



To which world regions does the valence–dominance model of social perception apply?

Over the past 10 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 judgements of faces. Because this model has primarily been developed and tested in Western regions, it is unclear whether these findings apply to other regions. We addressed this question by replicating Oosterhof and Todorov’s methodology across 11 world regions, 41 countries and 11,570 participants. When we used Oosterhof and Todorov’s original analysis strategy, the valence–dominance model generalized across regions. When we used an alternative methodology to allow for correlated dimensions, we observed much less generalization. Collectively, these results suggest that, while the valence–dominance model generalizes very well across regions when dimensions are forced to be orthogonal, regional differences are revealed when we use different extraction methods and correlate and rotate the dimension reduction solution.

Protocol registration

The stage 1 protocol for this Registered Report was accepted in principle on 5 November 2018. The protocol, as accepted by the journal, can be found at <https://doi.org/10.6084/m9.figshare.7611443.v1>.

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 trustworthy⁶, vote for individuals whose faces are evaluated as more competent⁷, and seek romantic relationships with individuals whose faces are evaluated as more attractive⁸. Facial appearance can even influence life-or-death outcomes. For example, untrustworthy-looking defendants are more likely to receive death sentences⁹. 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 behaviour^{10,11}.

Over the past decade, Oosterhof and Todorov’s valence–dominance model¹² has emerged as the most prominent account of how we evaluate faces on social dimensions⁵. 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 impressions¹². 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 viewer¹². 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 viewer¹². 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 behaviour more broadly, which typically draws general assumptions from analyses of Western participants’ responses¹⁵. Kline et al.¹⁶ recently termed this problematic practice the Western centrality assumption and argued that regional

variation, rather than universality, is probably the default for human behaviour.

Consistent with Kline et al.’s notion that human behaviour is best characterized by regional variation, two recent studies of social evaluation of faces by Chinese participants indicate that 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 perceptions¹⁷. 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.²⁴ demonstrated face-processing differences between Chinese participants living in mainland China and Chinese participants living in nearby countries, such as Malaysia. 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 replicated Oosterhof and Todorov’s methodology¹² in a wide range of world regions (Africa, Asia, Australia and New Zealand, Central America and Mexico, Eastern Europe, the Middle East, the United States and Canada, Scandinavia, South America, the United Kingdom and Western Europe; see Table 1). Our study is the most comprehensive test of social evaluations of faces to date, including more than 11,000 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}. In contrast, the scale and scope of our study allows us to generate the most comprehensive picture of the world regions to which the valence–dominance model does and does not apply.

We tested two specific competing predictions: (1) the valence–dominance model applies to all world regions; and (2) the valence–dominance model applies in Western-world regions, but not other world regions.

Results

Analysed dataset. Following the planned data exclusions (see the Supplementary Information for a breakdown of these exclusions; code 1.5), the analysed dataset is summarized in Table 2.

Main analysis (principal component analysis (PCA); code 2.1). Oosterhof and Todorov reported the results of a PCA with orthogonal components, no rotation and retaining components with eigenvalues of >1 . We conducted an identical analysis and report: (1) the number of components extracted per the registered criteria; (2) whether the first and second components had the same primary pattern as Oosterhof and Todorov reported; and (3) the similarity of the first and second factors as quantified with a congruence coefficient.

We extracted the same number of components (two) as Oosterhof and Todorov in two world regions (Africa and South America) and a different number of components (three) in the other world regions (see Fig. 1). In the world regions where a third component was extracted, the trait ratings of unhappy and weird tended to have the highest loadings on that component, but those ratings also crossloaded on the first component. We hesitate to interpret or describe this component with any authority because it varied across world regions, consisted of crossloaded traits and explained only a small proportion of additional variance.

The primary pattern reported by Oosterhof and Todorov (a first component that correlated strongly with rated trustworthiness but not with rated dominance and a second component that correlated strongly with rated dominance but not with rated trustworthiness) was present in all world regions except Eastern Europe. In Eastern Europe, dominance was correlated with the first component more strongly than our registered criterion (i.e., that dominance would correlate weakly with the first component; $r < 0.5$). Figure 1 shows the full loading matrices for each region and Table 3 shows how these relate to our registered criteria.

We report Tucker’s coefficient of congruence, ϕ , which quantifies the loading similarity of Oosterhof and Todorov’s reported component to the corresponding component we extracted. However, it is important to interpret ϕ with caution when the numbers of components differ across the solutions being compared. When comparing loadings across solutions, an assumption is that the configuration of the traits to components is the same (that is, configural invariance). To the extent that the structures of the loading matrices differ across solutions, the comparability of the loadings is compromised (that is, loadings estimated from different dimensional spaces are not on the same scale). For world regions that did not have the same configuration of traits to components (that is, those with a different number

Table 1 | World regions, countries and localities of data collection

World region	Countries and localities
Africa	Kenya, (Nigeria) and South Africa
Asia	China, India, Malaysia, Taiwan and Thailand
Australia and New Zealand	Australia and New Zealand
Central America and Mexico	El Salvador and Mexico
Eastern Europe	Hungary, Lithuania, Poland, Russia, Serbia and Slovakia
The Middle East	Iran, Israel and Turkey
United States and Canada	Canada and the United States
Scandinavia	Denmark, (Finland), Norway and (Sweden)
South America	Argentina, Brazil, Chile, Colombia and Ecuador
United Kingdom	England, Scotland and Wales
Western Europe	Austria, Belgium, France, Germany, (Greece), Italy, the Netherlands, Portugal, Spain and Switzerland

We collected data from a minimum of 350 raters per world region based on the simulations described in the Methods. Countries in parentheses were added to the list after acceptance in principle of the stage 1 protocol. Ecuador was incorrectly classified as Central America and Mexico in our stage 1 submission, but has been classified as South America for analyses and in our stage 2 submission.

of components extracted or a different primary pattern observed), ϕ was uninterpretable. This is because the differences in configuration across the two solutions were conflated with the loading differences.

Our analyses indicated that the first component was equal to the first component in Oosterhof and Todorov’s original study for all world regions ($\phi > 0.95$). The second component was equal to ($\phi > 0.95$) or fairly similar to ($\phi > 0.85$) the second component reported by Oosterhof and Todorov in all of the world regions except Asia ($\phi = 0.848$). Table 4 summarizes these results.

Together, these results suggest that the valence–dominance model generalizes across world regions when using an identical analysis to that used in Oosterhof and Todorov’s original study. Thus, the results of our PCA support prediction 1 (that the valence–dominance model will apply to all world regions) but not prediction 2 (that the valence–dominance model will apply in Western-world regions but not other world regions). However, we note here that in most world regions we extracted a third component not extracted in the original study: that Eastern Europe did not demonstrate the same primary pattern and that ϕ should be interpreted with caution for all world regions except Africa and South America.

Robustness analyses (exploratory factor analysis (EFA); code 2.2). Following our analysis plan, we conducted additional robustness analyses that directly addressed criticisms of the type of statistical analyses used by Oosterhof and Todorov (see ref. ²⁸ for a discussion of these criticisms). These robustness analyses employed EFA with an oblimin rotation as the model and used parallel analysis to identify the number of factors to extract. The goal of an EFA with an oblimin rotation is to simplify the loading matrix and yield interpretable factors.

We conducted this analysis on Oosterhof and Todorov’s original data and found a similar result to their PCA solution: two factors extracted, with factor 1 characterized by a high loading for trustworthiness and factor 2 characterized by a high loading for dominance.

Table 2 | Number of participants per region and Cronbach's α values following data quality checks and exclusions

