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A measure of group dissimilarity for psychological attributes

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Group functioning and performance in different contexts is related to the extent to which group members are complementary or supplementary in terms of psychological attributes. This paper describes a procedure for quantifying the degree of dissimilarity at group level. Unlike most existing techniques the one described here is normalized and is both location and scale invariant, thereby making it suitable for comparing dissimilarity on interval and ratio scales with different ranges and in groups of different sizes. Dissimilarity is measured in relative terms regardless of the exact place on the scale at which individuals are located. When a combination of several scales is not theoretically justified, the dissimilarity for each scale can be quantified. Additionally, dyadic and individual contributions to either the global or scale index can be obtained. The descriptive measures are complemented by statistical significance values in order to compare the results obtained with several discrete distributions of reference, both symmetrical and skewed, which can be specified using the expressions developed. The information that can be provided by the indices and the *p* values – both obtainable through an R package – is illustrated using data from an empirical study.

In the current study a measure of dissimilarity in psychological attributes among group[1] members is presented. Measuring the compatibility

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[1] Groups can be conceptualized in different terms according to their origin, aim, etc. (Sundstrom, McIntyre, Halfhill, & Richards, 2000). However given that the current study is focused on measuring it is not necessary to distinguish between different types of groups.

in terms of personality, social interaction, task demands, and interpersonal perception is relevant for understanding and improving team effectiveness. For instance, the attraction-selection-attrition framework (Halfhill, Nielsen, & Sundstrom, 2008) states that individuals in the same organization are expected to be similar to one another. Moreover, it has been shown that compatibility in profiles is related to group cohesion and group satisfaction. These group features can increase both when there is similarity in personality attributes (Morse & Caldwell, 1979) and in the case of dissimilarity (Dryer & Horowitz, 1997), corresponding, respectively, to the supplementary and complementary fit (Muchinsky & Monahan, 1987). According to circumplex models (Plutchik & Conte, 1997), the former type of fit is expected when people seek companionship (i.e., to get along), whereas the latter is more probable in interactions related to power (i.e., to get ahead).

Regarding the measurement of attributes at the group level, it is important to note that composites of individual measures have commonly been used (Humphreys, Morgeson, & Mannor, 2009). One of the alternatives is to study whether the individual measures are homogeneous and, thus, whether it is justified to aggregate them to obtain a quantification at the group level (e.g., Sánchez & Amo, 2004). Homogeneity is also important in order to know whether the mean of individual measures can be used to represent the group (Cohen, Doveh, & Eick, 2001). For measuring dissimilarity, standard deviation (SD) or variance can be used, two indices included in Chan's (1998) dispersion models and in Harrison and Klein's (2007) conceptualization of diversity as separation (i.e., dissimilarity[2] in quantitative scales measuring attitudes, opinions, and attributes). For these measures there is evidence that different patterns may lead to the same value, i.e., no distinction is made between minority belief, bimodal, and fragmented patterns (DeRue, Hollenbeck, Ilgen, & Feltz, 2010). Another measure of separation based on comparing discrepancies among all group members is the mean Euclidean distance (MED).

The need for the index presented in the current article as an alternative for SD and MED, arises from the fact that it is both location and scale invariant and thus it is applicable to variables measured in either interval or

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We will use the term "teams" in case the applications of the dissimilarity measures are more closely related to organizations.

[2] Throughout the article we use indistinctly the terms "dissimilarity" and "diversity", with the former term arising from Statistics, given the way the indices presented here are computed, whereas the latter term is based on conceptualizations such as the one made by Harrison and Klein (2007).

ratio scale. Another differential aspect in comparison to SD and MED is that in the index presented here absolute instead of squared differences between pairs of scores are computed. Whereas squaring gives greater weight to larger differences, despite the square root operation (Roberson, Sturman, & Simons, 2007), using absolute differences implies a linear increase in dissimilarity. We consider that applied researchers should have both kinds of models available so that they can choose the one appropriate for their field and specific aim, given that it is not *a priori* clear which of them is the optimal model when studying, for instance, the functional relationship between dissimilarity and team performance.

Regarding the dissimilarity measure presented here, it will be shown that it is possible to obtain a quantification for each attribute separately and also a global measure of dissimilarity for several attributes, provided that adding up all scales into a general composite has psychological meaning. Moreover, individual and dyadic contributions to global or scale-specific dissimilarity become useful in order to identify those group members or pairs of members mainly responsible for heterogeneity. All these quantifications are potentially relevant for understanding group processes and may help to improve group output predictions (Andrés, Salafranca, & Solanas, 2011).

