Basic Values Survey (BVS): A 20-nation validation study

Roosevelt Vilar
School of Psychology, Massey University, New Zealand

This research was supported by Grant FA2386-15-1-0003 from the Asian Office of Aerospace Research and Development

This research was also supported by Grant #206803/2014-1 for the Doctoral scholarship provided for the author by the Brazilian Council for Scientific Research and Development.

Address correspondence to:

Roosevelt Vilar
School of Psychology
Massey University
Auckland, New Zealand 0632
Email: roosevelt.vilar@gmail.com

Basic Values Survey (BVS): A 20-nation validation study

Abstract. The present paper tests the structure and invariance of the Functional Theory of Human Values across 20 countries ($N = 21,362$). This theory proposes that values have the functions of guiding behaviour and expressing needs. The interplay between these two functions produces six subfunctions that in turn produce distinct content. These subfunctions are operationalised in the Basic Values Survey with three items each, forming an 18-item measure. Although this measure has been used for more than two decades, studies examining its psychometric properties in multiple-group data are scarce. Using multidimensional scaling (MDS), it was found that values were organised in a bidimensional space according to the hypothesised degree of congruence between subfunctions. Also, Confirmatory Factor Analysis (CFA) with a Bayes estimator and approximate zero cross-loadings and residual correlations supported the six-factor structure. A strict CFA with Robust-ML estimator did not support the model. Metric invariance was supported for all the items, except religiosity, using the alignment method and approximate Bayesian invariance.

Keywords: human values, value structure, cross-cultural analyses, invariance, Bayes estimator.

Introduction

Human values are an important construct in psychology that aid in understanding attitudes and behaviours. This has been demonstrated in the literature on values-attitudes-behaviours (Homer & Kahle, 1988; Milfont, Duckitt, & Wagner, 2010) and values-beliefs-norms hierarchies (Stern, Dietz, Abel, Guagnano, & Kalof, 1999), wherein values are theorised as a motivator of human action. Values represent a combination of personal experiences and cultural characteristics, and are defined as “concepts or beliefs that pertain to desirable end states or behaviours, transcend specific situations, guide selection or evaluation of behaviour and events, and are ordered by relative importance” (Schwartz, 1992; pp. 4). Given their central role in social psychology, and importance in guiding people’s attitudes and behaviours, the psychometric properties of instruments that measure human values have received considerable attention (Cieciuch, Davidov, Schmidt, Algesheimer, & Schwartz, 2014a; Cieciuch, Davidov, Vecchione, Beierlein, & Schwartz, 2014b; Davidov, Meulemann, Schwartz, & Schmidt, 2014; Vecchione et al., 2015; Fontaine, Poortinga, Delbeke, & Schwartz, 2008; Spini, 2003; for assumptions about the universality of values see Schwartz, 1992).

Values have been measured with prominence since the *Rokeach Values Survey*, which measured this construct separated from personality and attitudes for the first time (Rokeach, 1973). However, with Schwartz’s (1992) inventory, values can be said to have come of age as a topic in the international literature. Schwartz (1992) theorised that values are organised by a universal motivational typology, and provided empirical evidence for this assertion in more than 70 countries (Schwartz, 1990). Over the years, Schwartz has proposed several instruments and refined his theory by making changes in the structure of his typology, and this has generated some criticism regarding focus and parsimony (Gouveia, Milfont, & Guerra, 2014a; Gouveia, Milfont, & Guerra, 2014b). For instance, Schwartz and Bilsky

(1987) initially developed their model with seven motivational domains, but later on refined it to ten (Schwartz, 1992), eleven (Schwartz, 1994), and nineteen (Schwartz et al., 2012) types. In response, the *Functional Theory of Human Values* has been developed (Gouveia, 2013) with a focus on the function values serve, and with a claim of parsimony that has been successful at explaining data generated by Schwartz's more complex typology (Gouveia et al., 2014b). Nevertheless, as a new theory, there have not been enough studies testing its psychometric properties across different cultures, which will be the focus of the present research.

The Functional Theory of Human Values

The *Functional Theory of Human Values* defines values as guiding principles that represent people's needs (Gouveia et al., 2014a). Gouveia (2013), differentiates three types of values orientation according to the function of their pursued goals (social, central and personal), and two types of motivation based on the function of expressing needs (thriving needs and survival needs). The interplay between the three types of orientation and the two types of motivators results in six clusters (see Figure 1) that are commonly used to predict attitudes, intentions, behaviours, etc. Gouveia's clusters are often called subfunctions because they are a by-product of the combination of two main functions; pursuing goals and expressing needs.

[Figure 1 around here]

The six subfunctions of the functional model are interactive, normative, suprapersonal, existence, excitement, and promotion (see Figure 1, also Gouveia et al., 2014a; Gouveia, Milfont, Vione, & Santos, 2015a). The first two subfunctions represent social goals (i.e., others-oriented), but they differ on motivations. Interactive represents thriving needs, and normative survival needs. While the interactive subfunction is focused on the affective

experiences among individuals (e.g., affectivity, social support), the normative subfunction is more pragmatically oriented and focused on the relationship between the individual and social institutions (e.g., tradition, obedience) (Gouveia et al., 2014a; Schwartz, 1992). The suprapersonal and existence subfunctions represent central goals, but they also differ as to their motivation. Amongst all values subfunctions, suprapersonal is the one that best represents thriving needs, and is a reference point for the other two dimensions (interactive and excitement) that also belong to such a motivator (Gouveia et al., 2015a). This value subfunction is focused on humanitarian ideas, representing people that are selfless and open-minded (e.g., knowledge, maturity). On the other hand, the existence subfunction is the purest representation of the survival motivator (Gouveia et al., 2015a). This value subfunction is focused on pragmatic issues (e.g., health, survival) and is a point of reference for the other two dimensions that share the same motivation (normative and promotion). Finally, the excitement and promotion subfunctions represent personal goals (i.e., self-oriented), but the first represents thriving needs and the second survival needs. Because of its thriving focus, the excitement subfunction emphasises people's desire for stimulation with a particular focus on enjoying life (e.g., emotion, pleasure). In contrast, the promotion subfunction has a closer relationship with institutions, but differently from that of the normative subfunction; here the focus is therefore on the achievement and progress of one's own career (e.g., prestige, power).

Besides organising values in six subfunctions, each representing specific characteristics, Gouveia et al. (2014a) argue further that the six subfunctions of values present degrees of congruence between them, with some being stronger than others. For the *Functional Theory of Human Values*, the subfunctions that share the same goals show the strongest degree of congruence (e.g., interactive-normative and excitement-promotion) and the dimensions that share the same motivator show a moderate congruence (e.g., interactive-

excitement and normative-promotion). A low congruence is attributed to the subfunctions that do not share goals or type of motivator (e.g., interactive-promotion and normative-excitement). An exception in the degree of congruence is given to central goals. Gouveia (2013) argues that they are the backbone of all other values, and therefore should be compatible with all the value subfunctions. Even though suprapersonal and existence express different motivators (thriving and survival needs), they co-exist harmoniously (Inglehart, 1991) and should be highly correlated with all the other values. The congruence between values is important because it highlights the parts of the model that are theoretically adjacent.

Human values scales

Considering values from an individual's perspective, where they are understood as a result of people's experiences and cultural influence, the models of Rokeach (1973), Schwartz (1992), and Gouveia (2003) are the most prominent ones. To measure values, Rokeach (1973) developed a scale composed of 36 items that assessed terminal and instrumental values, but the lack of factorial structure testing and criticism regarding the lack of criteria for item selection limited its application. Nevertheless, Rokeach's typology was influential for his successors. Schwartz and Bilsky (1987, 1990), for instance, conceptualised their circumplex theory based on a re-organisation of Rokeach's typology using the motivational aspects of values as a reference. In the 1990s, Schwartz proposed his first instrument (Schwartz Value Survey - SVS) to measure his 10 or 11 value types (Schwartz, 1992, 1994). The scale was strongly influenced by Rokeach's items, but instruments from other cultures and religious texts were also used to build his new scale, as stated by Schwartz (1992). Fifty-six items were gathered or developed, and they were answered in a nine-point scale varying from -1 (opposed to my values) to 7 (supreme importance).

In the 2000s, Schwartz et al. (2001) proposed a new survey (Portrait Values Questionnaire - PVQ) that measured the same 10 value types. The PVQ is different from the

SVS because it uses a different methodology regarding how participants are asked to evaluate the items. This scale became especially popular with its inclusion in the European Social Survey (ESS), but to fit in a large survey like the ESS, the PVQ had to be shortened. The PVQ-21 or ESS human values scale was then developed (Davidov, Schmidt, & Schwartz, 2008). More recently, Schwartz et al. (2012) developed a new scale with 57 items to measure 19 motivational types of values (PVQ-5X) instead of the original 10. New versions (PVQ-R and PVQ-RR) have also been presented to solve problems with model fit on the PVQ-5X (Schwartz, 2017). This plethora of measures for the same construct seems to represent a continuing search for the best-fitting questionnaire, and might confuse scholars who are aiming to use values in their research for the first time.

More recently, Gouveia (2003) proposed the Basic Values Survey – BVS to measure his *Functional Theory of Human Values*. Gouveia (2003) has a claim of parsimony that is novel because of the theory-driven approach adopted to develop his model. In contrast to Schwartz (1992), who built his model and then subsequently changed it based on empirical findings, Gouveia designed a six-factor structure that is theoretically grounded on two hypothesised functions of values. As the number of factors/subfunctions operationalised by Gouveia (2003, 2013) reflects the theoretical function that values serves (values express needs and guide actions), there are no expectations for changes in the number of subfunctions. Gouveia (2003, 2013) built his theory based on the functional perspective of Maslow (1954) but also adapted typologies found by previous researchers, such as Rokeach's social-personal typology (Rokeach, 1973), and Inglehart's materialism and post-materialism typology (Inglehart, 1991).

The basic values survey

Gouveia developed a 24-item scale based on Maslow's theory of needs (1954). Two experts evaluated whether the 24 items represented needs as postulated by Maslow (1954)

and the six-factor structure proposed by Gouveia (2003) was confirmed with multidimensional scaling (MDS). This scale was later reduced to 18 items (Gouveia, 2013) and showed good fit using both CFA and MDS approaches (Gouveia et al., 2014a) on a large Brazilian sample. The decision to represent values with 18 items was made to contribute to the literature with a short and easy-to-use scale that could fit either short or long questionnaires (Gouveia, 2013), but the number of values items might change. In fact, the structure proposed by Gouveia can even be examined with scales proposed by competing theories, since the focus of Gouveia's theory is on the proposition of six subfunctions of values, and not on the items that are being used (Gouveia et al., 2014b). Since 2003, the BVS has been used with several samples from Brazil (Coelho et al., 2018; Gouveia et al., 2014a; Gouveia, Milfont, Fischer, Coelho, 2009; Gouveia, Vione, Milfont, & Fischer, 2015b); two PhD theses (in Portuguese) presented the first cross-cultural findings (Medeiros, 2011; Soares, 2016). They were successful in showing cross-cultural validity through MDS, but a model fit was not satisfactory using CFA. In the present research, I contribute to the literature on human values by evaluating the cross-cultural appropriateness of the BVS scale across 20 countries.

Methods commonly used to examine the structure of values

The structure of Schwartz's and Gouveia's values have usually been tested using a more interpretive approach, multidimensional scaling (Bilsky, Janik, & Schwartz, 2011; Coelho et al., 2018; Fontaine, Poortinga, Delbeke, & Schwartz, 2008; Gouveia et al., 2014b; Koivula & Verkasalo, 2006; Schwartz, 1994). Less often, studies have also provided empirical findings using confirmatory factor analysis (CFA) (Davidov, 2010; Gouveia et al., 2014a; Schwartz & Boehnke, 2004; Vecchione, Casconi, & Barbaranelli, 2009). The CFA has presented a great challenge for researchers studying human values for several reasons. One of them is the fact that correlations among values dimensions are naturally high, since

values share similar goals or motivators, but in a strict approach, such as CFA, cross-loadings and residual correlations are fixed at zero (Lu, Chow, & Loken, 2017). Values scales are also supposed to cover a vast range of information, and the selection of items might not include items sufficiently homogeneous to represent each dimension, especially in short scales (Knoppen & Saris, 2009). The lack of homogeneity within the items from the same latent factor might complicate the identification of independent latent variables. This is because the lack of homogeneity would not produce a cohesive factor capable of showing a clear distinction from the other latent variables. The independence between latent factors is central for CFA (Brown, 2006).

As a response to the challenges imposed by CFAs to examine correlated structures and small scales, researchers have employed a different strategy to show evidence of latent structure and invariance called the magnifying glass strategy (Cieciuch, Davidov, Vecchione, Beierlein, & Schwartz, 2014; Cieciuch & Schwartz, 2012). This strategy consists of examining the structure of values considering adjacent dimensions rather than full models. This has shown to be successful because it lessens the complexity of the models and focuses on the question of utmost interest: the extent to which adjacent values are distinct. Also, a closer look into adjacent dimensions can make it easier to detect lack of homogeneity, since the dimensions that supposedly present the highest correlations are emphasised. For instance, by using this strategy, Knoppen and Saris (2009) found that the item “being rich” (i.e., It is important to him to be rich. He wants to have a lot of money and expensive things. ESS/BEING RICH) from Schwartz’s power dimension showed greater correlations with the dimension of achievement rather than with other items from the power dimension (i.e., It is important to him to be in charge and tell others what to do. He wants people to do what he says. ESS/IN CHARGE). The power and achievement dimensions are adjacent to each other and are usually combined to form a higher order factor called self-enhancement (Schwartz,

1992). Knoppen and Saris (2009) speculate that one of the reasons for this misspecification might be the fact that “being rich” gives people power, but it is not necessarily a measure of power, as the item “in charge” seems to represent. However, although the magnifying glass strategy has the theoretical relevance of examining whether adjacent dimensions are independent, ignoring cross-loadings and residual correlations between non-adjacent factors limits the application of an overall values model. This is because this strategy does not offer empirical support for using the value subfunctions as latent variables simultaneously.

