Invariance of the trait emotional intelligence construct across populations and

sociodemographic variables

#### Abstract

Cultural, linguistic and sociodemographic peculiarities may influence trait Emotional Intelligence (trait EI). An instrument capable of assessing trait EI in different populations can foster cross-cultural research and make an important contribution to the construct's nomological network. Accordingly, the present study aimed to examine the relationship between trait EI and key sociodemographic variables through univariate analyses of variance and tests of multigroup measurement equivalence. We used datasets Trait Emotional Intelligence Questionnaire (TEIQue-SF) datasets from four countries. Collectively, these datasets comprised 2,228 participants, 23% from Brazil, 15% from Chile, 23% from Italy, and 39% from the United Kingdom. The sociodemographic variables that we used for trait EI comparisons were gender, age, educational level, civil and occupational status. Our results indicated significant global trait EI differences across countries for civil status, occupation, educational attainment, and age. Measurement invariance across the datasets was acceptable, especially for age, gender and education. In conclusion, the present psychometric evidence supports the suitability of the TEIQue-SF for the accurate assessment of trait EI in transcultural research.

Keywords: trait emotional intelligence, measurement invariance, TEIQue, cross-cultural.

## Trait emotional intelligence theory and the Trait Emotional Intelligence Questionnaires

Trait EI is formally defined as a constellation of emotional perceptions assessed through questionnaires and rating scales (Petrides, Pita, & Kokkinaki, 2007). The construct essentially concerns people's perceptions of their emotional and social effectiveness (Van der Linden et al., 2017), providing a framework for the integration of the affective aspects of personality, which were previously partly overlooked and partly scattered across multiple, allegedly orthogonal, dimensions (Petrides et al., 2016).

Trait EI has a vast and expanding nomological network, including associations with health outcomes (Batselé, Stefaniak, Fantini-Hauwel, 2019; Martins, Ramalho, & Morin, 2010; Schinckus, Avalosse, Van den Broucke, & Mikolajczak, 2018), academic performance (MacCann et al., 2020), job satisfaction (Li, Pérez-Díaz, Mao & Petrides, 2018), life satisfaction and subjective happiness (Stamatopoulou, Galanis, & Prezerakos, 2016), stress management (Martínez-Monteagudo, Inglés, Granados, Aparisi, & García-Fernández, 2019; Saddki, Sukerman, & Mohamad, 2017), and other fundamental psychological variables (Di Fabio & Kenny, 2019; Farnia, Nafukho, & Petrides, 2018).

The Trait Emotional Intelligence Questionnaire (TEIQue), was specifically developed as the operationalisation vehicle for trait emotional intelligence theory, and it is the only instrument that comprehensively covers the sampling domain of the construct. In contrast to other emotional intelligence (EI) measures, the TEIQue has a detailed and fully developed theoretical basis and nomological network. Its factor structure comprises global trait EI at its apex, four interrelated factors in the middle (Well-being, Self-control, Emotionality and Sociability), and fifteen narrow facets at the bottom (Petrides, 2009). The short form of the TEIQue (TEIQue-SF) is a thirty-item questionnaire designed to yield a global trait EI score. Although it is possible to also obtain scores on the four factors from it, they tend to be somewhat less reliable than those obtained from the full form of the instrument. The TEIQue-SF does not yield scores on the 15 trait EI facets (Cooper & Petrides, 2010; Petrides, 2009). In addition, there are other TEIQue forms tailored for children, adolescents, and other particular purposes, all of which have been developed with explicit and full reference to the trait EI theory, as conceived by Petrides and colleagues (see Petrides, 2009).

## Gender differences supported by trait EI

Due to the variety of trait EI measures used in the literature and variations on whether analyses are performed on a global trait EI composite or subscales scores, it is sometimes difficult to accumulate evidence on certain topics, which is why TEIQue-specific meta-analyses have been reported in the past (Andrei, Siegling, Aloe, Baldaro & Petrides, 2016). In addition, most previous research has exclusively relied on t-tests or ANOVAs, which are subject to measurement error (Vandenberg & Lance, 2000) and can be considered as suboptimal. Without conducting measurement invariance analyses, the constancy of a construct across genders is unwarranted (e.g., Petrides, Jackson, Furnham & Levine, 2003). Additionally, studies comprising small or unbalanced samples usually lack the statistical power necessary for generalising gender interpretations. Lastly, cross-cultural research addressing gender invariance with heterogeneous populations is scarce, as most studies have exclusively relied on samples comprising university students (see Siegling, Furnham & Petrides, 2015).

