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

Benedict C. Jones¹‡* (psysciacc.001@gmail.com), Lisa M. DeBruine¹‡, Jessica K. Flake²‡, Marco Tullio Liuzza³, Jan Antfolk⁴, Nwadiogo C. Arinze⁵, Izuchukwu L. G. Ndukaihe⁵, Nicholas G. Bloxson⁶, Savannah C. Lewis⁶, Francesco Foroni⁷, Megan L. Willis⁷, Carmelo P. Cubillas⁸, Miguel A. Vadillo⁸, Enrique Turiegano⁸, Michael Gilead⁹, Almog Simchon⁹, S. Adil Saribay¹⁰, Nicholas C. Owsley¹¹, Channing Jang¹¹, Georgina Mburu¹¹, Dustin P. Calvillo¹², Anna Wlodarczyk¹³, Yue Qi¹⁴, Kris Ariyabuddhiphongs¹⁵, Somboon Jarukasemthawee¹⁵, Harry Manley¹⁵, Panita Suavansri¹⁵, Nattasuda Taephant¹⁵, Ryan M. Stolier¹⁶, Thomas R. Evans¹⁷, Judson Bonick¹⁸, Jan W. Lindemans¹⁸, Logan F. Ashworth¹⁹, Amanda C. Hahn¹⁹, Coralie Chevallier²⁰, Aycan Kapucu²¹, Aslan Karaaslan²¹, Juan David Leongómez²², Oscar R. Sánchez²², Eugenio Valderrama²², Milena Vásquez-Amézquita²², Nandor Hajdu^{23, 24}, Balazs Aczel²⁴, Peter Szecsi²⁴, Michael Andreychik²⁵, Erica D. Musser²⁶, Carlota Batres²⁷, Chuan-Peng Hu²⁸, Qing-Lan Liu²⁹, Nicole Legate³⁰, Leigh Ann Vaughn³¹, Krystian Barzykowski³², Karolina Golik³², Irina Schmid³³, Stefan Stieger³³, Richard Artner³⁴, Chiel Mues³⁴, Wolf Vanpaemel³⁵, Zhongqing Jiang³⁶, Qi Wu³⁶, Gabriela M. Marcu³⁷, Ian D. Stephen³⁸, Jackson G. Lu³⁹, Michael C. Philipp⁴⁰, Jack D. Arnal⁴¹, Eric Hehman², Sally Y. Xie², William J. Chopik⁴², Martin Seehuus⁴³, Soufian Azouaghe^{44, 79}, Abdelkarim Belhaj⁴⁴, Jamal Elouafa⁴⁴, John P. Wilson⁴⁵, Elliott Kruse⁴⁶, Marietta Papadatou-Pastou⁴⁷, Anabel De La Rosa-Gómez⁴⁸, Isaac González-Santoyo⁴⁹, Tsuyueh Hsu⁵⁰, Chun-Chia Kung⁵⁰, Hsiao-Hsin Wang⁵⁰, Jonathan B. Freeman⁵¹, DongWon Oh⁵², Vidar Schei⁵³, Therese E. Sverdrup⁵³, Carmel A. Levitan⁵⁴, Corey L. Cook⁵⁵, Priyanka Chandel⁵⁶, Pratibha Kujur⁵⁶, Arti Parganiha⁵⁶, Noorshama Parveen⁵⁶, Atanu Kumar Pati⁵⁶, Sradha Pradhan⁵⁶, Margaret M. Singh⁵⁶, Babita Pande⁵⁷, Jozef Bavolar⁵⁸, Pavol Kačmár⁵⁸, Ilya Zakharov⁵⁹, Sara Álvarez-Solas⁶⁰, Ernest Baskin⁶¹, Martin Thirkettle⁶², Kathleen Schmidt⁶³, Cody D. Christopherson⁶⁴, Trinity Leonis⁶⁴, Jordan W. Suchow⁶⁵, Jonas K. Olofsson⁶⁶, Teodor Jernsäther⁶⁶, Ai-Suan Lee⁶⁷, Jennifer L. Beaudry⁶⁸, Taylor D. Gogan⁶⁸, Julian A. Oldmeadow⁶⁸, Benjamin Balas⁶⁹, Laura M. Stevens⁷⁰, Melissa F. Colloff⁷⁰, Heather D. Flowe⁷⁰, Sami Gülgöz⁷¹, Mark J. Brandt⁷², Karlijn Hoyer⁷², Bastian Jaeger⁷², Dongning Ren⁷², Willem W. A. Sleegers⁷², Joeri Wissink⁷², Gwenaël Kaminski⁷³, Victoria A. Floerke⁷⁴, Heather L. Urry⁷⁴, Sau-Chin Chen⁷⁵, Gerit Pfuhl⁷⁶, Zahir Vally⁷⁷, Dana M. Basnight-Brown⁷⁸, Hans IJzerman⁷⁹, Elisa Sarda⁷⁹, Lison Neyroud⁸⁰, Touhami Badidi⁸¹, Nicolas Van der Linden⁸², Chrystalle B. Y. Tan⁸³, Vanja Kovic⁸⁴, Waldir Sampaio⁸⁵, Paulo Ferreira⁸⁶, Diana Santos⁸⁶, Debora I. Burin⁸⁷, Gwendolyn Gardiner⁸⁸, John Protzko⁸⁹, Christoph Schild⁹⁰, Karolina A. Ścigala⁹⁰, Ingo Zettler⁹⁰, Erin M. O'Mara Kunz⁹¹, Daniel Storage⁹², Fieke M. A. Wagemans⁹³, Blair Saunders⁹⁴, Miroslav Sirota⁹⁵, Guyan V. Sloane⁹⁵, Tiago J. S. Lima⁹⁶, Kim Uittenhove⁹⁷, Evie Vergauwe⁹⁷, Katarzyna Jaworska¹, Julia Stern⁹⁸, Lilian Carvalho, Karl Ask⁹⁹, Casper J. J. van Zyl¹⁰⁰, Anita Körner¹⁰¹, Sophia C. Weissgerber¹⁰², Jordane Boudesseul¹⁰³, Fernando Ruiz-Dodobara¹⁰³, Kay L. Ritchie¹⁰⁴, Nicholas M. Michalak¹⁰⁵, Khandis R. Blake^{106, 142}, David White¹⁰⁶, Alasdair R. Gordon-Finlayson¹⁰⁷, Michele Anne¹⁰⁸, Steve M. J. Janssen¹⁰⁸, Kean Mun Lee¹⁰⁸, Tonje K. Nielsen¹⁰⁹, Christian K. Tamnes¹⁰⁹, Janis H. Zickfeld¹⁰⁹, Anna Dalla Rosa¹¹⁰, Michelangelo Vianello¹¹⁰, Ferenc Kocsor¹¹¹, Luca Kozma¹¹¹, Ádám Putz¹¹¹, Patrizio Tressoldi¹¹², Natalia Irrazabal¹¹³, Armand Chatard¹¹⁴, Samuel Lins¹¹⁵, Isabel R. Pinto¹¹⁵, Johannes Lutz¹¹⁶, Matus Adamkovic¹¹⁷, Peter Babincak¹¹⁷, Gabriel Baník¹¹⁷, Ivan Ropovik^{118, 143}, Vinet Coetzee¹¹⁹, Barnaby J. W. Dixon¹²⁰, Gianni Ribeiro¹²⁰, Kim Peters¹²⁰, Niklas K. Steffens¹²⁰, Kok Wei Tan¹²¹, Christopher A. Thorstenson¹²², Ana Maria Fernandez¹²³, Rafael M. C. S. Hsu¹²⁴, Jaroslava V. Valentova¹²⁴, Marco A. C. Varella¹²⁴, Nadia S. Corral-Frías¹²⁵, Martha Frías-Armenta¹²⁵, Javad Hatami¹²⁶, Arash Monajem¹²⁶, MohammadHasan Sharifian¹²⁶, Brooke Frohlich¹²⁷, Huse Lin¹²⁸, Michael Inzlicht¹²⁸,

