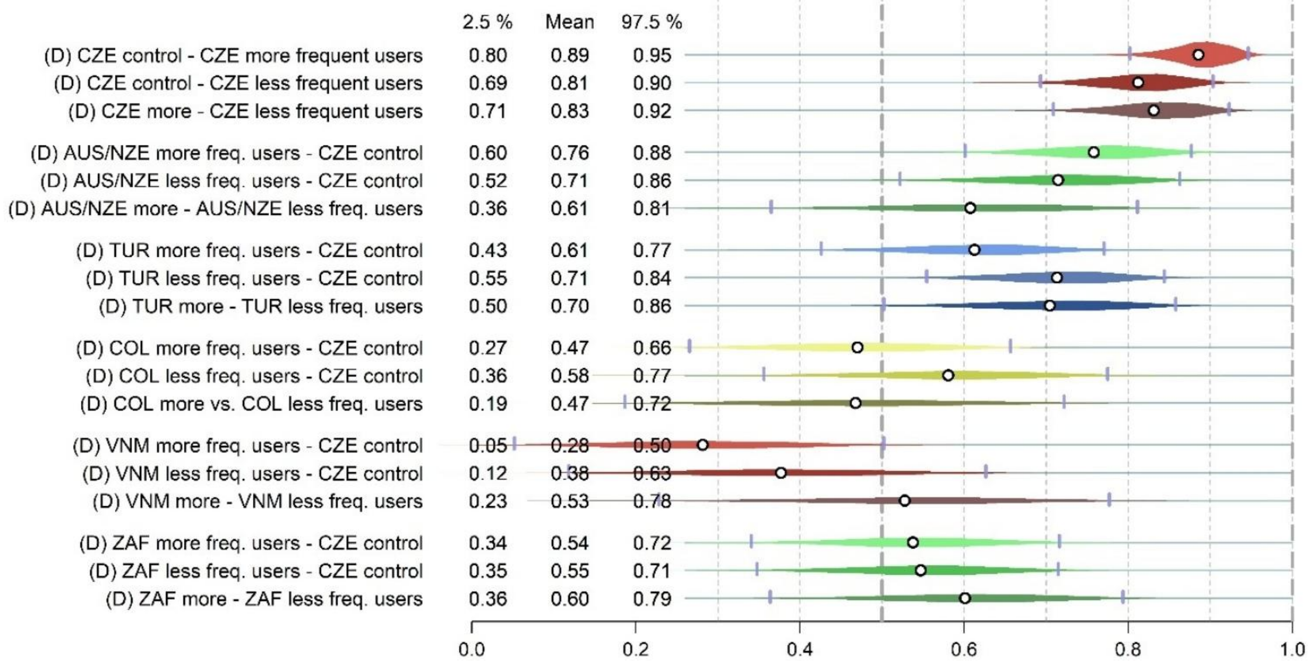


Figure S43: Correlations between <u>dominance</u> ratings by different raters' samples. Model with GMM, L*, and Age, male subsample.