Region	Aggressive	Attractive	Caring	Confident	Dominant	Emotionally stable	Intelligent	Mean	Responsible	Sociable	Trustworthy	Unhappy	Weird
Western Europe	$\alpha=0.978$ $n=152$	$\alpha=0.991$ $n=147$	$\alpha=0.976$ $n=136$	$\alpha=0.985$ $n=156$	$\alpha=0.973$ $n=150$	$\alpha=0.981$ $n=141$	$\alpha=0.975$ $n=141$	$\alpha=0.969$ $n=120$	$\alpha=0.978$ $n=138$	$\alpha=0.988$ $n=188$	$\alpha=0.978$ $n=141$	$\alpha=0.983$ $n=140$	$\alpha=0.982$ $n=113$
United States and Canada	$\alpha=0.983$ $n=248$	$\alpha=0.991$ $n=224$	$\alpha=0.986$ $n=257$	$\alpha=0.989$ $n=303$	$\alpha=0.977$ $n=246$	$\alpha=0.986$ $n=270$	$\alpha=0.979$ $n=239$	$\alpha=0.984$ $n=270$	$\alpha=0.984$ $n=269$	$\alpha=0.988$ $n=246$	$\alpha=0.984$ $n=263$	$\alpha=0.985$ $n=252$	$\alpha=0.987$ $n=226$
United Kingdom	$\alpha=0.879$ $n=16$	$\alpha=0.949$ $n=22$	$\alpha=0.936$ $n=34$	$\alpha=0.93$ $n=30$	$\alpha=0.886$ $n=34$	$\alpha=0.9$ $n=30$	$\alpha=0.911$ $n=34$	$\alpha=0.87$ $n=27$	$\alpha=0.892$ $n=37$	$\alpha=0.932$ $n=28$	$\alpha=0.92$ $n=27$	$\alpha=0.937$ $n=24$	$\alpha=0.899$ $n=18$
South America	$\alpha=0.948$ $n=97$	$\alpha=0.982$ $n=108$	$\alpha=0.944$ $n=112$	$\alpha=0.968$ $n=108$	$\alpha=0.957$ $n=121$	$\alpha=0.949$ $n=100$	$\alpha=0.938$ $n=110$	$\alpha=0.949$ $n=95$	$\alpha=0.937$ $n=117$	$\alpha=0.974$ $n=110$	$\alpha=0.952$ $n=107$	$\alpha=0.961$ $n=87$	$\alpha=0.973$ $n=116$
Scandinavia	$\alpha=0.95$ $n=48$	$\alpha=0.969$ $n=44$	$\alpha=0.949$ $n=46$	$\alpha=0.96$ $n=56$	$\alpha=0.941$ $n=49$	$\alpha=0.955$ $n=67$	$\alpha=0.958$ $n=54$	$\alpha=0.912$ $n=36$	$\alpha=0.915$ $n=37$	$\alpha=0.969$ $n=64$	$\alpha=0.949$ $n=58$	$\alpha=0.952$ $n=55$	$\alpha=0.952$ $n=39$
Middle East	$\alpha=0.912$ $n=32$	$\alpha=0.949$ $n=32$	$\alpha=0.934$ $n=42$	$\alpha=0.943$ $n=39$	$\alpha=0.9$ $n=35$	$\alpha=0.903$ $n=33$	$\alpha=0.896$ $n=48$	$\alpha=0.901$ $n=36$	$\alpha=0.87$ $n=34$	$\alpha=0.944$ $n=41$	$\alpha=0.895$ $n=42$	$\alpha=0.943$ $n=57$	$\alpha=0.896$ $n=32$
Eastern Europe	$\alpha=0.941$ $n=59$	$\alpha=0.971$ $n=58$	$\alpha=0.926$ $n=56$	$\alpha=0.946$ $n=60$	$\alpha=0.952$ $n=74$	$\alpha=0.923$ $n=56$	$\alpha=0.939$ $n=64$	$\alpha=0.937$ $n=68$	$\alpha=0.953$ $n=65$	$\alpha=0.955$ $n=68$	$\alpha=0.937$ $n=54$	$\alpha=0.964$ $n=74$	$\alpha=0.956$ $n=53$
Central America and Mexico	$\alpha=0.845$ $n=26$	$\alpha=0.93$ $n=25$	$\alpha=0.788$ $n=24$	$\alpha=0.89$ $n=32$	$\alpha=0.859$ $n=33$	$\alpha=0.835$ $n=23$	$\alpha=0.832$ $n=33$	$\alpha=0.817$ $n=23$	$\alpha=0.824$ $n=22$	$\alpha=0.882$ $n=28$	$\alpha=0.851$ $n=27$	$\alpha=0.771$ $n=27$	$\alpha=0.842$ $n=15$
Australia and New Zealand	$\alpha=0.956$ $n=77$	$\alpha=0.98$ $n=88$	$\alpha=0.964$ $n=90$	$\alpha=0.972$ $n=93$	$\alpha=0.936$ $n=66$	$\alpha=0.957$ $n=88$	$\alpha=0.951$ $n=81$	$\alpha=0.947$ $n=71$	$\alpha=0.937$ $n=68$	$\alpha=0.972$ $n=95$	$\alpha=0.953$ $n=72$	$\alpha=0.948$ $n=85$	$\alpha=0.962$ $n=70$
Asia	$\alpha=0.932$ $n=59$	$\alpha=0.957$ $n=52$	$\alpha=0.948$ $n=73$	$\alpha=0.959$ $n=72$	$\alpha=0.917$ $n=55$	$\alpha=0.908$ $n=55$	$\alpha=0.927$ $n=64$	$\alpha=0.909$ $n=51$	$\alpha=0.931$ $n=63$	$\alpha=0.952$ $n=65$	$\alpha=0.93$ $n=61$	$\alpha=0.937$ $n=61$	$\alpha=0.942$ $n=49$
Africa	$\alpha=0.808$ $n=45$	$\alpha=0.873$ $n=38$	$\alpha=0.865$ $n=44$	$\alpha=0.805$ $n=31$	$\alpha=0.79$ $n=38$	$\alpha=0.779$ $n=38$	$\alpha=0.756$ $n=37$	$\alpha=0.889$ $n=51$	$\alpha=0.811$ $n=36$	$\alpha=0.819$ $n=34$	$\alpha=0.867$ $n=49$	$\alpha=0.795$ $n=43$	$\alpha=0.889$ $n=37$

However, for all other world regions, we extracted more than two factors using parallel analysis. Full EFA loading matrices for each region and Oosterhof and Todorov's original data are shown in Fig. 2. The four-factor solution for the USA and Canada did not converge. We did not register a contingency for nonconvergence, but because parallel analysis can lead to over extraction, we reran the EFA with one fewer than the number of suggested factors. The model converged when estimating three factors.

In contrast with the PCA, the results of our robustness analyses showed less evidence that the valence–dominance model generalizes across world regions. For example, we extracted a different number of factors than the original solution for all world regions. A summary of the results for our replication criteria is given in Table 5.

Because the number of factors differed from the original solution in all world regions and the loading matrices were differentially rotated from the original solution, it is not valid to compare the differences in the loadings from the original solution with those observed in the world regions reported here, as we had initially planned. Loadings quantify the relationship of traits to a factor. To compare loadings across samples, we must first determine whether we extracted the same factor in each sample (that is, satisfied the assumption of configural invariance). Our registered analyses included the calculation of Tucker's coefficient of congruence, ϕ in order to compare the first factor from the original study with the first factor we extracted in a given world region, and to compare the second factor from the original study with the second factor extracted in a given world region. However, because we extracted a different number of factors from the original solution in all world regions, it is not valid to compare the loadings across these different factors, or to quantify their differences using ϕ .

The congruence coefficient is only appropriate to report when we can ensure that the factors are comparable across samples. That the number of factors extracted did not replicate the original pattern and that the EFAs were rotated differently across world regions negates the comparability of the loadings. Consistent with our

registered analysis code, we reported ϕ for the relationship of the first factor from Oosterhof and Todorov to the factor with the most explained variance in a world region, and ϕ for the relationship of the second factor from Oosterhof and Todorov to the factor with the second most explained variance in a world region only in the Supplementary Information. However, we stress that these coefficients are quantifying loadings that link to different factors from different dimensional spaces and are not necessarily comparable.

In summary, the results of our EFA support neither prediction 1 (that the valence–dominance model will apply to all world regions) nor prediction 2 (that the valence–dominance model will apply to Western-world regions but not other world regions).

Discussion

Our primary analyses—PCAs identical to those reported by Oosterhof and Todorov—suggested that the valence–dominance model of social perception of faces generalizes well across world regions. Although most world regions showed a third component not discussed in the original work¹², this third component is actually similar to the third component in Oosterhof and Todorov's original study. In Oosterhof and Todorov's original study, they did not interpret the third component because its eigenvalue was below 1, whereas in our analyses the eigenvalues of the third components in most of the regions were just above 1. Nonetheless, the third component in each region had a factor congruence between 0.77 and 0.90 with the third component for Oosterhof and Todorov's data. However, we emphasize here that many of these dimensions accounted for a relatively small proportion of the variance explained and, thus, may be of limited theoretical importance.

In contrast with the results of our PCAs, an alternative analysis that addressed common criticisms of the type of analysis Oosterhof and Todorov employed showed much less generalization across world regions. We used modern extraction techniques and EFAs with correlated factor rotations. The correlated rotation methods aim to simplify the loading matrix with the goal of estimating



Fig. 1 | PCA loading matrices for each region. Positive loadings are shaded red and negative loadings are shaded blue. Darker colours correspond to stronger loadings. The proportion of variance (Prop.Var) explained by each component is included at the top of each table.

Table 3 | Replication criteria for the PCA for each region

Region	Component 1		Component 2		Replicated
	Trustworthy	Dominant	Dominant	Trustworthy	
Oosterhof and Todorov ¹²	0.941	−0.244	0.929	−0.060	Yes
Africa	0.924	0.271	0.843	−0.065	Yes
Asia	0.922	0.370	0.863	−0.006	Yes
Australia and New Zealand	0.943	0.257	0.907	−0.076	Yes
Central America and Mexico	0.918	0.007	0.915	−0.050	Yes
Eastern Europe	0.938	0.599	0.755	−0.113	No
Middle East	0.831	0.490	0.810	−0.382	Yes
Scandinavia	0.953	0.392	0.881	−0.121	Yes
South America	0.898	0.309	0.905	−0.151	Yes
United Kingdom	0.944	0.331	0.851	−0.121	Yes
United States and Canada	0.966	0.406	0.841	−0.073	Yes
Western Europe	0.957	0.357	0.875	−0.166	Yes

Oosterhof and Todorov's valence-dominance model was judged to have been replicated in a given world region if the first component had a loading of >0.7 with trustworthiness and <0.5 with dominance, and if the second component had a loading of >0.7 with dominance and <0.5 with trustworthiness.

interpretable factors, and in our data revealed more regional variation. These results suggest that, if the dimensions of face perception are indeed correlated, using analytical techniques that force these dimensions to be uncorrelated may be obscuring important regional differences in the structure of face perceptions.

A necessary next step for moving forward in person perception research is to address which analysis model (PCA or EFA) best aligns with theory, so that models and theories can be revised and expanded appropriately in future research. Crucially, the two models make different assumptions about trait ratings of faces.

Table 4 | Factor congruence for each region's PCA

Region	Component 1		Component 2	
	Loading	Congruence	Loading	Congruence
Africa	0.980	Equal	0.947	Fairly similar
Asia	0.974	Equal	0.843	Not similar
Australia and New Zealand	0.982	Equal	0.959	Equal
Central America and Mexico	0.992	Equal	0.935	Fairly similar
Eastern Europe	0.953	Equal	0.948	Fairly similar
Middle East	0.952	Equal	0.859	Fairly similar
Scandinavia	0.973	Equal	0.960	Equal
South America	0.976	Equal	0.953	Equal
United Kingdom	0.976	Equal	0.938	Fairly similar
United States and Canada	0.972	Equal	0.952	Equal
Western Europe	0.975	Equal	0.936	Fairly similar

The PCA model does not assume that a latent factor causes the trait ratings of the faces. The component captures linear combinations of the original variables, maximized to explain variance. Furthermore, in the original valence–dominance model, those components were assumed to be orthogonal. In contrast, the theory underlying the EFA model is that a latent factor causes the trait

ratings and any unexplained variance in that rating is measurement error. Additionally, our EFA models allowed for the factors to be correlated.

Theory can guide which model we use to analyse person perception data. A person perception theory that aligns with a PCA model would state that there are no underlying latent factors that cause a person to rate a face in a particular way. There are, instead, perceptual processes that vary across contexts, those doing the rating and those being rated, and the differential processes give rise to components that can be used to reduce the data. This theory of person perception would move forward with identifying the shared processes across contexts, raters and ratees to see whether there are predictable patterns in how the data are reduced.