Bayesian confirmatory factor analysis.

As an alternative to strict CFA, a more liberal CFA with Bayes estimation has been proposed (Muthén & Asparouhov, 2012; Asparouhov, Muthén, & Morin, 2015). The CFA using the Robust-ML is stricter than the analysis using the Bayes estimator because the model for the Robust-ML is examined with exact zeros for cross-loadings and residual correlations. The Bayesian estimation is more liberal because approximate zero cross-loadings and residual correlations are estimated instead of exact zeros. Muthén and Asparouhov (2010) affirm that approximate zero is more realistic in social sciences and reflect substantive theories better than absolute zeros when examining cross-loadings and residual correlations. These authors argue further that the traditional CFA (with maximum likelihood estimation) is unnecessarily strict and often leads to rejection of models. Indeed, many of the studies examining human values scales have failed to present satisfactory fit, and often demand modification in the model to yield acceptable fit (Ardilla et al., 2012; Cieciuch et al., 2014b; Davidov, 2010; Gouveia et al., 2010; Schwartz & Boehnke, 2004; Schwartz & Butenko, 2014). To the best of my knowledge, no study has applied the Bayesian estimation to examine the structure of human values scales, perhaps because the development of statistical packages to apply this method is fairly new (Asparouhov et al., 2015; Muthén and Asparouhov, 2010). However, the CFA with a Bayes estimator has been successfully applied

to examine scales in other areas of psychology (De Bondt & Van Petegem, 2015; Dombrowski, Golay, McGill, & Canivez, 2017; Fong & Ho., 2014). Therefore, the structure of values is examined using both the MDS and strict CFA, but also a Bayesian CFA with the estimation of approximate zero cross-loadings and residual correlations.

Method

Participants and procedure

Data for this study come from a cross-cultural project (World Digital Influence Project) with two waves of panel data. Representative samples come from 20 countries in the Americas, Europe, Asia and South Africa. The measures used in this study were embedded in a larger survey, including multiple psychological and communications constructs (for further details, see Gil de Zúñiga, Diehl, Huber, & Liu, 2017; Liu, Milojev, Gil de Zúñiga, & Zhang, 2018). The project was based at Massey University (New Zealand) and at the Media Innovation Lab (MiLab; University of Vienna, Austria). Participants ($N = 21,362$) were recruited online from September 14-24, 2015, and several steps were taken in order to ensure the quality of the data. A large group of competent scholars worked on the translations and back translations of the surveys. An online poll survey platform was used for data collection (Qualtrics), and it was employed by Nielsen, a well-known media polling company that partnered with local providers to generate a stratified quota sample (on gender, age, and region) drawn from a massive pool with over 10 million potential participants. The average duration for participants to complete the survey was 35 minutes, and the response rate was 77%. Rewards received for participation varied across countries, as they were determined by the local commercial survey panel provider. To ensure that the data were representative for each country, the demographics of each country were compared with their respective census (see Gil de Zúñiga & Liu, 2017). A pairwise missing deletion was used because there was only a small number of missing cases per item of human values (less than 2%).

Instruments

Basic Values Survey (BVS; Gouveia 2003). This self-report instrument is composed by 18 items, representing six value subfunctions. In a Likert scale ranging from 1 (Completely unimportant) to 7 (Of the utmost importance), participants are instructed to indicate the level of importance given to each of the values (items) described as a guiding principle to their lives. Two descriptions are given to each item, aiming at exemplifying the content of the value clearly. For instance, *Affectivity* is described as “To have a deep and enduring affectionate relationship” and “to have somebody to share successes and failures,” and *Tradition* is described as “To follow the social norms of your country” and “to respect the traditions of your society.” Descriptive statistics and alpha reliability are displayed in Table S1 at the supplementary materials. Average Alphas for all the subfunctions were close to .60, or higher, which is similar to previous research using the BVS (Gouveia et al., 2014a) and other value scales (e.g., Schwartz, 2005).

Data Analysis

I first examined the structure of human values through MDS, which is the most commonly used method to provide evidence of value structure (Bilsky et al., 2011; Fischer et al., 2011; Fontaine, Poortinga, Delbeke, & Schwartz, 2008; Koivula & Verkasalo, 2006; Schwartz, 1994), and confirmatory factor analysis, which is a stricter statistical procedure used to evaluate latent structures, also used in the values literature (Davidov, 2010; Gouveia et al., 2014a; Schwartz & Boehnke, 2004; Vecchione, Casconi, & Barbaranelli, 2009). Following this, two methods were used to estimate the CFA. I estimated a strict CFA with Robust-ML estimator and a more liberal CFA with a Bayesian estimator that allows approximate zero cross-loadings and residual correlations. To examine the MDS and CFA

with independent data, I split the sample in two random split-halves¹ each composed by approximately 50% of the original dataset. Splitting the data is recommended when one is examining the same model with different methods. That is to check whether a model estimated with one method can be replicated with another method, but with a sample that has not been previously assessed (Cudeck & Browne, 1983). Details of the original dataset and each random half can be seen in Table 1 and details about each method used in the present study are provided as follows.

[Table 1 around here]

Multidimensional scaling and generalised Procrustes rotation.

Using the first split-half of the data, MDS was implemented using SPSS (version 25.0.0.1), through the Proxscal algorithm, ordinal proximity transformations, Torgerson initial configuration, Euclidean distances measures, and Z-score transformations of values. This statistical technique compares a theoretical framework to the observed data, but instead of fixing the relationships between items and latent factors, MDS uses theoretical hypotheses to fix coordinates for the observed data in a multidimensional space (Gouveia et al., 2014a; Jaworska & Chupetlovska-Anastasova, 2009; Sturrock and Rocha, 2000). I followed the steps described in Gouveia et al. (2014a) to specify the expected coordinates that the data should fit (the coordinates replicate the structure shown in Figure 1). Model fit for the MDS was assessed using S-Stress (Jaworska & Chupetlovska-Anastasova, 2009) following the cut-off criteria recommended by Sturrock and Rocha (2000). These authors recommend a cut-off point of .263 when examining a bidimensional model with 18 items (see Sturrock & Rocha, 2000; pp. 57). S-Stress lower than .263 indicates good fit. I also used the Tucker's coefficient of congruence (Tucker's Phi) to examine the model fit, where values greater than .90 indicate

¹ Data was split in SPSS using the select cases option and the random samples of cases function.

good fit (van de Vijver & Leung, 1997). Besides examining the fit of each country one at a time, I also examined the invariance of the structure of values using MDS (Schwartz & Sagiv, 1995). More specifically, I compared the coordinates derived from each country with the coordinates derived from the pooled within-group correlation matrix. For the comparisons, the Generalised Procrustes Rotation (GPA) was applied. Using the GPA was necessary because coordinates derived from different datasets cannot be directly compared (Fischer et al., 2011). The GPA facilitates the comparisons by rotating the two sets of coordinates that are being examined to correspond as closely as possible to each other without affecting the relative distance between points within each configuration. A total fit congruence coefficient greater than .85 represents fairly similar structures, and greater than .95 represents identical structures (Lorenzo-Seva & ten Berge, 2006).

Confirmatory factor analysis (CFA) Robust-ML and Bayes estimators

For the second split-half of the data, confirmatory factor analyses (CFA) were tested in Mplus (version 8.4). Single group CFA were estimated using the Robust-Maximum Likelihood (Robust-ML) and the Bayes estimators. While the CFA with Robust-ML is simple to code and apply, the CFA with a Bayesian estimator demands more coding since all the possible cross-loadings and residual correlations can be estimated through the application of approximate zero prior variation. I followed the recommendations from Muthén and Asparouhov (2012) and Asparouhov et al. (2015) regarding prior specifications. Three models were tested using Bayesian estimation. The first model specified small variance for the cross-loadings (i.e., .001) but did not estimate residual correlations; this assumes zero residual correlations. For the second model, small variances for the cross-loadings and for the residual correlations were specified. In both models the prior variance of cross-loadings was specified as .001, which allows a 95% credibility interval of $\pm .06$. In this case, it is expected that cross-loadings will fall between -.06 and +.06 in strength. Regarding the variance in the

residual correlations, inversed Wishard priors IW (dD, d) were specified. For the value of d , Asparouhov et al. (2015) provide guidelines for starting values depending on the sample size. For instance, if the sample has approximately 500 participants, a starting value of 100 is recommended. The third CFA with a Bayesian estimator was similar to the second, but a stricter value of d (150) was applied. According to Asparouhov et al. (2015), the value of d can be selected in a post hoc manner. In this case, if the starting value of d satisfies the model, one can increase this value to examine whether a more strict prior variation yields good fit. Values for D were residual variances estimated in the CFA analysis with cross-loadings only.

To examine whether the model fit the data satisfactorily, several indexes were considered. For the CFA with the Robust-ML estimator, model fit was examined using CFI (comparative fit index), SRMR (standardised root mean squared residual) and RMSEA (root mean squared error approximation). The guidelines to indicate reasonably good fit are: CFI must be close to .95 (Hu & Bentler, 1999), but values higher than .90 are considered acceptable (e.g., Carlson & Mulaik, 1993); SRMR must be .08 or less; and RMSEA values must be close to .06 or lower (Hu & Bentler, 1999), but a value of .08 is considered acceptable (Browne & Cudeck, 1993). Regarding the RMSEA's cutoff point, Kenny, Kaniskan, & McCoach (2015) highlight that researchers should be careful when interpreting the RMSEA for models with low degrees of freedom to prevent false rejections. These authors observed that even a cutoff of .10 might present false rejections when the degrees of freedom are too low. A threshold of .10 has been used in the literature to indicate acceptable fit (Zemojtel-Piotrowska et al., 2017). Results for chi-square are also provided, but as this fit index is sensitive to sample size (Chen, 2007), it was not used to accept or reject model fit.

For the CFA with Bayesian estimator, the most used indexes to examine model fit are the Posterior Predictive P-value (PPP) and the 95% credibility interval associated with this

value. The PPP indicator compares chi-square values of the replicated and the observed data and represents the proportion of the chi-square of the replicated data that is larger than the values of chi-square attributed to the observed data. According to Asparouhov et al. (2015), PPP values should be higher than .05 to indicate acceptable fit, and values close to .50 are considered excellent fit. Regarding the 95% credibility interval, a good fit is indicated when zero is part of the credibility interval (Asparouhov, Muthén, & Morin, 2015; Muthén & Asparouhov, 2012). Besides the PPP and the 95% credibility interval, a new development in the Mplus statistical package (Version 8.4) makes the fit indexes of CFI and RMSEA available for Bayesian estimation. However, as these fit indexes are implemented for the Bayesian approach only recently, they are used as supplementary information, not as the main criteria to decide the fit of the models. The criteria used to examine the model fit with CFI and RMSEA are the same as reported for the analyses with a Robust-ML estimator. For all the analysis using a Bayes estimator, the minimum number of Markov Chain iterations was 15,000.

The alignment method and approximate Bayesian invariance

I provide evidence of invariance using the alignment method (Asparouhov & Muthén, 2014), and approximate Bayesian invariance (Muthén & Asparouhov, 2013). Each of these methods has been used to examine invariance in value scales (Asparouhov & Muthén, 2014; Cieciuch et al., 2014a; Cieciuch et al., 2019). However, each values cluster is examined one at a time, since these analyses can be employed for single-factor structures only (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2013). These methods are seen as more realistic for analysis considering many groups (Davidov, Muthén, & Schmidt, 2018; Marsh et al., 2018; Muthén & Asparouhov, 2018). Factor loadings, item intercepts, factor means, and factor variances are estimated for the alignment method without equality restrictions (Asparouhov & Muthén, 2014; Fischer & Karl, 2019). The analysis examines a configural model and

applies an optimisation using a component loss function to identify an approximation of invariance. Similar to the alignment method, approximate Bayesian invariance freely estimates factor means, variances, and covariances across groups, but constraints based on priors are applied to variation of loadings and intercepts between groups. For instance, using a prior of .01, the distribution of loadings and intercepts is normal with mean = 0 and variance = .01 (Cieciuch et al., 2014a). Simulations have shown that allowing the loadings and intercepts to vary to a small degree (e.g., variance equal to .01 or .05) does not bias conclusions for multiple group comparisons (Muthén and Asparouhov, 2013; Van de Schoot et al., 2013).

The invariance test using the alignment method and approximate Bayesian invariance was conducted for the full sample. For the alignment method, Asparouhov and Muthén (2014) suggest that a scale can be considered invariant if parameters are invariant for at least 80% of the groups. Also, these authors suggest that the scale can be considered as non-invariant if there is non-invariance for 25% or more of the groups. Regarding the approximate Bayesian invariance, invariance is considered acceptable when the PPP (posterior predictive p-value) is higher than .050 or close to .500 and includes zero in its credibility interval (Muthén & Asparouhov, 2013; Van de Schoot et al., 2013). The software Mplus (version 8.4) was used to perform these analyses.

