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To Which World Regions Does the Valence-Dominance Model of Social Perception Apply?

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Abstract

Over the last ten years, Oosterhof and Todorov's valence-dominance model has emerged as the most prominent account of how people evaluate faces on social dimensions. In this model, two dimensions (valence and dominance) underpin social judgments of faces. To which world regions this model applies is a critical, yet unanswered, question. We will address this question by replicating Oosterhof and Todorov's methodology across multiple world regions.

To Which World Regions Does the Valence-Dominance Model of Social Perception Apply?

People quickly and involuntarily form impressions of others based on their facial appearance[1-3]. These impressions then influence important social outcomes[4,5]. For example, people are more likely to cooperate in socioeconomic interactions with individuals whose faces are evaluated as more trustworthy[6], vote for individuals whose faces are evaluated as more competent[7], and seek romantic relationships with individuals whose faces are evaluated as more attractive[8]. Facial appearance can even influence life-or-death outcomes. For example, untrustworthy-looking defendants are more likely to receive death sentences[9]. Given that such evaluations influence profound outcomes, understanding how people evaluate others' faces can provide insight into a potentially important route through which social stereotypes impact behavior[10,11].

Over the last decade, Oosterhof and Todorov's valence-dominance model[12] has emerged as the most prominent account of how we evaluate faces on social dimensions[5]. Oosterhof and Todorov identified 13 different traits (aggressiveness, attractiveness, caringness, confidence, dominance, emotional stability, unhappiness, intelligence, meanness, responsibility, sociability, trustworthiness, and weirdness) that perceivers spontaneously use to evaluate faces when forming trait impressions[12]. From these traits, they derived a two-dimensional model of perception: *valence* and *dominance*. *Valence,* best characterized by rated trustworthiness, was defined as the extent to which the target was perceived as having the *intention* to harm the viewer[12]. *Dominance,* best characterized by rated dominance, was defined as the extent to which the target was perceived as having the *ability* to inflict harm on the viewer[12]. Crucially, the model proposes that these two dimensions are sufficient to drive social evaluations of faces. As a consequence, the majority of research on the effects of social evaluations of faces has focused on one or both of these dimensions[4,5].

Successful replications of the valence-dominance model have only been conducted in Western samples[13,14]. This focus on the West is consistent with research on human behavior more broadly, which typically draws general assumptions from analyses of Western participants' responses[15]. Kline et al. recently termed this problematic practice the *Western centrality assumption* and argued that regional variation, rather than universality, is likely the default for human behavior[16].

Consistent with Kline's notion that human behavior is best characterized by regional variation, two recent studies of social evaluation of faces by Chinese participants indicate different factors underlie their impressions[17,18]. Both studies reported that Chinese participants' social evaluations of faces were underpinned by a valence dimension similar to that reported by Oosterhof and Todorov for Western participants, but not by a corresponding dominance dimension. Instead, both studies reported a second dimension, referred to as *capability*, which was best characterized by rated intelligence. Furthermore, the ethnicity of the faces rated only subtly affected perceptions[17]. Research into potential cultural differences in the effects of experimentally manipulated facial characteristics on social perceptions has also found little evidence that cultural differences in social perceptions of faces depend on the ethnicity of the faces presented[19-21]. Collectively, these results suggest that the Western centrality assumption may be an important barrier to understanding how people evaluate faces on social dimensions. Crucially, these studies also suggest that the valence-dominance model is not necessarily a universal account of social evaluations of faces and warrants further investigation in the broadest set of samples possible.

Although the studies described above demonstrate that the valence-dominance model is not perfectly universal, to which specific world regions it does and does not apply are open and important questions. Demonstrating differences between British and Chinese raters is evidence against the universality of the valence-dominance model, but it does not adequately address these questions. Social perception in China may be unique in not fitting the valence-dominance model because of the atypically high general importance placed on status-related traits, such as capability, during social interactions in China[22,23]. Indeed, Tan et al. demonstrated face-processing differences between Chinese participants living in mainland China and Chinese participants living in nearby countries, such as Malaysia[24]. Insights regarding the unique formation of social perceptions in other cultures and world regions are lacking. Only a large-scale study investigating social perceptions in many different world regions can provide such insights.

