Factorial Invariance in a Repeated Measures Design: An Application to the Study of Person-Organization Fit

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An important methodological concern of any research based on a person-environment (P-E) fit approach is the operationalization of the fit, which imposes some measurement requirements that are rarely empirically tested with statistical methods. Among them, the assessment of the P and E components along commensurate dimensions is possibly the most cited one. This paper proposes to test the equivalence across the P and E measures by analyzing the measurement invariance of a multi-group confirmatory factor analysis model. From a methodological point of view, the distinct aspect of this approach within the context of P-E fit research is that measurement invariance is assessed in a repeated measures design. An example illustrating the procedure in a person-organization (P-O) fit dataset is provided. Measurement invariance was tested at five different hierarchical levels: (1) configural, (2) first-order factor loadings, (3) second-order factor loadings, (4) residual variances of observed variables, and (5) disturbances of first-order factors. The results supported the measurement invariance across the P and O measures at the third level. The implications of these findings for P-E fit studies are discussed.

Keywords: measurement invariance, confirmatory factor analysis, person-organization fit, commensurability analysis.

Un importante aspecto metodológico de las investigaciones basadas en el enfoque del ajuste persona-ambiente (P-A) se refiere a la operacionalización del ajuste P-A, que impone una serie de supuestos que raramente se evalúan utilizando métodos estadísticos. Entre ellos, la evaluación de los componentes P y A en dimensiones conmensurables o equivalentes, es posiblemente uno de los más citados. En este artículo se propone que la equivalencia entre las medidas de P y A puede evaluarse mediante el análisis de la invarianza factorial de un modelo de análisis factorial confirmatorio multi-grupo. Desde un punto de vista metodológico, la aportación del enfoque propuesto a la investigación del ajuste P-A es que la invarianza en la medida se evalúa en un diseño de medidas repetidas. El artículo también presenta un ejemplo que ilustra el procedimiento propuesto con datos para una medida de ajuste persona-organización (P-O). La invarianza en la medida se evalúa en cinco niveles jerárquicos: (1) configural, (2) saturaciones de primer orden, (3) saturaciones de segundo orden, (4) varianzas error de las variables observadas y (5) errores típicos asociados a los factores de primer orden. Los resultados dan apoyo a la invarianza factorial en las medidas de P y O en el tercer nivel. Por último, se discuten las implicaciones del enfoque propuesto para los estudios de ajuste P-A.

Palabras clave: invarianza en la medida, análisis factorial confirmatorio, ajuste persona-organización, análisis de la conmensurabilidad.

The P-E fit framework constitutes an approach aimed to explain the behavior as a function of the match between person characteristics (P) and environmental characteristics (E). This approach emerges from interactional psychology (Pervin & Lewis, 1978) and has been adopted for the development of traditional theories, for instance, Holland's (1985) RIASEC theory and the theory of work adjustment by Dawis and Lofquist (1984).

In the words of Schneider (2001, p. 141): "Of all of the issues in psychology that have fascinated scholars and practitioners alike, none has been more pervasive than the one concerning the fit of person and environment". Unfortunately, despite the widespread acceptance and success of P-E fit models, there remain significant methodological challenges to overcome. The crux of P-E fit models is the ability of P-E fit to make meaningful predictions of an outcome. As shown in the recent meta-analysis with different types of P-E fit conducted by Kristof-Brown, Zimmerman, and Johnson (2005), the amount of variance accounted for by P-E fit and outcome remains modest. Tinsley (2000) noted that this may be the result of a failure to meet the measurement assumptions of P-E fit models. One of the most discussed ones is the assessment of the P and E components along commensurate or theoretically similar dimensions (Caplan, 1987; Edwards, 1994). Without this standard it is impossible to compare directly P and E values with an outcome either if the P-E fit is operationalized as a single index (e.g., a difference score like $d = E - P$ or $d^2 = (E - P)^2$) or if the procedure of polynomial regression proposed by Edwards (1991, 1994) is used to assess the relation between P, E, and the outcome in three-dimensional surface plots.