Results

MDS and GPA

MDSs were performed for each country one at a time and for the pooled within-sample correlation matrix. Table 2 shows the fit for each MDS performed, and Figure 2 displays the common space plot of the pooled within-sample correlation matrix. Tucker's Phi was greater than .90 and S-Stress was lower than .263 for all the analyses, indicating that

forcing the items to adopt the proposed coordinates fits the data well (Gouveia et al., 2014a; Sturrock & Rocha, 2000; van de Vijver & Leung, 1997). The Tucker's Phi and S-Stress parameters reported in the present study are comparable with other studies using the same theory of values (Ardila et al., 2012; Fischer et al., 2011; Gouveia et al., 2014a) and also with research using Schwartz's model of values (Gouveia et al., 2014b; Schwartz, 1992). A table with the raw stress for each item is provided in the supplementary materials (Table S2). Results showed a low raw stress for all items except religiosity. Although there was a satisfactory fit for the overall model, the high score of raw stress for religiosity indicates that this item is poorly estimated. To test the invariance of the structure of values found using the MDS approach, GPA analyses were executed. GPA was used to compare the coordinates derived from the pooled within correlation matrix with the coordinates derived from each individual country.² As can be observed in Table 2, the total fit congruence coefficient showed values higher than .85 for all countries, indicating that the structure proposed by Gouveia et al. (2014) is fairly equivalent across 20 countries.

[Figure 2 around here]

[Table 2 around here]

CFA with Robust-ML and Bayes estimators

I examined CFAs with Robust-ML and Bayes estimators. When testing the full structure of values (a six-factor model) using the Robust-ML estimator, the model was non-identified for all 20 countries (the correlation matrix was non-positive definite). Detailed examination made it possible to see that the misspecification happened because some of the correlations between latent factors were higher than 1.00. This suggests the need for the

² Comparisons between the coordinates derived from the pooled within correlation matrix and the individual countries are performed for each country at a time. In this case, as 20 countries were examined, 20 GPA were performed.

specification of cross-loadings. There are different ways to deal with a non-positive correlation matrix. One can make adjustments in the model following modification indices (which can include the addition of cross-loadings and residual correlations), collapse different factors to reduce multicollinearity, eliminate problematic items, or use a different estimation method (Landis, 2013; Sheng, Kong, Cortina, & Hou, 2016; Wothke, 1993).

Although modifications to the model are possible alternatives (e.g., estimation of cross-loadings), research points out that these should be avoided, since the modifications can change the meaning of the factors and bias the interpretation of the results (Fornell & Larcker, 1981). Adding cross-loadings in a short scale like the BVS is even trickier since they will weigh substantially on the new latent factor. Therefore, cross-loadings were not assessed in the CFA analysis with Robust-ML estimator. Excluding problematic items might work if there is a good reason why the excluded item does not fit (Joseph, Ng, Koh, & Ang, 2007), but when short scales are being used, this option is limited. Therefore, the exclusion of items was not employed until all the other alternatives were examined. I then tested whether collapsing subfunctions or using a different estimator (i.e., Bayes estimator) would yield a better fit to the data.

Although collapsing subfunctions is not the best solution based on the Functional Theory of Human Values, alternative structures are worth testing because it might be that the proposed framework makes sense theoretically, but does not work empirically. Gouveia (2003) affirms that the six-factor structure best represents his theory, but models with two factors (thriving and survival needs) and three factors (social, central, and personal goals) are also plausible structures, and they have been tested in previous research (e.g., Gouveia et al., 2010, 2014a; Marques, Silva, & Taveira, 2018; Mohamed, Elebrashi, & Saad, 2018). My results showed that the six-factor structure showed a better fit than the three and two-factor models. When collapsing subfunctions (i.e., adjacent subfunctions were collapsed when

testing the three-factor model), although there was no improvement in the model fit (see Table S3 in the supplementary materials), it was possible to see that the number of countries with a misspecification on the positive definite correlation matrix decreased. This suggests that one of the biggest problems in Gouveia's measure is the amount of cross-loadings observed for adjacent dimensions. However, as the more parsimonious models (two and three factors) did not show improvement of model fit, it is likely that residual correlations also play an important role in the lack of model fit.

I examined whether approximate zero cross-loadings and residual correlations would therefore improve model fit. Approximate zero cross-loadings and residual correlations are modelled when using Bayesian estimation. This method has the advantage of estimating a more liberal model without changing the meaning of the latent factors (Asparouhov et al., 2015; Muthén and Asparouhov, 2010). Using Bayesian estimation, I first tested a model with approximate zero cross-loadings (prior variance = .001) but keeping exact zeros for residual correlations. This was to see whether the addition of small cross-loadings would be enough to achieve acceptable fit or whether this addition would improve the model in comparison with the CFA using Robust-ML estimation. Table 3 shows the model fit for the CFA using the Robust-ML (Model 1) versus Bayesian estimation with approximate zero cross-loadings (Model 2). It is possible to identify an improvement in the CFI between the two models, but as the analysis using the Robust-ML showed a misspecification, the CFI is not reliable for this estimator. A positive aspect of the analysis using the Bayes estimator is that the misspecification on the correlation matrix is no longer an issue. Loadings and cross-loadings for each country using Bayesian estimation and approximate zero cross-loadings are available in the supplementary materials (Table S4). Most of the items loaded strongly on the latent factor they were supposed to belong and most of the cross-loadings fell between -.06 and

+.06. However, as the model fit was still non-satisfactory, the most likely reason for the lack of fit is the exact zero residual correlations.

Nevertheless, before examining approximate zero residual correlations, repeating the same strategy employed when examining the CFA with Robust-ML estimation, I examined alternative structures with one, two, and three factors (see Table A5 in the supplementary materials). Although more parsimonious models did not show encouraging results when using the Robust-ML estimator, I tested whether using a liberal approach (i.e., approximate zero cross-loadings) would show a better fit for the alternative models in comparison to the six-factor structure. Results showed that the six-factor structure showed the better fit to the data in all cases (see Table 3 and Table S5 in the supplementary materials). However, as the model fit was still non-satisfactory, analyses were examined with approximate zero cross-loadings and residual correlations.

[Tables 8 and 9 around here]

I followed the guidelines outlined by Asparouhov et al. (2015) to specify the inverse-Wishart (dD, d) prior variation to estimate approximate zero residual correlations. Using a d of 100, there was a prior variation of approximately .02 for most of the countries, and the model fitted the data satisfactorily. This prior represents a variation in residual correlations from -.28 to +.28 (see Muthén and Asparouhov, 2010). The value of d can be selected in a post-hoc manner (Asparouhov et al. 2015) with greater values indicating stricter prior variation. Increasing the value of d to 150 also yields acceptable fit for all the countries (see Table 4), suggesting that the structure of values can be satisfactorily represented in a confirmatory approach when small cross-loadings and residual correlations are estimated. The prior variation for a d of 150 showed an averaged prior variation of .005, indicating that the strength of most of the residual correlations fell between -.14 and +.14. Detailed

information about the residual correlations for the model with a d of 150 is available at the supplementary materials (Table S6). If the value of d is increased even further to 200, the PPP becomes lower than the .050 cut-off, which represents a non-satisfactory fit. Therefore, a d of 150 representing a prior variation around .005 fits the data the best when estimating the residual correlations in the structure of values.

Evidence of invariance using the alignment method and the approximate Bayesian invariance.

Regarding the alignment method and approximate Bayesian invariance, I tested the invariance of each value subfunction one at a time (interactive, normative, suprapersonal, existence, excitement, and promotion). For all the analysis using the alignment method, a fixed alignment was employed. Most of the items showed invariance for the loadings, which is in line with the previous analyses using MGCFA. Invariance of loadings was observed for the subfunctions of interactive, suprapersonal, existence, excitement, and promotion (see Tables S7 and S8 in the supplementary materials). When invariance was assessed for the normative subfunction, the model showed a misspecification (the residual covariance matrix is not positive-definite) in five countries (Chile, Estonia, Italy, Spain, and Turkey). I then examined a model for the normative subfunction removing these five countries. For the 15 remaining countries, results showed that only the items of obedience and tradition were invariant in terms of loadings, and none of the items showed invariance of intercepts. The five countries with misspecification seemed to be influenced by the parameters of the item “religiosity,” since there was a large residual variance observed for this item across most of the countries. As there were only three items designed for this value subfunction, an alternative model for normative values was not examined. Besides religiosity, the item emotion should be used with caution since it was right on the cut-off point of 25% non-invariance.

For most of the items there was (non)invariance of intercepts in more than 25% of the countries, suggesting that the items do not achieve scalar invariance. Although there was non-invariance for most of the intercepts, some items in each dimension showed promising findings with non-invariance in less than 20% of the countries. They were social support (interactive subfunction), beauty (suprapersonal subfunction), health and personal stability (existence subfunction), and pleasure (excitement subfunction).

Regarding Bayesian approximate invariance, invariance was observed for most of the items, except religiosity. Invariance for the interactive, suprapersonal and existence value dimensions were achieved with a prior of .01. For promotion, the prior had to be increased to .02; for excitement, a prior of .03 was necessary to achieve invariance. For the normative dimension, invariance was not achieved even with a prior of .05. However, the exclusion of the item religiosity improved the fit, and invariance was established with a prior of .01 (see Table S9 in the supplementary materials). As the loadings and intercepts are estimated at the same time, these findings suggest a partial metric and scalar invariance for all the subfunctions, except for the item religiosity. Nevertheless, as scalar invariance failed in the alignment method, these results need to be interpreted with caution.

Discussion

The present study aimed to assess the structure and invariance of the six subfunctions (interactive, normative, suprapersonal, existence, excitement, and promotion) proposed by the *Functional Theory of Human Values*. Liberal (MDS, GPA, CFA with Bayes estimator, alignment invariance, and approximate Bayesian invariance) and strict methods (CFA with Robust-ML estimator) were used to examine the psychometric properties of the BVS. This variety of methods was employed because the literature on values has shown inconsistent findings when strict approaches are examined (e.g., Ardilla et al., 2012; Cieciuch et al., 2014b; Davidov, 2010; Gouveia et al., 2010; Schwartz & Boehnke, 2004; Schwartz &

Butenko, 2014). However, there are more promising findings when more liberal approaches are used (e.g., Bilsky et al., 2011; Fontaine, Poortinga, Delbeke, & Schwartz, 2008; Gouveia et al., 2014b; Koivula & Verkasalo, 2006; Schwartz, 1994).

The rather more recent CFA with Bayesian estimation (Muthén & Asparouhov, 2012; Asparouhov et al., 2015) has not yet been applied to examine the structure of values, but it has shown to be useful to examine the structure of other variables in psychology (e.g., De Bondt & Van Petegem, 2015; Dombrowski et al., 2017; Fong & Ho., 2014). This method is not as liberal as MDS, or as strict as CFA with a Robust-ML estimator, and is described by Asparouhov et al. (2015) and Muthén and Asparouhov (2010) as a more realistic approach to examining substantive theories. The proposed six-factor structure of values (Gouveia, 2003, 2013) was supported when using both MDS and CFA with Bayesian estimation. These results bring novelty to value research, showing that their structure fits the data in a confirmatory approach if small cross-loadings and residual correlations are allowed. This is different from the approach usually applied in the values literature, in which cross-loadings/residual correlations are estimated in a data-driven approach (following modification indices) and without constraints regarding their strength (Cieciuch et al., 2014b; Davidov, 2010). According to Muthén and Asparouhov (2010), there is a large chance of misspecification when one uses modification indices to adjust the model. On the other hand, the approximate zero cross-loadings and residual correlations do not impact on the meaning of the latent factors (Asparouhov et al., 2015; Morin, Arens, & Marsh, 2016; Muthén & Asparouhov, 2012). These techniques therefore represent an important venue to examine complex structures like values (Gouveia et al., 2014a), personality traits (McCrae, Zonderman, Costa Jr., Bond, & Paunonen, 1996), and moral foundations (Davies, Sibley, & Liu, 2014), which usually fail to fit strict CFA criteria.

Examining the structure of values with the strict CFA (Robust-ML) was discouraging. Model misspecification was found for all the countries because correlation between latent factors was greater than 1. However, collapsing subfunctions did not improved model fit, suggesting that the problem was not the number of proposed latent factors, but on the existence of cross-loadings and residual correlations. Items did load strongly enough solely on their corresponding subfunctions, but zero cross-loadings and residual correlations did not seem realistic for the model. Thus, the lack of fit for the strict CFA for the full structure of values limit the methods that can be used with the BVS. For instance, if one is interested in examining a structural equation model (SEM) with values as predictors, estimating the subfunctions as latent factors would result in a misspecified model. In this case, the problem would not necessarily be on the lack of correlations between values and the external outcomes, but from the estimation of the structure of values itself. This is a considerable limitation since structural equation modelling is one of the most robust techniques to examine the relationship between different variables. This problem with the BVS is also the same for the much larger literature using Schwartz values. Therefore, despite Gouveia's claim of parsimony and theoretical contributions, there is quite a long way to go before Gouveia's theory can be considered to have advanced the literature on values beyond Schwartz.