Moreover, we will illustrate how a correlational analysis can be carried out between dyadic and individual contributions to diversity and dyadic and individual measures referring to reciprocity (Kenny, Kashy, & Cook, 2006) and concordance in interpersonal perceptions (Solanas, Leiva, & Manolov, 2010). Answering questions such as "Are those dyads or individuals that contribute more to dissimilarity in psychological attributes also responsible for the main discordance in interpersonal perceptions?" may lead to a better understanding of group processes.

Finally, and in order to enhance the applicability of the procedure, R functions were developed for both descriptive and inferential purposes. Inference is possible in comparison with discrete distributions of different shapes via mathematical expressions developed for specifying the mass probability function.

Analysis at the global level

The first aim of the present study consists in proposing an index for measuring the dissimilarity among group members' attributes when n individuals have been measured on p psychological attributes. According to Harrison and Sin (2006) such a composite of individual measures would be reasonable in the case of reflective indicators, that is, operationalizations

correlated with each other, which are assumed to be part of the same underlying construct that is assumed to have a theoretical justification. By contrast, formative indicators imply that a composite measure would be a simple sum of uncorrelated scales and, therefore, their combination is not meaningful (Harrison & Klein, 2007). For the latter type of indicators, the scale index presented later can be applied to each scale separately.

Suppose a matrix **X** in which the *n* rows and *p* columns correspond respectively to group members and psychological attributes (e.g., several intelligence characteristics):

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix}.$$

Now, consider the first column vector of the matrix **X**, that is, $(x_{11}, x_{21},\ldots, x_{n1})'$, which includes the scores of all individuals for the psychological attribute k = 1 (e.g., verbal reasoning). An index for quantifying the degree of dissimilarity among group members' scores on a single attribute may be founded on absolute differences and, just like association coefficients, it is not sensitive to changes in location and scale parameters (i.e., for changes in mean and variance values). A similar quantification has been described in Stuart and Ord (1994) as the coefficient of mean difference, attributed to Friedrich Helmert, and it has been applied to demographic variables. Suppose that the following index is computed for the scale *k*:

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_{ik} - x_{jk}\right| = 2\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left|x_{ik} - x_{jk}\right| \geq 0.$$

Its minimum value obviously equals zero, that is, all individuals score the same value. It should be noted that the minimum value will be obtained irrespectively of where the individuals are located along the psychological dimension. As regards the maximum value, this occurs when team members are divided into two balanced sets at the extremes of the psychological dimension. The maximum value for the previously presented index is

$\delta(x_{max(k)}-x_{min(k)})$, where δ equals $n^2/2$ if n is even and $(n^2 - 1)/2$ if n is odd, and where $x_{min(k)}$ and $x_{max(k)}$ denote, respectively, the minimum and maximum values for the scale k. The maximum value corresponds to the empirical mass of probability for which half the individuals score $x_{min(k)}$ and the other half $x_{max(k)}$ if n is even, this being consistent with the definition of a separation measure. Only a minor change is required to obtain the maximum value if n is odd, that is, $(n - 1)/2$ individuals score, for example, the minimum value of the scale while the remaining $(n + 1)/2$ individuals take values equal to the scale's maximum. Therefore, the following index is bounded as shown:

$$0 \leq \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\left|x_{ik} - x_{jk}\right|}{\delta r_k} \leq 1,$$

where $r_k = x_{max(k)} - x_{min(k)}$, that is, the difference between the maximum and minimum values for the scale k, which is a novelty with respect to the coefficient of mean difference. Note that in order to normalize the index it is necessary to know the bounds of the measurement scale, as is usually the case for instruments measuring psychological attributes. To obtain a global index for p psychological scales, the following expression can be used:

$$\lambda = \sum_{k=1}^{p}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\left|x_{ik} - x_{jk}\right|}{p\delta r_k} = 2\left(p\delta\right)^{-1}\sum_{k=1}^{p}\left(r_k^{-1}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left|x_{ik} - x_{jk}\right|\right), 0 \leq \lambda \leq 1.$$

The index λ is equal to *1* if the sum of the absolute differences reaches its maximum value, given the range of the p scales. If the index equals zero, this means that all individuals have scored the same value for each of the psychological scales, although this value can be different for each scale as long as the individuals coincide.