To establish the world regions to which the valence-dominance model applies, we will replicate Oosterhof and Todorov's methodology[12] in a wide range of world regions (Africa, Asia, Australia and New Zealand, Central America and Mexico, Eastern Europe, the Middle East, the USA and Canada, Scandinavia, South America, the UK, and Western Europe; see Table 1). Our study will be the most comprehensive test of social evaluations of faces to date, including more than 9,000 participants. Participating research groups were recruited via the Psychological Science Accelerator project[25-27]. Previous studies compared two cultures to demonstrate regional differences[17,18]. By contrast, the scale and scope of our study will allow us to generate the most comprehensive picture of the world regions to which the valence-dominance model does and does not apply.

We will test two specific competing predictions.

Prediction 1. The valence-dominance model will apply to all world regions.

Prediction 2. The valence-dominance model will apply in Western-world regions, but not other world regions.

Table 1

World Regions, Countries, and Localities of Planned Data Collection

World region	Countries and Localities
Africa	Kenya, South Africa
Asia	China, India, Malaysia, Taiwan, Thailand
Australia and New Zealand	Australia, New Zealand
Central America and Mexico	Ecuador, El Salvador, Mexico
Eastern Europe	Hungary, Lithuania, Poland, Russia, Serbia, Slovakia

The Middle East	Iran, Israel, Turkey
The USA and Canada	Canada, the USA
Scandinavia	Denmark, Norway
South America	Argentina, Brazil, Chile, Colombia
The UK	England, Scotland, Wales
Western Europe	Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal, Spain, Switzerland

Note. We will collect data from a minimum of 350 raters per world region based on the simulations described in the Methods section below.

Methods

Ethics

Each research group has approval from their local Ethics Committee or IRB to conduct the study, has explicitly indicated that their institution does not require approval for the researchers to conduct this type of face-rating task, or has explicitly indicated that the current study is covered by a preexisting approval. Although the specifics of the consent procedure will differ across research groups, all participants will provide informed consent. All data will be stored centrally on University of Glasgow servers.

Procedure

Oosterhof and Todorov derived their valence-dominance model from a principal components analysis of ratings (by US raters) of 66 faces for 13 different traits (aggressiveness, attractiveness, caringness, confidence, dominance, emotional stability, intelligence, meanness, responsibility, sociability, trustworthiness, unhappiness, and weirdness)[12]. Using the criteria of the number of components with eigenvalues greater than 1.0, this analysis produced two principal components. The first component explained 63% of the variance in trait ratings, strongly correlated with rated trustworthiness (r = .94), and weakly correlated with rated dominance (r = -.24). The second component explained 18% of the variance in trait ratings, strongly correlated with rated dominance (r = .93), and weakly correlated with rated trustworthiness (r = -.06). We will replicate Oosterhof and Todorov's method[12] and primary analysis in each world region we examine.

Stimuli in our study will come from an open-access, full-color, face image set[28] consisting of 60 men and 60 women taken under standardized photographic conditions (M_{age} = 26.4 years, *SD* = 3.6 years, Range = 18 to 35 years). These 120 images will consist of 30 Black (15 male, 15 female), 30 White (15 male, 15 female), 30 Asian (15 male, 15 female), and 30 Latin faces (15 male, 15 female). As in Oosterhof and Todorov's study[12], the individuals photographed posed looking directly at the camera with a neutral expression, and all of background, lighting, and clothing (here, a grey t-shirt) are constant across images.

In our study, adult raters will be randomly assigned to rate the 13 adjectives tested by Oosterhof and Todorov using scales ranging from 1 (*Not at all*) to 9 (*Very*) for all 120 faces in a fully randomized order at their own pace. Because all researchers will collect data through an identical interface (except for differences in instruction language), data collection protocols will be highly standardized across labs. Each participant will complete the block of 120 face-rating trials twice so that we can report test-retest reliabilities of ratings; ratings from the first and second blocks will be averaged for all analyses (see CODE 1.5.5 in the Supplemental Materials).