Rounds, Dawis, and Lofquist (1987) defined three aspects of commensurate measurement that, in practice, are rarely empirically demonstrated with a rigorous evaluation approach. The first, commensurate concepts, consists of the description of the P and E characteristics belonging to parallel conceptual domains. The method commonly applied to warrant this issue is to use the same items in both measures. The second, commensurate units, consists of the use of an equivalent interval of measurement continuum to answer the P and E measures. That is, it is assumed that one unit increase or decrease on the P measure is equal to a respective one unit increase or decrease on the E measure. The use of similar response formats in both measures is considered enough to warrant commensurate units. The third, commensurate structures, consists of the parallel and equivalent organization of both person and environmental characteristics. This issue has been addressed by using exploratory factor analysis, considering that P and E are commensurate structures if both factorial solutions have similar factors, regardless of the difference in the number of factors and explained variance, and of goodness-of-fit statistics.

The present paper proposes the use of a specific statistical procedure to assess commensurate measurement in P-E fit studies. We suggest that confirmatory factor analysis (CFA) is a useful framework for investigating two of the aspects of commensurability analysis defined by Rounds et al. (1987): the commensurability of units and the commensurability of structure. In particular, the measurements of P and E will be commensurate depending on the degree of invariance achieved by a multi-group CFA model.

We present an example of the assessment of commensurability in a P-E fit measure using a second-order CFA model. Because P and E are multifaceted constructs, the factor analysis model turns out to be a second-order factor analysis, where the second-order P and E factors are defined upon a first-order factorial structure that should be equivalent for P and E. Moreover, given that we are testing the equivalence of the P and E factorial structures when they are measured in the same group of subjects, this example involves a repeated measures design. As pointed out by a reviewer, the use of repeated measures in P-E fit research is rare. Typically, the environment is measured using a sample that is totally independent of the sample that provides information about personal characteristics. The CFA framework proposed in this paper can accommodate both kinds of research designs: independent groups and repeated measurements. We have chosen a repeated measurement design in order to estimate the correlation coefficient between the measures of P and E. However, the use of a repeated measures design in P-E fit research provides a weaker test of commensurability than a design with two independent samples. This is so because the factorial structures for P and E depend on the personal characteristics of the same individuals.

Traditionally, measurement invariance consists of testing the equivalence of measured constructs in two or more independent groups to ensure that the same constructs are being assessed in each group. However, in P-E fit studies there are two sets of items that are answered separately (one for P and another for E), each of them with the same number of items and response formats; and the aim is to test the equivalence of the measured constructs in a single group to ensure that the same constructs are assessed in the P and E measures, and therefore that either a P-E fit discrepancy index for each individual can be computed or that polynomial regression can be used. That is, we test the equivalence of the P and E factorial structures when they are measured in the same group of subjects. Thus, measurement invariance is assessed in a repeated measures design. Moreover, it is tested with the first and second-order factorial structures for P and E.

There are two classes of methods for testing measurement invariance (Reise, Widaman, & Pugh, 1993).

One approach is based on CFA and the other is based on item response theory (IRT). CFA models are based on a linear relationship between the latent variable and its indicators. They account for the covariance between test items. On the other hand, IRT models are based on a nonlinear function that accounts for the relation between the subject's level on a latent variable and the probability of the item responses. As Vandenberg and Lance (2000) pointed out, the CFA approach is able to handle multiple latent variables and multiple populations simultaneously more easily than IRT. However, the IRT approach is better suited to evaluating the relation between the latent variable and the item responses (Raju, Laffittee, & Byrne, 2002). Given that the P and E measures are multidimensional in nature, in this study we use the CFA method to examine the equivalence of the P and E measures.

The CFA model (Jöreskog & Sörbom, 1981) can be given as:

$$\mathbf{y} = \mathbf{\Lambda}_y \mathbf{\eta} + \mathbf{\varepsilon}, \qquad (1)$$

where $\mathbf{y}$ is a vector of p observed variables, $\mathbf{\eta}$ is a vector of q factors such that $q < p$, $\mathbf{\Lambda}_y$ is a $p \times q$ matrix of factor loadings, and $\mathbf{\varepsilon}$ is a vector of p measurement error variables. It is assumed that $E(\mathbf{y}) = E(\mathbf{\eta}) = E(\mathbf{\varepsilon}) = \mathbf{0}$ and that $E(\mathbf{\eta}\mathbf{\varepsilon}) = \mathbf{0}$. The random vector $\mathbf{y}$ contains the responses for P and E ($\mathbf{y}_P$ and $\mathbf{y}_E$). Then, expanding Equation 1 yields:

$$\begin{bmatrix} \mathbf{y}_P \\ \mathbf{y}_E \end{bmatrix} = \begin{bmatrix} \mathbf{\Lambda}_{y_P} & \mathbf{0} \\ \mathbf{0} & \mathbf{\Lambda}_{y_E} \end{bmatrix} \begin{bmatrix} \mathbf{\eta}_P \\ \mathbf{\eta}_E \end{bmatrix} + \begin{bmatrix} \mathbf{\varepsilon}_P \\ \mathbf{\varepsilon}_E \end{bmatrix}, \qquad (2)$$

where $\mathbf{\eta}_P$ and $\mathbf{\eta}_E$ are the first-order factors measured by the P and E items, and $\mathbf{\varepsilon}_P$ and $\mathbf{\varepsilon}_E$ are the corresponding measurement error variables.

The covariance matrix for $\mathbf{y}$ denoted by $\mathbf{\Sigma}_{yy}$ is:

$$\mathbf{\Sigma}_{yy} = \mathbf{\Lambda}_y \mathbf{\Sigma}_{\eta\eta} \mathbf{\Lambda}_y ' + \mathbf{\Sigma}_{\varepsilon\varepsilon}, \qquad (3)$$

where $\mathbf{\Sigma}_{\eta\eta}$ is the $q \times q$ covariance matrix of $\mathbf{\eta}$ and $\mathbf{\Sigma}_{\varepsilon\varepsilon}$ the $p \times p$ covariance matrix of $\mathbf{\varepsilon}$. For convenience, it is usually assumed that $\mathbf{\Sigma}_{\eta\eta} = \mathbf{I}$ and that $\mathbf{\Sigma}_{\varepsilon\varepsilon}$ is diagonal.

The second-order factor model assumes that the variables $\mathbf{\eta}$ can be accounted for by a set of factors $\mathbf{\xi}$, so-called second-order factors, so that:

$$\mathbf{\eta} = \mathbf{\Gamma}\mathbf{\xi} + \mathbf{\zeta}, \qquad (4)$$

where $\mathbf{\Gamma}$ is a matrix of second-order factor loadings and $\mathbf{\zeta}$ is a vector of unique variables (or disturbances) for the first-order factors $\mathbf{\eta}$. Therefore, $\mathbf{\Sigma}_{\eta\eta} = \mathbf{\Gamma}\mathbf{\Sigma}_{\xi\xi}\mathbf{\Gamma}' + \mathbf{\Sigma}_{\zeta\zeta}$.

As in Equation 2, expanding Equation 4 yields:

$$\begin{bmatrix} \mathbf{\eta}_P \\ \mathbf{\eta}_E \end{bmatrix} = \begin{bmatrix} \mathbf{\Gamma}_{\eta_P} & \mathbf{0} \\ \mathbf{0} & \mathbf{\Gamma}_{\eta_E} \end{bmatrix} \begin{bmatrix} \xi_P \\ \xi_E \end{bmatrix} + \begin{bmatrix} \mathbf{\zeta}_P \\ \mathbf{\zeta}_E \end{bmatrix}, \qquad (5)$$

where ξ_P and ξ_E are the second-order factors for P and E, and $\mathbf{\zeta}_P$ and $\mathbf{\zeta}_E$ are the corresponding disturbances for the first-order factors.

Chen, Sousa, and West (2005) stated that measurement invariance of second-order factor models can be tested at different hierarchical levels:

Configural invariance (Model 1). The most basic requirement of measurement invariance in a repeated measures design is that the model specification is the same in the P and E measures; however, the factor loadings can differ. That is, the $\mathbf{\Lambda}_{y_P}$ and $\mathbf{\Lambda}_{y_E}$ matrices in Equation 2 have the same size and the same pattern of fixed and free elements. Following Widaman and Reise (1997), when this level of invariance is achieved, similar, but not identical, latent variables are present in the P and E measures. This level of invariance is the one tested in previous research to warrant the commensurate structures requirement defined by Rounds et al. (1987). However, previous studies only refer to the comparison of separate exploratory factor analyses for P and E items, regardless of goodness-of-fit statistics.