Index strengths and limitations

These abovementioned bounds show that the global index is normalized and allows comparisons across scales with different metrics, unlike SD and MED (Harrison & Klein, 2007). The λ index satisfies location invariance, such that dissimilarity values remain unchanged if a positive constant is added to everyone's score. The index is therefore applicable to interval scale variables. Moreover, it is applicable to ratio

scale variables as it also has the property of scale invariance, as is shown in the following equality:

$$\lambda = 2(p\delta)^{-1}\sum_{k=1}^{p}\left((m_k r_k)^{-1}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left|m_k x_{ik} - m_k x_{jk}\right|\right) = 2(p\delta)^{-1}\sum_{k=1}^{p}\left(r_k^{-1}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left|x_{ik} - x_{jk}\right|\right),$$

where m_k denotes a nonnegative scale factor for scale k. As λ remains unchanged if a change of units is introduced, the relative contributions to dissimilarity do not depend on the minimum and maximum values of psychological scales. Another strength of the index is the possibility to obtain dyadic and individual contributions. Only for MED have there been developments for computing an individual's similarity to the remaining group members (O'Reilly, Caldwell, & Barnett, 1989).

Among the limitations of the global index it should be reiterated that it is only applicable in the case of reflective indicators. In that sense, as the global index can be expressed as the average of the scale indices it would not be useful when there are dissimilarities for some but not all of the scales, as this mean value would misrepresent all of them. Related to this limitation, it has to be mentioned that both the global index and the scale index presented below are quantifications for the whole group. However, it would be more informative for applied researchers if they used the measurements developed in the faultlines framework (Shaw, 2004; Trezzini, 2008) to detect possible subgroups on the basis of categorical data and, afterwards, quantify dissimilarity in quantitative attributes with the indices presented here. Otherwise, a group dissimilarity quantification may be a misrepresentation of these subgroups. Finally, the fact that the index is normalized entails a limitation (i.e., it does not show at which point of the scale similarity takes place when present) and a requirement (i.e., the bounds of the scale ought to be known).

Scale analysis

When the global index has no psychological meaning (i.e., for formative indicators), researchers ought to quantify dissimilarity for each scale of interest. Thus, the index λ should be decomposed into specific scale heterogeneities, denoted by λ_k, as follows:

$$\lambda = p^{-1}\sum_{k=1}^{p}\left(2(\delta r_k)^{-1}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\left|x_{ik} - x_{jk}\right|\right) = p^{-1}\sum_{k=1}^{p}\lambda_k,\ 0 \le \lambda_k \le 1.$$

If researchers are interested in obtaining a normalized measurement (i.e., ranging from *0* to *1*) of the contribution of each scale to the global dissimilarity values, this can be obtained by $\xi_k = \lambda_k/\lambda p$ for $\lambda \neq 0$. For instance, suppose that two scales reach an identical and maximal dissimilarity, and that the other scales show complete similarity, $\lambda_k = 0$. Therefore, the λ_k values of the former two scales will be equal to 1, and thus $\xi_k = .5$.

Dyadic level of analysis

The dyadic level of analysis is required to detect the most significant pairs of individuals responsible for the dissimilarity. The global dyadic contribution can be obtained as follows:

$$\lambda = \sum_{i=1}^{n}\sum_{j=1}^{n}\left((p\delta)^{-1}\sum_{k=1}^{p}\frac{|x_{ik}-x_{jk}|}{r_k}\right) = \sum_{i=1}^{n}\sum_{j=i+1}^{n}\left((p\delta)^{-1}\sum_{k=1}^{p}2r_k^{-1}|x_{ik}-x_{jk}|\right) = \sum_{i=1}^{n}\sum_{j=i+1}^{n}\beta_{ij},\ \beta_{ij}=\beta_{ji}.$$

Global dyad contributions can range between *0* and $2/\delta$. Note that the maximum value for dyadic contributions only depends on group size. Taking into account the maximum value, the index can be normalized by $\omega_{ij} = \delta\beta_{ij} / 2$. If the dyadic contributions are to be obtained with regard to each scale, it is only necessary to set *p* equal to 1 in the expression presented above and carry out a separate analysis for the scale *k* of interest.

Individual level of analysis

The main aim of the individual level of analysis consists in identifying those individuals who contribute more to the global dissimilarity measurement. The index can be expressed in such a way that individuals' contributions can be obtained as follows:

$$\lambda = \sum_{i=1}^{n}\left((p\delta)^{-1}\sum_{k=1}^{p}r_k^{-1}\sum_{j=1}^{n}|x_{ik}-x_{jk}|\right) = \sum_{i=1}^{n}\alpha_i.$$

Individuals' contributions can range between *0* and $(n-1)/\delta$. Note that this only depends on the number of individuals, and is independent of the range of the scales. The upper bound quickly approaches zero as the number of individuals tends to infinity. The index can be normalized by $\tau_i =$

$\delta\alpha_i$ /(n − 1) for n ≥ 2. In order to obtain the individual contributions to dissimilarity for each scale, it is only necessary to set p equal to 1 in the expression presented above and compute the specific λ_k for the scale k.