A way that values subfunctions can be simultaneously used is if they are estimated as a manifested variable (mean of items). This approach is less sophisticated and presents relevant limitations, but would not depend on the correct estimation of cross-loadings and residual correlations. This is the way many studies in the values field have assessed the association between values and external outcomes (Araujo et al., 2019; Schwartz et al., 2016; Stern et al., 1999). It is important to highlight that using manifested variables does not mean one can ignore factor analysis. On the contrary, evidence of factor analysis still needs to be provided, but it does not need to be a test of the full model (i.e., magnifying glass strategy)

(Schwartz et al., 2016; Vecchione et al., 2015), or even a strict CFA (i.e., Exploratory Factor Analysis or MDS). However, if a strict CFA is not provided for the full model, typically, latent variable modelling is not employed (i.e., structural equation modelling).

Finally, analyses of invariance showed evidence that the loadings of the BVS were equivalent across the 20 countries, except for the item of religiosity. GPA showed that the coordinates from every country were identical to the coordinates derived from the pooled-within correlation matrix. Using the alignment method and approximate Bayesian invariance results showed that all the items from the subfunctions of interactive, normative, suprapersonal, existence, excitement, and promotion were metric invariant, except for the item religiosity. When using the alignment method to examine the normative subfunctions, there was a misspecification in five countries that was influenced by high residuals associated to the item of religiosity. Excluding the five countries (namely Chile, Estonia, Italy, Spain, and Turkey), results showed that obedience and tradition were metric invariant, but not religiosity. Approximate Bayesian invariance was also sensitive to the variation of the item religiosity across countries and showed poor fit when this item was included on the analysis. Once the item religiosity was excluded, the model showed acceptable fit. Scalar invariance was only supported using approximate Bayesian invariance. Although these results for scalar invariance are encouraging, they demand caution since other liberal approaches (i.e., alignment method) did not show the same conclusion. It is also important to highlight that the item emotion was in the threshold (25% non-invariance) to represent a non-invariant item when the alignment method was used. However, as this item showed metric invariance when using the approximate Bayesian invariance, it was not removed from the scale. Nevertheless, results should be interpreted with caution when using the excitement subfunction.

Conclusion

This study examines cross-cultural validation of the Basic Values Survey (BVS) and its invariance in 20 countries/societies. The data used is especially robust because it is representative of the countries in terms of age, gender, and region (Gil de Zúñiga & Liu, 2017). Also, it includes data from Latin America and Asia, which are often neglected in psychological research (Henrich, Heine, & Norenzayan, 2010). The findings suggest that the six-factor structure proposed by Gouveia (2003, 2013) using the Basic Values Survey is appropriate when liberal methods of factor analysis are employed. However, Gouveia's model did not fit a strict CFA. In future studies, a refinement of Gouveia's items should be conducted to examine whether a strict CFA can be fitted using a larger item set. Future research can also examine whether the structure proposed by Schwartz (1992) fits the data using the CFA with a Bayesian estimator, and a replication of Gouveia et al. (2014b) could assess whether Gouveia's framework can be fitted with Schwartz data using an approach less liberal than the MDS.

References

- Araujo, R. C. R., Bobowik, M., Vilar, R., Liu, J. H., Gil de Zuñiga., Kus, L., Lebedeva, N., & Gouveia, V. V. (2019). Human values, right-wing authoritarianism, and social dominance as predictors of attitudes toward immigrants across 20 countries: The country-level moderating role of threat. *European Journal of Social Psychology, 50*, 534-546.
- Ardilla, R., Gouveia, V. V., Medeiros, E. D. (2012). Human values of colombian people. Evidence for the functionalist theory of values. *Revista Latinoamericana de Psicologia, 44*, 105-117.
- Asparouhov, T., & Muthén, B. (2014). Auxiliary Variables in Mixture Modeling: Three-Step Approaches Using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal, 21*, 329–341.
- Asparouhov, T., Muthén, B., & Morin, A. J. S. (2015). Bayesian structural equation modelling with cross-loadings and residual covariances: Comments on Stromeyer et al. *Journal of Management, 41*, 1561-1577.
- Bilsky, W., Janik, M., & Schwartz, S. H. (2011). The structural organization of human values – Evidence from three rounds of the European Social Survey (ESS). *Journal of Cross-Cultural Psychology, 42*, 759-776.
- Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford.
- Browne, M.W., & Cudeck, R. (1993). *Alternative Ways of Assessing Model Fit*. Sage Publications, Newbury Park, CA.
- Carlson, M., & Mulaik, S. A. (1993). Trait Ratings from Descriptions of Behavior As Mediated by Components of Meaning. *Multivariate Behavioral Research, 28*, 111–159.

- Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 14, 464-504.
- Cieciuch, J., & Schwartz, S. H. (2012). The number of distinct basic values and their structure assessed by PQV-40. *Journal of Personality Assessment*, 94, 321-328.
- Cieciuch, J., Davidov, E., Schmidt, P., Algesheimer, R., & Schwartz, S. H. (2014a). Comparing results of an exact vs. an approximate (Bayesian) measurement invariance test: A cross-country illustration with a scale to measure 19 human values. *Frontiers in Psychology*, 5.
- Cieciuch, J., Davidov, E., Vecchione, M., Beierlein, C., & Schwartz, S. H. (2014b). The Cross-National Invariance Properties of a New Scale to Measure 19 Basic Human Values: A Test Across Eight Countries. *Journal of Cross-Cultural Psychology*, 45, 764–776.
- Coelho, G. L. H., Hanel, P. H. P., Vilar, R., Monteiro, R. P., Gouveia, V. V., & Maio, G. R. (2018). Need for affect and attitudes toward drugs: The mediating role of values. *Substance Use & Misuse*, 53, 2232-2239.
- Cudeck, R., & Browne, M. W. (1983). Cross-Validation of covariance structures. *Multivariate Behavioral Research*, 18, 147-167.
- Davidov, E. (2010). Testing for comparability of human values across countries and time with the third round of the European Social Survey. *International Journal of Comparative Sociology*, 51, 171-191.
- Davidov, E., Meulemann, B., Schwartz, S. H., & Schmidt, P. (2014). Individual values, cultural embeddedness, and anti-immigration sentiments: Explaining differences in the effect of values on attitudes toward immigration across Europe. *KZfSS Kölner Zeitschrift Für Soziologie Und Sozialpsychologie*, 66, 263–285.

- Davidov, E., Muthen, B., & Schmidt, P. (2018). Measurement invariance in cross-national studies: Challenging traditional approaches and evaluating new ones. *Sociological Methods & Research*, 47, 631-636.
- Davidov, E., Schmidt, P., & Schwartz, S. H. (2008). bringing values back in the adequacy of the European Social Survey to measure values in 20 countries. *Public Opinion Quarterly*, 3, 420-445.
- Davies, C. L., Sibley, C. G., & Liu, J. H. (2014). Confirmatory factor analysis of the Moral Foundations Questionnaire: Independent scale validation in a New Zealand sample. *Social Psychology*, 45, 431–436.
- De Bondt, N., & Van Petegem, P. (2015). Psychometric evaluation of the overexcitability questionnaire-two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance. *Frontiers in Psychology*, 6, article 1963.
- Dombrowski, S. C., Golay, P., McGill, R. J., & Canivez, G. L. (2017). Investigating the theoretical structure of the DAS-II core battery at school age using Bayesian structural equation modeling. *Psychology in the Schools*, 55, 190-207.
- Fischer, R., & Karl, J. A. (2019). A Primer to (Cross-Cultural) Multi-Group Invariance Testing Possibilities in R. *Frontiers in Psychology*, 10.
- Fischer, R., Milfont, T. L., & Gouveia, V. V. (2011). Does Social Context Affect Value Structures? Testing the Within-Country Stability of Value Structures With a Functional Theory of Values. *Journal of Cross-Cultural Psychology*, 42, 253–270.
- Fong & Ho., 2014
- Fong, T. C. T., & Ho, R. T. H. (2014). Testing gender invariance of the hospital anxiety and depression scale using the classical approach and Bayesian approach. *Quality of Life Research*, 23, 1421-1426.

- Fontaine, J. R. J., Poortinga, Y. H., Delbeke, L., & Schwartz, S. H. (2008). Structural equivalence of the values domain across cultures: Distinguishing sampling fluctuations from meaningful variation. *Journal of Cross-Cultural Psychology*, 39, 345-365.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J Mark Res*, 18, 39-50.
- Gil de Zúñiga, H. G., & Liu, J. H. (2017). Second Screening Politics in the Social Media Sphere: Advancing Research on Dual Screen Use in Political Communication with Evidence from 20 Countries. *Journal of Broadcasting & Electronic Media*, 61, 193–219.
- Gil de Zúñiga, H., Diehl, T., Huber, B., & Liu, J. (2017). Personality traits and social media use in 20 countries: how personality relates to frequency of social media use, social media news use, and social media use for social interaction. *Cyberpsychology, Behavior, and Social Networking*, 20, 540–552.
- Gouveia V. V. (2003). The motivational nature of human values: Evidences of a new typology [in Portuguese]. *Estudos de Psicologia*, 8, 431-443.
- Gouveia, V. V. (2013). *Functional theory of human values: Fundaments, applications and perspectives [in Portuguese]*. São Paulo: Casa do Psicólogo.
- Gouveia, V. V., Milfont, T. L., & Guerra, V. M. (2014a). Functional theory of human values: Testing its content and structure hypotheses. *Personality and Individual Differences*, 60, 41-47.
- Gouveia, V. V., Milfont, T. L., & Guerra, V. M. (2014b). The functional theory of human values: From intentional overlook to first acknowledgement—A reply to Schwartz (2014). *Personality and Individual Differences*, 68, 250–253.

- Gouveia, V. V., Milfont, T. L., Fischer, R., Coelho, J. A. P. M. (2009). Teoria funcionalista dos valores humanos: Aplicações para as organizações. *Revista de Administração Mackenzie*, 10, 34-59.
- Gouveia, V. V., Santos, W. S., Milfont, T. L., Fischer, R., Clemente, M., & Espinosa, P. (2010). Teoría funcionalista de los valores humanos en España: Comprobación de las hipótesis de contenido y estructura (Functionalist theory of human values in Spain: Testing the content and structure hypotheses). *Revista Interamericana de Psicología*, 44, 203-214
- Gouveia, V. V., Vione, K. C., Milfont, T. L., & Fischer, R. (2015b). Patterns of value change during the life span: some evidence from a functional approach to values. *Personality and Social Psychology Bulletin*, 41, 1276–1290.
- Gouveia, V., Milfont, T., Vione, K. C., & Santos, W. S. (2015a). Guiding actions and expressing needs: on the psychological functions of values. *Psyche*, 24, 1-14.
- Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, 33, 61-83.
- Homer, P. M., & Kahle, L. R. (1988). A structural equation of the test of the value-attitude-behavior hierarchy. *Personality Processes and Individual Differences*, 54, 638-646.
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6, 1-55.
- Inglehart, R. (1991). *El cambio cultural en las sociedades industriales avanzadas*. Madrid: Siglo XXI.
- Jaworska, N., & Chupetlovska-Anastasova, A. (2009). A review of multidimensional scaling (MDS) and its utility in various psychological domains. *Tutorials in Quantitative Methods for Psychology*, 5, 1-10.

- Joseph, D., Ng, K., Koh, C., & Ang, S. (2007). Turnover of information technology professionals: a narrative review, meta-analytic structural equation modeling, and model development. *MIS Quarterly* 31, 547–577.
- Kenny, D. A., Kaniskan, B., McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research*, 44, 486-507.
- Knoppen, D., & Saris, W. (2009). Do we have to combine Values in the Schwartz' Human Values Scale? A Comment on the Davidov Studies. *Survey Research Methods*, 3, 91-103.
- Koivula, N., & Verkasalo, M. (2006). Value structure among students and steel-workers. *Journal of Applied Social Psychology*, 36, 1263-1273.
- Landis, R. S. (2013). Successfully combining meta-analysis and structural equation modeling: Recommendations and strategies. *Journal of Business and Psychology*, 28, 251-261.
- Liu, J. H., Milojev, P., Gil de Zúñiga, H., & Zhang, R. J. (2018). The Global Trust Inventory as a “Proxy Measure” for Social Capital: Measurement and Impact in 11 Democratic Societies. *Journal of Cross-Cultural Psychology*, 49, 789–810.
- Lorenzo-Seva, U., & ten Berge, J. M. F. (2006). Tucker’s Congruence Coefficient as a Meaningful Index of Factor Similarity. *Methodology*, 2, 57-64.
- Lu, Z., Chow, S., & Loken, E. (2017). A comparison of Bayesian and frequentist model selection methods for factor analysis models. *Psychological Methods*, 22, 361-381.
- Marques, C., Silva, A. D., Taveira, M. C., & Gouveia, V. V. (2016). Functional Theory of Values: results of a confirmatory factor analysis with Portuguese youths. *Revista Interamericana de Psicologia/Interamerican Journal of Psychology*, 50, 392-401.
- Marsh, H. W., Guo, J., Parker, P. D., Nagengast, B., Asparouhov, T., Muthén, B., Dicke, T. (2018). What to do when scalar invariance fails: The extended alignment method for

multi-group factor analysis comparison of latent means across many groups.

Psychological Methods, 23, 524-545.

Maslow, A. H. (1954). *Motivation and personality*. New York: Harper & Row.

McCrae, R. R., Zonderman, A. B., Costa Jr., P. T., Bond, M. H., & Paunonen, S. V. (1996).