A person perception theory that aligns with an EFA model makes different assumptions about the processes that give rise to face ratings. This theory would state that latent factors (for example, valence or dominance) cause the trait ratings and, once we account for the correct latent factors, any variability left in the ratings is measurement error. We suggest that more careful and explicit consideration of how theory connects to these approaches, and of which approach is best suited to different research questions, will benefit the field.

Our study is one of several recent studies that have begun to utilize different statistical models and to explore more dynamic theories of trait ratings^{21,29,30} by exploring how the structures of trait ratings vary systematically. This growing body of work catalogues variations in trait ratings by target demographic^{21,29,31}, target status³², target age³³, perceiver knowledge³⁴ and cultural factors^{17,18}. Furthermore, this growing body of work proposes dynamic theories of person perception and more flexible statistical models for capturing them^{21,29,30,35}.



Fig. 2 | EFA loading matrices for each region. Positive loadings are shaded red and negative loadings are shaded blue. Darker colours correspond to stronger loadings. The proportion of variance explained by each factor is included at the top of each table.

Table 5 | Replication criteria for the EFA for each region

Region	Factor 1		Factor 2		Replicated
	Trustworthy	Dominant	Dominant	Trustworthy	
Oosterhof and Todorov ¹²	0.826	0.228	0.970	−0.288	Yes
Africa	0.786	0.200	0.069	0.214	No
Asia	0.761	0.487	0.110	0.236	No
Australia and New Zealand	0.730	0.157	0.071	0.281	No
Central America and Mexico	0.268	0.108	0.241	0.591	No
Eastern Europe	0.843	0.750	0.609	−0.322	No
Middle East	0.177	0.502	0.600	−0.686	No
Scandinavia	0.744	0.428	0.293	0.211	No
South America	−0.458	0.778	0.261	0.058	No
United Kingdom	0.338	0.249	0.265	0.510	No
United States and Canada	0.768	0.491	0.264	0.189	No
Western Europe	0.398	0.111	0.256	0.164	No

Oosterhof and Todorov's valence–dominance model was judged to have been replicated in a given world region if the first factor had a loading >0.7 with trustworthiness and <0.5 with dominance and the second factor had a loading >0.7 with dominance and <0.5 with trustworthiness.

Our results are consistent with this recent work in that they do not provide strong evidence that there are a few generalizable latent factors that cause the trait ratings across world regions. However, they do suggest a dynamic process of person perception and elucidate the differential patterns of ratings across world regions. We can use these data, representing impressions formed on a global scale, to expand or refine our theories and to guide the selection of statistical models to represent those theories. Given the accumulating evidence for variation in trait ratings, it is important that the connection between the statistical models used to represent theories of person perception are explicit and can accommodate the complexities of the impression formation process.

Methods

Ethics. Each research group had approval from their local ethics committee or institutional review board to conduct the study, had explicitly indicated that their institution did not require approval for the researchers to conduct this type of face-rating task or had explicitly indicated that the current study was covered by a pre-existing approval. Although the specifics of the consent procedure differed across research groups, all participants provided informed consent. All data were stored centrally on University of Glasgow servers.

Procedure. Oosterhof and Todorov derived their valence–dominance model from a PCA 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 ($r=0.94$) and weakly correlated with rated dominance ($r=-0.24$). The second component explained 18% of the variance in trait ratings, strongly correlated with rated dominance ($r=0.93$) and weakly correlated with rated trustworthiness ($r=-0.06$). We replicated Oosterhof and Todorov's method¹² and primary analysis in each world region we examined.

Stimuli in our study came from an open-access, full-colour face image set³⁶ consisting of images of the faces of 60 men and 60 women taken under standardized photographic conditions ($M_{\text{age}} = 26.4$ years; $s.d. = 3.6$ years; range = 18–35 years). These 120 images consisted 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 reported by Oosterhof and Todorov's study¹², the individuals photographed posed looking directly at the camera with a neutral expression, and the background, lighting and clothing (here, a grey t-shirt) were constant across images.

In our study, adult raters were 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 collected data through an identical interface (except for differences in instruction language), data collection protocols were highly standardized across

laboratories. Each participant completed the block of 120 face-rating trials twice so that we could report test–retest reliabilities of ratings; ratings from the first and second blocks were averaged for all analyses (see code 1.5.5 in the Supplementary Information).

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

Raters completed 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 were provided. Twelve of these dictionary definitions had previously been used to test for effects of social impressions on the memorability of face photographs³⁷. Dominance (not included in that study) was defined as strong and 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 analysed 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 inter-rater reliability coefficients (Cronbach's α values > 0.80). 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 inter-rater reliability coefficients (Cronbach's α values > 0.80). Thus, averages of ratings from 25 or more raters will have produced reliable dependent variables in our analyses; we planned 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 were 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 range³⁸. Age ratings were not included in analyses relating to replications of Oosterhof and Todorov's valence–dominance model. These age ratings were collected to allow for planned exploratory analyses including rated age, but we did not perform these analyses.

Analysis plan. The code used for our analyses is included in the Supplementary Information and publicly available from the Open Science Framework (<https://osf.io/87rbg/>). The specific sections of code are cited below.

Ratings from each world region were analysed separately and anonymous raw data have been published on the Open Science Framework. Our main analyses directly replicated the PCA reported by Oosterhof and Todorov to test their theoretical model in each region sampled (code 2.1). First, we calculated the average rating for each face separately for each of the 13 traits (code 2.1.2). We then subjected

these mean ratings to PCA with orthogonal components and no rotation, as Oosterhof and Todorov did (code 2.1.3). Using the criteria they reported, we retained and interpreted components with eigenvalues greater than 1.0 (code 2.1.3.1).

Criteria for replicating Oosterhof and Todorov's valence–dominance model. We used multiple sources of evidence to judge whether Oosterhof and Todorov's valence–dominance model replicated in a given world region. First, we examined the solution from the PCA conducted in each region and determined whether Oosterhof and Todorov's primary pattern replicated according to three criteria: (1) the first two components had eigenvalues greater than 1.0; (2) the first component (that is, the one explaining more of the variance in ratings) correlated strongly with trustworthiness ($r > 0.7$) and weakly with dominance ($r < 0.5$); and (3) the second component (that is, the one explaining less of the variance in ratings) correlated strongly with dominance ($r > 0.7$) and weakly with trustworthiness ($r < 0.5$). If the solution in a world region met all three of these criteria, we concluded 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 also reported Tucker's coefficient of congruence^{39,40}. The congruence coefficient, ϕ , ranges from -1 to 1 and quantifies the similarity between two vectors of loadings⁴¹. 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 ($i = 1, \dots, n$ number of indicators in the analysis) onto factors x and y , respectively. For the purposes of the current research, we compared the vector of loadings from the first component from Oosterhof and Todorov with the vector of loadings from the first component estimated from each world region. We repeated this analysis for the second component. This produced a standardized measure of component similarity for each component in each world region that was not sensitive to the mean size of the loadings⁴². Furthermore, this coefficient was 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 guidelines⁴³, we concluded that the components reported by Oosterhof and Todorov were not similar to those estimated in a given world region if the coefficient was < 0.85 , were fairly similar if it was between 0.85 and 0.94 and were equal if it was > 0.95 (code 2.1.4).

Thus, we reported whether the solution had the same primary pattern that Oosterhof and Todorov found and quantified 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 applies to all world regions) was supported if the solution from the PCA conducted in each region satisfied all of the criteria described above. Specifically, the primary pattern was replicated and the components had at least a fair degree of similarity as quantified by a value of ϕ of 0.85 or greater.

Prediction 2 (the valence–dominance model applies in Western-world regions but not other world regions) was supported if the solutions from the PCA conducted in Australia and New Zealand, the United States and Canada, Scandinavia, the United Kingdom and Western Europe, but not Africa, Asia, Central America and Mexico, Eastern Europe, the Middle East or South America, satisfied the criteria described above.

Exclusions. Data from raters who failed to complete all 120 ratings in the first block of trials or who provided the same rating for 75% or more of the faces were excluded from the analyses (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 was checked by separately calculating the inter-rater agreement (indicated by Cronbach's α and test–retest reliability) for each trait in every world region (code 2.1.1). A trait was only included in the analysis for that region if the coefficient exceeded 0.70 . Cases in which the coefficient did not exceed 0.70 are reported and discussed. There were no cases in which the coefficient did not exceed 0.70 . Test–retest reliability of traits was not used to exclude traits from analysis.

Power analysis. Simulations showed that we had more than 95% power to detect the key effect of interest (that is, 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 replication¹³ of Oosterhof and Todorov's research to generate a variance–covariance matrix representative of typical inter-relationships among the 13 traits tested in our study. We then generated 1,000 samples of 120 faces from these distributions and ran our planned PCA (which is identical to that reported by Oosterhof and Todorov) on each sample (see <https://osf.io/87rbg/> for code and data). The results of $> 99\%$ of these analyses matched our criteria for replicating Oosterhof and Todorov's findings. Thus, 120 faces gave 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 PCA. As described above,

we directly replicated their method in our main analyses but acknowledge that this type of analysis has been criticized.

First, it has been argued that EFA with rotation, rather than an unrotated PCA, is more appropriate when one intends to measure correlated latent factors, as was the case in the current study^{43,44}. 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^{45,46}.

To address these limitations, we repeated our main analyses using EFA with an oblimin rotation as the model and a parallel analysis to determine the number of factors to extract. We also recalculated the congruence coefficient described above for these EFA results (code 2.2.2).

We used 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^{43,47,48} (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 with the eigenvalue for each component from the real data. Components are then retained if their eigenvalues exceed those from the randomly generated data⁴⁹.

The purpose of these additional analyses was twofold: (1) to address potential methodological limitations in the original study; and (2) to ensure that the results of our replication of Oosterhof and Todorov's study are robust to the implementation of those more rigorous analytical techniques. The same criteria for replicating Oosterhof and Todorov's model described above were applied to this analysis (code 2.2.1.3).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

Full data are publicly available at <https://osf.io/87rbg/>.

Code availability

Full analysis code is publicly available at <https://osf.io/87rbg/>.