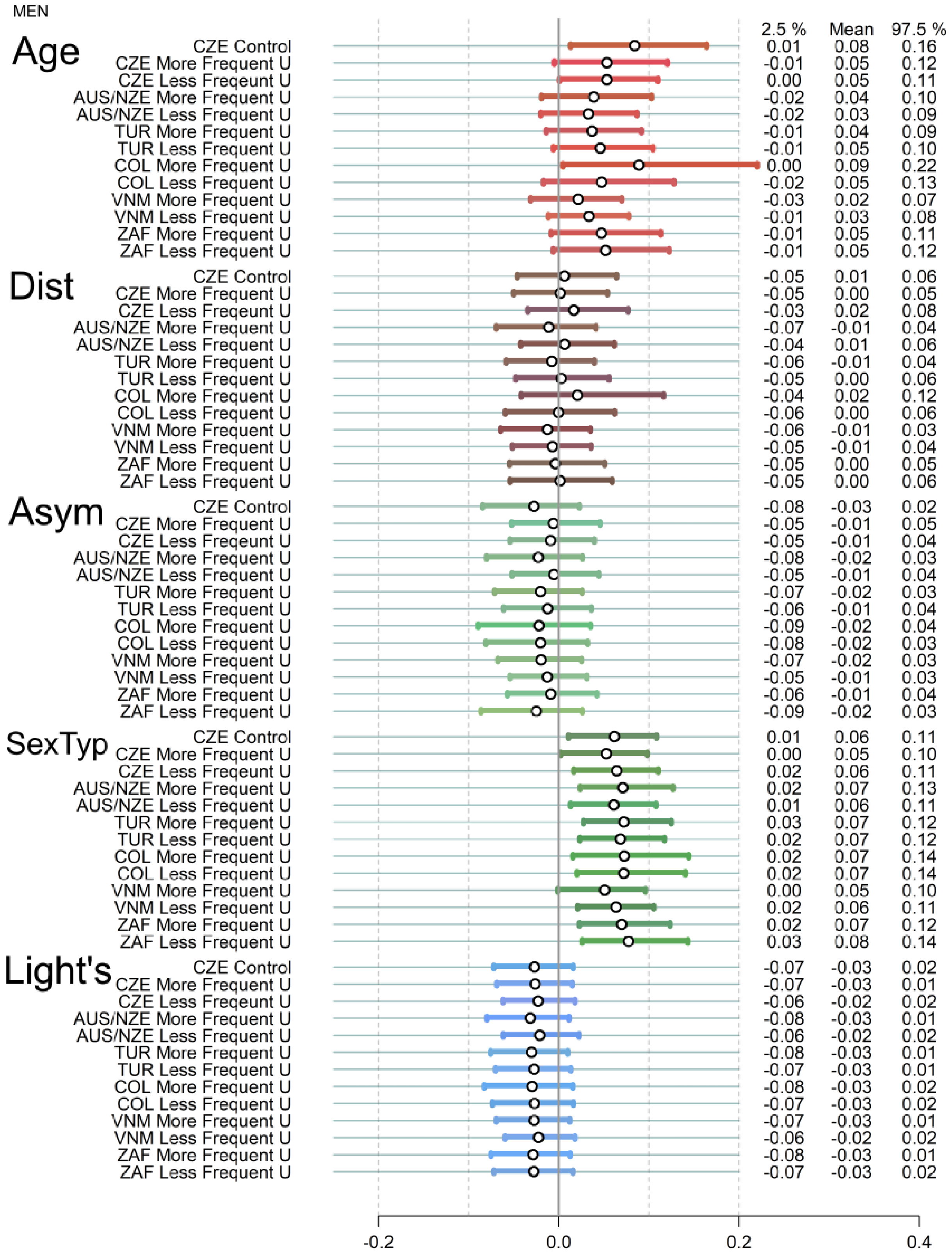


Figure S44. Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived dominance, rated by different groups. Male subsample.