Ravin Alaei¹²⁸, Nicholas O. Rule¹²⁸, Claus Lamm¹²⁹, Ekaterina Pronizius¹²⁹, Martin Voracek¹²⁹, Jerome Olsen¹³⁰, Erik Mac Giolla¹³¹, Aysegul Akgoz¹³², Asil A. Özdoğru¹³², Matthew T. Crawford¹³³, Brooke Bennett-Day¹³⁴, Monica A. Koehn¹³⁵, Ceylan Okan¹³⁶, Daniel Ansari¹³⁷, Tripat Gill¹³⁸, Jeremy K. Miller¹³⁹, Yarrow Dunham¹⁴⁰, Xin Yang¹⁴⁰, Sinan Alper¹⁴¹, Martha Lucia Borrás-Guevara¹⁴⁴, Sun Jun Cai¹⁴⁵, Dong Tiantian¹⁴⁵, Alexander F. Danvers¹⁴⁶, David R. Feinberg¹⁴⁷, Marie M Armstrong¹⁴⁷, Eva Gilboa-Schechtman¹⁴⁸, Randy J. McCarthy¹⁴⁹, Jose Antonio Muñoz-reyes¹⁵⁰, Pablo Polo¹⁵⁰, Victor K.M. Shiramazu¹⁵¹, Wen-Jing Yan¹⁵², Patrick S. Forscher⁸⁰, Christopher R. Chartier⁶, Nicholas A. Coles¹⁵³