With these limitations in mind, the following studies have presented trait EI measurement invariance for gender with large samples. Tsaousis and Kazi (2013) provided robust evidence in favour of measurement invariance for the construct when assessed by the Greek Scale of

Emotional Intelligence (GEIS). These authors evaluated trait EI through subscale-scores instead of providing an overall composite in Greece, on a sample of over 2000 individuals. Similarly, Siegling et al. (2015) tested gender invariance for trait EI in a cross-cultural study with over 2700 university students, concluding that the construct is invariant for gender when taking the global trait EI composite as the criterion.

As for gender means differences, the results tend to vary in the literature. For instance, a significant mean difference has been reported favouring women over men regarding global trait EI (Cooper & Petrides, 2010). Conversely, Shahzad and Bagum (2012) informed a significant difference favouring the latter. Petrides and Furnham (2000, 2006) did not find any significant gender differences in the U.K, nor did Ugarriza (2001) when comparing total EQ-i (Emotional Quotient Inventory) scores in Peru. Other scholars have also reported non-significant results on gender comparisons (see Atta, Ather & Bano, 2013; Lyusin, 2006; Saklofske, Austin, Galloway & Davidson, 2007; Pérez-Diaz & Petrides, 2019; Siegling, Sfeir & Smyth, 2014). The general conclusion seems to be that any gender differences in global trait EI are usually accompanied by small effect sizes (see also MacCann et al., 2020).

# Sociodemographic differences supported by trait EI

Most trait EI studies have relied on WEIRD (western, educated, industrialised, rich and democratic) student samples, with the inherent bias that generalisations taken from these samples entail, especially regarding emotions, cognitions and motivations (Henrich, Heine & Norenzayan, 2010). Exceptions are rare; for instance, Ugarriza (2001) approached a heterogenous general population sample in Peru, similar to Pérez-Díaz and Petrides (2019) in Chile.

Many researchers have reported positive and significant correlations between trait EI and age (Bar-On, 1997; Chapman & Hayslip, 2006; Derksen, Kramer, & Katz, 2002; Petrides & Furnham, 2006; Tsaousis & Kazi, 2013; Ugarriza, 2001), although a few others have not (Fernández-Berrocal, Extremera & Ramos, 2004; Shipley, Jackson & Segret, 2010). The findings here are not settled, even though the literature provides stronger support for a positive and significant association between trait EI and age.

Other sociodemographic variables, such as educational attainment and civil and occupational status, have not been extensively investigated in the literature since participants are typically described in terms of gender and age only. Regarding occupation, individual differences—such as personality and EI traits—exert a strong influence on career choice (Chaudhary & Rangnekar, 2017; Farnia et al., 2018; Sanchez-Ruiz, Mavroveli, & Poullis, 2013). For instance, Siegling et al. (2014) reported higher global trait EI scores for a sample of managers compared to the normative general population. Our research aims to furnish further evidence regarding the relationship between trait EI and these sociodemographic characteristics.

# The role and importance of measurement invariance

Measurement invariance tests for the psychometric equivalence of a construct across different target cultures (Greiff & Iliescu, 2017). In quantitative psychology, cross-cultural comparability is usually evaluated through multigroup confirmatory factor analysis (MGCFA). A technique capable of testing cross-national equivalence over several countries (Jöreskog, 1971; Meitinger, 2017).

In our study, we tested measurement invariance through progressive nested models, ranging from configural to scalar invariance (Vandenberg & Lance, 2000). Configural invariance represents the baseline. It assumes that groups share the same conceptual framework without equality constraints on any parameter. Metric invariance requires equivalence of factor loadings, meaning that each item contributes to the latent construct similarly across different groups. Scalar invariance allows for the comparison of latent means across groups (Putnick & Bornstein, 2016). This type of invariance analysis derives from constraining intercepts to be equal among groups. If there is enough evidence for scalar invariance, then scores are considered invariant, i.e., equivalent (Chen, 2007; Tóth-Király, Bõthe, Rigó, & Orosz, 2017). Changes of the fit statistics across the nested models from configural to scalar invariance should fall within a specific range. For instance, changes in CFI and RMSEA up to -.010 and .015, respectively support the invariance of the more restricted (nested) model when compared to the less restricted model. Similarly, changes in SRMR of .015 and .030 support metric and scalar invariance, respectively (Chen, 2007). All of these types of invariance are necessary to claim that a construct is fully invariant.