Evaluating replicability of factors in the Revised NEO Personality Inventory:

Confirmatory factor analysis versus Procrustes rotation. *Journal of Personality and*

Social Psychology, 70, 552–566.

Milfont, T. L., Duckitt, J., & Wagner, C. (2010). A cross-cultural test of the value-attitude-

behavior hierarchy. *Journal of Applied Social Psychology*, 40, 2791-2813.

Mohamed, A. A., Elebrashi, R. M., & Saad, M. (2018). A Test of the Functional Theory of

Human Values in Egypt. *The Social Science Journal*, 56, 118-126.

Morin, A. J. S., Arens, A. K., & Marsh, H. W. (2016). A Bifactor Exploratory Structural

Equation Modeling Framework for the Identification of Distinct Sources of Construct-

Relevant Psychometric Multidimensionality. *Structural Equation Modeling: A*

Multidisciplinary Journal, 23, 116–139.

Muthén, B., & Asparouhov, T. (2010). Bayesian structural equation modeling: A more

flexible representation of substantive theory. *Psychological Methods*, 17, 313-335.

Muthén, B., & Asparouhov, T. (2013). BSEM measurement invariance analysis. Mplus WEB

Note No. 17, retrieved from

<https://www.statmodel.com/examples/webnotes/webnote17.pdf>

Muthén, B., & Asparouhov, T. (2018). Recent methods for the study of measurement

invariance with many groups: Alignment and random effects. *Sociological Methods &*

Research, 47, 637-664.

Rokeach, M. (1973). *The nature of human values*. New York, NY, US: Free Press.

- Schwartz, S. H. (1990). Individualism-Collectivism: Critique and proposed refinements. *Journal of Cross-Cultural Psychology*, 21, 139-157. Schwartz, 1992
- Schwartz, S. H. (1994). Are there universal aspects in the structure and contents of human values? *Journal of Social Issues*, 50, 19-45.
- Schwartz, S. H. (2005). Robustness and fruitfulness of a theory of universals in individual values. In A. Tamayo & J. B. Porto (Eds.), *Valores e comportamento nas organizacoes [Values and behavior in organizations]* (pp. 21–55). Petropolis, Brazil: Vozes.
- Schwartz, S. H. (2017). The refined theory of basic values. In S. Roccas & L. Sagiv (Eds.), *Values and behavior: Taking a cross-cultural perspective* (pp. 51-73). Cham, Switzerland: Springer International Publishing.
- Schwartz, S. H., & Bilsky, W. (1987). Toward a universal psychological structure of human values. *Journal of Personality and Social Psychology*, 53, 550-562.
- Schwartz, S. H., & Bilsky, W. (1987). Toward a universal psychological structure of human values. *Journal of Personality and Social Psychology*, 53, 550-562.
- Schwartz, S. H., & Bilsky, W. (1990). Toward a theory of the universal content and structure of values: Extensions and Cross-Cultural Replications. *Journal of Personality and Social Psychology*, 58, 878-891.
- Schwartz, S. H., & Boehnke, K. (2004). Evaluating the structure of Human Values with confirmatory factor analysis. *Journal of Research in Personality*, 38, 230-255.
- Schwartz, S. H., & Butenko, T. (2014). Values and behavior: Validating the refined value theory in Russia. *European Journal of Social Psychology*, 44, 799–813.
- Schwartz, S. H., & Sagiv, L. (1995). Identifying culture-specifics in the content and structure of values. *Journal of Cross-Cultural Psychology*, 26, 92-116.

Schwartz, S. H., Cieciuch, J., Vecchione, M., Davidov, E., Fischer, R., Beierlein, C., ...

Konty, M. (2012). Refining the theory of basic individual values. *Journal of Personality and Social Psychology*, 103, 663-688.

Schwartz, S. H., Cieciuch, J., Vecchione, M., Torres, C., Dirilen-Gumus, O., & Butenko, T. (2016). *European Journal of Social Psychology*, 47, 241-258.

Schwartz, S. H., Melech, G., Lehmann, A., Burgess, S., Harris, M., Owens, V. (2001).

Extending the cross-cultural validity of the theory of basic human values with a different method of measurement. *Journal of Cross-Cultural Psychology*, 32, 519-542.

Sheng, Z., Kong, W., Cortina, J. M., & Hou, S. (2016). Analyzing matrices of meta-analytic correlations: current practices and recommendations. *Research Synthesis Methods*, 7, 187-208.

Spini, D. (2003). Measurement equivalence of 10 value types from the Schwartz Value Survey across 21 countries. *Journal of Cross-Cultural Psychology*, 34, 3-23.

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, 6, 81-97.

Sturrock, K., & Rocha, J. (2000). A Multidimensional Scaling Stress Evaluation Table. *Field Methods*, 12, 49-60.

van de Schoot, R., Kaplan, D., Denissen, J., Asendorpf, J. B., Neyer, F. J., & van Aken, M.

A. G. (2013). A Gentle Introduction to Bayesian Analysis: Applications to Developmental Research. *Child Development*, 85, 842-860.

van de Vijver, F. J. R., & Leung, K. (1997). *Cross-cultural psychology series, Vol. 1.*

Methods and data analysis for cross-cultural research. Thousand Oaks, CA, US: Sage Publications, Inc.

- Vecchione, M., Casconi, T., & Barbaranelli, C. (2009). Assessing the circular structure of the portrait values questionnaire: A confirmatory factor analysis approach. *European Journal of Psychological Assessment*, 25, 231-238.
- Vecchione, M., Schwartz, S. H., Caprara, G. V., Schoen, H., Cieciuch, J., Silvester, J., ... Alessandri, G. (2015). Personal values and political activism: A cross-national study. *British Journal of Psychology*, 106(1), 84–106.
- Wothke, W. (1993). Nonpositive definite matrices in structural modeling. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 256-293). Newbury Park, CA: Sage.
- Zemojtel-Piotrowska, M., Piotrowski, J. P., Cieciuch, J... Maltby, J. (2017). Measurement invariance of personal well-being index (PWI-8) across 26 countries. *Journal of Happiness Studies*, 18, 1697-1711.

Figure 1. The structure of human values according to the Functional Theory

Note. Continuous lines separate goals and the dashed lines separate needs.

Figure 2. Spatial representation of the marker values from confirmatory multidimensional scaling

Note. Triangles refer to social values, circles to central values and squares to personal values. Black symbols refer to survival values and white symbols refer to thriving values. The plot is based on the pooled within-sample correlation matrix.

Table 1. *Sample Characteristics*

Nation	Full data			First random half			Second random half		
	N	Age (SD)	♀ (%)	N	Age (SD)	♀ (%)	N	Age (SD)	♀ (%)
Argentina	1145	40.8 (14.3)	51.7	560	40.9 (14.9)	51.0	585	40.6 (13.7)	52.4
Brazil	1086	35.9 (12.0)	49.8	541	35.8 (12.1)	52.0	545	35.9 (12.0)	47.6
Chile	964	35.1 (13.1)	51.3	486	35.6 (13.0)	49.4	478	34.4 (13.2)	53.2
China	1005	38.7 (12.0)	44.4	480	38.6 (12.3)	42.8	525	38.7 (11.7)	46.0
Estonia	1168	47.8 (17.2)	48.8	601	47.4 (16.8)	50.3	567	48.1 (17.5)	47.1
Germany	1093	45.1 (15.1)	53.9	539	45.0 (15.0)	56.2	554	45.1 (15.1)	51.6
Indonesia	1080	32.8 (9.8)	39.5	550	33.0 (10.2)	41.4	530	32.5 (9.6)	37.4
Italy	1041	41.7 (12.2)	55.3	543	41.7 (13.3)	57.4	498	41.7 (13.0)	53.0
Japan	975	46.7 (12.9)	42.2	512	46.4 (13.0)	43.0	463	47.0 (12.8)	41.2
Korea	943	38.9 (12.7)	46.7	456	39.3 (12.6)	46.8	487	38.4 (12.8)	46.6
NZ	1157	49.5 (17.3)	56.4	572	49.2 (17.6)	57.4	585	49.8 (17.1)	55.5
Philippines	1064	34.2 (11.0)	61.2	539	34.3 (10.9)	59.6	525	34.0 (11.1)	62.8
Poland	1060	42.0 (14.5)	54.0	539	41.2 (14.6)	52.8	521	42.7 (14.4)	55.3
Russia	1145	38.2 (12.8)	50.9	573	38.7 (13.2)	50.9	572	37.5 (12.3)	51.0
Spain	1019	41.0 (12.6)	52.6	507	40.4 (12.6)	50.2	512	41.4 (12.7)	55.1
Taiwan	1008	36.3 (10.9)	50.8	485	36.0 (10.9)	53.5	523	36.5 (10.9)	48.3
Turkey	961	33.9 (11.0)	44.0	477	33.8 (10.9)	40.1	484	34.0 (11.1)	47.8
UK	1064	50.6 (15.6)	54.1	538	50.9 (15.7)	52.9	526	50.3 (15.5)	55.4
Ukraine	1223	33.9 (9.40)	44.0	624	34.2 (9.7)	43.7	599	33.5 (9.0)	44.3
USA	1161	49.8 (16.4)	59.5	587	50.0 (16.6)	59.3	574	49.5 16.2	59.7

Table 2. *Multidimensional scaling and general Procrustes rotation analyses*

	Multidimensional Scaling		General Procrustes Rotation	
	S-Stress	Tucker's Phi	Total fit	Total Loss
Pooled within matrix	.187	.969		
Argentina	.195	.965	.981	.018
Brazil	.093	.980	.946	.053
Chile	.224	.969	.968	.031
China	.132	.958	.905	.095
Estonia	.171	.956	.933	.066
Germany	.260	.953	.967	.032
Indonesia	.037	.984	.938	.061
Italy	.196	.964	.949	.050
Japan	.212	.949	.910	.089
Korea	.241	.957	.932	.067
NZ	.190	.967	.973	.026
Philippines	.084	.965	.884	.115
Poland	.152	.977	.967	.032
Russia	.222	.966	.968	.031
Spain	.260	.957	.972	.027
Taiwan	.198	.966	.959	.040
Turkey	.109	.972	.952	.048
UK	.198	.962	.971	.028
Ukraine	.204	.970	.965	.034
USA	.115	.976	.947	.052

Table 3. *Model fit of the CFA using the Robust-ML and Bayes estimation with approximate zero cross-loadings*

	Model 1				Model 2			
	MLR estimator				Bayes Estimator			
					Prior = .001 for cross-loadings			
	$S\chi^2$ (120)	CFI	RMSEA	SRMR	PPP	CFI	RMSEA	95% C.I.
Argentina	793.15 ^a	.726	.098	.078	.000	.785	.096	634.759, 734.135
Brazil	742.29 ^a	.824	.098	.074	.000	.844	.104	753.307, 878.405
Chile	647.61 ^a	.759	.096	.081	.000	.823	.090	475.223, 583.915
China	685.42 ^a	.848	.095	.090	.000	.900	.088	464.295, 571.182
Estonia	931.85 ^a	.740	.109	.096	.000	.797	.108	764.585, 876.730
Germany	775.28 ^a	.699	.102	.091	.000	.782	.099	596.319, 706.960
Indonesia	848.30 ^a	.830	.107	.138	.000	.902	.095	590.504, 699.935
Italy	801.26 ^a	.761	.107	.091	.000	.814	.109	696.590, 807.603
Japan	919.20 ^a	.707	.120	.127	.000	.778	.126	909.258, 1019.104
Korea	649.02 ^a	.788	.095	.077	.000	.820	.102	600.559, 703.917
NZ	861.06 ^a	.695	.103	.091	.000	.785	.097	630.420, 728.490
Philippines	968.53 ^a	.782	.116	.088	.000	.837	.114	901.680, 1013.839
Poland	779.21 ^a	.734	.103	.112	.000	.796	.105	679.597, 781.401
Russia	860.44 ^a	.727	.104	.085	.000	.788	.106	768.749, 883.740
Spain	1029.07 ^a	.688	.122	.153	.000	.790	.104	797.777, 916.699
Taiwan	677.29 ^a	.827	.094	.076	.000	.851	.104	685.013, 796.763
Turkey	738.19 ^a	.805	.103	.081	.000	.824	.110	734.562, 839.989
UK	811.37 ^a	.753	.105	.088	.000	.815	.103	639.081, 751.002
Ukraine	838.20 ^a	.733	.100	.089	.000	.797	.104	755.264, 877.342
USA	789.18 ^a	.755	.099	.085	.000	.817	.094	585.151, 694.580

a = the correlation matrix was non-positive definite

Table 4. *Model fit of the CFA using the Bayes estimation with approximate zero cross-loadings and approximate zero residual correlations*

	Model 3				Model 4			
	Bayes Estimator				Bayes Estimator			
	Prior = .001 for cross-loadings and $d=100$				Prior = .001 for cross-loadings and $d=150$			
	for residuals				for residuals			
	PPP	CFI	RMSEA	95% C.I.	PPP	CFI	RMSEA	95% C.I.
Argentina	.389	.997	.020	-46.576, 57.556	.316	.996	.023	-43.242, 68.012
Brazil	.306	.997	.024	-46.146, 73.897	.346	.998	.022	-46.717, 69.089
Chile	.379	.997	.022	-40.079, 63.232	.282	.994	.031	-36.529, 72.951
China	.511	1.000	.000	-51.681, 53.941	.421	.999	.017	-47.530, 54.027
Estonia	.257	.996	.028	-38.801, 75.566	.129	.992	.040	-18.780, 98.744
Germany	.353	.996	.025	-42.276, 66.319	.184	.991	.036	-32.850, 81.734
Indonesia	.390	.999	.020	-45.795, 61.440	.352	.998	.026	-43.854, 71.611
Italy	.274	.995	.029	-39.361, 73.291	.201	.994	.037	-29.956, 83.364
Japan	.269	.995	.030	-33.233, 72.927	.252	.995	.034	-39.010, 69.691
Korea	.370	.998	.020	-43.579, 66.485	.377	.997	.022	-45.136, 64.713
NZ	.334	.996	.024	-41.312, 68.387	.198	.993	.034	-29.803, 79.383
Philippines	.256	.997	.028	-31.561, 77.901	.228	.997	.032	-30.941, 77.405
Poland	.266	.995	.029	-37.057, 69.045	.209	.993	.036	-32.998, 80.600
Russia	.358	.996	.025	-48.281, 71.737	.304	.996	.028	-39.333, 71.944
Spain	.241	.994	.032	-35.000, 80.941	.204	.993	.037	-29.512, 88.405
Taiwan	.310	.997	.026	-38.202, 67.906	.265	.996	.032	-38.900, 72.279
Turkey	.214	.995	.032	-33.093, 80.010	.216	.995	.034	-32.242, 81.439
UK	.361	.997	.023	-41.527, 66.390	.302	.996	.027	-39.139, 71.790
Ukraine	.385	.997	.021	-43.438, 65.953	.321	.996	.028	-48.817, 74.347
USA	.344	.997	.023	-37.826, 64.797	.200	.993	.034	-30.942, 83.731

SUPPLEMENTARY MATERIALS

Table S1.