Received: 18 May 2018; Accepted: 23 October 2020;

Published online: 4 January 2021

References

- Olivola, C. Y. & Todorov, A. Elected in 100 milliseconds: appearance-based trait inferences and voting. *J. Nonverbal Behav.* **34**, 83–110 (2010).
- Ritchie, K. L., Palermo, R. & Rhodes, G. Forming impressions of facial attractiveness is mandatory. *Sci. Rep.* **7**, 469 (2017).
- Willis, J. & Todorov, A. First impressions: making up your mind after 100 ms exposure to a face. *Psychol. Sci.* **17**, 592–598 (2006).
- Olivola, C. Y., Funk, F. & Todorov, A. Social attributions from faces bias human choices. *Trends Cogn. Sci.* **18**, 566–570 (2014).
- Todorov, A., Olivola, C. Y., Dotsch, R. & Mende-Siedlecki, P. Social attributions from faces: determinants, consequences, accuracy, and functional significance. *Annu. Rev. Psychol.* **66**, 519–545 (2015).
- Van 't Wout, M. & Sanfey, A. G. Friend or foe: the effect of implicit trustworthiness judgments in social decision-making. *Cognition* **108**, 796–803 (2008).
- Todorov, A., Mandisodza, A. N., Goren, A. & Hall, C. C. Inferences of competence from faces predict election outcomes. *Science* **308**, 1623–1626 (2005).
- Langlois, J. H. et al. Maxims or myths of beauty? A meta-analytic and theoretical review. *Psychol. Bull.* **126**, 390–423 (2000).
- Wilson, J. P. & Rule, N. O. Facial trustworthiness predicts extreme criminal-sentencing outcomes. *Psychol. Sci.* **26**, 1325–1331 (2015).
- Todorov, A., Said, C. P., Engell, A. D. & Oosterhof, N. N. Understanding evaluation of faces on social dimensions. *Trends Cogn. Sci.* **12**, 455–460 (2008).
- Jack, R. E. & Schyns, P. G. Toward a social psychophysics of face communication. *Annu. Rev. Psychol.* **68**, 269–297 (2017).
- Oosterhof, N. N. & Todorov, A. The functional basis of face evaluation. *Proc. Natl Acad. Sci. USA* **105**, 11087–11092 (2008).
- Morrison, D., Wang, H., Hahn, A. C., Jones, B. C. & DeBruine, L. M. Predicting the reward value of faces and bodies from social perception. *PLoS ONE* **12**, e0185093 (2017).
- Wang, H., Hahn, A. C., DeBruine, L. M. & Jones, B. C. The motivational salience of faces is related to both their valence and dominance. *PLoS ONE* **11**, e0161114 (2016).
- Henrich, J., Heine, S. & Norenzayan, A. The weirdest people in the world? *Behav. Brain Sci.* **33**, 61–83 (2010).
- Kline, M. A., Shamsuddeen, R. & Broesch, T. Variation is the universal: making cultural evolution work in developmental psychology. *Phil. Trans. R. Soc. B* **373**, 20170059 (2018).

17. Sutherland, C. A. M. et al. Facial first impressions across culture: data-driven modeling of Chinese and British perceivers' unconstrained facial impressions. *Pers. Soc. Psychol. Bull.* **44**, 521–537 (2018).
18. Wang, H. et al. A data-driven study of Chinese participants' social judgments of Chinese faces. *PLoS ONE* **14**, e0210315 (2019).
19. Han, C. et al. Cultural differences in preferences for facial coloration. *Evol. Hum. Behav.* **39**, 154–159 (2018).
20. Perrett, D. I. et al. Effects of sexual dimorphism on facial attractiveness. *Nature* **394**, 884–887 (1998).
21. Xie, S. Y., Flake, J. K. & Hehman, E. Perceiver and target characteristics contribute to impression formation differently across race and gender. *J. Pers. Soc. Psychol.* **117**, 364–385 (2019).
22. Li, N. P., Valentine, K. A. & Patel, L. Mate preferences in the US and Singapore: a cross-cultural test of the mate preference priority model. *Pers. Individ. Differ.* **50**, 291–294 (2011).
23. Ting-Toomey, S. In *The Challenge of Facework: Cross-Cultural and Interpersonal Issues* (ed. Ting-Toomey, S.) 1–14 (State Univ. New York Press, 1994).
24. Tan, C. B. Y., Stephen, I. D., Whitehead, R. & Sheppard, E. You look familiar: how Malaysian Chinese recognize faces. *PLoS ONE* **7**, e29714 (2012).
25. Chartier, C., McCarthy, R. & Urry, H. *The Psychological Science Accelerator* (Association for Physical Science, 2018).
26. Chawla, D. S. A new 'accelerator' aims to bring big science to psychology. *Science* <https://doi.org/10.1126/science.aar4464> (2017).
27. Moshontz, H. et al. The Psychological Science Accelerator: advancing psychology through a distributed collaborative network. *Adv. Methods Pract. Psychol. Sci.* **1**, 501–515 (2018).
28. Widaman, K. F. On common factor and principal component representations of data: implications for theory and for confirmatory replications. *Struct. Equ. Modeling* **25**, 829–847 (2018).
29. Hehman, E., Sutherland, C. A., Flake, J. K. & Slepian, M. L. The unique contributions of perceiver and target characteristics in person perception. *J. Pers. Soc. Psychol.* **113**, 513–529 (2017).
30. Sutherland, C. A., Rhodes, G., Burton, N. S. & Young, A. W. Do facial first impressions reflect a shared social reality? *Br. J. Psychol.* **111**, 215–232 (2020).
31. Oh, D., Dotsch, R., Porter, J. & Todorov, A. Gender biases in impressions from faces: empirical studies and computational models. *J. Exp. Psychol. Gen.* **149**, 323–342 (2020).
32. Oh, D., Shafir, E. & Todorov, A. Economic status cues from clothes affect perceived competence from faces. *Nat. Hum. Behav.* **4**, 287–293 (2020).
33. Collova, J. R., Sutherland, C. A. & Rhodes, G. Testing the functional basis of first impressions: dimensions for children's faces are not the same as for adults' faces. *J. Pers. Soc. Psychol.* **117**, 900–924 (2019).
34. Stoller, R. M., Hehman, E., Keller, M. D., Walker, M. & Freeman, J. B. The conceptual structure of face impressions. *Proc. Natl Acad. Sci. USA* **115**, 9210–9215 (2018).
35. Stoller, R. M., Hehman, E. & Freeman, J. B. A dynamic structure of social trait space. *Trends Cogn. Sci.* **22**, 197–200 (2018).
36. Ma, D. S., Correll, J. & Wittenbrink, B. The Chicago Face Database: a free stimulus set of faces and norming data. *Behav. Res. Methods* **47**, 1122–1135 (2015).
37. Bainbridge, W. A., Isola, P. & Oliva, A. The intrinsic memorability of face photographs. *J. Exp. Psychol. Gen.* **142**, 1323–1334 (2013).
38. Sutherland, C. A. et al. Social inferences from faces: ambient images generate a three-dimensional model. *Cognition* **127**, 105–118 (2013).
39. Burt, C. The factorial study of temperament traits. *Br. J. Psychol. Stat. Sect.* **1**, 178–203 (1948).
40. Tucker, L. R. *A Method for Synthesis of Factor Analysis Studies* Personnel Research Section Report No. 984 (Department of the Army, 1951).
41. Davenport, E. C. Jr Significance testing of congruence coefficients: a good idea? *Educ. Psychol. Meas.* **50**, 289–296 (1990).
42. Lorenzo-Seva, U. & ten Berge, J. M. F. Tucker's congruence coefficient as a meaningful index of factor similarity. *Methodology* **2**, 57–64 (2006).
43. Fabrigar, L. R., Wegener, D. T., MacCallum, R. C. & Strahan, E. J. Evaluating the use of exploratory factor analysis in psychological research. *Psychol. Methods* **4**, 272–299 (1999).
44. Park, H. S., Dailey, R. & Lemus, D. The use of exploratory factor analysis and principal components analysis in communication research. *Hum. Commun. Res.* **28**, 562–577 (2002).
45. Cliff, N. The eigenvalues-greater-than-one rule and the reliability of components. *Psychol. Bull.* **103**, 276–279 (1988).
46. Zwick, W. R. & Velicer, W. F. Comparison of five rules for determining the number of components to retain. *Psychol. Bull.* **99**, 432–442 (1986).
47. O'Connor, B. P. SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behav. Res. Methods Instrum. Comput.* **32**, 396–402 (2000).
48. Schmitt, T. A. Current methodological considerations in exploratory and confirmatory factor analysis. *J. Psychoeduc. Assess.* **29**, 304–321 (2011).
49. Courtney, M. G. R. Determining the number of factors to retain in EFA: using the SPSS R-Menu v2.0 to make more judicious estimations. *Pract. Assess. Res. Eval.* **18**, 1–14 (2013).