# The present study

Since different populations, cultures, languages, as well as sociodemographic and economic peculiarities may affect the interpretation and cross-cultural validity of trait EI, the present study has two main aims. First, to test trait EI differences across influential sociodemographic variables (i.e., gender, age, educational level, civil status, and occupation). Second, to provide cross-cultural evidence of measurement invariance in relation to the preceding sociodemographic features. Each included country has distinct characteristics, such as socio-political and geographic location, spoken language, culture, economy, and so forth, which creates a diversity suitable for studying measurement invariance (see Millsap, 2011).

#### Method

**Participants.** We included data from 2228 participants in the study, 512 of whom were from Brazil (23%), 335 from Chile (15%), 515 from Italy (23%) and 866 from the U.K. (39%). All datasets but the Italian have been employed in previous research: Cooper and Petrides (2010; UK), Perazzo et al., (2020; Brazil), Pérez-Díaz and Petrides (2019; Chile). From the pooled dataset, 1021 participants were women (46%), 1205 men (54%), and two undisclosed. Most participants were under thirty years old (M = 28.22, SD = 11.38, Minimum = 17, Maximum = 80). Regarding their main occupation, most were students (53%), followed by those employed in the private sector (24%). A third cluster comprised high school teachers and university lecturers (7%). Those employed in the public sector accounted for 6% of the sample. The unemployed and those who declared a "non-listed" occupation accounted for 3% and 7% of the total sample, respectively. Regarding educational attainment, 47% of participants had obtained or were in the process of obtaining a higher education certificate or university degree, 34% had obtained a qualification of secondary education, 11% had completed primary education, while 9% held a postgraduate degree. Participants did not receive any compensation. The inclusion criterion was: (a) aged 17 years or above. The exclusion criteria were: (a) being a current mental health patient, and (b) having any diagnosis of severe psychopathology.

We implemented multiple imputations by chained equations for treating missing values with the R package MICE (Van Buuren & Groothuis-Oudshoorn, 2011). All of the TEIQue-SF items in the original datasets were complete. However, values were missing for the sociodemographic variables gender (82, representing 3.68% of the observations), age (106, representing 4.76% of the observations), education (577, representing 25.90% of the

observations), civil status (581, representing 26.07% of the observations) and occupation (582, representing 26.12% of the observations). We followed White, Royston and Wood's (2010) recommendation to include predictors with incomplete data in the imputation model, as this is advantageous for two reasons: 1) It makes the assumption of missing at random (MAR) more plausible, thus reducing bias, and 2) It reduces the standard errors of the estimates in the model. We performed 26 imputation models, as this was the maximum percentage of missing values in any of our sociodemographic predictors.

**Measures.** We used the TEIQue-SF questionnaire in the U.K. (Cooper & Petrides, 2010; Petrides, 2009), along with the Brazilian (Perazzo et al., 2020), Chilean (Pérez-Díaz & Petrides, 2019), and Italian (Di Fabio & Palazzeschi, 2011) adaptations of it. The questionnaires comprise thirty statements and are responded on a 7-point Likert scale, ranging from 1 (Completely Disagree) to 7 (Completely Agree). All surveys included questions on the relevant sociodemographic variables.

**Design and Procedure.** In all four countries, participants completed paper-and-pencil or online versions of the questionnaires, collectively or individually. Pertinent local ethics boards approved all data collections.

**Data analysis plan.** We first determined that the observations followed the multivariate normal distribution for global trait EI. We also determined that the assumption of homogeneity of variances was met for all the sociodemographic variables, as assessed by Levene's statistic. We then implemented univariate analyses of variance (ANOVA) with post-hoc analyses and t-tests, as appropriate. We used Cohen's *d* and Eta Squared ( $\eta 2$ ) as measures of effect size, besides

Hochberg's GT2 as a post-hoc statistic. These effect size statistics are recommended for comparing clusters of unequal size (Field, 2013).