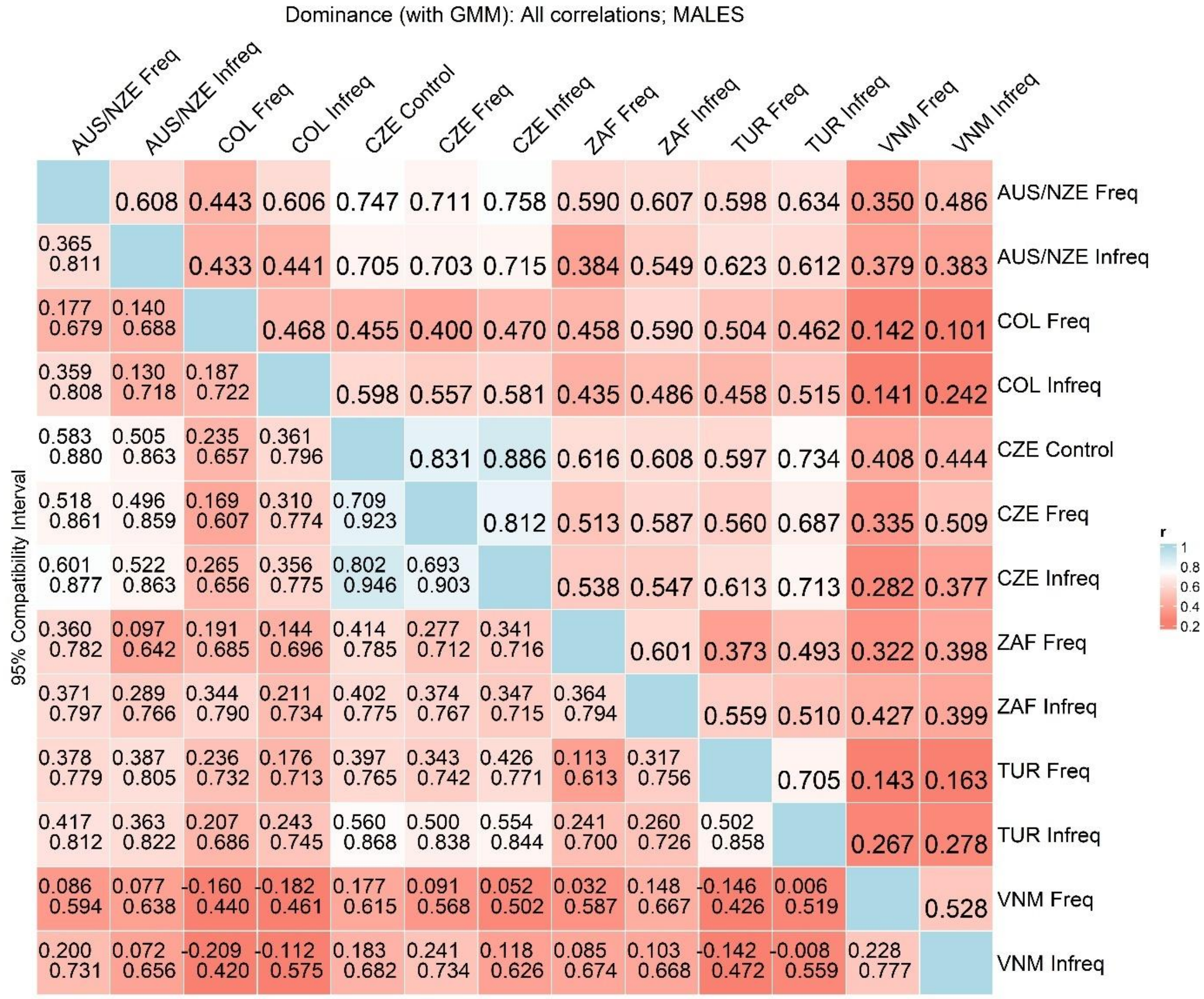


Figure S45. Correlations' heatmap, Dominance, model with GMM, L*, and Age. Male subsample.