Acknowledgements

C.L. was supported by the Vienna Science and Technology Fund (WWTF VRG13-007); L.M.D. was supported by ERC 647910 (KINSHIP); D.I.B. and N.I. received funding from CONICET, Argentina; L.K., E.K. and Á. Putz were supported by the European Social Fund (EFOP-3.6.1-16-2016-00004; 'Comprehensive Development for Implementing Smart Specialization Strategies at the University of Pécs'). K.U. and E. Vergauwe were supported by a grant from the Swiss National Science Foundation (PZ00P1_154911 to E. Vergauwe). T.G. is supported by the Social Sciences and Humanities Research Council of Canada (SSHRC). M.A.V. was supported by grants 2016-T1/SOC-1395 (Comunidad de Madrid) and PSI2017-85159-P (AEI/FEDER UE). K.B. was supported by a grant from the National Science Centre, Poland (number 2015/19/D/HS6/00641). J. Bonick and J.W.L. were supported by the Joep Lange Institute. G.B. was supported by the Slovak Research and Development Agency (APVV-17-0418). H.I.J. and E.S. were supported by a French National Research Agency 'Investissements d'Avenir' programme grant (ANR-15-IDEX-02). T.D.G. was supported by an Australian Government Research Training Program Scholarship. The Raipur Group is thankful to: (1) the University Grants Commission, New Delhi, India for the research grants received through its SAP-DRS (Phase-III) scheme sanctioned to the School of Studies in Life Science; and (2) the Center for Translational Chronobiology at the School of Studies in Life Science, PRSU, Raipur, India for providing logistical support. K. Ask was supported by a small grant from the Department of Psychology, University of Gothenburg. Y.Q. was supported by grants from the Beijing Natural Science Foundation (5184035) and CAS Key Laboratory of Behavioral Science, Institute of Psychology. N.A.C. was supported by the National Science Foundation Graduate Research Fellowship (R010138018). We acknowledge the following research assistants: J. Muriithi and J. Ngugi (United States International University Africa); E. Adamo, D. Cafaro, V. Ciambone, F. Dolce and E. Tolomeo (Magna Graecia University of Catanzaro); E. De Stefano (University of Padova); S. A. Escobar Abadia (University of Lincoln); L. E. Grimstad (Norwegian School of Economics (NHH)); L. C. Zamora (Franklin and Marshall College); R. E. Liang and R. C. Lo (Universiti Tunku Abdul Rahman); A. Short and L. Allen (Massey University, New Zealand); A. Ateş, E. Güneş and S. Can Özdemir (Boğaziçi University); I. Pedersen and T. Roos (Åbo Akademi University); N. Paetz (Escuela de Comunicación Mónica Herrera); J. Green (University of Gothenburg); M. Krainz (University of Vienna, Austria); and B. Todorova (University of Vienna, Austria). The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Author contributions

Conceptualization: B.C.J., L.M.D., J.K.F., J.P.W., J.B.F., S.Á.-S., H.I., S.M.J.J., H.L. Data curation: B.C.J., L.M.D., N.C.A., N.G.B., Y.Q., J.W.L., K.G., G.M.M., J.G.L., J.B.F., P.C., A.P., N.P., S.P., M.M.S., B.P., M.J.B., V.K., J.P., D.S., S.C.W., J.V.V., P.S.F., C.R.C., N.A.C. Formal analysis: B.C.J., L.M.D., J.K.F., Y.Q., J.B.F. Funding acquisition: N.C.O., Y.Q., J.W.L., C.C., J. Leongómez, O.R.S., E. Valderrama, M.V.-A., J.G.L., M.C.P., J.B.F., J.K.O., G.K., H.I., H.D.F., T.J.S.L., E. Vergauwe, K. Ask, K.W.T., M.I., C.L., P.S.F., C.R.C. Investigation: B.C.J., L.M.D., M.T.L., J.A., I.L.G.N., N.G.B., S.C.L., F.F., M.L.W., C.P.C., M.A.V., S.A.S., N.C.O., D.P.C., A.W., Y.Q., H.M., P. Suavansri, T.R.E., J. Bonick, J.W.L., C.C., A. Kapucu, A. Karaaslan, J. Leongómez, O.R.S., E. Valderrama, M.V.-A., B.A., P. Szecsi, M. Andreychik, E.D.M., C.B., C.-P.H., Q.-L.L., L.A.V., K.B., K.G., I.S., S.S., R.A., C.M., W.V., Z.J., Q.W., G.M.M., I.D.S., J.G.L., M.C.P., J.D.A., E.H., S.Y.X., W.J.C., M. Seehuus, J.P.W., E.K., M.P.-P., A.E.B.-S., A.d.-G., I.G.-S., H.-H.W., J.B.F., D.W.O., V.S., T.E.S., C.A.L., C.L.C., A.K.P., J. Bavalor, P. Kačmár, I. Zakharov, S.Á.-S., E.B., M.T., K.S., C.D.C., J.W.S., J.K.O., A.-S.L., T.D.G., J.A.O., B.J.W.D., L.M.S., G.R., M.J.B., B.J., D.R., G.K., V.A.F., H.L.U., S.-C.C., G.P., Z.V., D.M.B.-B., H.I., N.V.d.L., C.B.Y.T., V.K., M.F.C., H.D.F., D.I.B., G.G., J.P., C.S., K.A.S., E.M.O.K., D.S., B.S., M. Sirota, G.V.S., T.J.S.L., K.U., E. Vergauwe, J.S., K. Ask, C.J.J.v.Z., A. Körner, S.C.W., J. Boudesseul, F.R.-D., K.L.R., N.M.M., K.R.B., D.W., A.R.G.-F., M. Anne, S.M.J.J., K.M.L., T.K.N., C.K.T., J.H.Z., A.D.R., L.K., M. Vianello, N.I., A.C., S.L., J. Lutz, M. Adamkovic, P.B., G.B., I.R., V.C., K.P., N.K.S., K.W.T., C.A.T., A.M.F., R.M.C.S.H., J.V.V., N.S.C.-F., M.F.-A., J.H., A.M., M. Sharifian, B.F., H.L., M.I., C.L., E.P., M. Voracek, J.O., E.M.G., A.A., A.A.Ö., M.T.C., B.B.-D., M.A.K., C.O., T.G., J.K.M., Y.D., X.Y., S. Alper, P.S.F., C.R.C., N.A.C. Methodology: B.C.J., L.M.D., J.K.F., S.C.L., L.A.V., M. Seehuus, S. Azouaghe, A.B., J.E., J.P.W., J.B.F., C.A.L., C.D.C., K.H., B.J., J.W., G.K., H.I., T.B., N.V.d.L., H.D.F., J.P., F.M.A.W., S.M.J.J., H.L. Project administration: B.C.J., L.M.D., N.G.B., S.C.L., M.L.W., M.G., A.S., N.C.O., A.W., Y.Q., H.M., R.M.S., J. Bonick, J.W.L., C.C., A. Kapucu, A. Karaaslan, J. Leongómez, O.R.S., E. Valderrama, M.V.-A., B.A., C.B., C.-P.H., L.A.V., K.B., K.G., I.S., S.S., I.D.S., M.C.P., S.Y.X., W.J.C., M. Seehuus, A.d.-G., I.G.-S., C.-C.K., J.B.F., D.W.O., C.A.L., J. Bavalor, P. Kačmár, I. Zakharov, K.S., C.D.C., J.W.S., J.L.B., J.A.O., B.J.W.D., M.J.B., B.J., D.R., G.P., Z.V., E.S., N.V.d.L., V.K., M.F.C., H.D.F., J.P., C.S., K.A.S., E.M.O.K., B.S., M. Sirota, T.J.S.L., K.U., E. Vergauwe, K. Ask, C.J.J.v.Z., S.C.W., J. Boudesseul, F.R.-D., K.L.R., D.W., S.M.J.J., C.K.T., J.H.Z., L.K., S.L., V.C., N.K.S., K.W.T., R.M.C.S.H., J.V.V., A.M., M. Sharifian, B.F., H.L., C.L., E.P., M. Voracek, A.A., A.A.Ö., M.A.K., T.G., X.Y., S. Alper, P.S.F., C.R.C., N.A.C.

Resources: B.C.J., L.M.D., M.T.L., S.C.L., C.P.C., M.A.V., S.A.S., A.W., Y.Q., K. Ariyabuddhiphongs, S.J., H.M., P. Suavansri, N.T., R.M.S., C.C., A. Kapucu, J. Leongómez, M.V.-A., N.H., C.B., L.A.V., K.B., K.G., Z.J., G.M.M., I.D.S., J.G.L., S.Y.X., W.J.C., M. Seehuus, S. Azouaghe, A.B., J.E., A.d.-G., C.-C.K., J.B.F., C.A.L., A.K.P., P. Kačmár, I. Zakharov, E.B., K.S., C.D.C., J.K.O., J.L.B., B.J.W.D., D.R., W.W.A.S., S.-C.C., G.P., D.M.B.-B., T.B., C.B.Y.T., V.K., H.D.F., G.G., C.S., K.A.S., E.M.O.K., B.S., M. Sirota, G.V.S., T.J.S.L., K.U., E. Vergauwe, K.J., K. Ask, J. Boudesseul, F.R.-D., N.M.M., S.M.J.J., C.K.T., A.D.R., F.K., Á.P., P.T., M. Vianello, A.C., S.L., J. Lutz, M. Adamkovic, P.B., V.C., A.M.F., R.M.C.S.H., J.V.V., N.S.C.-F., M.F.-A., A.M., M. Sharifian, H.L., C.L., M. Voracek, E.M.G., A.A.Ö., M.A.K., C.O., X.Y., S. Alper, P.S.F., C.R.C. Software: B.C.J., L.M.D., J.K.F., G.M.M., I.D.S., N.P., B.P., C.D.C., H.D.F., C.S., K.R.B., R.M.C.S.H., C.R.C., N.A.C. Supervision: B.C.J., L.M.D., J.K.F., M.T.L., S.C.L., M.L.W., N.C.O., A.W., H.M., J.W.L., C.C., A. Kapucu, J. Leongómez, O.R.S., E. Valderrama, M.V.-A., M. Andreychik, E.D.M., C.B., L.A.V., K.B., I.D.S., M.C.P., E.H., W.J.C., M. Seehuus, C.-C.K., J.B.F., C.A.L., P. Kačmár, I. Zakharov, K.S., C.D.C., J.W.S., J.K.O., A.-S.L., J.L.B., J.A.O., B.J.W.D., M.J.B., H.I., V.K., M.F.C., H.D.F., J.P., C.S., E.M.O.K., D.S., B.S., M. Sirota, T.J.S.L., K.U., E. Vergauwe, K. Ask, C.J.J.v.Z., D.W., S.M.J.J., A.C., S.L., K.P., N.K.S., K.W.T., A.M.F., J.V.V., M. Sharifian, M.L., C.L., M. Voracek, A.A., A.A.Ö., M.A.K., S. Alper, P.S.F., C.R.C., N.A.C. Validation: B.C.J., L.M.D., J.K.F., C.C., Q.W., S.Y.X., M. Seehuus, C.L.C., A.K.P., I. Zakharov, J.W.S., E.S., V.K., H.D.F., J.P., M. Sirota, E. Vergauwe, C.J.J.v.Z., P.T., J.H., M. Voracek, M.A.K. Visualization: B.C.J., L.M.D., J.K.F., H.D.F., M.A.K., P.S.F. Writing (original draft): B.C.J., L.M.D., J.K.F., F.F., Y.Q., C.B., I.G.-S., J.B.F., K.S., B.J.W.D., G.K., H.L.U., H.I., H.D.F., D.I.B., J.P., C.S., D.S., K.L.R., S.M.J.J., A.D.R., N.K.S., J.O., A.A.Ö., M.A.K., P.S.F., N.A.C. Writing (review & editing): B.C.J., L.M.D., J.K.F., M.T.L., J.A., L.L.G.N., S.C.L., F.F., M.L.W., M.A.V., A.S., D.P.C., A.W., Y.Q., K. Ariyabuddhiphongs, H.M., T.R.E., J. Bonick, J.W.L., C.C., J. Leongómez, B.A., N.H., P. Szecsi, M. Andreychik, E.D.M., C.B.,