We tested measurement invariance across three stages: Configural, Metric and Scalar (see Putnick & Bornstein, 2016), following the recommendations by Hu and Bentler (1995), Cheung and Rensvold (2002), Chen (2007), and Meade, Johnson and Braddy (2008). We contrasted model fit through MLR estimations (Maximum likelihood with robust standard errors) at each stage. We later applied decision rules to whether they complied or not with the type of studied invariance, based on sample size, type of invariance, and fit-statistic used for comparison (see Meade et al., 2008). In all cases, we started with a basic Bifactor ESEM model since this has proved suitable in previous research with two of the included country datasets (see Perazzo et al., 2020; Pérez-Díaz & Petrides, 2019). This model is depicted in Figure 1.

#### PLEASE INSERT FIGURE 1 HERE

#### Results

**Reliability analyses.** These analyses revealed that the global trait EI score was highly reliable in the four datasets ( $\omega = .90$ ). In addition, all trait EI factors turned to have fair-to-good Omega reliability indices, except for Sociability (Well-being = .84, Self-control = .83, Emotionality = .64, Sociability = .35). As predicted (see Zinbarg, Revelle, Yovel & Li, 2005),  $\alpha = .88$ , was at the lower bound of reliability for the global trait EI score. The proportion of scale variance due to the general factor only (global trait EI), as estimated by  $\omega h$ , was 50%. As Pérez-Díaz and Petrides reported with the Chilean dataset (2019), Sociability had previously shown the lowest Omega reliability, even though the estimate was higher when assessed by the traditional Alpha index ( $\alpha = .61, 95\%$  CI [.58,.63]). As for the remaining factors, all showed adequate alphas (Taber, 2018): Well-being = .76, Self-control = .61, Emotionality = .67, although the values were considerably

lower than that of the global trait EI score, which the TEIQue-SF was specifically designed to measure. In light of the lower than desired reliability scores at the factor level, we performed our mean difference analyses on global trait EI, since it showed a high internal consistency throughout.

**Cross-cultural comparisons of global trait EI.** We performed a preliminary one-way ANOVA with global trait EI as the dependent variable and the four countries as the different levels of a between-subjects independent variable. This analysis showed that country explained 6% of the variance in global trait EI, which is considered a small-to-moderate effect size [ $F(3, 2227) = 48.98, p < .01, \eta 2 = .062$ ]. Descriptive statistics of global trait EI means in each country are depicted in Table 1.

PLEASE INSERT TABLE 1 HERE

**Trait EI mean differences across sociodemographic variables.** We contrasted the countries on the chosen sociodemographic variables after checking that global trait EI followed a normal distribution, and the assumption of homogeneity of variances was met across the respective levels of the predictors. We also tested for possible interactions between sociodemographic predictors across the four countries through univariate analyses of variance. These analyses revealed the absence of two-way interactions between the chosen sociodemographic variables on global trait EI, in any of the studied countries (p > .05).

Gender and age differences in trait EI. Except for Chile, all countries showed statistically significant global trait EI gender differences, yet of small effect size. Regarding age, except for Italy, all countries showed statistically significant global trait EI age differences, of small-to-mid effect size. These differences are depicted in Table 2. We treated the age variable as categorical, which is a common practice for investigating measurement invariance (Millsap, 2011). Accordingly, we created two subsamples based on the quartiles of the age distribution. We labelled them as Younger (17-32), and Older (33-80). Additionally, we performed a Pearson correlation between global trait EI and age (as a continuous variable) on the merged dataset, which did not reach significance [r (2228) = .034, p = .11].

#### PLEASE INSERT TABLE 2 HERE

**Trait EI differences by educational attainment.** The Chilean and Italian datasets revealed significant global trait EI differences for educational attainment through ANOVA, although the U.K. dataset did not. These results are presented in Table 3. In Chile, higher educational attainment was linked to higher global trait EI scores, as Hochberg's GT2 revealed substantial differences on global trait EI between participants with a secondary education certificate only and those with either a university or a master's degree (d = 0.79, and d = 0.81, respectively). Similarly, in Italy, participants with a master's degree scored significantly higher on global trait EI, than those with a university degree (d = 1.09), those with a secondary education certificate only (d = 0.17), and those in the 'others' category (d = 0.20).

# PLEASE INSERT TABLE 3 HERE

**Trait EI differences by civil status.** The Chilean and the Italian datasets showed significant global trait EI differences for civil status through ANOVA, although the U.K. did not. In Chile, we found significant differences in global trait EI between married and single participants (d = 0.58), as well as between married and divorced or separated participants (d = 0.39). In Italy, the largest trait EI differences were between married participants and those separated or divorced (d = 1.41), who also scored significantly lower than participants with a 'non-listed' civil status (d = 1.81). Single participants in Italy also showed significantly higher global trait EI than those divorced or separated (d = 1.29).