Statistical testing

Assessing statistical significance requires specifying a meaningful null distribution against which to contrast the data at hand. This appropriate null distribution will depend on the research aim, the type of instrument used, and the attributes of the participants. For instance, a uniform distribution can be used, implying that each score between the minimum and maximum of the scale is equally probable, as a way of representing randomness. In that case two directional null hypotheses can be tested. Regarding the lower tail of the sampling distribution of λ or λ_k, if the obtained value is, for example, one of the lower 5% values, then there is evidence that the group is more similar than expected by chance. Similar evidence regarding the upper tail is suggestive of group dissimilarity beyond random fluctuation. The dyadic and individual contributions to dissimilarity can also be compared to random contributions, and their statistical significance can be estimated as the proportion of pseudostatistic values that are as large as or larger than (or as small as or smaller than) the value computed for the actual data.

Apart from using the uniform distribution, the researcher can specify the mass probability function on the basis of previous studies in the field of interest. For example, there is some evidence that personality traits like neuroticism and extraversion can be normally distributed (Norris, Larsen, & Cacioppo, 2007). In contrast, when applying an instrument like the Beck Depression Inventory (Beck, Steer, & Brown, 1996) the distribution in nonclinical samples has been found to be positively skewed (Long, 2005). Complementarily, it can logically be expected that for the clinical population more individuals would score with higher values. Finally, asymmetric distributions have been found (Micceri, 1989) to be common for scores on psychological attributes such as anxiety, sociability, and locus of control, as well as certain clinical scales.

Several expressions have been derived in order to obtain mass probability functions for discrete skewed and symmetric distributions (see Appendix for the mathematical details and Figure 1 for an example). The potential usefulness of skewed distributions was commented above, whereas a symmetric discrete triangular or inverted-U-shaped model may be useful for modeling approximately normal distributions when the variables of interest are not continuous. The U-shaped distribution may not

have direct applicability to psychological attributes, but as shown in the Appendix it is easily obtained from the inverted-U distribution. The expressions were developed in order to avoid the need both to transform continuous distributions into discrete ones (e.g., Timmerman, & Lorenzo-Seva, 2011) and to specify the mass probabilities individually (e.g., LeBreton & Senter, 2008), which becomes time consuming for psychological scales with many possible values.