N.L., L.A.V., K.B., I.S., S.S., Z.J., I.D.S., M.C.P., J.D.A., E.H., S.Y.X., W.J.C., M. Seehuus, S. Azouaghe, A.B., J.E., J.P.W., E.K., M.P.-P., A.E.B.-S., A.d.-G., J.B.F., V.S., T.E.S., C.A.L., C.L.C., P.C., P. Kujur, A.P., N.P., A.K.P., S.P., M.M.S., B.P., P. Kačmár, I. Zakharov, S.Á.-S., E.B., M.T., K.S., C.D.C., J.W.S., J.K.O., A.-S.L., J.L.B., T.D.G., J.A.O., B.J.W.D., G.R., M.J.B., K.H., B.J., G.K., V.A.F., H.L.U., G.P., Z.V., H.I., T.B., N.V.d.L., C.B.Y.T., V.K., M.F.C., H.D.F., D.I.B., G.G., C.S., E.M.O.K., D.S., B.S., M. Sirota, T.J.S.L., K.U., E. Vergauwe, J.S., K. Ask, C.J.J.v.Z., A. Körner, K.L.R., K.R.B., D.W., A.R.G.-F., S.M.J.J., T.K.N., C.K.T., J.H.Z., M. Vianello, N.I., M. Adamkovic, G.B., I.R., V.C., K.P., N.K.S., K.W.T., C.A.T., A.M.F., R.M.C.S.H., J.V.V., B.F., H.L., C.L., E.P., M. Voracek, J.O., E.M.G., A.A., A.A.Ö., B.B.-D., M.A.K., T.G., J.K.M., Y.D., P.S.F., C.R.C., N.A.C.

The following people did not indicate specific contributions: A.F.D., A.C.H., A.D.L.R.-G., D.R.F., D.T., E.T., E.G.-S., H.I.J., I. Zettler, I.R.P., J.A.M.-R., J.D.L., L.N., L.F.A., M.A.C.V., M.M.A., M.L.B.-G., M.H.S., N.O.R., P.P., P.F., R.J.M., S.G., S.J.C., T.H., V.K.M.S., W.-J.Y.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at <https://doi.org/10.1038/s41562-020-01007-2>.

Correspondence and requests for materials should be addressed to B.C.J.

Peer review information Primary Handling Editor: Stavroula Kousta.

Reprints and permissions information is available at www.nature.com/reprints.

© The Author(s), under exclusive licence to Springer Nature Limited 2021

Benedict C. Jones ^{1,156} , **Lisa M. DeBruine** ^{2,156}, **Jessica K. Flake**^{3,156}, **Marco Tullio Liuzza** ⁴, **Jan Antfolk** ⁵, **Nwadiogo C. Arinze** ⁶, **Izuchukwu L. G. Ndukaihe**⁶, **Nicholas G. Bloxson**⁷, **Savannah C. Lewis** ⁷, **Francesco Foroni** ⁸, **Megan L. Willis** ⁸, **Carmelo P. Cubillas**⁹, **Miguel A. Vadillo** ⁹, **Enrique Turiegano** ¹⁰, **Michael Gilead**¹¹, **Almog Simchon** ¹¹, **S. Adil Saribay** ¹², **Nicholas C. Owsley**¹³, **Chaning Jang** ¹³, **Georgina Mburu**¹³, **Dustin P. Calvillo**¹⁴, **Anna Włodarczyk** ¹⁵, **Yue Qi**¹⁶, **Kris Ariyabuddhiphongs** ¹⁷, **Somboon Jarukasemthawee**¹⁷, **Harry Manley** ¹⁷, **Panita Suavansri** ¹⁷, **Nattasuda Taephant**¹⁷, **Ryan M. Stoller** ¹⁸, **Thomas R. Evans** ¹⁹, **Judson Bonick** ²⁰, **Jan W. Lindemans** ²⁰, **Logan F. Ashworth**²¹, **Amanda C. Hahn** ²¹, **Coralie Chevallier** ²², **Aycan Kapucu** ²³, **Aslan Karaaslan** ²³, **Juan David Leongómez** ²⁴, **Oscar R. Sánchez** ²⁴, **Eugenio Valderrama** ²⁴, **Milena Vásquez-Amézquita** ²⁴, **Nandor Hajdu** ^{25,26}, **Balazs Aczel** ²⁶, **Peter Szecsi** ²⁶, **Michael Andreychik** ²⁷, **Erica D. Musser** ²⁸, **Carlota Batres** ²⁹, **Chuan-Peng Hu** ³⁰, **Qing-Lan Liu**³¹, **Nicole Legate** ³², **Leigh Ann Vaughn** ³³, **Krystian Barzykowski** ³⁴, **Karolina Golik** ³⁴, **Irina Schmid** ³⁵, **Stefan Stieger** ³⁵, **Richard Artner** ³⁶, **Chiel Mues** ³⁶, **Wolf Vanpaemel** ³⁷, **Zhongqing Jiang** ³⁸, **Qi Wu**³⁸, **Gabriela M. Marcu** ³⁹, **Ian D. Stephen** ⁴⁰, **Jackson G. Lu** ⁴¹, **Michael C. Philipp** ⁴², **Jack D. Arnal** ⁴³, **Eric Hehman**³, **Sally Y. Xie**³, **William J. Chopik** ⁴⁴, **Martin Seehuus**⁴⁵, **Soufian Azouaghe** ^{46,47}, **Abdelkarim Belhaj**⁴⁶, **Jamal Elouafa**⁴⁶, **John P. Wilson** ⁴⁸, **Elliott Kruse**⁴⁹, **Marietta Papadatou-Pastou** ⁵⁰, **Anabel De La Rosa-Gómez** ⁵¹, **Alan E. Barba-Sánchez** ⁵¹, **Isaac González-Santoyo** ⁵², **Tsuyueh Hsu** ⁵³, **Chun-Chia Kung** ⁵³, **Hsiao-Hsin Wang**⁵³, **Jonathan B. Freeman** ⁵⁴, **Dong Won Oh** ⁵⁵, **Vidar Schei** ⁵⁶, **Therese E. Sverdrup** ⁵⁶, **Carmel A. Levitan** ⁵⁷, **Corey L. Cook**⁵⁸, **Priyanka Chandel** ⁵⁹, **Pratibha Kujur** ⁵⁹, **Arti Parganiha** ⁵⁹, **Noorshama Parveen** ⁵⁹, **Atanu Kumar Pati** ⁵⁹, **Sraddha Pradhan** ⁵⁹, **Margaret M. Singh**⁵⁹, **Babita Pande** ⁶⁰, **Jozef Bavolar** ⁶¹, **Pavol Kačmár** ⁶¹, **Ilya Zakharov** ⁶², **Sara Álvarez-Solas** ⁶³, **Ernest Baskin** ⁶⁴, **Martin Thirkettle** ⁶⁵, **Kathleen Schmidt** ⁶⁶, **Cody D. Christopherson** ⁶⁷, **Trinity Leonis**⁶⁷, **Jordan W. Suchow**⁶⁸, **Jonas K. Olofsson** ⁶⁹, **Teodor Jernsäther** ⁶⁹, **Ai-Suan Lee** ⁷⁰, **Jennifer L. Beaudry** ⁷¹, **Taylor D. Gogan** ⁷¹, **Julian A. Oldmeadow** ⁷¹, **Benjamin Balas**⁷², **Laura M. Stevens**⁷³,