**Trait EI differences by occupation.** The Chilean and the Italian datasets showed significant global trait EI differences for occupation through ANOVA, although the U.K. did not. We discovered significant differences in global trait EI between teachers/lecturers and students in Chile, favouring the former (d = 0.83). In Italy, teachers/lecturers scored significantly higher on global trait EI than employees in the private sector (d = 1.70) and the unemployed (d = 2.74), while employees working in the public sector, as well as students, scored higher than employees in the private sector (d = 1.07 and d = 0.55, respectively).

**Measurement invariance.** The analyses revealed that trait EI, as measured by the TEIQue-SF, was invariant up to the scalar (latent means) level for gender, age and education. The CFI reached the less stringent .9 cut-off threshold, with CFI changes across nested models below the .01 cut-off criterion recommended by Cheung and Rensvold (2002). Changes in the RMSEA and SRMR were within the ranges recommended by Cheun (2007); i.e.,  $\leq$  .015 and  $\leq$  .030, respectively. When we tested gender invariance separately for each country, the results showed non-invariance, especially at the scalar level. In these analyses, the CFI changes between the nested models were considerably above .01, although the RMSEA and SRMR, were below 0.06 and 0.08, respectively, which are the recommended thresholds (see Hu & Bentler, 1999).

Concerning civil status and occupation, although both variables provided fair evidence for metric invariance, our analyses revealed non-invariance at the scalar level, since the CFI changes between the models were above .01, which does not allow for a full cross-cultural comparison on trait EI even though the RMSEA and SRMR indices were again below 0.06 and 0.08 (see Hu & Bentler, 1999). Detailed results for these analyses are depicted in Table 4. PLEASE INSERT TABLE 4 HERE

#### Discussion

Our results revealed that despite some specific differences, the four datasets returned broadly similar results. ANOVA and follow-up pairwise comparisons exposed significant gender, age and civil status differences in most countries. The previous contrasts with the findings by Platsidou (2010), who reported non-significant effects for these sociodemographic variables on global trait EI in a sample of 123 school teachers in Greece, which is one of the few studies that examined the relationship between trait EI and other sociodemographic variables beyond gender and age. We argue that our results may be more reliable due to our larger sample sizes, better gender balances (excluding the Brazilian sample), broader age range, and the utilisation of a highly conservative statistic for pairwise comparisons (Hochberg's GT2), which is suitable for contrasting uneven groups.

Our study is methodologically comparable to Cooper and Petrides (2010), Pérez-Diaz & Petrides, 2019, Siegling et al. (2014), and Ugarriza (2001), researchers who reported small effect size effects for gender or age through ANOVA and pairwise comparisons. One novelty is our approach regarding trait EI differences by civil status and occupation, for which we have been unable to find comparable designs in the literature.

Regarding educational attainment, our results show some similarity to those of Petrides, Frederickson and Furnham (2004), who posed that trait EI is positively associated to academic performance, particularly in vulnerable groups of students. Similarly, Perera and DiGiacomo (2013) and MacCann et al. conducted two independent meta-analyses on the relationship between trait EI and academic performance, both concluding that trait EI has a positive effect. These findings provide a basis for understanding global trait EI differences across the levels of educational attainment found in Chile and Italy. Concerning occupation, the literature highlights that some professions, especially those related to leadership or educational roles, usually have higher levels of trait EI (Li et al., 2018; Platsidou, 2010; Siegling et al., 2014). Our results are broadly consistent with these findings, as can be observed in the subsample of teachers/lecturers scoring higher on global trait EI than other professionals both in Chile and in Italy.

Regarding measurement invariance, our analyses support strong cross-cultural invariance of trait EI (as measured by the TEIQue-SF) with respect to age, gender and education. The main advantages of our approach in comparison to previous relevant research (e.g., Siegling et al., 2015; Tsaousis & Kazi, 2013) are three. First, the implementation of a multidimensional baseline model, which included both the global and the factor levels of the construct, whereas previous research has modelled either a global score or factor scores exclusively. Second, the richness of our datasets, with participants coming from four different countries and being assessed in their respective native languages. Third, the strategy of testing for trait EI invariance beyond gender and age, which are the only two sociodemographic variables previously examined in this context.