Invariance of first-order factor loadings (Model 2). The second level of invariance is factor loadings invariance of first-order factors. That is, $\mathbf{\Lambda}_{y_P} = \mathbf{\Lambda}_{y_E}$ in Equation 2. When the item loadings on the first-order factor are equal in the P and E measures, the unit of measurement of the underlying factor is identical. When this level of factor invariance is achieved, relations between the first-order factors and other external variables can be compared in the P and E measures, because the unit of measurement of the first-order factors is equal in the P and E structures. Then, in addition to the support for the equality of the factorial structure for the P and E measures (i.e., the issue of commensurate structures), the fulfillment of this level of invariance provides a direct method of assessment for the issue of commensurate units. We propose that the achievement of this level of invariance should be the minimal criterion used to warrant commensurate measurement.

Invariance of first and second-order factor loadings (Model 3). The third level of invariance implies that factor loading invariance must also be tested for the second-order factor loadings. That is, $\mathbf{\Lambda}_{y_P} = \mathbf{\Lambda}_{y_E}$ and $\mathbf{\Gamma}_{\eta_P} = \mathbf{\Gamma}_{\eta_E}$ in Equations 2 and 5. When this level of factor invariance is achieved, relations between the second-order factors and other external variables can be compared in the P and E factors, because the unit of measurement would be equal

in the second-order factors (P and E). The fulfillment of this level of invariance makes it possible to summarize the P and E first-order factorial structures in a single measure for P and E. This assumption is not indispensable for commensurate measurement but could be appealing to P-E fit studies as the interest lies in studying the P and E separate and joint (P-E fit) effects on an outcome (e.g., job satisfaction).

Invariance of first and second-order factor loadings, and residual variances of observed variables (*Model 4*). The fourth level of invariance is residual invariance. The residual associated with each observed variable is constrained to be equal in each measure, in addition to the first and second-order factor loadings. That is, following Equations 2 and 5: $\Lambda_{y_P} = \Lambda_{y_E}$, $\Gamma_{\eta_P} = \Gamma_{\eta_E}$, and $Var(\varepsilon_P) = Var(\varepsilon_E)$. When this level of invariance holds, all the differences in the P and E items are due only to differences in the first-order factors. Residual invariance, however, represents an ideal standard that is difficult to fulfill (see Widaman & Reise, 1997).

Invariance of first and second-order factor loadings, residual variances of observed variables, and disturbances of first-order factors (*Model 5*). In addition to testing the invariance of the residual variances of the observed variables, the invariance of the disturbances (unique factors) of the first-order factors can also be tested. That is, following Equations 2 and 5: $\Lambda_{y_P} = \Lambda_{y_E}$, $\Gamma_{\eta_P} = \Gamma_{\eta_E}$, $Var(\varepsilon_P) = Var(\varepsilon_E)$, and $Var(\zeta_P) = Var(\zeta_E)$. When this level of invariance holds, the disturbances of the lower-order factors are equivalent across the P and E measures. As in residual invariance, disturbances of first-order factors invariance can be difficult to achieve. Both residual and disturbances invariance are not indispensable for P-E fit studies but, if they are satisfied, it would demonstrate that strong assumptions of commensurate measurement are achieved.

Empirical Example

This section offers an empirical example to illustrate the measurement invariance approach to assessing the equivalence of an organizational P-E fit measure based on the theory of work adjustment (Dawis & Lofquist, 1984) which conceptualizes P-E fit as the correspondence between the person's needs (P) and the degree to which the organization rewards them (O).

Method

Participants

A sample of 490 participants was recruited from former university students. Of the 490 participants, 249 were men and 241 were women with an average age of 35 years (standard deviation: 6.21), and 60% worked in management positions and the remaining 40% in average to low-level positions (e.g., administrative, commercial, and technical).

Materials and procedure.

The P and O components were measured with nine items each one. The items measuring individual preferences (P) were based on the Minnesota Importance Questionnaire (MIQ, Gay, Weiss, Hendel, Dawis, & Lofquist, 1971) and the items measuring the perceived degree to which the organization rewards these individual preferences (O) were based on the Minnesota Job Description Questionnaire (MJDQ, Borgen, Weiss, Tinsley, Dawis, & Lofquist, 1972). Both the MIQ and the MJDQ measure six commensurate dimensions: Safety, Autonomy, Comfort, Altruism, Achievement, and Status. The present study only referred to three of these dimensions to obtain a more manageable and simple model. These dimensions are: *Safety* or the extent to which the organization provides stability for its members, *Autonomy* or the extent to which the organization stimulates the initiative, and *Achievemen*t or the extent to which the organization promotes the accomplishment of objectives (see Dawis & Lofquist, 1984, pp. 82-88). Each dimension was defined by three items rated on a five-point Likert response scale (a description of these items is given in the footnote for Table 1). The two questionnaires were administered separately at different temporal times. First, respondents answered on the importance of the nine items in terms of individual preferences (P). Second, respondents answered the same items in terms of the degree to which the organization rewards the individual preferences (O).