Descriptive statistics and alpha reliability for the BVS

	Interactive			Normative			Suprapersonal			Existence			Excitement			Promotion		
	<i>M</i>	<i>SD</i>	α	<i>M</i>	<i>SD</i>	α	<i>M</i>	<i>SD</i>	α	<i>M</i>	<i>SD</i>	α	<i>M</i>	<i>SD</i>	α	<i>M</i>	<i>SD</i>	α
Argentina	5.57	.87	.59	5.02	1.02	.53	5.47	.87	.57	5.90	.81	.65	4.97	1.02	.53	4.45	1.08	.60
Brazil	5.44	1.08	.72	5.57	1.22	.68	5.56	1.07	.74	5.88	1.06	.79	4.94	1.11	.59	4.83	1.12	.63
Chile	5.42	.97	.63	4.89	1.07	.50	5.41	.99	.64	5.72	.93	.67	5.05	1.07	.64	4.61	1.06	.54
China	5.22	.94	.78	5.09	.89	.60	5.06	.91	.77	5.43	.94	.77	4.64	.95	.60	4.82	.98	.73
Estonia	5.40	.86	.56	4.64	.89	.44	5.05	.87	.64	5.92	.80	.68	4.47	1.04	.60	4.05	1.02	.70
Germany	5.38	.91	.61	4.33	1.03	.51	5.09	.89	.60	5.65	.83	.59	4.80	.98	.59	3.98	1.07	.64
Indonesia	5.50	.92	.78	5.57	.97	.78	5.30	.94	.75	5.73	.99	.85	4.93	.98	.68	4.83	1.00	.65
Italy	5.40	.96	.68	4.79	1.08	.58	5.32	.97	.72	5.71	.94	.72	4.67	1.10	.63	4.54	1.08	.62
Japan	4.33	.99	.72	3.83	.88	.53	4.16	.92	.68	4.85	1.03	.76	4.13	.95	.61	3.76	.96	.66
Korea	4.93	.85	.69	4.55	.90	.51	4.92	.84	.68	5.41	.88	.76	4.70	.90	.62	4.70	.88	.66
NZ	5.21	.87	.58	4.47	1.05	.52	4.90	.86	.59	5.73	.76	.60	4.38	1.03	.58	4.09	.97	.64
Philippines	5.68	.94	.76	5.50	.94	.63	5.49	.91	.68	6.01	.96	.83	5.15	.99	.63	4.93	1.02	.63
Poland	5.28	.96	.69	4.86	1.08	.65	4.93	.90	.62	5.46	.94	.70	4.49	1.01	.63	4.22	1.00	.61
Russia	5.37	.90	.63	4.67	1.02	.57	5.28	.92	.65	5.70	.94	.71	4.73	1.00	.53	4.60	1.04	.64
Spain	5.33	.97	.64	4.52	1.03	.48	5.24	.97	.70	5.74	.97	.76	4.97	.96	.62	4.37	1.01	.55
Taiwan	5.04	.96	.77	4.74	.94	.65	4.96	.99	.79	5.34	.95	.76	4.53	.97	.60	4.57	.97	.68
Turkey	5.62	1.09	.79	5.31	1.08	.57	5.42	1.02	.70	5.67	1.08	.74	4.62	1.14	.57	4.96	1.11	.66
UK	5.17	.96	.64	4.52	1.14	.57	4.96	.97	.67	5.65	.90	.71	4.48	1.10	.62	4.13	1.10	.67
Ukraine	5.40	.95	.69	4.83	1.02	.56	5.40	.93	.66	5.82	.94	.73	4.50	1.02	.48	4.77	1.03	.59
USA	5.32	.95	.64	4.81	1.17	.61	5.04	.95	.63	5.78	.85	.69	4.36	1.16	.63	4.20	1.07	.65
Average	5.57	.87	.68	5.02	1.02	.57	5.47	.87	.67	5.90	.81	.72	4.97	1.02	.60	4.45	1.08	.64

Table S2

Raw stress per item and per country

	Int1	Int2	Int3	Nor1	Nor2	Nor3	Sup1	Sup2	Sup3	Exi1	Exi2	Exi3	Exc1	Exc2	Exc3	Pro1	Pro2	Pro3
Argentina	.034	.032	.057	.024	.026	.173	.040	.077	.097	.027	.084	.041	.152	.105	.045	.034	.082	.104
Brazil	.070	.023	.022	.027	.038	.079	.035	.050	.031	.024	.025	.023	.073	.067	.017	.022	.031	.067
Chile	.046	.016	.040	.055	.063	.238	.060	.049	.041	.040	.035	.040	.072	.040	.023	.031	.095	.112
China	.062	.062	.070	.025	.056	.357	.103	.144	.084	.036	.071	.078	.124	.040	.061	.041	.037	.030
Estonia	.096	.126	.160	.048	.092	.296	.097	.090	.055	.055	.081	.032	.092	.062	.075	.032	.027	.044
Germany	.077	.066	.105	.050	.123	.233	.102	.045	.057	.072	.105	.092	.086	.047	.075	.065	.139	.109
Indonesia	.031	.039	.029	.009	.029	.019	.058	.021	.035	.015	.022	.018	.076	.057	.014	.014	.060	.019
Italy	.043	.041	.087	.021	.023	.233	.098	.056	.038	.032	.062	.034	.082	.057	.050	.020	.119	.175
Japan	.081	.108	.104	.050	.068	.363	.069	.143	.063	.063	.057	.064	.089	.068	.184	.068	.085	.059
Korea	.053	.044	.108	.052	.061	.184	.061	.078	.077	.055	.071	.064	.145	.050	.117	.049	.180	.059
NZ	.030	.032	.096	.027	.067	.192	.048	.053	.053	.067	.111	.052	.067	.043	.034	.005	.085	.101
Philippines	.034	.056	.050	.027	.071	.227	.072	.135	.071	.058	.071	.053	.044	.060	.091	.034	.043	.045
Poland	.028	.038	.037	.017	.030	.183	.042	.055	.026	.042	.046	.021	.035	.024	.045	.027	.059	.079
Russia	.087	.037	.054	.029	.020	.241	.040	.093	.036	.038	.063	.035	.057	.079	.100	.016	.114	.077
Spain	.073	.057	.079	.031	.103	.232	.050	.078	.049	.042	.065	.069	.108	.083	.072	.040	.145	.155
Taiwan	.026	.058	.042	.032	.029	.260	.025	.065	.020	.048	.104	.048	.104	.081	.068	.012	.114	.078
Turkey	.051	.035	.036	.017	.076	.107	.071	.047	.038	.020	.085	.027	.147	.072	.064	.007	.054	.054
UK	.059	.073	.085	.033	.052	.226	.064	.055	.044	.058	.092	.091	.071	.021	.067	.024	.130	.087
Ukraine	.023	.042	.033	.048	.024	.262	.026	.051	.030	.045	.045	.028	.038	.113	.081	.024	.075	.081
USA	.036	.056	.082	.015	.078	.074	.036	.034	.035	.032	.068	.028	.058	.030	.034	.018	.076	.061
Pooled-within	.018	.028	.050	.020	.045	.305	.045	.039	.032	.042	.063	.042	.052	.066	.029	.032	.103	.101

Note. Int1 = Belonging, Int2 = Social Support, Int3 = Affectivity, Nor1 = Obedience, Nor2 = Tradition, Nor3 = Religiosity, Sup1 = Beauty, Sup2 = Maturity, Sup3 = Knowledge, Exi1 = Personal Stability, Exi2 = Survival, Exi3 = Health, Exc1 = Sexuality, Exc2 = Emotion, Exc3 = Pleasure, Pro1 = Success, Pro2 = Power, Pro3 = Prestige.

Table S3.

Examining alternative structure of values with three, two, and one factor, and a Robust-ML estimator

	Robust ML estimator											
	3 Factors				2 Factors				1 Factor			
	X2 (132)	CFI	RMSEA	SRMR	X2 (134)	CFI	RMSEA	SRMR	X2 (135)	CFI	RMSEA	SRMR
Argentina	844.38 ^a	.710	.096	.083	917.25	.681	.100	.087	921.17	.680	.100	.087
Brazil	838.53	.801	.099	.076	861.87	.795	.100	.079	860.44	.795	.099	.079
Chile	726.34 ^a	.729	.097	.085	761.89	.714	.099	.088	763.31	.713	.099	.087
China	795.11 ^a	.822	.098	.084	867.75	.803	.102	.086	871.01	.802	.102	.086
Estonia	1052.89	.705	.111	.101	1369.85	.605	.128	.109	1353.54	.610	.126	.109
Germany	895.24 ^a	.649	.105	.098	921.30	.638	.105	.099	942.49	.629	.106	.099
Indonesia	919.45	.816	.106	.086	935.18	.813	.106	.090	938.20	.813	.106	.090
Italy	919.46	.724	.109	.098	1064.49 ^a	.674	.118	.103	1061.17	.675	.117	.103
Japan	984.02	.688	.118	.114	1006.20	.680	.119	.117	1006.46	.681	.118	.116
Korea	749.98	.753	.098	.081	789.75	.737	.100	.084	787.34	.739	.100	.084
NZ	963.55	.658	.104	.090	1113.53	.597	.112	.097	1126.31	.593	.112	.097
Philippines	1050.63 ^a	.764	.116	.091	1095.51 ^a	.753	.117	.092	1096.37	.753	.117	.092
Poland	845.15	.712	.102	.110	1067.75	.623	.116	.111	1068.37	.623	.115	.111
Russia	924.34	.708	.102	.089	957.80	.696	.104	.092	947.83	.700	.103	.092
Spain	1046.34	.686	.116	.110	1056.95	.683	.116	.113	1058.11	.683	.116	.113
Taiwan	851.31	.777	.102	.080	880.273	.769	.103	.082	892.04	.766	.104	.082
Turkey	879.27 ^a	.764	.108	.092	916.17 ^a	.753	.110	.089	923.67	.751	.110	.089
UK	954.33	.706	.109	.094	1114.34	.650	.118	.101	1124.92	.646	.118	.102
Ukraine	905.36	.712	.099	.091	933.56	.702	.100	.094	931.88	.703	.099	.094
USA	922.82 ^a	.711	.102	.095	1102.14	.646	.112	.099	1106.24	.645	.099	.112

a = countries which the correlation matrix was non positive definite.

Table S4.