5.3.2. Females

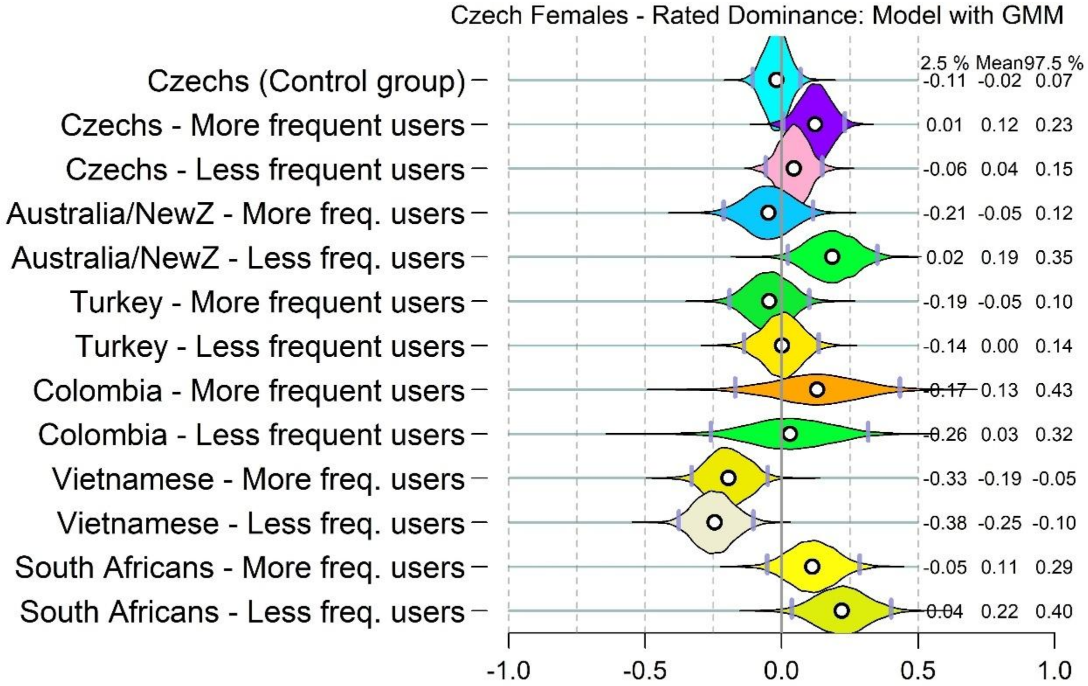


Figure 46. How assigned <u>dominance</u> differs (relatively) between the samples – model with GMM, L*, and Age, female subsample.