Statistical analyses.

The factorial structure is depicted in Figure 1 and included eighteen observed variables (nine item pairs for the P and O measures), six first-order factors (representing the three-factor model hypothesized for the P and O items), and two second-order factors (P and O). Given that the items in P and O had similar wording, the model allowed for correlated measurement errors between them.

The ordinal nature of the data suggested the use of asymptotically distribution-free estimation procedures (ADF; Browne, 1984). However, Browne (1984) and Flora and Curran (2006) suggested that ADF "will tend to become infeasible" as the number of variables approaches 20 because the estimation of the asymptotic covariance matrix is inaccurate. Jöreskog and Sörbom (1996) suggested that generalized least squares (GLS) estimation is more appropriate than ADF in this situation. Thus, analyses were conducted using GLS estimation and the AMOS 7.0 program (Arbuckle, 2006).

Measurement invariance was hierarchically tested at each of the levels (configural, first-order factor loadings, second-order factor loadings, residual variances of observed variables, and disturbances of first-order factors). In comparing the fit of hypothesized models, chi-square tests and goodness-of-fit indexes were used. The chi-square test assesses the magnitude of the discrepancy between the sample and fitted covariance matrices (a significant test is indicative of a poor fit). However, when the sample size is large, as is usually required in CFA models, a small discrepancy from the model that may be of no practical or theoretical interest can lead the chi-square test to reject the model. Consequently, we also reported three fit indexes that showed good performance in a simulation study by Hu and Bentler (1999). The root mean squared error of approximation (RMSEA; Steiger, 1990), which is a measure of the estimated discrepancy between the population and model implied population covariance matrices per degree of freedom. Browne and Cudeck (1993) suggested that RMSEA values below .05 indicate a close fit, from .05 to .08 a fair fit, from .08 to .10 a mediocre fit, and above .10 an unacceptable fit. The test of close fit (*p*-close) was also reported (a significant test is indicative of a poor fit). The standardized root mean square residual (SRMR; Hu & Bentler, 1999) is a measure of the average of the standardized fitted residuals. An SRMR value of less than .08 indicates a good fit. The comparative fit index (CFI; Bentler, 1990) is derived from a comparison of a restricted model (one in which a structure is imposed on the data) with a null model (one in which all pairs of observed variables are assumed to be uncorrelated). A CFI value of .95 or greater is indicative of an adequate fit.

Finally, given that a series of hierarchically nested models are tested, the chi-square difference (likelihood ratio) test ($\Delta\chi^2$) was used to compare the fit for two nested models (Bentler & Bonett, 1980). If the chi-square difference test was significant, the constraints on the more restricted model might be too strict and the results of the less restricted model should be accepted. However, once again, the performance of the chi-square difference test is also affected by the large sample size so that goodness-of-fit indexes are typically also used to assess model fit. Following the recommendations by Chen (2007) and Cheung and Rensvold (2002), we also used the change in the value of CFI (i.e., ΔCFI). A value of ΔCFI smaller than or equal to -.01 indicated that the null hypothesis of measurement invariance should not be rejected.

Results

Table 1 shows the descriptive statistics and correlations for the P and O items. As can be seen, the means were in general higher in P than in O.

Table 2 presents the fit statistics for each model. In testing the *configural invariance* (*Model 1*), an unrestricted baseline model was specified. That is, the structure of the P and O items was identical, but different estimates were allowed for the corresponding parameters in P and O. As seen from Table 2, the results indicated an adequate fit of the model to the data (RMSEA = .042, *p*-close = .944; SRMR = .061; and CFI = .951).

In testing the *invariance of first-order factor loadings* (*Model* 2), all the first-order factor loadings were constrained to be equal in the P and O corresponding item pairs. The results indicated an adequate fit of the model to the data (RMSEA = .042, *p*-close = .931; SRMR = .071; and CFI = .950). This level of invariance was nested within Model 1. As can be seen from Table 2, the chi-square difference test was not significant, $\Delta\chi^2_{(\Delta df = 6)} = 14.84$, and the ΔCFI value was smaller than -.01. Therefore, the first-order factor loadings were invariant across the P and O measures. The achievement of this level of factor invariance implied that the unit of measurement of the first-order factors was equal in the P and O structures. That is, the results indicated that both the commensurate units and commensurate structures requirements were satisfied.