Loadings and cross-loadings for the CFA with Bayes estimation and approximate zero cross-loadings

	Interactive	Normative	Suprapersonal	Existence	Excitement	Promotion
Belonging	.61*, .59*, .56*, .76*, .68*, .54*, .91*, .69*, .69*, .72*, .64*, .82*, .64*, .61*, .55*, .81*, .74*, .59*, .62*, .63*	.00, -.02, .00, .01, .00, .04, -.02, .01, .00, .01, .01, .00, .02, .05, .01, .04, -.01, .03, .03, .02	-.01, -.01, -.01, -.01, .00, -.01, -.03, -.02, -.01, -.02, -.02, -.02, -.01, -.02, -.02, -.02, -.01, -.01, -.01, -.02	-.02, -.02, -.01, -.01, -.01, -.01, -.04, -.02, -.04, -.02, -.01, -.02, -.01, -.02, -.02, -.01, -.02, -.01, -.01	-.02, .00, -.01, -.01, -.02, .00, -.01, .01, .00, -.01, -.01, -.06*, .00, -.02, .00, -.02, .00, .01, -.02, -.01	.00, .00, .00, -.01, -.01, .01, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
S. Support	.65*, .83*, .73*, .79*, .62*, .76*, .75*, .71*, .78*, .73*, .62*, .81*, .73*, .73*, .76*, .77*, .80*, .78*, .75*, .65*	-.01, .00, -.02, -.01, -.01, -.04, -.02, -.03, -.01, -.01, -.01, -.02, -.02, -.03, .00, -.02, .00, -.02, -.03, -.03	.01, .00, .01, .00, -.01, .00, .02, .01, .00, .00, .00, .00, .01, .01, .00, .00, .00, .01, .02	.00, .00, .00, .00, .00, -.01, -.01, .00, .00, .01, .01, .00, .00, .00, .01, -.01, -.01, .01, .00, .00	.01, .00, .01, .00, .01, -.01, .02, .01, .00, .00, -.01, .02, .01, .01, -.01, .00, .02, -.01, .01, .01	.00, .00, .00, .00, .01, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .01, .01, .00, .00, .00
Affectivity	.58*, .71*, .57*, .75*, .53*, .63*, .75*, .68*, .71*, .60*, .47*, .72*, .64*, .63*, .67*, .60*, .76*, .60*, .65*, .55*	-.01, .01, .00, -.02, -.01, -.02, .00, .00, -.01, -.01, -.01, -.01, -.01, -.03, .00, -.02, -.01, .00	.00, .00, .00, .01, .00, .00, -.01, .00, .00, .00, .01, .00, .01, .00, .00, .00, .00, .00, .00, .00	.01, .01, .00, .00, .00, .00, .01, .01, .01, .01, .00, .00, .00, .01, .00, .00, .00, .00, .00	.01, .00, .01, .01, .01, .00, -.01, -.01, .00, .01, .01, .02, -.01, .00, .00, .00, .00, .00, .00, .00	.00, .00, .00, .01, .01, .00, .00, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Obedience	-.01, -.02, -.02, -.03, -.01, -.01, -.04, -.01, -.02, -.01, -.01, -.04, -.01, -.01, -.02, -.02, -.01, -.01, -.02, -.02	.73*, .94*, .92*, .90*, .83*, .92*, .93*, .89*, .82*, .79*, .86*, .97*, .87*, .78*, .1.01*, .85*, .81*, .88*, .88*, .85*	-.01, -.01, -.02, -.03, -.02, -.02, -.04, .00, -.02, -.01, -.02, -.03, -.02, -.01, -.02, -.01, -.02, -.02, -.02	.00, -.02, -.02, -.02, -.01, -.02, -.03, .00, -.01, .01, .00, .00, -.02, -.01, .00, .00, .00, .00, .00, .00, .00	-.02, -.02, -.02, -.01, -.01, -.03, -.01, -.02, -.02, -.02, -.04, -.06*, -.03, -.02, -.03, -.01, -.02, -.02, -.02, -.02	.00, -.01, .00, -.01, .00, -.01, .00, -.01, .00, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Tradition	.00, .01, .02, .00, .00, .01, .00, .00, .00, .00, .01, .02, .00, .01, .01, .01, .00, .00, .01, .01	.65*, .52*, .57*, .80*, .60*, .54*, .82*, .66*, .70*, .58*, .48*, .61*, .68*, .68*, .43*, .76*, .60*, .63*, .55*, .53*	.01, .01, .02, .01, .02, .02, .01, .00, .01, .01, .01, .03, .01, .02, .02, .01, .00, .01, .01, .04	.00, .01, .01, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.01, .02, .03, .01, .00, .03, .01, .01, .01, .01, .03, .05, .02, .01, .03, .00, .02, .01, .02, .03	.00, .01, .00, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Religiosity	.00, .00, .00, .03, .02, -.01, .01, .00, .01, .01, .00, .02, .00, .00, .00, .01, .00, .00, .00, .00	.32*, .52*, .18*, .18*, .11, .28*, .64*, .23*, .16*, .30*, .40*, .29*, .40*, .29*, .02, .28*, .44*, .31*, .26*, .48*	.00, .00, .00, .04*, .02, .00, .01, -.01, .03, .01, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00	-.01, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.00, .01, .01, .04*, .03, .02, .01, .01, .04, .01, .01, .06*, .01, .01, .02, .02, .00, .01, .02, .00	.00, .01, .00, .02*, .02, .00, .00, .01, .01, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Beauty	-.01, -.01, -.01, -.02, -.01, -.02, -.02, -.01, -.01, -.01, -.01, -.02, -.01, -.01, -.01, -.01, -.01, -.01, -.01, -.01	-.01, -.03, -.01, .00, .01, -.02, -.02, .01, -.01, -.01, -.01, -.03, -.01, .00, .00, .03, -.01, -.02, .01, -.03	.61*, .65*, .62*, .80*, .65*, .52*, .78*, .64*, .68*, .63*, .62*, .68*, .59*, .60*, .65*, .72*, .67*, .58*, .62*, .65*	-.01, -.02, -.01, -.01, -.01, -.02, -.03, -.01, -.03, -.02, -.01, -.03, -.01, -.03, -.03, .01, -.01, -.02, -.02, -.01	-.01, .00, -.01, -.01, -.03, -.01, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.00, .00, .00, -.01, -.02, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Maturity	-.01, -.01, .01, .03, .02, .03, .02, -.01, .03, .01, .02, -.01, .03, -.01, .00, .03, .01, .02, .01, .00, .00	.01, .03, .05, .04, .02, .04, .03, -.02, .04, .01, .03, .04, .03, -.03, .03, .04, .01, .04, -.02, .07*	.61*, .78*, .59*, .65*, .68*, .63*, .74*, .89*, .59*, .67*, .62*, .83*, .58*, .83*, .80*, .68*, .77*, .69*, .74*, .58*	.01, .03, .02, .03, .04, .04, .05, .01, .09*, .05, .02, .04, .03, .02, .02, .05*, .01, .03, .02, .04	-.01, -.02, -.02, .01, .00, -.02, -.02, -.02, -.01, -.01, -.02, -.07*, -.03, -.03, -.03, -.02, -.02, -.03, -.01, -.03	.00, .02, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Knowledge	.00, .01, -.01, -.01, -.01, -.01, -.01, .01, -.02, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	-.01, -.01, -.04, -.04, -.05, -.02, -.03, .01, -.03, .01, -.03, -.04, -.03, .03, .03, -.03, -.04, -.03, .03, .03	.59*, .75*, .71*, .81*, .66*, .58*, .83*, .56*, .76*, .74*, .57*, .61*, .60*, .50*, .58*, .90*, .72*, .67*, .58*, .64*	-.01, -.01, -.02, -.02, -.04, -.02, -.03, -.01, -.05*, -.02, -.01, -.03, -.03, -.01, -.01, -.02, -.03, -.02	.02, .01, .02, .02, .04, .02, .02, .04, .01, .01, .01, .01, .02, .07*, .03, .04*, .03, .02, .03, .03, .02	.00, .02, .00, .01, .02, .01, .00, .02, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Stability	-.01, -.01, -.01, -.01, -.02, -.02, -.02, .00, -.01, .01, -.01, -.01, -.01, -.01, -.01, -.01, -.01, -.01, -.01, -.01	.00, .00, -.02, -.03, -.01, .03, -.03, .02, .00, .02, .07*, -.02, .00, .03, .03, .03, -.01, .00, .05*, .01, .03	-.01, -.02, -.01, .01, -.03, -.04, -.01, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.65*, .84*, .65*, .75*, .91*, .70*, .88*, .63*, .76*, .79*, .57*, .82*, .69*, .76*, .74*, .83*, .59*, .62*, .81*, .63*	.00, -.01, .01, .03, -.02, -.03, .01, .03, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.00, .00, .00, .02, .00, .00, .01, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Survival	.00, .01, .01, -.01, -.01, .01, .00, .02, -.01, -.02, -.01, -.03, .00, .01, -.01, -.01, .00, .00, .00, .00	-.02, -.03, .02, .02, -.01, -.06, .00, -.03, -.02, -.02, -.07*, .00, -.02, -.04, -.03, .00, .00, .04, -.03, .04	.01, .00, .01, -.03, .01, .02, -.01, .00, -.02, -.01, .00, .01, .01, .00, .00, .00, .00, .00, .00	.64*, .84*, .71*, .82*, .71*, .56*, .85*, .86*, .85*, .66*, .63*, .96*, .73*, .79*, .84*, .76*, .82*, .82*, .75*, .68*	-.02, .00, -.03, -.03*, .01, -.01, -.01, -.03, -.02, -.01, -.02, -.06*, -.02, -.01, -.03, -.01, .00, .04, .00, .03	-.01, -.01, .00, .02, -.02, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Health	.00, .01, .01, .01, .02, .01, .00, .01, .01, .00, .00, .02, .01, .01, .01, .01, .01, .00, .01, .02, .00	-.01, .00, -.02, -.02, -.01, -.03, .00, .01, .00, .00, .00, -.03, -.01, .01, -.01, -.03, .01, .00, .01, .00	.00, .01, .02, .01, .04, .02, .00, .00, .01, .01, .01, .01, .01, .00, .00, .00, .00, .00, .00	.70*, .64*, .62*, .75*, .46*, .62*, .83*, .67*, .73*, .68*, .58*, .75*, .58*, .61*, .71*, .63*, .81*, .82*, .58*, .75*	.01, .02, .03, .01, .05*, .04, -.01, .01, .01, .01, .02, .05*, .02, .03, .03, .01, -.01, .02, .03, .00	.00, .01, .00, .01, .02, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Sexuality	.00, .01, .00, .04*, .01, .01, .04, .02, -.01, .01, .01, -.03, .02, .02, .00, .02, .01, .00, .02, .00	.00, .03, .02, .06*, .02, .00, .05*, .02, -.01, .01, .00, .03, .02, .03, .00, .03, .01, .01, .05, .00	.00, .01, .00, .03, .00, .00, .03, .02, -.01, .00, .00, .02, .00, .00, .00, .00, .00, .00, .00	.00, .03, .01, .05*, .02, .01, .05*, .02, -.02, .01, -.01, -.02, .02, .04, .01, .02, .01, .00, .051*, .00	.50*, .61*, .53*, .54*, .51*, .58*, .51*, .49*, .60*, .50*, .54*, .65*, .50*, .55*, .61*, .48*, .39*, .50*, .55*, .49*	.00, -.01, .00, .00, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Emotion	.01, -.01, .00, -.02, -.01, -.02, .01, -.02, -.02, -.01, .01, .01, .01, -.01, -.02, -.01, .00, .00, -.02, .01	.01, -.04, -.02, -.02, -.01, -.02, .01, -.02, -.03, .00, .01, .01, .02, -.01, -.04, -.02, .00, -.02, .02, .00	.01, -.01, .00, -.01, .01, -.01, .01, -.01, .00, .00, .01, .01, .01, -.01, -.02, .00, .00, .00, .02, .01	.00, -.03, .00, -.02, -.02, -.03, .00, -.02, -.03, -.02, .01, .00, .01, -.03, -.04, .00, .00, .00, .00, .00	.55*, .55*, .75*, .82*, .78*, .67*, .68*, .74*, .81*, .77*, .70*, .72*, .71*, .61*, .68*, .89*, .81*, .81*, .50*, .68*	.00, .01, .00, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Pleasure	-.01, .00, .00, -.01, .00, .03, -.03, .00, .04, .00, .00, .01, -.02, -.01, .01, .01, .00, .00, .00, .00	.00, .01, -.01, -.02, .00, .05, -.04, .00, .05*, .00, .01, .02, -.03, -.02, .04, .01, -.01, .01, -.02, .00	-.01, .00, -.01, -.01, .00, .02, -.02, .00, .02, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00	.00, .01, -.01, -.01, .01, .05, -.03, .00, .08*, .02, .00, .02, -.02, .01, .02, .00, .00, .00, .00	.59*, .66*, .61*, .56*, .57*, .44*, .75*, .61*, .47*, .56*, .43*, .66*, .67*, .51*, .52*, .36*, .53*, .50*, .51*, .61*	.00, .00, .00, .00, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Success	.10*, .05*, .07*, .08*, .05*, .07*, .16*, .08*, .07*, .05*, .09*, .14*, .09*, .08*, .09*, .06*, .10*, .09*, .07*, .08*	.09*, .14*, .18*, .11*, .08*, .13*, .19*, .10*, .09*, .06*, .11*, .20*, .09*, .07*, .18*, .07*, .10*, .09*, .10*, .09*	.09*, .05*, .08*, .05, .04, .06*, .13*, .11*, .06*, .06*, .08*, .10*, .07*, .10*, .13*, .02, .07*, .08*, .08*, .08*	.10*, .10*, .11*, .09*, .09*, .10*, .17*, .10*, .13*, .11*, .06*, .14*, .09*, .13*, .15*, .08*, .08*, .09*, .13*, .07*	.03, -.01, .05, -.02, .00, .03, .02, .01, .05, .03, .05, .09*, .03, .02, .08*, .02, -.01, .03, .01, .02	.30*, .48*, .17*, .52*, .57*, .46*, .19*, .45*, .32*, .39*, .37*, .20*, .29*, .31*, .12*, .56*, .47*, .43*, .37*, .35*
Power	-.01, -.01, .00, -.04, -.03, -.02, -.01, -.03, -.01, -.01, -.01, -.01, -.02, .00, .00, .00, .00, .00, .00, .00	.00, .04, .00, -.04, -.04, -.04, .01, -.04, -.02, -.02, -.01, -.02, -.01, -.02, .00, .00, .00, .00, .00	-.01, -.01, .00, -.02, -.02, -.02, -.01, -.03, -.01, -.01, -.01, -.01, -.02, .00, .00, .00, .00, .00	-.01, -.03, .00, .04, -.05*, -.03, -.01, -.03, -.03, -.03, -.01, -.01, -.02, .00, .00, .00, .00, .00	.69*, .65*, .74*, .82*, .73*, .75*, .79*, .82*, .85*, .74*, .90*, .80*, .83*, .76*, .77*, .66*, .76*, .81*, .77*, .70*	.00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00
Prestige	-.01, -.01, -.01, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	-.01, -.03, -.02, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	-.01, -.01, -.01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	-.01, -.02, -.01, .01, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00, .00	.70*, .64*, .69*, .69*, .71*, .67*, .82*, .65*, .72*, .75*, .65*, .72*, .70*, .67*, .71*, .62*, .63*, .62*, .64*, .73*

Note. Loadings are highlighted in grey.