¹University of Glasgow, Institute of Neuroscience and Psychology, UK. ²McGill University, Department of Psychology, Canada. ³"Magna Graecia" University of Catanzaro, Department of Medical and Surgical Sciences, Italy. ⁴Åbo Akademi University, Faculty of Arts, Psychology and Theology, Finland. ⁵Alex Ekwueme Federal University Ndufu Alike, Department of Psychology, Nigeria. ⁶Ashland University, Department of Psychology, USA. ⁷Australian Catholic University, School of Behavioural and Health Sciences, Australia. ⁸Autonomous University of Madrid, Department of Basic Psychology, Spain. ⁹Ben-Gurion University of the Negev, Department of Psychology, Israel. ¹⁰Boğaziçi University, Department of Psychology, Turkey. ¹¹Busara Center for Behavioral Economics, Kenya. ¹²California State University San Marcos, Psychology Department, USA. ¹³Catholic University of the North, School of Psychology, Chile. ¹⁴CAS Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China. ¹⁵Chulalongkorn University, Faculty of Psychology, Thailand. ¹⁶Columbia University, Department of Psychology, USA. ¹⁷Coventry University, School of Psychological, Social and Behavioural Sciences, UK. ¹⁸Duke University, Center for Advanced Hindsight, USA. ¹⁹Humboldt State University, Department of Psychology, USA. ²⁰Laboratoire de Neurosciences Cognitives et Computationnelles, Département d'Études Cognitives, INSERM U960, École Normale Supérieure, France. ²¹Ege University, Psychology Department, Turkey. ²²Universidad El Bosque, Faculty of Psychology, Colombia. ²³ELTE Eötvös Loránd University, Doctoral School of Psychology, Hungary. ²⁴ELTE Eötvös Loránd University, Institute of Psychology, Hungary. ²⁵Fairfield University, Department of Psychology, USA. ²⁶Florida International University, Department of Psychology, USA. ²⁷Franklin and Marshall College, Department of Psychology, USA. ²⁸Leibniz Institute for Resilience Research, Germany. ²⁹Hubei University, Department of Psychology, China. ³⁰Illinois Institute of Technology, Department of Psychology, USA. ³¹Ithaca College, Department of Psychology, USA. ³²Jagiellonian University, Institute of Psychology, Poland. ³³Karl Landsteiner University of Health Sciences, Department of Psychology and Psychodynamics, Austria. ³⁴Katholieke Universiteit Leuven, Research Group of Quantitative Psychology and Individual Differences, Belgium. ³⁵Katholieke Universiteit Leuven, Faculty of Psychology and Educational Sciences, Belgium. ³⁶Liaoning Normal University, Department of Psychology, China. ³⁷Lucian Blaga University of Sibiu, Department of Psychology, Romania. ³⁸Macquarie University, Department of Psychology, Australia. ³⁹Massachusetts Institute of Technology, Sloan School of Management, USA. ⁴⁰Massey University, School of Psychology, New Zealand. ⁴¹McDaniel College, Psychology Department, USA. ⁴²Michigan State University, Department of Psychology, USA. ⁴³Middlebury College, Department of Psychology, USA. ⁴⁴Mohammed V University in Rabat, Department of Psychology, Morocco. ⁴⁵Montclair State University, Psychology Department, USA. ⁴⁶Monterrey Institute of Technology and Higher Education, EGADE Business School, Mexico. ⁴⁷National and