Raters will also complete a short questionnaire requesting demographic information (sex, age, ethnicity). These variables were not considered in Oosterhof and Todorov's analyses but will be collected in our study so that other researchers can use them in secondary analyses of the published data. The data from this study will be the largest and most comprehensive open access set of face ratings from around the world with open stimuli by far, providing an invaluable resource for further research addressing the Western centrality assumption in person perception research.

Raters will complete the task in a language appropriate for their country (see below). To mitigate potential problems with translating single-word labels, dictionary definitions for each of the 13 traits will be provided. Twelve of these dictionary definitions have previously been used to test for effects of social impressions on the memorability of face photographs[19]. Dominance (not included in that study) will be defined as "strong, important."

Participants

Simulations determined that we should obtain at least 25 different raters for each of the 13 traits in every region (see https://osf.io/x7fus/ for code and data). We focused on ratings of attractiveness and intelligence for the simulations because they showed the highest and lowest agreement among the traits analyzed by Oosterhof and Todorov, respectively. First, we sampled from a population of 2,513 raters, each of whom had rated the attractiveness of 102 faces; these simulations showed that more than 99% of 1,000 random samples of 25 raters produced good or excellent interrater reliability coefficients (Cronbach's αs >.80). We then repeated these simulations sampling from a population of 37 raters, each of whom rated the intelligence of 100 faces, showing that 93% of 1,000 random samples of 25 raters produced good or excellent interrater reliability coefficients (Cronbach's αs >.80). Thus, averages of ratings from 25 or more raters will produce reliable dependent variables in our analyses; we plan to test at least 9,000 raters in total.

In addition to rating the faces for the 13 traits examined by Oosterhof and Todorov, 25 participants in each region will be randomly assigned to rate the targets' age in light of Sutherland et al.'s results showing that a youth/attractiveness dimension emerged from analyses of a sample of faces with a very diverse age range[30]. Age ratings will not be included in analyses relating to replications of Oosterhof and Todorov's valence-dominance model, but analyzed only in additional exploratory analyses.

Analysis Plan

The code to be used for these analyses is included in the Supplemental Materials and publicly available from the Open Science Framework (https://osf.io/87rbg/). To facilitate assessment of the Stage 1 Registered Report, the specific sections of code are cited below as (CODE x.x.x).

Ratings from each world region will be analyzed separately and anonymous raw data will be published on the Open Science Framework. Our analyses will directly replicate the principal component analysis reported by Oosterhof and Todorov to test their theoretical model in each region sampled (CODE 2.1). First, we will calculate the average rating for each face separately for each of the 13 traits (CODE 2.1.2). We will then subject these mean ratings to principal component analysis with orthogonal components and no rotation, as Oosterhof and Todorov did (CODE 2.1.3). Using the criteria reported they reported, we will retain and interpret components with eigenvalues greater than 1.0 (CODE 2.1.3.1).

Criteria for replicating Oosterhof and Todorov's valence-dominance model. We will use multiple sources of evidence to judge whether Oosterhof and Todorov's valence-dominance model replicated in a given world region. First, we will examine the solution from the principal components analysis conducted in each region and determine if Oosterhof and Todorov's primary pattern replicated according to three criteria: (i) the first two components have eigenvalues greater than 1.0, (ii) the first component (i.e., the one explaining more of the variance in ratings) correlates strongly with trustworthiness ($\lambda > .7$) and weakly with dominance ($\lambda < .5$), and (iii) the second component (i.e., the one explaining less of the variance in ratings) correlates strongly with dominance ($\lambda > .7$) and weakly with trustworthiness ($\lambda < .5$). If the solution in a world region meets all three of these criteria, we will conclude that the primary pattern of the model replicated in that region (CODE 2.1.3.3).