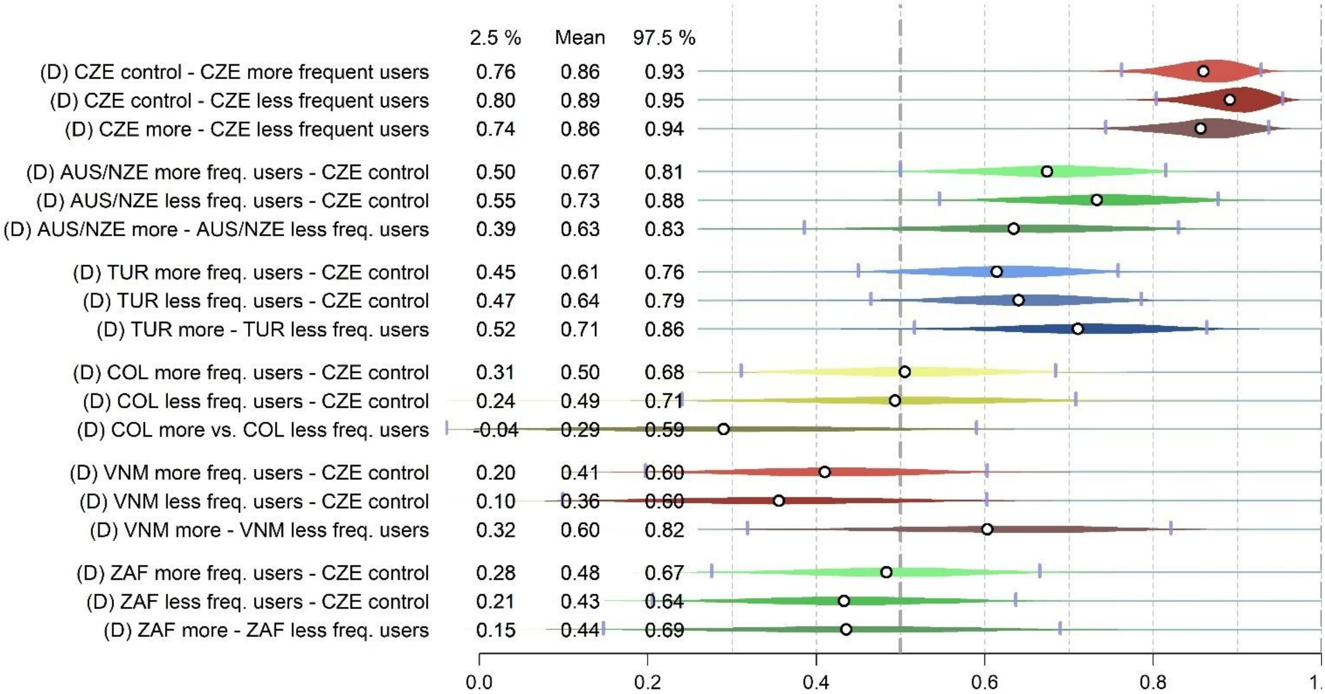


Figure S47. Correlations between <u>dominance</u> ratings by different raters' samples. Model with GMM. Female subsample.