Kapodistrian University of Athens, School of Education, Greece. ⁴⁸National Autonomous University of Mexico, School of Higher Studies Iztacala, Mexico. ⁴⁹National Autonomous University of Mexico, Department of Psychology, ⁵⁰National Cheng Kung University, Department of Psychology, Taiwan. ⁵¹New York University, Department of Psychology and Center for Neural Science, USA. ⁵²New York University, Department of Psychology, USA. ⁵³NHH Norwegian School of Economics, Department of Strategy and Management, Norway. ⁵⁴Occidental College, Department of Cognitive Science, USA. ⁵⁵Pacific Lutheran University, Department of Psychology, USA. ⁵⁶Pandit Ravishankar Shukla University, School of Studies in Life Science, India. ⁵⁷Pandit Ravishankar Shukla University, Center for Basic Sciences, India. ⁵⁸Pavol Jozef Šafárik University in Košice, Department of Psychology, Slovakia. ⁵⁹Psychological Institute of Russian Academy of Education, Developmental Behavioral Genetics Lab, Russia. ⁶⁰Universidad Regional Amazónica Ikiam, Facultad de Ciencias de la Vida, Ecuador. ⁶¹Saint Joseph's University, Department of Food Marketing, USA. ⁶²Sheffield Hallam University, Centre for Behavioural Science and Applied Psychology, UK. ⁶³Southern Illinois University, School of Psychological and Behavioral Sciences, USA. ⁶⁴Southern Oregon University, Psychology Department, USA. ⁶⁵Stevens Institute of Technology, School of Business, USA. ⁶⁶Stockholm University, Department of Psychology, Sweden. ⁶⁷Sunway University, Department of Psychology, Malaysia. ⁶⁸Swinburne University of Technology, Department of Psychological Sciences, Australia. ⁶⁹North Dakota State University, Department of Psychology, USA. ⁷⁰University of Birmingham, School of Psychology, UK. ⁷¹Koç University, Turkey. ⁷²Tilburg University, Department of Social Psychology, Netherlands. ⁷³Toulouse University, CLLE, France. ⁷⁴Tufts University, Department of Psychology, USA. ⁷⁵Tzu-Chi University, Department of Human Development and Psychology, Taiwan. ⁷⁶UiT The Arctic University of Norway, Department of Psychology, Norway. ⁷⁷United Arab Emirates University, Department of Psychology & Counseling, United Arab Emirates. ⁷⁸United States International University-Africa, Kenya. ⁷⁹Université Grenoble Alpes, LIP/PC2S, France. ⁸⁰Université Grenoble Alpes, Department of Psychology, France. ⁸¹Université Ibn Tofail Kénitra, Department of Psychology, Morocco. ⁸²Université Libre de Bruxelles, Center for Social and Cultural Psychology, Belgium. ⁸³Universiti Malaysia Sabah, Department of Community and Family Medicine, Malaysia. ⁸⁴University of Belgrade, Department of Psychology, Faculty of Philosophy, Serbia. ⁸⁵Universidade Federal de São Carlos, Brazil, ⁸⁶Universidade Federal da Grande Dourados, Brazil, ⁸⁷Universidad de Buenos Aires, Instituto de Investigaciones, Facultad de Psicología, Argentina. ⁸⁸University of California, Riverside, Department of Psychology, USA. ⁸⁹University of California, Santa Barbara, Department of Psychological & Brain Sciences, USA. ⁹⁰University of Copenhagen, Department of Psychology, Denmark. ⁹¹University of Dayton, Department of Psychology, USA. ⁹²University of Denver, Department of Psychology, USA. ⁹³University of Duisburg-Essen, Institute for Socio-Economics, Germany. ⁹⁴University of Dundee, School of Social Sciences, UK. ⁹⁵University of Essex, Department of Psychology, UK. ⁹⁶University of Brasília, Department of Social and Work Psychology, Brazil. ⁹⁷University of Geneva, Faculty of Psychology and Educational Sciences, Switzerland. ⁹⁸University of Goettingen, Department of Psychology, Germany. ⁹⁹University of Gothenburg, Department of Psychology, Sweden. ¹⁰⁰University of Johannesburg, Department of Psychology, South Africa. ¹⁰¹University of Kassel, Department of Psychology, Germany. ¹⁰²University of Kassel, Department of Psychology, Germany. ¹⁰³University of Lima, Institute of Scientific Research, Peru. ¹⁰⁴University of Lincoln, School of Psychology, UK. ¹⁰⁵University of Michigan, Department of Psychology, USA. ¹⁰⁶University of New South Wales Sydney, Evolution and Ecology Research Centre, Australia. ¹⁰⁷University of