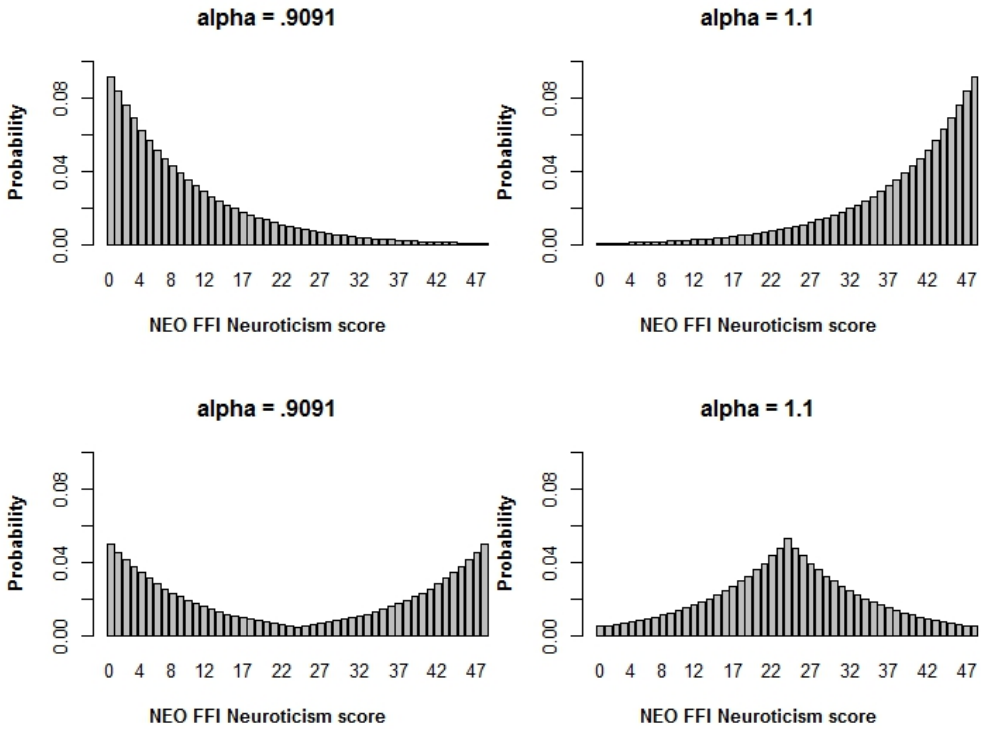

Figure 1. Four different mass probability functions of neuroticism according to different combinations of α and symmetry values: a) U-shaped distribution (α = .9091 and symmetric), b) triangular distribution (α = 1.1 and symmetric), c) positively skewed distribution (α = .9091 and asymmetric), and d) negatively skewed distribution (α = 1.1 and asymmetric).

Monte Carlo sampling can be used to estimate the moments of the null distribution and the probability that the scores in the group belong to the population described by the null model. Monte Carlo sampling entails drawing random samples (i.e., matrices with the same dimension as the original one) from the null distribution chosen, and it has already been used in previous research (Cohen et al., 2001) for approximating statistical significance. The indices presented in this paper (namely, λ, λ_k, ξ_k, β_{ij}, ω_{ij}, α_i, and τ_i) have been incorporated into an R package called *dissimilarity* (available from the authors upon request), which is intended to enhance the application of the procedure. This package also enables statistical decisions regarding dissimilarity to be made on the basis of the reference distributions modeled by the expression in the Appendix. Furthermore, given that the expressions do not cover all possible distributional shapes, researchers may, via the *dissimilarity* package, define any mass probability they desire.

An illustration with social psychology data

The use of the indices presented here is illustrated with data from a study involving 16 four-member groups which had to solve a set of social dilemmas, with the number of agreements reached being used as an indicator of group performance (for more details, see Andrés et al., 2011). The NEO-FFI (Costa & McCrae, 2002) was administered to collect personality data. These data were used to calculate the composites using the mean, SD, and MED, as well as λ_k, in order to describe group dissimilarity in each of the traits separately, given that each scale can be conceptualized as a formative indicator of an independent latent variable. Table 1 shows the personality scores for one of the groups and the descriptive results for mean, SD, and MED.

For this group, statistical significance was estimated by means of a Monte Carlo sampling procedure included in the *dissimilarity.test* function of the *dissimilarity* R package. For illustrative purposes a uniform null distribution was assumed, drawing 99,999 random samples from it in order to estimate the sampling distributions of dissimilarity indices. Results for λ_k measures (Table 2) show that Extraversion is the only personality trait for which the similarity is greater than expected by chance (λ_E = .172 with a lower tail p = .031).

As regards dyadic contributions to dissimilarity on the Extraversion scale (chosen here due to the fact that statistically significant similarities were obtained for it), ω_{ij} values do not reveal any dyad whose contribution to dissimilarity is greater than expected by chance, whereas the dyad 1-2 is significantly similar at the .10 level (see Table 3). Finally, none of the

individual contributions to dissimilarity were found to be significant; in fact, and as shown in Table 4, their contribution values are significantly lower than would be expected by chance, except for individual 4.

Table 1. Personality trait scores for each of the four participants (P1 to P4) and indices values for the five personality traits.

	N	E	O	A	C
P1	15	24	33	41	40
P2	3	22	25	41	31
P3	12	27	22	37	35
P4	32	32	32	22	28
Mean	15.50	26.25	28	35.25	33.50
SD	10.5	3.77	4.64	7.82	4.50
MED	14.37	5.20	6.51	10.70	6.23

SD – standard deviation; MED – Mean Euclidean distance. N – Neuroticism; E – Extraversion; O – Openness to experience; A – Agreeableness; C – Conscientiousness.

In order to study the relationship between group-level measures of dissimilarity and team performance separate regression analyses were then conducted with the standard deviation in Neuroticism accounting for 26.9% of the outcome variability among the sixteen groups and the dissimilarity measure λ_k for the same trait accounting for 33.9%. In substantive terms, greater diversity in Neuroticism was associated with fewer agreements are reached in the groups.