In testing the *invariance of first and second-order factor loadings* (*Model* 3), all first and second-order factor loadings were constrained to be equal in the P and O corresponding measures. The results indicated an adequate fit of the model to the data (RMSEA = .043, *p*-close = .921; SRMR = .073; and CFI = .947). This level of invariance was nested within Model 2. The chi-square difference test was not significant, $\Delta\chi^2_{(\Delta df = 2)} = 6.11$, and the ΔCFI value was smaller than -.01. This result indicated that the P and O factorial structures could be summarized in a single measure for P and O (the second-order factors).

In testing the *invariance of first and second-order factor loadings, and residual variances of observed variables* (*Model* 4), the residual variances associated with each observed variable were constrained to be equal in the P and O measures, in addition to the first and second-order factor loadings. The results indicated a poor fit of the model to the data (RMSEA = .075, *p*-close < .001; SRMR = .106; and CFI = .884). The chi-square difference test between Model 4 and Model 3 was significant, $\Delta\chi^2_{(\Delta df = 9)} = 270.95$ ($p < .001$), and the ΔCFI value indicated that a substantial change in fit had occurred. Therefore, the constraints of residual variances of the observed variables might be too strict and the results of Model 3 (see Figure 1) should be accepted.

In testing *invariance of first and second-order factor loadings, residual variances of observed variables, and disturbances of first-order factors* (*Model* 5), the disturbances associated with the first-order factors were constrained to be equal in the P and O measures, in addition to the residual variances of the observed variables, and the first and second-order factor loadings.

Table 1
Descriptive Statistics and Correlations

Items[*]	M	SD	Correlation matrix																	
Y1	4.38	.73																			
Y2	4.07	.88	.16																		
Y3	3.95	.81	.07	.35																	
Y4	4.36	.67	.05	.10	.06																
Y5	4.38	.63	.01	.15	.30	.46															
Y6	4.34	.65	.08	.14	.27	.34	.50														
Y7	4.44	.62	.05	.15	.19	.33	.35	.29													
Y8	4.21	.85	.23	.25	.17	.15	.22	.22	.19												
Y9	3.47	.93	.09	.22	.23	.19	.12	.12	.18	.24											
Y10	2.82	1.12	.08	.08	.02	.06	.02	.02	.08	-.02	.07										
Y11	2.83	1.10	-.04	.21	.13	.12	.02	.00	.05	-.02	.11	.33									
Y12	3.26	1.09	.03	.03	.13	.13	.05	.05	.03	.00	.04	.23	.43								
Y13	3.03	1.11	-.04	-.04	.04	.15	.07	.07	.09	-.08	.10	.29	.45	.35							
Y14	2.77	1.07	-.10	-.10	.10	.07	.22	.06	.04	-.10	.09	.35	.47	.46	.61						
Y15	3.05	1.12	-.07	-.07	.07	.08	.19	.10	.08	-.10	.03	.36	.46	.46	.53	.63					
Y16	4.07	1.09	.02	.02	.12	.07	.15	.06	.12	.02	.08	.13	.36	.48	.36	.36	.36				
Y17	2.29	.98	-.08	-.08	.05	.15	.10	-.02	.08	.03	.14	.44	.56	.41	.44	.51	.47	.33			
Y18	2.31	.93	-.05	-.05	.02	.08	.12	.00	.08	-.06	.22	.37	.47	.45	.49	.57	.49	.32	.60		

Note. M and SD are the means and standard deviations.

[*] Items Y1 to Y9 were answered in terms of "for me it is important that…" (P), while items Y10 to Y18 were answered in terms of "for my organization it is important that…" (O), where: Y1 and Y10: I could have a safe job, Y2 and Y11: My group leader would provide for my continuing membership, Y3 and Y12: My group leader would communicate expectations well, Y4 and Y13: I could make decisions on my own, Y5 and Y14: I could try out my own ideas, Y6 and Y15: I could plan things independently, Y7 and Y16: I could gain a feeling of accomplishment, Y8 and Y17: I could have an opportunity for self-advancement, and Y9 and Y18: I could be somebody in the group