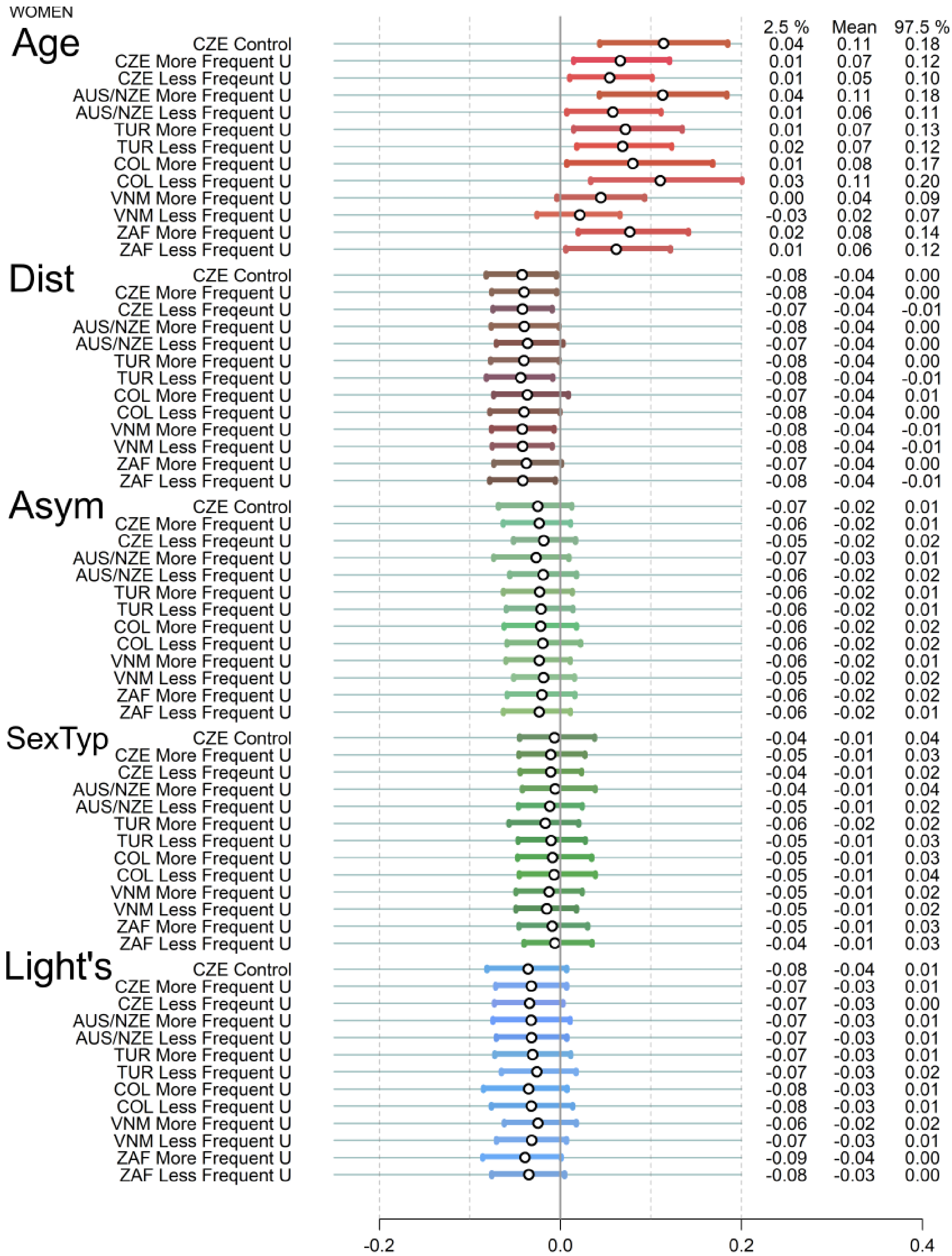


Figure S48. Selected linear coefficients, estimates on how GMM, Age and Skin L* predict perceived dominance, rated by different groups. Female subsample.