The following example serves to illustrate how the study of group processes can benefit from the joint analysis of psychological attributes and interpersonal perceptions at different levels (i.e., dyadic and individual). For the same group shown in Table 1, interpersonal perception scores were obtained for the item "Her/his dialogue was useful for solving the task" (Table 5). Using these data, dyadic and individual contributions to reciprocity in interpersonal perception were computed (Table 6) by a recently proposed procedure (Solanas et al., 2010). The correlation between measures at the same level is explored to determine whether differences in

traits and discrepancies in interpersonal perceptions are associated. For the data presented in Tables 3 and 6, dyadic contributions show a correlation value equal to −.041, indicating lack of relationship between the dyadic contributions to dissimilarity in Extraversion and those to disagreement in interpersonal perception regarding the usefulness of a given individual's participation in solving the task. A similar analysis at the individual level led to obtaining a correlation value of −.919 indicating that the individuals most dissimilar in Extraversion are those who agree more in their interpersonal perceptions regarding the question about solving the task.

Table 2. Dissimilarity for each scale (λ_k). A Monte Carlo sampling with 99,999 samples was carried out in order to estimate the sampling distributions of the index values and their statistical significance under a uniform null distribution.

	λ_N	λ_E	λ_O	λ_A	λ_C
Index value	.469	.172	.208	.318	.208
Upper tail *p* value	.606	.973	.954	.851	.954
Lower tail *p* value	.402	.031	.051	.158	.051
Mean	.511	.511	.511	.511	.511
Variance	.031	.031	.031	.031	.031
Minimum	.016	.016	.016	.016	.016
25% percentile	.385	.385	.385	.385	.385
50% percentile	.521	.521	.521	.521	.521
75% percentile	.641	.641	.641	.641	.641
Maximum	.990	.990	.990	.990	.990

DISCUSSION

In the present study an index for measuring group dissimilarity as separation (following Harrison and Klein's [2007] typology) has been proposed as a normalized version (i.e., ranging between 0 and 1) of the coefficient of mean difference, a normalization which is possible when the

bounds of the scales are known. Apart from quantifying dissimilarity in psychological attributes the index may also measure lack of consensus, for instance, when group members are rating a group outcome such as team efficacy (Bayazit & Mannix, 2003).

Table 3. Results for normalized dyadic contributions to dissimilarity (ω_{ij}) on the Extraversion scale. Index values are shown above the main diagonal of the table, while values below the diagonal represent lower tail *p* values, given that the upper tail *p* values were greater than .05.

	P1	P2	P3	P4
P1	-	.042	.062	.167
P2	.098	-	.104	.208
P3	.139	.213	-	.104
P4	.320	.384	.213	-

Table 4. Normalized individual contributions (τ_i) to dissimilarity on the Extraversion scale. Statistical significance was estimated by means of a Monte Carlo sampling under the uniform null distribution.

	τ_i statistic value	Upper tail *p* value	Lower tail *p* value
P1	.090	.980	.024
P2	.118	.958	.049
P3	.090	980	.024
P4	.160	.904	.108

Table 5. Interpersonal perception matrix for the example about the item "Her/his dialogue was useful for solving the task", for the same group whose personality dissimilarity measures are presented in Table 1.

	P1	P2	P3	P4
P1	-	4	2	2
P2	2	-	2	2
P3	6	6	-	5
P4	6	4	4	-

Table 6. Dyadic (upper-triangular matrix) and individual contributions (rightmost column) to the lack of reciprocity in interpersonal perception for the item "Her/his dialogue was useful for solving the task".

	P1	P2	P3	P4	Individual contribution
P1	-	.027	.107	.107	.120
P2		-	.107	.027	.080
P3			-	.007	.110
P4				-	.007

The fact that the index is normalized enhances both interpretation (the values obtained can be compared to the known bounds of the index) and comparisons between different scales and different-sized groups. It should be noted that the normalized indices can yield the maximum value for both even and odd groups. However, in the case of the latter it is not possible to have a bipolar distribution at both extremes of the scale. Thus, in conceptual terms what is achieved is not the maximum separation but rather the maximum *possible* separation given the group size.

The λ index is only applicable to attributes for which reflective indicators can be used (e.g., intelligence), whereas the λ_k (expressed at the same level as SD and MED) is useful for formative indicators such as scales measuring specific orthogonal personality traits. Further quantifications were provided in terms of the contribution of each dyad and each individual to λ or λ_k. Therefore, researchers can use these quantifications to obtain additional information to that provided by extant indices. Note that dyadic and individual indices do not quantify diversity as separation, but only the contributions of dyads and participants to global or scale diversity.