In addition to reporting whether the primary pattern was replicated in each region, we will also report Tucker's coefficient of congruence[31,32]. The congruence coefficient, ϕ, ranges from -1 to 1 and quantifies the similarity between two vectors of loadings[33]. It is:

$$\phi(x, y) = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2 \sum y_i^2}}$$

where x_i and y_i are the loadings of variable i (i = 1, …, n number of indicators in the analysis) onto factors x and y. For the purposes of the current research we will compare the vector of loadings from the first component from Oosterhof and Todorov to the vector of loadings from the first component estimated from each world region. We will repeat this analysis for the second component. This will produce a standardized measure of component similarity for each component in each world region that is not sensitive to the mean size of the loadings[34]. Further, this coefficient is fitting for the current study because it does not require an a priori specification of a factor structure for each group, as would be needed if we were to compare the factor structures in a multiple-group confirmatory factor analysis. Following previous guidelines[34], we will conclude that the components in Oosterhof and Todorov are not similar to those estimated in a given world region if the coefficient is less than .85, are fairly similar if it is between .85 - .94, and equal if it is greater than .95. (CODE 2.1.4.2).

Thus, we will report whether the solution has the same primary pattern that Oosterhof and Todorov found and quantify the degree of similarity between each component and the corresponding component from Oosterhof and Todorov's work. This connects to our competing predictions:

Prediction 1 (The valence-dominance model will apply to all world regions) will be supported if the solution from the principal components analysis conducted in each region satisfy *all* of the criteria described above. Specifically, the primary pattern is replicated and the components have at least a fair degree of similarity as quantified by a ϕ of .85 or greater.

Prediction 2 (The valence-dominance model will apply in Western-world regions, but not other world regions) will be supported if the solutions from the principal components analysis conducted in Australia and New Zealand, The USA and Canada, Scandinavia, The UK, and Western Europe, but not Africa, Asia, Central America and Mexico, Eastern Europe, The Middle East, or South America, satisfy the criteria described above.

Exclusions. Data from raters who fail to complete all 120 ratings in the first block of trials or who provide the same rating for 75% or more of the faces will be excluded from analysis (CODES 1.5.1,1.5.3, and 1.5.5).

Data-quality checks. Following previous research testing the valence-dominance model[12-14], data quality will be checked by separately calculating the interrater agreement (indicated by Cronbach's α and test-retest reliability) for each trait in every world region (CODE 2.1.1). A trait will only be included in the analysis for that region if the coefficient exceeds .70. Cases in which the coefficient does not exceed .70 will be reported and discussed. Test-retest reliability of traits will be reported but not used to exclude traits from analysis.

Power analysis. Simulations show we have more than 95% power to detect the key effect of interest (i.e., two components meeting the criteria for replicating Oosterhof and Todorov's work, as described above). We used the open data from Morrison et al.'s replication[13] of Oosterhof and Todorov's research to generate a variance-covariance matrix representative of typical interrelationships among the 13 traits that will be tested in our study. We then generated 1,000 samples of 120 faces from these distributions and ran our planned principal components analysis (which is identical to that reported by

Oosterhof & Todorov) on each sample (see https://osf.io/87rbg/ for code and data). Results of >99% of these analyses matched our criteria for replicating Oosterhof and Todorov's findings. This demonstrates that 120 faces will give us more than 95% power to replicate Oosterhof and Todorov's results.

Robustness analyses. Oosterhof and Todorov extracted and interpreted components with an eigenvalue greater than 1.0 using an unrotated principal components analysis. As described above, we will directly replicate their method in our main analyses but acknowledge that this type of analysis has been criticized.

First, it has been argued that exploratory factor analysis with rotation, rather than an unrotated principal components analysis, is more appropriate when one intends to measure correlated latent factors, as is the case in the current study[35,36]. Second, the extraction rule of eigenvalues greater than 1.0 has been criticized for not indicating the optimal number of components, as well as for producing unreliable components[37,38].

To address these limitations, we will repeat our main analyses using exploratory factor analysis with an oblimin rotation as the model and a parallel analysis to determine the number of factors to extract. We will also recalculate the congruence coefficient described above for these exploratory factor analysis results (CODE 2.2.1).