Our study is not exempt from limitations. For instance, the sampling design was not representative, and thus, the levels within the sociodemographic variables were of unequal size, a limitation that we sought to – partially – address by the utilisation of Hochberg's GT2. With respect to the measurement invariance analyses, although it is possible to test all possible combinations of variables, we chose to adopt a pragmatic approach, since most variable combinations are of limited theoretical interest (Millsap, 2011). Furthermore, although our original datasets included sociodemographic variables with a considerable percentage of missing values, we aimed to counter this by the implementation of multiple imputation, an efficient technique that produces asymptomatically unbiased estimates and standard errors (White et al., 2010).

In summary, our ANOVA and post-hoc comparisons yielded results that are broadly in line with extant literature on trait EI and sociodemographic variables. Across four different countries as well as gender, age, education, civil status and occupation, trait EI latent variables were shown to be operationalised by qualitatively the same items (i.e., Configural invariance), and to have equivalent factor loadings (i.e., Metric invariance). Factor intercepts were comparable across country, gender, age and education (i.e., Scalar invariance), although we found evidence of non-invariance in the factor intercepts of occupation and civil status. This suggests that latent trait EI means diverged substantially across the different levels of the latter two variables, echoing our ANOVA results. Overall, our findings highlight the cross-cultural stability and validity of the trait EI construct, as measured by the TEIQue-SF, irrespective of cultural, linguistic, and other primary sociodemographic correlates. They also serve as a foundation for future research to continue scrutinising the role of trait emotional intelligence and its implications in widely different contexts, countries, and conditions.

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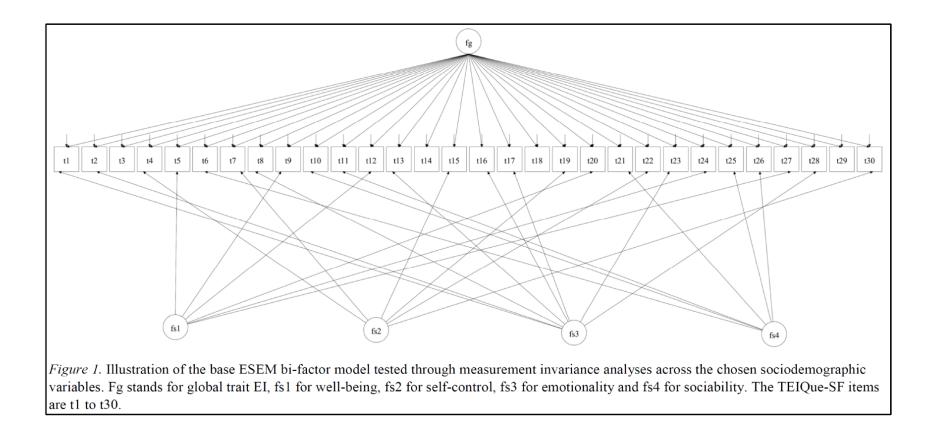
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Trait EI measure	Min	Max	М	SD	Skew	Kurt
1. Full cross-cultural dataset						
Global trait EI	2.00	7.00	4.85	0.77	-0.09	-0.28
Well-being	1.00	7.00	5.28	1.06	-0.57	0.20
Self-control	1.00	7.00	4.45	1.00	-0.11	0.01
Emotionality	1.63	7.00	4.94	0.98	-0.31	-0.33
Sociability	1.67	7.00	4.66	0.93	-0.06	-0.09
2. Brazil						
Global trait EI	2.27	6.73	4.83	0.79	-0.40	0.00
Well-being	1.00	7.00	5.38	1.18	-0.88	0.62
Self-control	1.00	6.83	4.14	1.08	-0.15	-0.35
Emotionality	2.25	7.00	5.15	0.89	-0.57	0.09
Sociability	1.67	7.00	4.57	0.94	-0.18	0.00
3. Chile						
Global trait EI	2.40	6.80	5.03	0.85	-0.19	-0.54
Well-being	1.00	7.00	5.43	1.17	-0.92	0.80
Self-control	1.33	7.00	4.76	1.05	-0.15	-0.14
Emotionality	2.13	7.00	4.98	1.03	-0.22	-0.51
Sociability	2.33	7.00	4.83	0.92	0.02	-0.50
4. Italy						
Global trait EI	2.73	6.53	4.53	0.74	0.41	-0.36
Well-being	2.00	7.00	4.86	0.98	0.08	-0.51
Self-control	1.33	7.00	4.33	0.89	-0.14	0.21
Emotionality	2.00	7.00	4.51	1.07	0.19	-0.66
Sociability	1.67	7.00	4.36	0.92	0.12	0.20
5. United Kingdom						
Global trait EI	1.67	7.00	5.41	0.90	-0.56	0.34
Well-being	1.67	7.00	5.41	0.90	-0.56	0.34
Self-control	1.83	7.00	4.57	0.92	-0.04	-0.03
Emotionality	1.63	7.00	5.05	0.87	-0.35	0.22
Sociability	1.83	7.00	4.82	0.89	-0.07	-0.10