Both the global and the scale indices are based on computing discrepancies between individual discrete measurements, regardless of the number of items that are included in the scale. In other words, the items can be measured on a Likert (i.e., ordinal) scale, but what is used for λ and λ_k are the sums of the items, which is considered in most research as an interval scale although this kind of scales approximate only roughly an interval scale as conceptualized in fundamental measurement theory (Townsend & Ashby, 1984). In such cases, λ and λ_k would be applicable, as they are invariant to changes in location. Moreover, they can be used for ratio scale variables, as λ and λ_k are also scale invariant. In general, separation indices are location invariant (Harrison & Klein, 2007), which makes them appropriate only for interval scales.

As an additional contribution, mention should be made of the expressions developed for simulating several discrete distributions, given that they allow statistical testing with several reference distributions, beyond uniform or normal distributions, which are not always appropriate (Bliese, Chan, & Ployhart, 2007) when making statistical decisions or when studying the statistical properties of different indices via simulation. These expressions also avoid the need to specify a set of arbitrary probability values according to the number of possible values in the scale. Finally, an R package for making the necessary computations was developed and is available from the authors upon request.

There is empirical evidence suggesting that dissimilarity in personality can be useful for predicting team output. For instance, dissimilarity in neuroticism among group members was found to be related to the number of agreements in a dilemmas task in an artificial setting (Andrés et al., 2011), and it has also been shown that indices based on dyads improve predictions of group performance in a natural educational context (Sierra, Andrés, Solanas, & Leiva, 2010). These results suggest that indices founded on dyadic discrepancies and dyadic relationships may be useful for obtaining composites at the group level. However, further field

tests are needed to gather evidence on the utility of these indices for predicting group performance in, for instance, organizational and educational settings. Specifically, it would be necessary to explore in more detail the association between dissimilarity in psychological attributes and interpersonal perception at different levels. In this regard, it should be noted that the present study only included an illustration of the possible correlation between dissimilarity and interpersonal perception measures for dyadic and individual levels. More research should therefore be carried out to test the usefulness of this analytical alternative.

RESUMEN

Una medida de la disimilitud en grupos para atributos psicológicos. El funcionamiento y el rendimiento de los grupos en contextos diferentes están relacionados con el grado en que las características de los miembros son complementarias o suplementarias. El presente artículo describe un procedimiento para cuantificar el grado de disimilitud a nivel de grupo. A diferencia de la mayoría de técnicas existentes, el procedimiento que aquí se describe está normalizado y es invariante a los cambios de localización y escala. Por lo tanto, es posible comparar la disimilitud en escalas con diferente métrica y en grupos de distinto tamaño. La disimilitud está medida en términos relativos, independientemente de la posición que ocupan los individuos en la dimensión que mide la escala. Cuando no existe una justificación teórica para combinar las diversas propiedades medidas, se puede cuantificar la disimilitud para cada escala por separado. También es posible obtener las contribuciones diádicas e individuales respecto a la diversidad global y la asignada a cada escala. Las medidas descriptivas pueden ser complementadas con la significación estadística para, así, comparar los resultados obtenidos con distribuciones discretas de referencia, ya sean simétricas o asimétricas. Se ha elaborado un paquete en R que permite obtener los índices descriptivos y los valores *p*, además de contener las expresiones desarrolladas para simular una amplia variedad de distribuciones discretas de probabilidad.

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APPENDIX

A result for geometrical series is used in what follows. Specifically,

$$ab^0 + ab^1 + ab^2 + ab^3 + \cdots + ab^{n-1} = \sum_{i=0}^{n-1} ab^i = \frac{a(1-b^n)}{1-b}, b \neq 1$$

Mass probability functions for a discrete and skew-distributed random variable for which $p_{i+1} = \alpha p_i$ can be obtained as follows:

$$\sum_{i=1}^{k} p_i = 1, k \geq 2$$

$$p_{i+1} = \alpha p_i, 1 \leq i \leq k-1; \alpha > 0 \text{ and } \alpha \neq 1$$

$$\sum_{i=1}^{k} p_i = \sum_{i=1}^{k} p_1 \alpha^{i-1} = \sum_{i=0}^{k-1} p_1 \alpha^i = \frac{p_1\left(1-\alpha^k\right)}{1-\alpha} = 1$$

$$p_1 = \frac{1-\alpha}{1-\alpha^k}$$

$$p_{1+j} = \frac{\alpha^j\left(1-\alpha\right)}{1-\alpha^k}, 0 \leq j \leq k-1$$

where p_i and k respectively denote the mass probability value for the ith score and the total number of values of the random variable. Note that if we take $\alpha = c$ and $\alpha = 1/c$, with c being a positive number greater than 1, we will obtain mirror distributions. Additionally, note that α is a parameter related to the skewness of the distribution. For values of α greater than 1, the distribution becomes more negatively skewed as α tends to infinity. On the other hand, if α is less than 1, the distribution is more positively skewed as α approximates zero.