Northampton, Faculty of Health, Education & Society, UK. ¹⁰⁸University of Nottingham Malaysia, School of Psychology, Malaysia. ¹⁰⁹University of Oslo, Department of Psychology, Norway. ¹¹⁰University of Padova, Department of Philosophy, Sociology, Education and Applied Psychology, Italy. ¹¹¹University of Pécs, Institute of Psychology, Hungary. ¹¹²University of Padova, Department of General Psychology, Italy. ¹¹³University of Palermo, Faculty of Social Sciences, Argentina. ¹¹⁴University of Poitiers, Psychology Department, France. ¹¹⁵University of Porto, Department of Psychology, Portugal. ¹¹⁶University of Potsdam, Department of Psychology, Germany. ¹¹⁷University of Presov, Institute of Psychology, Faculty of Arts, Slovakia. ¹¹⁸University of Presov, Faculty of Education, Slovakia. ¹¹⁹University of Pretoria, Department of Biochemistry, Genetics and Microbiology, South Africa. ¹²⁰University of Queensland, School of Psychology, Australia. ¹²¹University of Reading Malaysia, School of Psychology and Clinical Language Sciences, Malaysia. ¹²²University of Rochester, Department of Clinical and Social Sciences in Psychology, USA. ¹²³University of Santiago, Chile, School of Psychology, Chile. ¹²⁴University of São Paulo, Department of Experimental Psychology, Institute of Psychology, Brazil. ¹²⁵University of Sonora, Department of Psychology, Mexico. ¹²⁶University of Tehran, Department of Psychology, Iran. ¹²⁷University of Tennessee, Knoxville, Department of Psychology, USA. ¹²⁸University of Toronto, Department of Psychology, Canada. ¹²⁹University of Vienna, Faculty of Psychology, Department of Cognition, Emotion, and Methods in Psychology, Austria. ¹³⁰University of Vienna, Faculty of Psychology, Department of Applied Psychology: Work, Education, and Economy, Austria. ¹³¹University West, Department of Behavioral Sciences, Sweden. ¹³²Üsküdar University, Department of Psychology, Turkey. ¹³³Victoria University of Wellington, School of Psychology, New Zealand. ¹³⁴Wesleyan College, Department of Psychology, USA. ¹³⁵Western Sydney University, School of Psychology, Australia. ¹³⁶Western Sydney University, School of Social Science and Psychology, Australia. ¹³⁷Western University, Department of Psychology, Canada. ¹³⁸Wilfrid Laurier University, Lazaridis School of Business & Economics, Canada. ¹³⁹Willamette University, Department of Psychology, USA. ¹⁴⁰Yale University, Department of Psychology, USA. ¹⁴¹Yasar University, Department of Psychology, Turkey. ¹⁴²University of Melbourne, Melbourne School of Psychological Sciences, Australia. ¹⁴³Charles University, Faculty of Education, Institute for Research and Development of Education, Czechia. ¹⁴⁴University of St. Andrews, United Kingdom. ¹⁴⁵Qufu Normal University, China. ¹⁴⁶University of Oklahoma, USA. ¹⁴⁷McMaster University, Department of Psychology, Neuroscience, & Behaviour, Canada. ¹⁴⁸Bar-Ilan University, Israel. ¹⁴⁹Northern Illinois University. ¹⁵⁰Playa Ancha University of Educational Sciences, Chile. ¹⁵¹Federal University of Rio Grande do Norte, Brazil. ¹⁵²Wenzhou University, China. ¹⁵³Harvard University, Harvard Kennedy School, USA.

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. 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, correlate and rotate the dimension reduction solution.

Introduction

People quickly and involuntarily form impressions of others based on their facial appearance¹⁻³. 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 behavior^{10,11}.

Over the last 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 behavior more broadly, which typically draws general assumptions from analyses of Western participants' responses¹⁵. 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 behavior¹⁶.

Consistent with Kline et al.'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 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 presented¹⁹⁻²¹. 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 Malaysia²⁴. 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 replicate 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 USA and Canada, Scandinavia, South America, the UK, 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 project²⁵⁻²⁷. Previous studies compared two cultures to demonstrate regional differences^{17,18}. By 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 test two specific competing predictions:

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

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

Results

Analyzed data set. Following the planned data exclusions (see supplemental materials for a breakdown of these exclusions, CODE 1.5), the analyzed data set 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 > 1 . We conducted an identical analysis and report (1) the number of components extracted per the registered criteria, (2) if the 1st and 2nd components had the same primary pattern as Oosterhof and Todorov, and (3) the similarity of the 1st and 2nd factors as quantified with a congruence coefficient.