We will use parallel analysis to determine the number of factors to extract because it has been described as yielding the optimal number of components (or factors) across the largest array of scenarios[35,39,40] (CODE 2.2.1). In a parallel analysis, random data matrices are generated such that they have the same number of cases and variables as the real data. The mean eigenvalue from the components of the random data is compared to the eigenvalue for each component from the real data. Components are then retained if their eigenvalues exceed those from the randomly generated data[41].

The purpose of these additional analyses is twofold. First, to address potential methodological limitations in the original study and, second, to ensure that the results of our replication of Oosterhof and Todorov's study are robust to the implementation of those more rigorous analytic techniques. The same criteria for replicating Oosterhof and Todorov's model described above will be applied to this analysis (CODE 2.2.4-5).

References

1. Olivola, C. Y., & Todorov, A. (2010). Elected in 100 milliseconds: Appearance-based trait inferences and voting. Journal of Nonverbal Behavior, 34, 83-110.

2. Ritchie, K. L., Palermo, R., & Rhodes, G. (2017). Forming impressions of facial attractiveness is mandatory. Scientific Reports, 7, 469.

3. Willis, J., & Todorov, A. (2006). First impressions: Making up your mind after 100 ms exposure to a face. Psychological Science, 17, 592-598.

4. Olivola, C. Y., Funk, F., & Todorov, A. (2014). Social attributions from faces bias human choices. Trends in Cognitive Sciences, 18, 566-570.

5. Todorov, A., Olivola, C. Y., Dotsch, R., & Mende-Siedlecki, P. (2015). Social attributions from faces: Determinants, consequences, accuracy, and functional significance. Annual Review of Psychology, 66, 519-545.

6. Van 't Wout, M., & Sanfey, A. G. (2008). Friend or foe: The effect of implicit trustworthiness judgments in social decision-making. Cognition, 108, 796-803.

7. Todorov, A., Mandisodza, A. N., Goren, A., & Hall, C. C. (2005). Inferences of competence from faces predict election outcomes. Science, 308, 1623-1626.

8. Langlois, J. H., Kalakanis, L., Rubenstein, A. J., Larson, A., Hallam, M., & Smoot, M. (2000). Maxims or myths of beauty? A meta-analytic and theoretical review. Psychological Bulletin, 126, 390-423.

9. Wilson, J. P., & Rule, N. O. (2015). Facial trustworthiness predicts extreme criminal-sentencing outcomes. Psychological Science, 26, 1325-1331.

10. Todorov, A., Said, C. P., Engell, A. D., & Oosterhof, N. N. (2008). Understanding evaluation of faces on social dimensions. Trends in Cognitive Sciences, 12, 455-460.

11. Jack, R. E., & Schyns, P. G. (2017). Toward a social psychophysics of face communication. Annual Review of Psychology, 68, 269-297.

12. Oosterhof, N. N., & Todorov, A. (2008). The functional basis of face evaluation. Proceedings of the National Academy of Sciences of the USA, 105, 11087-11092.

13. Morrison, D., Wang, H., Hahn, A. C., Jones, B. C., & DeBruine, L. M. (2017). Predicting the reward value of faces and bodies from social perception. PLoS ONE, 12, e0185093.

14. Wang, H., Hahn, A. C., DeBruine, L. M., & Jones, B. C. (2016). The motivational salience of faces is related to both their valence and dominance. PLoS ONE, 11, e0161114.

15. Henrich, J., Heine, S., & Norenzayan, A. (2010). The weirdest people in the world? Behavioral and Brain Sciences, 33, 61-83.

16. Kline, M. A., Shamsudheen, R., & Broesch, T. (2018). Variation is the universal: Making cultural evolution work in developmental psychology. Philosophical Transactions of the Royal Society B, 373, 20170059.

17. Sutherland, C. A. M., Liu, X., Zhang, L., Chu, Y., Oldmeadow, J. A., & Young, A. W. (2018). Facial first impressions across culture: Data-driven modeling of Chinese and British perceivers' unconstrained facial impressions. Personality and Social Psychology Bulletin, 44, 521-537.