Table 1Descriptive Statistics for the TEIQue-SF Datasets

*Note* . All descriptive statistics refer to the pooled imputation dataset. EI = emotional intelligence. Min = minimum, Max = maximum, M = mean, SD = standard deviation, Skew = skewness, Kurt = kurtosis.

# Table 2

Independent Samples t-Tests with Global Trait EI as the DV and Gender and Age as the Two IVs across the Four Countries

	t	df	MD	SE	d
			<u>Brazil</u>		
Gender	2.70**	510	0.21	0.08	0.27
Age	-	-	-	-	-
			<u>Chile</u>		
Gender	0.07	331	0.01	0.09	0.01
Age	3.32**	333	0.30	0.09	0.37
			<u>Italy</u>		
Gender	2.85**	513	0.19	0.07	0.06
Age	0.72	513	0.05	0.07	0.06
		<u>Uni</u>	ted Kinga	l <u>om</u>	
Gender	2.36*	864	0.11	0.05	0.16
Age	1.99*	864	0.12	0.06	0.17
Brazil a = t-test, differen	Ve did not s the clust df = degr ce, SE = s istic. All $p$ < .01.	ers were ees of fr tandard	severely eedom, M error, d =	unequal in ID = mean Cohen's c	n size. t n l effect

# Table 3 Global Trait EI Analyses of Variance (ANOVAs) by Education, Civil Status, and Occupation

			<u>Chile</u>					<u>Italy</u>				Un	ited Kin	<u>gdom</u>	
	М	SD	F	df	η2	M	SD	F	df	η2	M	SD	F	df	η2
Education			16.96**	3,331	0.133			5.39**	3,511	0.031			1.39	4,861	0.006
Secondary (a)	4.71	0.82				4.57	0.74				4.93	0.74			
University (b)	5.33	0.75				4.06	0.41				5.02	0.66			
Master (c)	5.36	0.78	b > a	$a^{**}, c > a$	**	4.69	0.71	c > a*,	$c > b^{**}, c$	$c > e^*$	5.05	0.61			
PhD (d)	-	-				-	-				4.86	0.59			
Other (e)	5.12	0.92				4.54	0.76				5.08	0.67			
Civil Status			5.68**	4,330	0.064			4.96**	3,511	0.028			2.28	4,861	0.010
Single (f)	4.90	0.86				4.50	0.71				4.97	0.69			
In a relationship (g)	5.01	0.78				-	-				4.97	0.64			
Married (h)	5.37	0.74	h >	f**, h >	*	4.60	0.74	f>i*,]	$h > i^{**}, j$	> i**	5.13	0.67			
Divorced/Separated (i)	5.07	0.80				3.75	0.42				4.77	0.71			
Other (j)	4.56	1.05				4.84	0.74				5.08	0.62			
Occupation			6.38**	5,329	0.088			12.46**	5,509	0.109			1.33	5,509	0.008
Private sector (k)	5.08	0.84				4.36	0.68				5.01	0.67			
Public sector (1)	5.02	0.76				5.10	0.70				5.10	0.70			
Teacher/Lecturer (m)	5.48	0.69		ı**, m>	**	5.49	0.65	$l > k^{**}, 1$	> o*, m >	• k**, m	5.09	0.68			
Student (n)	4.83	0.86	III > I	l···, m ≥ ]	p	4.75	0.74	> 0	**, n > k*	*	4.94	0.69			
Unemployed (o)	5.08	0.77				4.06	0.35				4.96	0.75			
Other (p)	4.58	0.92				4.37	0.68				5.01	0.66			

*Note*. We excluded the Brazilian dataset from these analyses, as it mainly comprised single undergraduate students. M =mean, SD = standard deviation, F = Fisher's statistic, df = degrees of freedom,  $\eta^2$  = eta squared-effect size measure. All p-values are two-tailed. \* p < .05. \*\* p < .01.