Table 2
Summary of Fit Statistics for Testing Measurement Invariance of Second-Order Factor Model of P-O Fit

Model	χ^2	df	RMSEA (p-close)	SRMR	CFI	Model comparison	$\Delta\chi^2$	Δdf	ΔCFI
1. Configural invariance	220.49	119	.042 (p = .944)	.061	.951	-	-	-	-
2. First-order factorial invariance	235.33	125	.042 (p = .931)	.071	.950	2 vs. 1	14.84	6	-.001
3. First and second-order factorial invariance	241.44	127	.043 (p = .921)	.073	.947	3 vs. 2	6.11	2	-.003
4. First and second-order factor loadings, and residual variances of observed variables invariant	512.35	136	.075 (p < .001)	.106	.884	4 vs. 3	270.95*	9	-.090
5. First and second-order factor loadings, residual variances of observed variables, and disturbances of first-order factors invariant	540.38	139	.078 (p < .001)	.113	.873	5 vs. 4	28.03*	3	-.011

Note. RMSEA = root mean squared error of approximation; SRMR = standardized root mean square residual; CFI = comparative fit index.
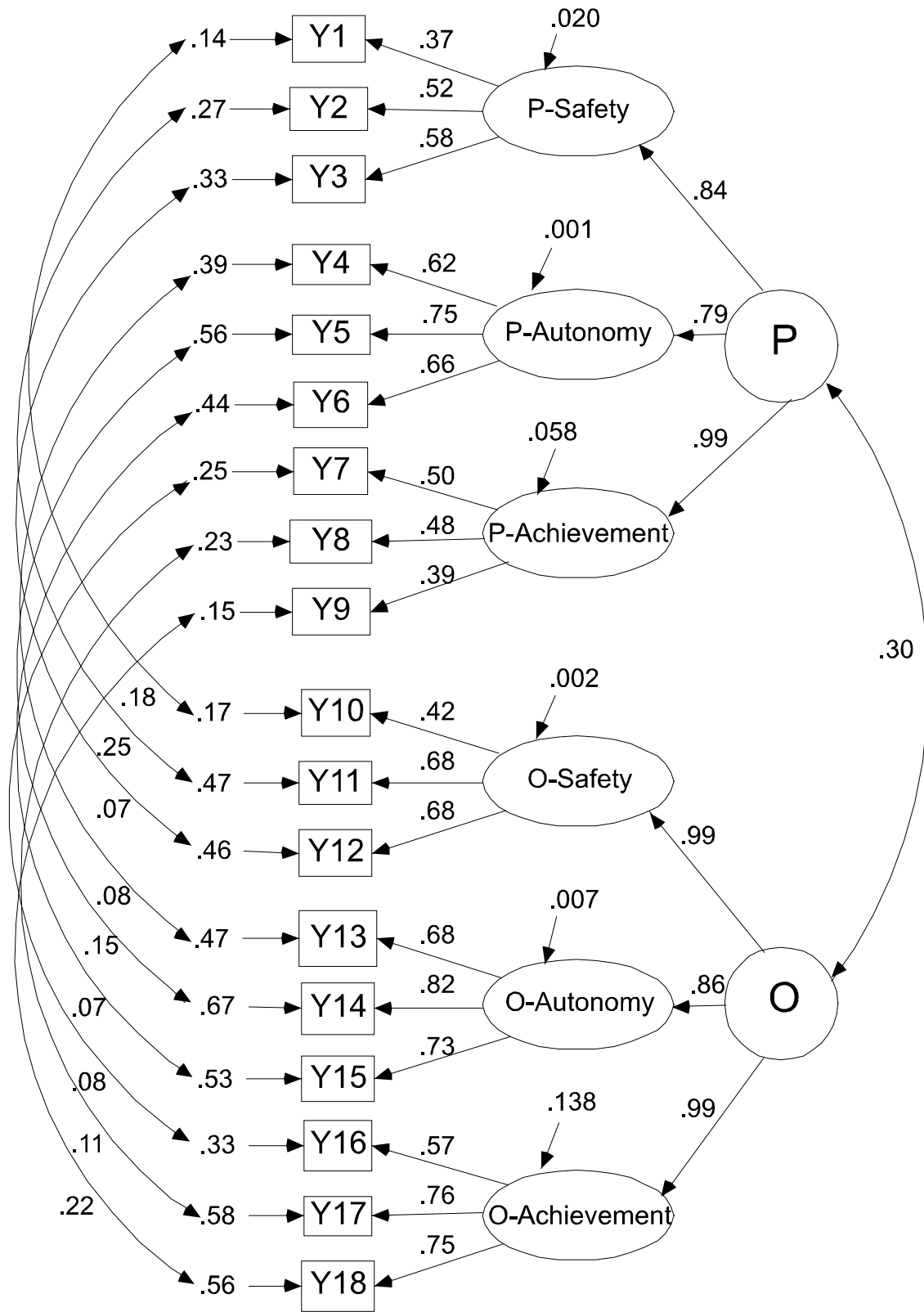* $p < .001$