We extracted the same number of components (2) as Oosterhof and Todorov in two world regions, Africa and South America, and a different number of components (3) in the other world regions (see Figure 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 strongly correlated with rated trustworthiness, but not with rated dominance, and a second component that strongly correlated with rated dominance, but not with rated trustworthiness) was present in all world regions except Eastern Europe, where

dominance was correlated with the first component more strongly than our registered criterion (that dominance would correlate weakly with the first component $< .5$). 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 number of components differs across the solutions being compared. When comparing loadings across solutions, an assumption is that the configuration of the traits to components is the same (i.e., configural invariance). To the extent that the structure of the loading matrices differs across solutions, the comparability of the loadings is compromised (i.e., 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 (different number of components extracted, different primary pattern observed), ϕ is uninterpretable. This is because the differences in configuration across the two solutions are conflated with the loading differences.

Our analyses indicated that the first component was equal to ($\phi > .95$) the first component in Oosterhof and Todorov's original study for all world regions. The second component was equal to ($\phi > .95$) or fairly similar to ($\phi > .85$) the second component reported by Oosterhof and Todorov in all of the world regions except Asia ($\phi = .848$). Table 4 summarizes these results.

Together, these results suggest the valence-dominance model generalizes across world regions when using an identical analysis to 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 3rd 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, 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 (see⁴² 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. 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 Figure 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 less than the number of suggested factors. The model converged when estimating three factors.

In contrast to 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 to 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 (i.e., satisfied the assumption of configural invariance). Our registered analyses included the calculation of Tucker's coefficient of congruence, ϕ , in order to compare the 1st factor from the original study to the 1st factor we extracted in a given world region, and to compare the 2nd factor from the original study to the 2nd 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 quantify their differences using ϕ .

The congruence coefficient is only appropriate to report when we can ensure 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 1st factor from Oosterhof and Todorov to the factor with the most explained variance in a world region, and ϕ for the 2nd factor from Oosterhof and Todorov to the factor with the 2nd most explained variance in a world region only in the supplemental materials. 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 (2008), 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 work, 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 are just above 1. Nonetheless, the third component in each region has 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 to 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 interpretable factors, and in our data, revealed more regional variation. These results suggest that, if the dimensions of face perception are indeed correlated, using analytic 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 those models and theories can be revised and expanded appropriately in future research. Crucially, the two models make different assumptions about trait ratings of faces. 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. By 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 analyze 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 if 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 (e.g., 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 explore more dynamic theories of trait ratings^{21,43,44} by exploring how the structure of trait ratings vary systematically. This growing body of work catalogues variations in trait ratings by target demographic^{21,43, 45}, target status⁴⁶, target age⁴⁷, perceiver knowledge⁴⁸, and cultural factors^{17,18}. Further, this growing body of work proposes dynamic theories of person perception and more flexible statistical models for capturing them^{21,43,44,49}.

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. They do, however, 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 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 IRB 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 preexisting approval. Although the specifics of the consent procedure differed across research groups, all participants provided informed consent. All data was 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 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-color, face image set²⁸ consisting of 60 men and 60 women taken under standardized photographic conditions ($M_{\text{age}} = 26.4$ years, $SD = 3.6$ years, Range = 18 to 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 in 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 labs. 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 Supplemental Materials).

Raters also completed a short questionnaire requesting demographic information (sex, age, 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 are 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 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 photographs¹⁹. Dominance (not included in that study) was 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 α > .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 α > .80). Thus, averages of ratings from 25 or more raters will produce 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 range³⁰. 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 Supplemental Materials and publicly available from the Open Science Framework (<https://osf.io/87rbg/>). The specific sections of code are cited below as (CODE x.x.x).

Ratings from each world region were analyzed separately and anonymous raw data is published on the Open Science Framework. Our main analyses directly replicated the principal component analysis 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 principal component analysis 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 principal components analysis conducted in each region and determined if Oosterhof and Todorov’s primary pattern replicated according to three criteria: (i) the first two components had eigenvalues greater than 1.0, (ii) the first component (i.e., the one explaining more of the variance in ratings) correlated strongly with trustworthiness ($r > .7$) and weakly with dominance ($r < .5$), and (iii) the second component (i.e., the one explaining less of the variance in ratings) correlated strongly with dominance ($r > .7$) and weakly with trustworthiness ($r < .5$). 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^{31,32}. The congruence coefficient, ϕ , ranges from -1 to 1 and quantifies the similarity between two vectors of loadings³³. 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 . For the purposes of the current research, we compared 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 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 loadings³⁴. Further, 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 guidelines³⁴, we concluded that the components in Oosterhof and Todorov were not similar to those estimated in a given world region if the coefficient was less than .85, were fairly similar if it was between .85 - .94, and were equal if it was greater than .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 principal components analysis 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 ϕ of .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 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, 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 analyses (CODES 1.5.1, 1.5.3, and 1.5.5).