Melissa F. Colloff⁷³, Heather D. Flowe⁷³, Sami Gülgöz⁷⁴, Mark J. Brandt⁷⁵, Karlijn Hoyer⁷⁵, Bastian Jaeger⁷⁵, Dongning Ren⁷⁵, Willem W. A. Sleegers⁷⁵, Joeri Wissink⁷⁵, Gwenaël Kaminski⁷⁶, Victoria A. Floerke⁷⁷, Heather L. Urry⁷⁷, Sau-Chin Chen⁷⁸, Gerit Pfuhl⁷⁹, Zahir Vally⁸⁰, Dana M. Basnight-Brown⁸¹, Hans I. Jzerman⁸², Elisa Sarda⁸², Lison Neyroud⁸², Touhami Badidi⁸³, Nicolas Van der Linden⁸⁴, Chrystalle B. Y. Tan⁸⁵, Vanja Kovic⁸⁶, Waldir Sampaio⁸⁷, Paulo Ferreira⁸⁸, Diana Santos⁸⁸, Debora I. Burin⁸⁹, Gwendolyn Gardiner⁹⁰, John Protzko⁹¹, Christoph Schild⁹², Karolina A. Ścigała⁹², Ingo Zettler⁹², Erin M. O'Mara Kunz⁹³, Daniel Storage⁹⁴, Fieke M. A. Wagemans⁹⁵, Blair Saunders⁹⁶, Miroslav Sirota⁹⁷, Guyan V. Sloane⁹⁷, Tiago J. S. Lima⁹⁸, Kim Uittenhove⁹⁹, Evie Vergauwe⁹⁹, Katarzyna Jaworska¹⁰², Julia Stern¹⁰⁰, Karl Ask¹⁰¹, Casper J. J. van Zyl¹⁰², Anita Körner¹⁰³, Sophia C. Weissgerber¹⁰³, Jordane Boudesseul¹⁰⁴, Fernando Ruiz-Dodobara¹⁰⁴, Kay L. Ritchie¹⁰⁵, Nicholas M. Michalak¹⁰⁶, Khandis R. Blake^{107,108}, David White¹⁰⁷, Alasdair R. Gordon-Finlayson¹⁰⁹, Michele Anne¹¹⁰, Steve M. J. Janssen¹¹⁰, Kean Mun Lee¹¹⁰, Tonje K. Nielsen¹¹¹, Christian K. Tamnes¹¹¹, Janis H. Zickfeld¹¹², Anna Dalla Rosa¹¹³, Michelangelo Vianello¹¹³, Ferenc Kocsor¹¹⁴, Luca Kozma¹¹⁴, Ádám Putz¹¹⁴, Patrizio Tressoldi¹¹⁵, Natalia Irrazabal¹¹⁶, Armand Chatard¹¹⁷, Samuel Lins¹¹⁸, Isabel R. Pinto¹¹⁸, Johannes Lutz¹¹⁹, Matus Adamkovic¹²⁰, Peter Babincak¹²⁰, Gabriel Baník¹²⁰, Ivan Ropovik^{121,122}, Vinet Coetzee¹²³, Barnaby J. W. Dixon¹²⁴, Gianni Ribeiro¹²⁴, Kim Peters¹²⁴, Niklas K. Steffens¹²⁴, Kok Wei Tan¹²⁵, Christopher A. Thorstenson¹²⁶, Ana Maria Fernandez¹²⁷, Rafael M. C. S. Hsu¹²⁸, Jaroslava V. Valentova¹²⁸, Marco A. C. Varella¹²⁸, Nadia S. Corral-Frías¹²⁹, Martha Frías-Armenta¹²⁹, Javad Hatami¹³⁰, Arash Monajem¹³⁰, MohammadHasan Sharifian¹³⁰, Brooke Frohlich¹³¹, Hause Lin¹³², Michael Inzlicht¹³², Ravin Alaei¹³², Nicholas O. Rule¹³², Claus Lamm¹³³, Ekaterina Pronizius¹³³, Martin Voracek¹³³, Jerome Olsen¹³⁴, Erik Mac Giolla¹³⁵, Aysegul Akgöz¹³⁶, Asil A. Özdoğru¹³⁶, Matthew T. Crawford¹³⁷, Brooke Bennett-Day¹³⁸, Monica A. Koehn¹³⁹, Ceylan Okan¹⁴⁰, Tripat Gill¹⁴¹, Jeremy K. Miller¹⁴², Yarrow Dunham¹⁴³, Xin Yang¹⁴³, Sinan Alper¹⁴⁴, Martha Lucia Borrás-Guevara¹⁴⁵, Sun Jun Cai¹⁴⁶, Dong Tiantian¹⁴⁶, Alexander F. Danvers¹⁴⁷, David R. Feinberg¹⁴⁸, Marie M. Armstrong¹⁴⁸, Eva Gilboa-Schechtman¹⁴⁹, Randy J. McCarthy¹⁵⁰, Jose Antonio Muñoz-Reyes¹⁵¹, Pablo Polo¹⁵¹, Victor K. M. Shiramazu¹⁵², Wen-Jing Yan¹⁵³, Lilian Carvalho¹⁵⁴, Patrick S. Forscher⁸², Christopher R. Chartier⁷ and Nicholas A. Coles¹⁵⁵

¹School of Psychological Sciences and Health, University of Strathclyde, Glasgow, UK. ²Institute of Neuroscience and Psychology, University of Glasgow, Glasgow, UK. ³Department of Psychology, McGill University, Montreal, Québec, Canada. ⁴Department of Medical and Surgical Sciences, Magna Græcia University of Catanzaro, Catanzaro, Italy. ⁵Faculty of Arts, Psychology and Theology, Åbo Akademi University, Turku, Finland. ⁶Department of Psychology, Alex Ekwueme Federal University Ndufu Alike, Ikwo, Nigeria. ⁷Department of Psychology, Ashland University, Danville, CA, USA. ⁸School of Behavioural and Health Sciences, Australian Catholic University, Sydney, New South Wales, Australia. ⁹Department of Basic Psychology, Autonomous University of Madrid, Madrid, Spain. ¹⁰Department of Biology, Autonomous University of Madrid, Madrid, Spain. ¹¹Department of Psychology, Ben-Gurion University of the Negev, Beersheba, Israel. ¹²Department of Psychology, Boğaziçi University, Beşiktaş, Turkey. ¹³Busara Center for Behavioral Economics, Nairobi, Kenya. ¹⁴Psychology Department, California State University San Marcos, San Marcos, CA, USA. ¹⁵School of Psychology, Catholic University of the North, Antofagasta, Chile. ¹⁶Department of Psychology, Renmin University of China, Beijing, China. ¹⁷Faculty of Psychology, Chulalongkorn University, Bangkok, Thailand. ¹⁸Department of Psychology, Columbia University, New York, NY, USA. ¹⁹School of Psychological, Social and Behavioural Sciences, Coventry University, Coventry, UK. ²⁰Center for Advanced Hindsight, Duke University, Durham, NC, USA. ²¹Department of Psychology, Humboldt State University, Arcata, CA, USA. ²²Laboratoire de Neurosciences Cognitives et Computationnelles, Département d'Études Cognitives, INSERM U960, École Normale Supérieure, Paris, France. ²³Psychology Department, Ege University, İzmir, Turkey. ²⁴Faculty of Psychology, Universidad El Bosque, Bogotá, Colombia. ²⁵Doctoral School of Psychology, ELTE Eötvös Loránd University, Budapest, Hungary. ²⁶Institute of Psychology, ELTE Eötvös Loránd University, Budapest, Hungary. ²⁷Department of Psychology, Fairfield University, Fairfield, CT, USA. ²⁸Department of Psychology, Florida International University, Miami, FL, USA. ²⁹Department of Psychology, Franklin and Marshall College, Lancaster, PA, USA. ³⁰Leibniz Institute for Resilience Research, Mainz, Germany. ³¹Department of Psychology, Hubei University, Wuhan, China. ³²Department of Psychology, Illinois Institute of Technology, Chicago, IL, USA. ³³Department of Psychology, Ithaca College, Ithaca, NY, USA. ³⁴Institute of Psychology, Jagiellonian University, Kraków, Poland. ³⁵Department of Psychology and Psychodynamics, Karl