18. Wang, H., Han, C., Hahn, A., Fasolt, V., Morrison, D.,... Jones, B. C. (2018). A data-driven study of Chinese participants' social judgments of Chinese faces. PsyArXiv.

19. Han, C., Wang, H., Hahn, A. C., Fisher, C. I., Kandrik, M., Fasolt, V., ... & Jones, B. C. (2018). Cultural differences in preferences for facial coloration. Evolution and Human Behavior, 39, 154-159.

20. Perrett, D. I., Lee, K. J., Penton-Voak, I., Rowland, D., Yoshikawa, S., Burt, D. M., ... & Akamatsu, S. (1998). Effects of sexual dimorphism on facial attractiveness. Nature, 394, 884.

21. Xie, S.Y., Flake, J.K., & Hehman, E. (in press). Perceiver and target characteristics contribute to impression formation differently across race and gender. Journal of Personality and Social Psychology.

22. Li, N. P., Valentine, K. A., & Patel, L. (2011). Mate preferences in the US and Singapore: A cross-cultural test of the mate preference priority model. Personality and Individual Differences, 50, 291-294.

23. Ting-Toomey, S. (1994). Face and facework: An introduction. In S. Ting-Toomey (Ed.),The Challenge of Facework: Cross-Cultural and Interpersonal Issues (pp. 1-14). Albany, NY: State University of New York Press.

24. Tan, C. B. Y., Stephen, I. D., Whitehead, R., Sheppard, E. (2012). You look familiar: How Malaysian Chinese recognize faces. PLoS ONE 7, e29714.

25. Chartier, C, McCarthy, R., & Urry, H. (2018). The Psychological Science Accelerator. APS Observer, 31, 30.

26. Chawla, D. S. (2017). A new 'accelerator' aims to bring big science to psychology. Science. doi:10.1126/science.aar4464

27. Moshontz, H., Campbell, L., Ebersole, C. R., IJzerman, H., Urry, H. L., Forscher, P. S., … Chartier, C. R. (in press). The Psychological Science Accelerator: Advancing psychology through a distributed collaborative network. Advances in Methods and Practices in Psychological Science.

28. Ma, Correll, & Wittenbrink (2015). The chicago face database: A free stimulus set of faces and norming data. Behavior Research Methods, 47, 1122-1135.

29. Bainbridge, W. A., Isola, P., & Oliva, A. (2013). The intrinsic memorability of face photographs. Journal of Experimental Psychology: General, 142, 1323-1334.

30. Sutherland, C. A., Oldmeadow, J. A., Santos, I. M., Towler, J., Burt, D. M., & Young, A. W. (2013). Social inferences from faces: Ambient images generate a three-dimensional model. Cognition, 127, 105-118.

31. Burt, C. (1948). The factorial study of temperament traits. British Journal of Psychology, Statistical Section, 1, 178-203.

32. Tucker, L. R. (1951). A method for synthesis of factor analysis studies (Personnel Research Section Report No. 984). Washington, DC: Department of the Army.

33. Davenport, E. C., Jr., (1990). Significance testing of congruence coefficients: A good idea? Educational and Psychological Measurement, 50, 289-296.

34. Lorenzo-Seva, U., & ten Berge, J. M. F. (2006). Tucker's congruence coefficient as a meaningful index of factor similarity. Methodology, 2, 57-64.

35. Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. Psychological Methods, 4, 272-299.

36. Park, H. S., Dailey, R., & Lemus, D. (2002). The use of exploratory factor analysis and principal components analysis in communication research. Human Communication Research, 28, 562-577.

37. Cliff, N. (1988). The Eigenvalues-greater-than-one rule and the reliability of components. Psychological Bulletin, 103, 276-279.

38. Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. Psychological Bulletin, 99, 432-442.

39. O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and velicer's MAP test. Behavior Research Methods, Instruments, & Computers, 32, 396-402.

40. Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. Journal of Psychoeducational Assessment, 29, 304-321.

41. Courtney, M. G. R. (2013). Determining the number of factors to retain in EFA_: Using the SPSS R-Menu v2.0 to make more judicious estimations. Practical Assessment, Research & Evaluation, 18, 1-14.

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