Table S5.

Examining alternative structure of values with three, two, and one factor, and a Bayesian estimator (approximate zero cross-loadings and exact zero residual correlations)

	Bayes Estimator											
	Prior = .001 for cross-loadings											
	3 Factors				2 Factors				1 Factor			
	Social, Central and Personal goals				Thriving and Survival needs				General factor			
	PPP	CFI	RMSEA	95% C.I.	PPP	CFI	RMSEA	95% C.I.	PPP	CFI	RMSEA	95% C.I.
Argentina	.000	.740	.103	771.02, 876.65	.000	.681	.113	969.20, 1053.20	.000	.679	.113	976.15, 1062.42
Brazil	.000	.808	.116	947.24, 1048.31	.000	.749	.120	1024.76, 1115.30	.000	.794	.120	1027.47, 1115.02
Chile	.000	.751	.108	690.82, 792.181	.000	.718	.114	798.05, 884.95	.000	.712	.115	815.09, 902.83
China	.000	.849	.106	720.66, 839.54	.000	.804	.120	972.51, 1059.12	.000	.802	.120	981.75, 1069.25
Estonia	.000	.751	.117	956.61, 1053.87	.000	.612	.143	1524.24, 1610.91	.000	.612	.143	1530.63, 1612.03
Germany	.000	.660	.117	962.97, 1062.73	.000	.640	.123	1025.04, 1121.26	.000	.622	.126	1080.82, 1170.49
Indonesia	.000	.872	.110	776.46, 898.40	.000	.807	.133	1218.39, 1307.95	.000	.806	.134	1228.66, 1314.63
Italy	.000	.775	.119	855.09, 966.98	.000	.666	.141	1307.63, 1400.11	.000	.666	.142	1305.66, 1399.15
Japan	.000	.697	.144	1248.14, 1375.98	.000	.676	.150	1363.84, 1446.48	.000	.674	.150	1372.64, 1457.04
Korea	.000	.755	.116	838.35, 926.97	.000	.731	.121	925.20, 1011.90	.000	.731	.121	927.92, 1014.92
NZ	.000	.702	.111	886.76, 992.59	.000	.606	.126	1204.96, 1288.76	.000	.599	.127	1222.91, 1308.51
Philippines	.000	.794	.131	1141.54, 1279.62	.000	.756	.142	1388.92, 1479.11	.000	.756	.143	1390.71, 1476.76
Poland	.000	.752	.114	836.83, 937.11	.000	.618	.140	1321.84, 1408.02	.000	.617	.139	1328.39, 1413.50
Russia	.000	.741	.116	959.67, 1069.06	.000	.691	.125	1162.76, 1254.47	.000	.691	.126	1167.35, 1261.52
Spain	.000	.694	.133	1199.12, 1295.11	.000	.684	.136	1240.86, 1329.95	.000	.682	.136	1250.67, 1337.27
Taiwan	.000	.799	.121	936.17, 1050.82	.000	.763	.129	1129.69, 1218.51	.000	.758	.131	1158.42, 1243.14
Turkey	.000	.805	.117	823.30, 926.54	.000	.745	.131	1095.64, 1183.58	.000	.745	.133	1098.54, 1185.57
UK	.000	.738	.119	933.01, 1048.443	.000	.654	.136	1263.86, 1351.31	.000	.646	.137	1289.61, 1378.73
Ukraine	.000	.755	.112	926.76, 1045.89	.000	.696	.123	1183.14, 1273.42	.000	.695	.124	1184.26, 1275.97
USA	.000	.749	.108	824.65, 933.02	.000	.647	.126	1187.48, 1271.49	.000	.642	.127	1206.90, 1290.50

Table S6.

Prior variation of the residual correlations for a d of 150

	Descriptive stats of prior variation				Categorisation of prior variation*								
	Minimum	Maximum	Mean	SD	≤.001	.001-.005	.005-.01	.01-.02	.02-.03	.03-.04	.04-.05	.05-.1	> .1
					1	2	3	4	5	6	7	8	9
Argentina	.001	.021	.005	.004	-	102	38	11	2	-	-	-	-
Brazil	.001	.020	.005	.004	2	92	40	19	-	-	-	-	-
Chile	.001	.026	.005	.004	1	94	43	12	3	-	-	-	-
China	.001	.010	.002	.001	33	116	4	-	-	-	-	-	-
Estonia	.001	.016	.004	.003	8	107	32	6	-	-	-	-	-
Germany	.001	.022	.005	.004	5	94	40	13	1	-	-	-	-
Indonesia	.001	.004	.001	.001	48	105	-	-	-	-	-	-	-
Italy	.001	.023	.005	.004	5	101	33	12	2	-	-	-	-
Japan	.001	.010	.003	.001	-	142	11	-	-	-	-	-	-
Korea	.001	.014	.003	.002	10	125	16	2	-	-	-	-	-
NZ	.001	.026	.005	.004	6	98	34	11	4	-	-	-	-
Philippines	.001	.012	.002	.002	32	107	13	1	-	-	-	-	-
Poland	.001	.017	.004	.003	2	119	25	7	-	-	-	-	-
Russia	.001	.019	.005	.003	3	107	34	9	-	-	-	-	-
Spain	.000	.021	.004	.004	18	91	34	9	1	-	-	-	-
Taiwan	.001	.010	.003	.002	28	109	15	1	-	-	-	-	-
Turkey	.001	.021	.005	.004	-	101	39	12	1	-	-	-	-
UK	.001	.031	.005	.005	3	99	33	13	4	1	-	-	-
Ukraine	.001	.023	.005	.004	-	96	41	15	1	-	-	-	-
USA	.001	.029	.005	.005	-	94	41	16	2	-	-	-	-

* The categorisation of prior variation represents the amount of correlations that fell within each range of prior variation.

Table S7.

Alignment invariance for interactive, normative and suprapersonal values

Items	(Non)Invariant countries	% (NI)	Fit	R^2
Interactive				
Intercepts				
Belonging	AR BR CL (CN) ES (GE) (IN) IT (JP) KO NZ (PH) PL RU SP (TA) (TU) UK UR US	35%	-111.768	.56
Social Support	AR BR CL CN ES GE (IN) IT JP KO NZ PH (PL) RU SP TA TU UK UR US	10%	-75.204	.89
Affectivity	AR BR CL (CN) ES GE IN IT JP (KO) NZ (PH) PL RU SP (TA) TU UK (UR) US	25%	-85.509	.87
Loadings				
Belonging	AR BR CL CN ES GE IN IT (JP) KO NZ PH PL (RU) (SP) TA TU UK UR US	15%	-78.438	.46
Social Support	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-76.683	.47
Affectivity	AR BR CL CN ES GE IN IT JP KO NZ PH PL (RU) SP TA TU UK UR US	5%	-67.137	.74
Normative				
Intercepts				
Obedience	(AR) BR (CN) GE (IN) JP KO NZ PH PL RU TA UK UR US	20%	-47.46	.85
Tradition	AR (BR) CN GE IN JP KO NZ PH PL (RU) TA UK UR (US)	20%	-56.95	.29
Religiosity	AR (BR) (CN) GE (IN) JP (KO) NZ (PH) (PL) RU (TA) UK UR (US)	53%	-98.73	.50
Loadings				
Obedience	AR BR CN GE IN JP KO NZ PH PL RU TA UK UR US	0%	-43.94	.50
Tradition	AR BR CN GE (IN) JP KO NZ PH PL RU TA UK UR US	6%	-48.05	.00
Religiosity	AR (BR) (CN) GE IN (JP) KO NZ PH PL RU TA UK UR (US)	26%	-58.21	.28
Suprapersonal				
Intercepts				
Beauty	AR BR CL CN ES (GE) IN IT JP KO NZ PH PL RU SP TA TU UK UR US	5%	-73.645	.92
Maturity	AR BR CL (CN) ES GE (IN) IT JP KO NZ PH PL RU SP (TA) TU UK (UR) US	20%	-85.539	.83
Knowledge	AR (BR) CL (CN) ES GE (IN) IT JP (KO) NZ (PH) (PL) RU SP (TA) TU UK UR (US)	30%	-86.182	.89
Loadings				
Beauty	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-69.213	.38
Maturity	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-76.394	.51
Knowledge	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-69.202	.62

AR = Argentina, BR = Brazil, CL = Chile, CN = China, ES = Estonia, GE = Germany, IN = Indonesia, IT = Italy, JP = Japan, KO = Korea, NZ = New Zealand, PH = Philippines, PL = Poland, RU = Russia, SP = Spain, TA = Taiwan, TU = Turkey, UK = United Kingdom, UR = Ukraine, US = the United States.

Table S8.

Alignment invariance for existence, excitement and promotion values

Items	(Non)Invariant countries	% (NI)	Fit	R^2
Existence				
Intercepts				
Per.Stability	AR BR (CL) CN ES GE IN IT (JP) (KO) NZ PH PL RU SP TA TU UK UR US	15%	-89.589	.80
Survival	AR BR CL CN ES (GE) (IN) IT JP KO (NZ) (PH) PL RU SP TA TU (UK) UR (US)	35%	-105.590	.51
Health	AR BR CL CN (ES) GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	5%	-76.041	.57
Loadings				
Per.Stability	AR BR CL CN ES GE IN IT (JP) KO NZ PH PL RU SP TA TU UK UR US	5%	-72.603	.56
Survival	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK (UR) US	5%	-64.319	.93
Health	AR BR CL CN (ES) GE IN IT JP KO NZ (PH) (PL) RU SP TA TU UK (UR) US	20%	-81.345	.40
Excitement				
Intercepts				
Sexuality	AR BR CL (CN) (ES) GE (IN) (IT) JP KO NZ (PH) (PL) (RU) SP (TA) TU UK (UR) US	45%	-124.880	.32
Emotion	(AR) (BR) CL CN ES (GE) IN (IT) JP KO NZ (PH) PL RU (SP) TA TU UK (UR) US	35%	-114.055	.06
Pleasure	AR BR CL CN ES (GE) IN IT (JP) KO NZ PH (PL) RU SP TA TU UK UR US	15%	-97.129	.56
Loadings				
Sexuality	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-68.737	.82
Emotion	(AR) (BR) CL CN ES GE (IN) IT JP KO (NZ) PH PL RU SP TA TU UK UR (US)	25%	-93.208	.00
Pleasure	AR BR CL CN ES GE IN IT (JP) KO NZ PH PL RU SP (TA) TU UK UR US	10%	-93.105	.00
Promotion				
Intercepts				
Success	(AR) BR (CL) (CN) ES GE IN (IT) (JP) KO NZ (PH) PL (RU) (SP) (TA) TU UK (UR) (US)	55%	-156.520	.39
Power	(AR) BR (CL) (CN) ES GE (IN) IT (JP) (KO) (NZ) (PH) (PL) (RU) (SP) (TA) (TU) (UK) UR (US)	75%	-72.789	.94
Prestige	(AR) BR (CL) CN ES GE (IN) IT JP KO (NZ) PH (PL) (RU) (SP) TA TU (UK) UR US	40%	-94.255	.77
Loadings				
Success	AR BR CL (CN) (ES) GE IN IT JP KO NZ PH PL RU (SP) (TA) TU UK UR US	20%	-103.449	.27
Power	AR BR CL CN (ES) (GE) IN IT JP (KO) NZ PH PL RU SP TA TU UK UR US	15%	-94.643	.00
Prestige	AR BR CL CN ES GE IN IT JP KO NZ PH PL RU SP TA TU UK UR US	0%	-67.190	.51

AR = Argentina, BR = Brazil, CL = Chile, CN = China, ES = Estonia, GE = Germany, IN = Indonesia, IT = Italy, JP = Japan,

KO = Korea, NZ = New Zealand, PH = Philippines, PL = Poland, RU = Russia, SP = Spain, TA = Taiwan, TU = Turkey, UK = United Kingdom, UR =

Table S9.

Approximate Bayesian invariance and intra-class correlation

	Approximate Invariance B [95% C.I.]
Interactive	Prior (.01) = .099 [-20.12, 91.70]
Normative	Prior (.01) = .000 [428.25, 598.24]
	Prior (.01) = .217 [-25.07, 59.67] ^a
Suprapersonal	Prior (.01) = .285 [-39.70, 69.33]
Existence	Prior (.01) = .100 [-22.27, 94.25]
Excitement	Prior (.01) = .000 [197.54, 349.56]
	Prior (.03) = .110 [-22.45, 96.24]
Promotion	Prior (.01) = .004 [28.54, 154.18]
	Prior (.02) = .178 [-29.27, 84.74]

a = The item religiosity was removed from the analysis.