Figure 1. Results for Model 3 (standardized solution).
Note. For the P dimension, the R^2 for the first-order factors were: Safety (.73), Autonomy (.62), and Achievement (.95). For the O dimension, the R^2 for the first-order factors were: Safety (.99), Autonomy (.77), and Achievement (.99).

The results indicated a poor fit of the model to the data (RMSEA = .078, p-close < .001; SRMR = .113; and CFI = .873). The chi-square difference test between Model 5 and Model 4 was significant, $\Delta\chi^2_{(\Delta df = 3)}$ = 28.03 (p < .001), and the ΔCFI value was larger than -.01. Therefore, the disturbances of first-order factors were not invariant across the P and O measures. This result indicates that neither the constraints of Model 4 nor the constraints of Model 5 could be accepted, and that Model 3 was the highest level of invariance that could be achieved for interpreting the data.

Summary and Discussion

The purpose of this paper was to deal with an important methodological concern of any research based on a person-environment (P-E) fit approach: the measurement assumption that imposes that the P and E components be assessed in commensurate or theoretically similar dimensions. One critical issue that has not been adequately addressed in this area of research is the assessment of commensurate measurement using a rigorous approach. Previous studies have usually assessed the commensurability by comparing the separate exploratory factor analyses for the P and E items, considering that P and E are commensurate if both factorial solutions have similar factors, regardless of the goodness-of-fit statistics. Moreover, the issue of commensurate units is not directly assessed. In this paper, we have proposed to test the equivalence across the P and E measures by analyzing the measurement invariance of a multi-group CFA model. More specifically, we presented an empirical example referred to a second-order CFA model, where the second-order P and E factors were defined upon a first-order factorial structure that should be equivalent for the P and E measures.

Traditionally, measurement invariance consists of testing the equivalence of measured constructs in two or more independent groups to ensure that the same constructs are being assessed in each group. Here we have tested the equivalence of the P and E factorial structures when they are measured in the same group of subjects, using a repeated measures design. For the purposes of the present research, measurement invariance was tested at five different hierarchical levels: (1) configural, (2) first-order factor loadings, (3) second-order factor loadings, (4) residual variances of observed variables, and (5) disturbances of first-order factors. Following the definition of Rounds et al. (1987), given that the invariance of first-order factor loadings allows the testing of the separate effects of the P and E dimensions on other external variables and the computation of a P-E fit index for each of these dimensions, it is proposed that commensurate measurement should satisfy at least level 2. This means that commensurate units and commensurate structure

are met. The satisfaction of level 3 is a desirable but not indispensable assumption for commensurate measurement. Finally, the satisfaction of levels 4 and 5 would imply that the strong assumptions of commensurate measurement are achieved.

An example illustrating the procedure in a person-organization (P-O) fit dataset was provided. The results supported that Model 3 was the highest level of invariance that could be satisfied, indicating that only first and second-order factor loadings invariance was achieved. Therefore, results supported the assumptions of commensurate units and commensurate structure across the P and O measures, while the rejection of Models 4 and 5 indicated that the residual variances of the observed variables and the disturbances of the first-order factors were not equivalent.

At one level, the present paper has provided a statistical basis to assess commensurate measurement in P-E fit studies. Given that this issue has not been addressed in previous studies, this can be useful to P-E fit researchers in practice. At another level, from a methodological point of view, the distinct aspect of this research is that, while previous research on measurement invariance has normally used two or more independent samples (i.e., with different individuals in each sample), the present work is an illustration of the assessment of measurement invariance in a repeated measures design, where the same individuals are measured at two different temporal times. This kind of design, less used by researchers in P-E fit studies, provides a direct assessment of commensurate measurement and has the advantage of providing an estimate of the correlation between the P and E constructs.

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