Data-quality checks. Following previous research testing the valence-dominance model¹²⁻¹⁴, data quality was 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 was only included in the analysis for that region if the coefficient exceeded .70. Cases in which the coefficient does not exceed .70 will be reported and discussed. There were no cases in which the coefficient did not exceed .70. Test-retest reliability of traits was not used to exclude traits from analysis.

Power analysis. Simulations showed we had 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 replication¹³ of Oosterhof and Todorov's research to generate a variance-covariance matrix representative of typical interrelationships among the 13 traits 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. 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 principal components analysis. 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 exploratory factor analysis with rotation, rather than an unrotated principal components analysis, is more appropriate when one intends to measure correlated latent factors, as was 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 repeated 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 also recalculated the congruence coefficient described above for these exploratory factor analysis 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^{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 data⁴¹.

The purpose of these additional analyses was 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 were to be applied to this analysis (CODE 2.2.1.3).

Protocol registration

The Stage 1 protocol for this Registered Report was accepted in principle on 05 November 2018. The protocol, as accepted by the journal, can be found at <https://dx.doi.org/10.6084/m9.figshare.7611443.v1>.

Data availability

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

Code availability

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

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Author contributions

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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., and N.A.C. contributed to Data Curation.

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N.C.O., Y.Q., J.W.L., C.C., J.L., O.R.S., E.V., M.V., J.G.L., M.C.P., J.B.F., J.K.O., G.K., H.I., H.D.F., T.J.S.L., E.V., K.A., K.T., M.I., C.L., P.S.F., and C.R.C. contributed to Funding Acquisition.

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T.K.N., C.K.T., J.H.Z., A.D., L.K., M.V., N.I., A.C., S.L., J.L., M.A., P.B., G.B., I.R., V.C., K.P., N.K.S., K.T., C.A.T., A.F., R.M.C.S.H., J.V.V., N.S.C., M.F., J.H., A.M., M.S., B.F., H.L., M.I., C.L., E.P., M.V., J.O., E.M., A.A., A.A.Ö., M.T.C., B.B., M.A.K., C.O., T.G., J.K.M., Y.D., X.Y., S.A., P.S.F., C.R.C., and N.A.C. contributed to Investigation.

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B.C.J., L.M.D., M.L., S.C.L., C.P.C., M.A.V., S.A.S., A.W., Y.Q., K.A., S.J., H.M., P.S., N.T., R.M.S., C.C., A.K., J.L., M.V., N.H., C.B., L.V., K.B., K.G., Z.J., G.M.M., I.D.S., J.G.L., S.Y.X., W.J.C., M.S., S.A., A.B., J.E., A.d., C.K., J.B.F., C.A.L., A.K.P., P.K., I.Z., 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., G.P., D.M.B., T.B., C.B.Y.T., V.K., H.D.F., G.G., C.S., K.A.S., E.M.O., B.S., M.S., G.V.S., T.J.S.L., K.U., E.V., K.J., K.A., J.B., F.R., N.M.M., S.M.J.J., C.K.T., A.D., F.K., Á.P., P.T., M.V., A.C.,

S.L., J.L., M.A., P.B., V.C., A.F., R.M.C.S.H., J.V.V., N.S.C., M.F., A.M., M.S., H.L., C.L., M.V., E.M., A.A.Ö., M.A.K., C.O., X.Y., S.A., P.S.F., and C.R.C. contributed to Resources.

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B.C.J., L.M.D., J.K.F., M.L., S.C.L., M.L.W., N.C.O., A.W., H.M., J.W.L., C.C., A.K., J.L., O.R.S., E.V., M.V., M.A., E.D.M., C.B., L.V., K.B., I.D.S., M.C.P., E.H., W.J.C., M.S., C.K., J.B.F., C.A.L., P.K., I.Z., K.S., C.D.C., J.W.S., J.K.O., A.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., D.S., B.S., M.S., T.J.S.L., K.U., E.V., K.A., C.J.J.v., D.W., S.M.J.J., A.C., S.L., K.P., N.K.S., K.T., A.F., J.V.V., M.S., M.I., C.L., M.V., A.A., A.A.Ö., M.A.K., S.A., P.S.F., C.R.C., and N.A.C. contributed to Supervision.

B.C.J., L.M.D., J.K.F., C.C., Q.W., S.Y.X., M.S., C.L.C., A.K.P., I.Z., J.W.S., E.S., V.K., H.D.F., J.P., M.S., E.V., C.J.J.v., P.T., J.H., M.V., and M.A.K. contributed to Validation.