If $\alpha = 1$,

$$\sum_{i=1}^{k} p_i = 1, k \geq 2$$
$$p_{i+1} = p_i, 1 \leq i \leq k-1$$
$$\sum_{i=1}^{k} p_i = \sum_{i=1}^{k} p_1 1^{i-1} = p_1 \sum_{i=1}^{k} 1 = kp_1 = 1$$
$$p_1 = \frac{1}{k}$$
$$p_{1+j} = \frac{1}{k}, 0 \leq j \leq k-1$$

we obtain the uniform discrete distribution.

In the case of symmetric patterns for k even,

$$\sum_{i=1}^{k} p_i = 1, k \geq 2 \text{ and } \operatorname{int}(k/2) = k/2$$
$$p_{i+1} = \alpha p_i, 1 \leq i \leq k/2-1; \alpha > 0 \text{ and } \alpha \neq 1$$
$$p_{k-i+1} = p_i, 1 \leq i \leq k/2$$
$$2\sum_{i=1}^{k/2} p_i = 1$$
$$2\sum_{i=1}^{k/2} p_1 \alpha^{i-1} = 2\sum_{i=0}^{k/2-1} p_1 \alpha^i = \frac{2p_1\left(1-\alpha^{k/2}\right)}{1-\alpha} = 1$$
$$p_1 = \frac{1-\alpha}{2\left(1-\alpha^{k/2}\right)}$$
$$p_{1+j} = \frac{\alpha^j(1-\alpha)}{2\left(1-\alpha^{k/2}\right)}, 0 \leq j \leq k/2-1$$

If $\alpha < 1$, the mass probability function is U-shaped. On the other hand, it follows a triangular distribution if $\alpha > 1$. Note that if we take $\alpha = c$ and $\alpha = 1/c$, with c being a positive number greater than 1, we will obtain inverse distributions. It is also possible to obtain the uniform discrete distribution for $\alpha = 1$,

$$2\sum_{i=1}^{k/2} p_1 1^{i-1} = 2p_1 \sum_{i=0}^{k/2} 1 = 2p_1 \frac{k}{2} = p_1 k = 1$$

$$p_1 = \frac{1}{k}$$

In the case of symmetric distributions for k odd,

$$\sum_{i=1}^{k} p_i = 1, k \geq 2 \text{ and } \operatorname{int}(k/2) = (k-1)/2$$

$$p_{i+1} = \alpha p_i, 1 \leq i \leq (k+1)/2; \alpha > 0 \text{ and } \alpha \neq 1$$

$$p_{k-i+1} = p_i, 1 \leq i \leq (k-1)/2$$

$$2\sum_{i=1}^{(k-1)/2} p_i + p_{(k+1)/2} = 1$$

$$2\sum_{i=1}^{(k-1)/2} p_1 \alpha^{i-1} + p_1 \alpha^{(k-1)/2} = 2\sum_{i=0}^{(k-1)/2-1} p_1 \alpha^{i} + p_1 \alpha^{(k-1)/2} = \frac{2p_1\left(1-\alpha^{(k-1)/2}\right)}{1-\alpha} + p_1 \alpha^{(k-1)/2}$$

$$= p_1 \frac{2-\alpha^{(k-1)/2}(1+\alpha)}{1-\alpha} = 1$$

$$p_1 = \frac{1-\alpha}{2-\alpha^{(k-1)/2}(1+\alpha)}$$

$$p_{1+j} = \frac{\alpha^j (1-\alpha)}{2-\alpha^{(k-1)/2}(1+\alpha)}, 0 \leq j \leq (k-1)/2$$

If $\alpha < 1$, the mass probability function resembles an inversion of the triangular. On the other hand, it follows a triangular distribution if $\alpha > 1$. Note that if we take $\alpha = c$ and $\alpha = 1/c$, with c being a positive number greater than 1, we will obtain inverse distributions. It is also possible to obtain the uniform discrete distribution for $\alpha = 1$,

$$2\sum_{i=1}^{(k-1)/2} p_1 1^{i-1} + p_1 1^{(k-1)/2} = p_1\left(k-1\right) + p_1 = 1$$

$$p_1 = \frac{1}{k}$$

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