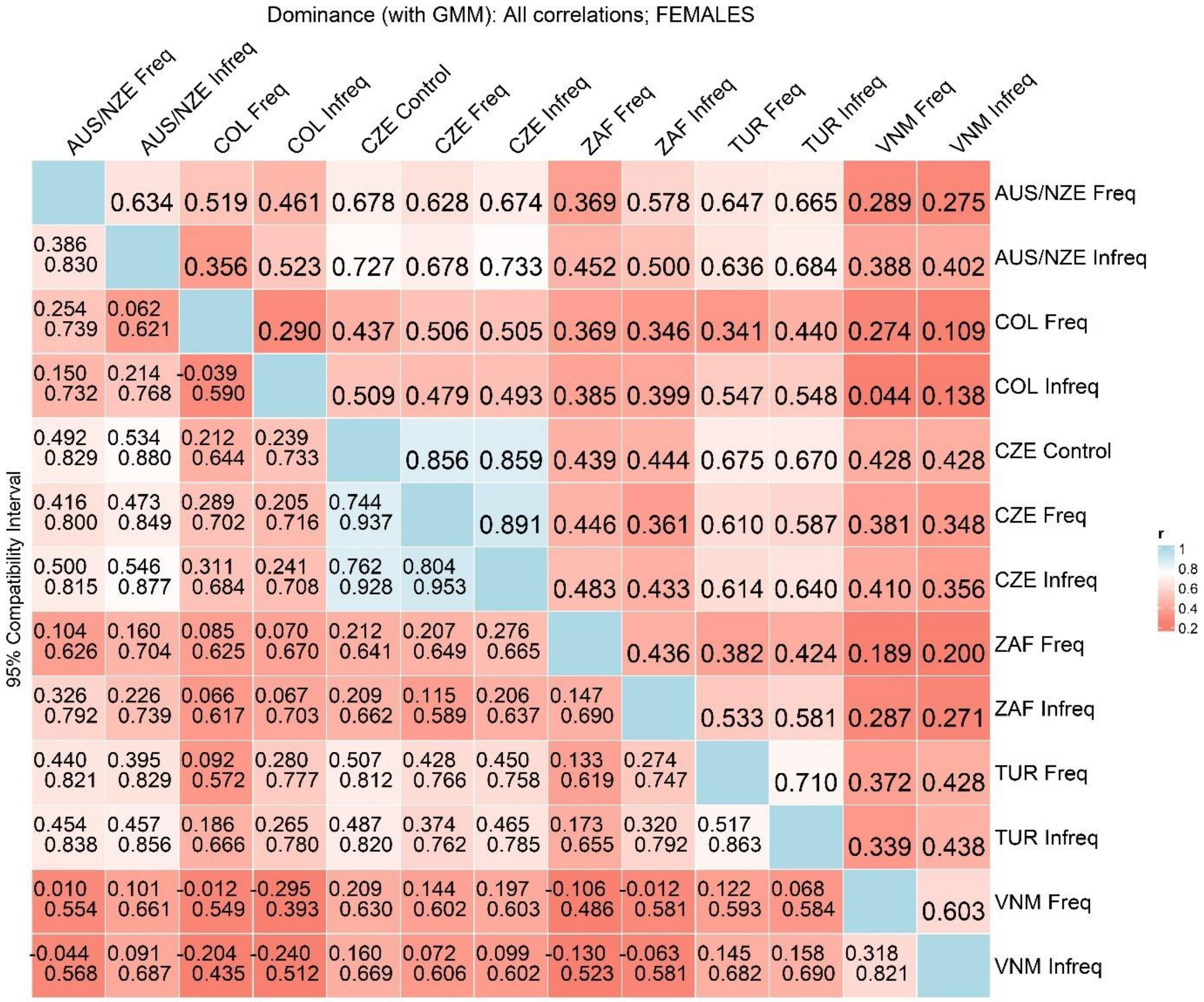


Figure S49. Correlations' heatmap, Dominance, model with GMM, L*, and Age. Male subsample.

Bonus: Justification of the hypothesis: Faces are ubiquitous on the internet ("The great facing").

Search for information on the internet usually consist of typing a chain of keywords in a search bar, followed by quick visual scan of the provided results. In this regard, seeing human faces in icons and landing images for example for tutorial videos, is unnecessary and may even disrupt the sense of the search. Human face is visually salient artifact: It serves for immediate first impression formation based on static neutral faces (Torodov et al., 2011), ascribing intentions and emotions to a face based on the emotional face (REFERENCE) and expecting communicative intensions (REFERENCE). Moreover, human gaze is considered a highly conspicuous structure, too (REFERENCE) as also advertises a highly likely communicative or confrontative intention (REFERENCE). There is evidence that a presence of a speaker affects learning ability from a video (REFERENCE), especially so when it comes to a language acquisition (REFERENCE). To sum up, seeing human face, especially in context of search for information other than faces, may present a sudden, highly demanding cognitive task that disrupt the attention of the person. Moreover, we reasonably expect that (i) such facial stimuli are put in the landing pages to get the users attentions for whatever means; (ii) is usually done by people who are not trained psychologists. In that regard, facial stimuli may present highly undesirable type of an object to be located on the landing page for a general population.

Moreover, current society uses various measures to account for various “disabilities” many people have, with the goal to create inclusive, safe environment in which no one feels discriminated or excluded (REFERENCES). This also applies for the information technologies: Windows, a prevailing operating system allows its users to... high contrast... voice control... keyboard on the screen... Text managers like MS Word and tools to prepare Slides actively advertises its users to mind that various users may have various special needs (REFERENCE). Yet, some groups are still largely ignored, and it seems that search engines’ algorithms and the whole “internet culture” even push forward stimuli that these people may find provocative, hard to grasp, or absolutely unbearable. There are several different groups, in which we may reasonably expect their special needs are ignored: People with social phobia (N % of the society) are afraid xxx. People with scotophobia (N % of the society). Together, these groups are estimated to present N % of society. It is reasonable to expect their cognitive performance on the internet is downgraded by visually salient stimuli.

Our goal, as the society shall be to omit a potentially harmful behaviour. Given the development of various programmes that anticipate certain groups may feel offended by intentional or unintentional xxx, it is surprising society ignores needs of above mentioned groups.

Google – search through videos:

(Trying to google some simple tasks that are, however, reasonable for a beginning user. None of the quotes suggest we are looking for a human face.)

Type search: “How to draw a square in MS Word” :15 of 60 first results (landing image) show a large conspicuous human face.

Type search: “How to make a sequence in R”: 24 of 60 first results (landing images) show a large conspicuous human face (plus several others show a small face).

Type search: “How to install WhatsApp on Windows 11”: 6 of 60 first results (landing images) show a large conspicuous human face (plus several others show a small face).

Type search: “Total Commander alternatives in 2025”: 17 of 60 first results (landing images) show a large conspicuous human face (plus many others show a small face). Note: the search engine was obviously not getting our search.

Type search: “Is my dog happy?”: 9 of 60 first results (landing images) show a large conspicuous human face. There are many others with smaller faces.