Landsteiner University of Health Sciences, Krems an der Donau, Austria. ³⁶Research Group of Quantitative Psychology and Individual Differences, Katholieke Universiteit Leuven, Leuven, Belgium. ³⁷Faculty of Psychology and Educational Sciences, Katholieke Universiteit Leuven, Leuven, Belgium. ³⁸Department of Psychology, Liaoning Normal University, Dalian, China. ³⁹Department of Psychology, Lucian Blaga University of Sibiu, Sibiu, Romania. ⁴⁰Department of Psychology, Macquarie University, Sydney, New South Wales, Australia. ⁴¹Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA, USA. ⁴²School of Psychology, Massey University, Palmerston North, New Zealand. ⁴³Psychology Department, McDaniel College, Westminster, CO, USA. ⁴⁴Department of Psychology, Michigan State University, East Lansing, MI, USA. ⁴⁵Department of Psychology, Middlebury College, Middlebury, VT, USA. ⁴⁶Department of Psychology, Mohammed V University in Rabat, Rabat, Morocco. ⁴⁷LIP/PC2S, Université Grenoble Alpes, Grenoble, France. ⁴⁸Psychology Department, Montclair State University, Montclair, NJ, USA. ⁴⁹EGADE Business School, Monterrey Institute of Technology and Higher Education, Monterrey, Mexico. ⁵⁰School of Education, National and Kapodistrian University of Athens, Athens, Greece. ⁵¹School of Higher Studies Iztacala, National Autonomous University of Mexico, Mexico City, Mexico. ⁵²Department of Psychology, National Autonomous University of Mexico, Mexico City, Mexico. ⁵³Department of Psychology, National Cheng Kung University, Tainan City, Taiwan. ⁵⁴Department of Psychology and Center for Neural Science, New York University, New York, NY, USA. ⁵⁵Department of Psychology, New York University, New York, NY, USA. ⁵⁶Department of Strategy and Management, Norwegian School of Economics (NHH), Bergen, Norway. ⁵⁷Department of Cognitive Science, Occidental College, Los Angeles, CA, USA. ⁵⁸Department of Psychology, Pacific Lutheran University, Tacoma, WA, USA. ⁵⁹School of Studies in Life Science, Pandit Ravishankar Shukla University, Raipur, India. ⁶⁰Center for Basic Sciences, Pandit Ravishankar Shukla University, Raipur, India. ⁶¹Department of Psychology, Pavol Jozef Šafárik University in Košice, Košice, Slovakia. ⁶²Developmental Behavioral Genetics Lab, Psychological Institute of Russian Academy of Education, Moscow, Russia. ⁶³Facultad de Ciencias de la Vida, Universidad Regional Amazónica Ikiam, Guayaquil, Ecuador. ⁶⁴Department of Food Marketing, Saint Joseph's University, Philadelphia, PA, USA. ⁶⁵Centre for Behavioural Science and Applied Psychology, Sheffield Hallam University, Sheffield, UK. ⁶⁶School of Psychological and Behavioral Sciences, Southern Illinois University, Carbondale, IL, USA. ⁶⁷Psychology Department, Southern Oregon University, Ashland, OR, USA. ⁶⁸School of Business, Stevens Institute of Technology, Hoboken, NJ, USA. ⁶⁹Department of Psychology, Stockholm University, Stockholm, Sweden. ⁷⁰Department of Psychology, Sunway University, Subang Jaya, Malaysia. ⁷¹Department of Psychological Sciences, Swinburne University of Technology, Melbourne, Victoria, Australia. ⁷²Department of Psychology, North Dakota State University, Fargo, ND, USA. ⁷³School of Psychology, University of Birmingham, Birmingham, UK. ⁷⁴Koç University, Istanbul, Turkey. ⁷⁵Department of Social Psychology, Tilburg University, Tilburg, the Netherlands. ⁷⁶CLLE, Toulouse University, Toulouse, France. ⁷⁷Department of Psychology, Tufts University, Medford, MA, USA. ⁷⁸Department of Human Development and Psychology, Tzu-Chi University, Hualien, Taiwan. ⁷⁹Department of Psychology, UiT The Arctic University of Norway, Tromsø, Norway. ⁸⁰Department of Psychology and Counseling, United Arab Emirates University, Abu Dhabi, United Arab Emirates. ⁸¹United States International University Africa, Nairobi, Kenya. ⁸²Department of Psychology, Université Grenoble Alpes, Saint-Martin-d'Hères, France. ⁸³Department of Psychology, Université Ibn Tofail, Kénitra, Morocco. ⁸⁴Center for Social and Cultural Psychology, Université Libre de Bruxelles, Brussels, Belgium. ⁸⁵Department of Community and Family Medicine, Universiti Malaysia Sabah, Kota Kinabalu, Malaysia. ⁸⁶Department of Psychology, Faculty of Philosophy, University of Belgrade, Belgrade, Serbia. ⁸⁷Universidade Federal de São Carlos, São Paulo, Brazil. ⁸⁸Universidade Federal da Grande Dourados, Dourados, Brazil. ⁸⁹Instituto de Investigaciones, Facultad de Psicología, Universidad de Buenos Aires, Buenos Aires, Argentina. ⁹⁰Department of Psychology, University of California, Riverside, Riverside, CA, USA. ⁹¹Department of Psychological and Brain Sciences, University of California, Santa Barbara, Santa Barbara, CA, USA. ⁹²Department of Psychology, University of Copenhagen, Copenhagen, Denmark. ⁹³Department of Psychology, University of Dayton, Dayton, OH, USA. ⁹⁴Department of Psychology, University of Denver, Denver, CO, USA. ⁹⁵Institute for Socio-Economics, University of Duisburg-Essen, Essen, Germany. ⁹⁶School of Social Sciences, University of Dundee, Dundee, UK. ⁹⁷Department of Psychology, University of Essex, Colchester, UK. ⁹⁸Department of Social and Work Psychology, University of Brasília, Brasília, Brazil. ⁹⁹Faculty of Psychology and Educational Sciences, University of Geneva, Geneva, Switzerland. ¹⁰⁰Department of Psychology, University of Goettingen, Goettingen, Germany. ¹⁰¹Department of Psychology, University of Gothenburg, Gothenburg, Sweden. ¹⁰²Department of Psychology, University of Johannesburg, Johannesburg, South Africa. ¹⁰³Department of Psychology, University of Kassel, Kassel, Germany. ¹⁰⁴Institute of Scientific Research, Faculty of Psychology, University of Lima, Lima, Peru. ¹⁰⁵School of Psychology, University of Lincoln, Lincoln, UK. ¹⁰⁶Department of Psychology, University of Michigan, Ann Arbor, MI, USA. ¹⁰⁷Evolution and Ecology Research Centre, University of New South Wales Sydney, Sydney, New South Wales, Australia. ¹⁰⁸Melbourne School of Psychological Sciences, University of Melbourne, Melbourne, Victoria, Australia. ¹⁰⁹Faculty of Health, Education and Society, University of Northampton, Northampton, UK. ¹¹⁰School of Psychology, University of Nottingham Malaysia, Semenyih, Malaysia. ¹¹¹Department of Psychology, University of Oslo, Oslo, Norway. ¹¹²Department of Management, Aarhus University, Aarhus, Denmark. ¹¹³Department of Philosophy, Sociology, Education and Applied Psychology, University of Padova, Padova, Italy. ¹¹⁴Institute of Psychology, University of Pécs, Pécs, Hungary. ¹¹⁵Department of General Psychology, University of Padova, Padova, Italy. ¹¹⁶Faculty of Social Sciences, University of Palermo, Buenos Aires, Argentina. ¹¹⁷Psychology Department, University of Poitiers, Poitiers, France. ¹¹⁸Department of Psychology, University of Porto, Porto, Portugal. ¹¹⁹Department of Psychology, University of Potsdam, Potsdam, Germany. ¹²⁰Institute of Psychology, Faculty of Arts, University of Presov, Presov, Slovakia. ¹²¹Faculty of Education, University of Presov, Presov, Slovakia. ¹²²Institute for Research and Development of Education, Faculty of Education, Charles University, Prague, Czechia. ¹²³Department of Biochemistry, Genetics and Microbiology, University of Pretoria, Pretoria, South Africa. ¹²⁴School of Psychology, University of Queensland, Brisbane, Queensland, Australia. ¹²⁵School of Psychology and Clinical Language Sciences, University of Reading Malaysia, Johor, Malaysia. ¹²⁶Department of Clinical and Social Sciences in Psychology, University of Rochester, Rochester, NY, USA. ¹²⁷School of Psychology, University of Santiago, Chile, Santiago, Chile. ¹²⁸Institute of Psychology, Department of Experimental Psychology, University of São Paulo, São Paulo, Brazil. ¹²⁹Department of Psychology, University of Sonora, Hermosillo, Mexico. ¹³⁰Department of Psychology, University of Tehran, Tehran, Iran. ¹³¹Department of Psychology, University of Tennessee, Knoxville, Knoxville, TN, USA. ¹³²Department of Psychology, University of Toronto, Toronto, Ontario, Canada. ¹³³Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Vienna, Austria. ¹³⁴Department of Applied Psychology: Work, Education and Economy, Faculty of Psychology, University of Vienna, Vienna, Austria. ¹³⁵Department of Behavioral Sciences, University West, Trollhättan, Sweden. ¹³⁶Department of Psychology, Üsküdar University, Istanbul, Turkey. ¹³⁷School of Psychology, Victoria University of Wellington, Wellington, New Zealand. ¹³⁸Department of Psychology, Wesleyan College, Middletown, CT, USA. ¹³⁹Discipline of Psychology, Faculty of Health, University of Canberra, Canberra, Australian Capital Territory, Australia. ¹⁴⁰School of Social Science and Psychology, Western Sydney University, Sydney, New South Wales, Australia. ¹⁴¹Lazaridis School of Business and Economics, Wilfrid Laurier University, Waterloo, Ontario, Canada. ¹⁴²Department of Psychology, Willamette University, Salem, OR, USA. ¹⁴³Department of Psychology, Yale University, New Haven, CT, USA. ¹⁴⁴Department of Psychology, Yasar University, Izmir, Turkey. ¹⁴⁵University of St. Andrews, St. Andrews, UK. ¹⁴⁶Qufu Normal University, Jining, China. ¹⁴⁷University of Oklahoma, Norman, OK, USA. ¹⁴⁸Department of Psychology, Neuroscience, and Behaviour, McMaster University, Hamilton, Ontario, Canada. ¹⁴⁹Bar-Ilan University, Tel Aviv, Israel. ¹⁵⁰Northern Illinois University, DeKalb, IL, USA. ¹⁵¹Playa Ancha University of Educational Sciences, Valparaíso, Chile. ¹⁵²Federal University of Rio Grande do Norte, Rio Grande do Norte, Brazil. ¹⁵³Wenzhou University, Wenzhou, China. ¹⁵⁴FGV/EAESP, Sao Paulo, Brazil. ¹⁵⁵Harvard Kennedy School, Harvard University, Cambridge, MA, USA. ¹⁵⁶These authors contributed equally: Benedict C. Jones, Lisa M. DeBruine, Jessica K. Flake. [✉]e-mail: psysciacc.001@gmail.com

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see our [Editorial Policies](#) and the [Editorial Policy Checklist](#).

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a Confirmed

- | | | |
|-------------------------------------|-------------------------------------|--|
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | The exact sample size (n) for each experimental group/condition, given as a discrete number and unit of measurement |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | The statistical test(s) used AND whether they are one- or two-sided
<i>Only common tests should be described solely by name; describe more complex techniques in the Methods section.</i> |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | A description of all covariates tested |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals) |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> | For null hypothesis testing, the test statistic (e.g. F , t , r) with confidence intervals, effect sizes, degrees of freedom and P value noted
<i>Give P values as exact values whenever suitable.</i> |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> | For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes |
| <input type="checkbox"/> | <input checked="" type="checkbox"/> | Estimates of effect sizes (e.g. Cohen's d , Pearson's r), indicating how they were calculated |

Our web collection on [statistics for biologists](#) contains articles on many of the points above.

Software and code

Policy information about [availability of computer code](#)

Data collection DeBruine. L.M. (2019, April 9). Experimentum: Beta release 1 (Version v.0.1). Zenodo. <http://doi.org/10.5281/zenodo.2634356>

Data analysis <https://osf.io/87rbg/>

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research [guidelines for submitting code & software](#) for further information.

Data

Policy information about [availability of data](#)

All manuscripts must include a [data availability statement](#). This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

<https://osf.io/87rbg/>

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see [nature.com/documents/nr-reporting-summary-flat.pdf](https://www.nature.com/documents/nr-reporting-summary-flat.pdf)

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Quantitative analysis of ratings data
Research sample	Student-type samples collected in eleven different world regions
Sampling strategy	Opportunistic sampling by individual research groups
Data collection	Rating of faces on one of thirteen randomly determined traits
Timing	Throughout 2019
Data exclusions	All data exclusions were described in the stage one protocol and in the analysis code
Non-participation	These data are given in the analysis code and output
Randomization	Participants were randomly allocated to rate one triat

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
<input checked="" type="checkbox"/>	<input type="checkbox"/> Antibodies
<input checked="" type="checkbox"/>	<input type="checkbox"/> Eukaryotic cell lines
<input checked="" type="checkbox"/>	<input type="checkbox"/> Palaeontology and archaeology
<input checked="" type="checkbox"/>	<input type="checkbox"/> Animals and other organisms
<input type="checkbox"/>	<input checked="" type="checkbox"/> Human research participants
<input checked="" type="checkbox"/>	<input type="checkbox"/> Clinical data
<input checked="" type="checkbox"/>	<input type="checkbox"/> Dual use research of concern

Methods

n/a	Involved in the study
<input checked="" type="checkbox"/>	<input type="checkbox"/> ChIP-seq
<input checked="" type="checkbox"/>	<input type="checkbox"/> Flow cytometry
<input checked="" type="checkbox"/>	<input type="checkbox"/> MRI-based neuroimaging

Human research participants

Policy information about [studies involving human research participants](#)

Population characteristics	Raters from a range of geographic regions and countries. Region and country information are reported.
Recruitment	Opportunistic recruitment by individual labs.
Ethics oversight	main ethics approval was from University of Glasgow, although some individual groups also obtained their own thicas approvals.

Note that full information on the approval of the study protocol must also be provided in the manuscript.