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B.C.J., L.M.D., J.K.F., M.L., J.A., I.L.G.N., S.C.L., F.F., M.L.W., M.A.V., A.S., D.P.C., A.W., Y.Q., K.A., H.M., T.R.E., J.B., J.W.L., C.C., J.L., B.A., N.H., P.S., M.A., E.D.M., C.B., N.L., L.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.S., S.A., A.B., J.E., J.P.W., E.K., M.P., A.E.B., A.d., J.B.F., V.S., T.E.S., C.A.L., C.L.C., P.C., P.K., A.P., N.P., A.K.P., S.P., M.M.S., B.P., P.K., I.Z., S.Á., E.B., M.T., K.S., C.D.C., J.W.S., J.K.O., A.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., C.B.Y.T., V.K., M.F.C., H.D.F., D.I.B., G.G., C.S., E.M.O., D.S., B.S., M.S., T.J.S.L., K.U., E.V., J.S., K.A., C.J.J.v., A.K., K.L.R., K.R.B., D.W., A.R.G., S.M.J.J., T.K.N., C.K.T., J.H.Z., M.V., N.I., M.A., G.B., I.R., V.C., K.P., N.K.S., K.T., C.A.T., A.F., R.M.C.S.H., J.V.V., B.F., H.L., C.L., E.P., M.V., J.O., E.M., A.A., A.A.Ö., B.B., M.A.K., T.G., J.K.M., Y.D., P.S.F., C.R.C., and N.A.C. contributed to Writing (review & editing).

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Competing interests

The authors declare no competing interests

Figure legends

Figure 1. Principal component analysis (PCA) loading matrices for each region. Positive loadings are shaded red and negative loadings shaded blue; darker colors correspond to stronger loadings. The proportion of variance explained by each component is included at the top of each table.

Figure 2. Exploratory factor analysis (EFA) loading matrices for each region. Positive

loadings are shaded red and negative loadings shaded blue; darker colors correspond to stronger loadings. The proportion of variance explained by each factor is included at the top of each table.

Tables (see following pages)

Table 1. World Regions, Countries, and Localities of Data Collection

World region	Countries and Localities
Africa	Kenya, (Nigeria), South Africa
Asia	China, India, Malaysia, Taiwan, Thailand
Australia and New Zealand	Australia, New Zealand
Central America and Mexico	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, (Finland), Norway, (Sweden)
South America	Argentina, Brazil, Chile, Colombia, Ecuador
The UK	England, Scotland, Wales
Western Europe	Austria, Belgium, France, Germany, (Greece), Italy, the Netherlands, Portugal, Spain, Switzerland

Note. We collected data from a minimum of 350 raters per world region based on the simulations described in the Methods section below. 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 our Stage 2 submission.

Table 2. Number of participants per region and Cronbach's alphas 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
USA & 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
UK	$\alpha = 0.879$ 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 & 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 & 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

Table 3. Replication criteria for the principal component analysis (PCA) for each region

Region	Component 1		Component 2		Replicated
	Trustworthy	Dominant	Dominant	Trustworthy	
(Oosterhof & Todorov, 2008)	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 & New Zealand	0.943	0.257	0.907	-0.076	Yes
Central America & 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
UK	0.944	0.331	0.851	-0.121	Yes
USA & Canada	0.966	0.406	0.841	-0.073	Yes
Western Europe	0.957	0.357	0.875	-0.166	Yes

Note. 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 $> .7$ with trustworthiness and $< .5$ with dominance, and the second component had a loading $> .7$ with dominance and $< .5$ with trustworthiness.

Table 4. Factor congruence for each region's principal component analysis (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 & New Zealand	0.982	equal	0.959	equal
Central America & 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
UK	0.976	equal	0.938	fairly similar
USA & Canada	0.972	equal	0.952	equal
Western Europe	0.975	equal	0.936	fairly similar

Table 5. Replication criteria for the exploratory factor analysis (EFA) for each region

Region	Factor 1		Factor 2		Replicated
	Trustworthy	Dominant	Dominant	Trustworthy	
(Oosterhof & Todorov, 2008)	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 & New Zealand	0.730	0.157	0.071	0.281	No
Central America & 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
UK	0.338	0.249	0.265	0.510	No
USA & Canada	0.768	0.491	0.264	0.189	No
Western Europe	0.398	0.111	0.256	0.164	No

Note. 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 $> .7$ with trustworthiness and $< .5$ with dominance, and the second factor had a loading $> .7$ with dominance and $< .5$ with trustworthiness.