 Table 4

 Multiple Group Measurement Invariance Comparisons by Sociodemographic Characteristics

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Configural         2112.63         —         1168         0.891         —         0.052         —         0.048         0.055         0.038         —           Metric         2712.17         599.54         1543         0.865         0.026         0.050         0.002         0.047         0.053         0.061         0.023           Scalar         3224.79         512.62         1618         0.814         0.051         0.057         0.007         0.055         0.060         0.055         0.006           4. Age
Metric         2712.17         599.54         1543         0.865         0.026         0.050         0.002         0.047         0.053         0.061         0.023           Scalar         3224.79         512.62         1618         0.814         0.051         0.057         0.007         0.055         0.060         0.055         0.006           4. Age         Configural         1191.70         —         564         0.957         —         0.032         —         0.029         0.034         0.023         —           Metric         1391.19         199.49         689         0.952         0.002         0.030         0.002         0.033         0.032         —           Scalar         1524.89         133.70         714         0.945         0.007         0.032         0.030         0.034         0.033         0.001
Scalar         3224.79         512.62         1618         0.814         0.051         0.057         0.007         0.055         0.060         0.055         0.006           4. Age         Configural         1191.70         —         564         0.957         —         0.032         —         0.029         0.034         0.023         —           Metric         1391.19         199.49         689         0.952         0.002         0.030         0.028         0.033         0.032         0.009           Scalar         1524.89         133.70         714         0.945         0.007         0.032         0.002         0.030         0.034         0.033         0.001
4. Age         Configural       1191.70       —       564       0.957       —       0.032       —       0.029       0.034       0.023       —         Metric       1391.19       199.49       689       0.952       0.002       0.030       0.002       0.028       0.033       0.032       0.009         Scalar       1524.89       133.70       714       0.945       0.007       0.032       0.002       0.030       0.034       0.033       0.001
Configural         1191.70         —         564         0.957         —         0.032         —         0.029         0.034         0.023         —           Metric         1391.19         199.49         689         0.952         0.002         0.030         0.002         0.028         0.033         0.032         0.009           Scalar         1524.89         133.70         714         0.945         0.007         0.032         0.002         0.030         0.034         0.033         0.001
Metric         1391.19         199.49         689         0.952         0.002         0.030         0.022         0.028         0.033         0.032         0.009           Scalar         1524.89         133.70         714         0.945         0.007         0.032         0.002         0.030         0.034         0.033         0.001
Scalar         1524.89         133.70         714         0.945         0.007         0.032         0.002         0.030         0.034         0.033         0.001
5. Education
Configural 2302.09 — 1164 0.925 — 0.042 — 0.039 0.045 0.031 —
Metric 2722.92 420.83 1539 0.922 0.003 0.037 0.005 0.035 0.040 0.045 0.014
Scalar 2912.34 189.42 1614 0.915 0.007 0.038 0.001 0.036 0.040 0.047 0.002
6. Civil status
Configural 3145.93 — 1460 0.897 — 0.051 — 0.048 0.053 0.033 —
Metric 3807.78 661.85 1960 0.892 0.005 0.046 0.005 0.044 0.048 0.048 0.015
Scalar         4093.87         286.09         2060         0.881         0.011         0.047         0.001         0.045         0.049         0.050         0.002
7. Occupation
Configural 3041.44 — 1460 0.896 — 0.050 — 0.048 0.053 0.032 —
Metric 3565.67 524.23 1960 0.894 0.002 0.044 0.006 0.041 0.046 0.055 0.023
Scalar         3888.43         322.76         2060         0.880         0.014         0.045         0.001         0.043         0.048         0.058         0.003

*Note*. Model 1 = gender, N = 2226, NWomen = 1016, NMen = 1210. Model 2 = women, N = 1021. Model 3 = men, N = 1205. Model 4 = age, N = 2228. Model 5 = education, N = 2217. Model 6 = civil status, N = 2176. Model 7 = occupation, N = 2158.  $\chi^2$  = chi squared difference, df = degrees of freedom, CFI = comparative fit index,  $\Delta CFI$  = CFI difference, RMSEA = root mean square error of approximation,  $\Delta$  RMSEA = RMSEA difference, RMSEALb = RMSEA lower bound, RMSEAUb = RMSEA upper bound. SRMR = standardized root mean residual,  $\Delta$  SRMR = SRMR difference.