The Internal Structure of Responses to the Trait Emotional Intelligence Questionnaire Short-Form: An Exploratory Structural Equation Modeling Approach

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Abstract

Notwithstanding the wide use of the Trait Emotional Intelligence Questionnaire Short-Form (TEIQue-SF) as a brief assessment of trait emotional intelligence (TEI), the psychometric properties of this measure have not been systematically examined. The present article reports on research conducted to evaluate the latent structure underlying TEIQue-SF item data and test the gender invariance of scores as critical initial steps in determining the psychometric robustness of the inventory. In doing so, the paper demonstrates an application of exploratory structural equation modeling as an alternative to the more restrictive independent clusters model of confirmatory factor analysis for examining factorially complex personality data. On the basis of 476 responses to the TEIQue-SF, evidence was obtained for the multidimensionality of the inventory reflected in a retained correlated traits solution. Tests of gender invariance revealed equivalence of item factor loadings, intercepts, uniquenesses, correlated uniquenesses, and the factor variance-covariance matrix, but not latent means. Men were found to be moderately higher on self-control and sociability than women whereas women scored marginally higher on emotionality than men. No significant gender differences were found on mean levels of well-being. The benefits of the multidimensionality of the TEIQue-SF, limitations of the study and directions for future research are discussed.

Recent years have witnessed a good deal of interest in the affective construct of trait emotional intelligence (TEI). Indeed, the recent special issue on emotional intelligence (EI) published in *Personality and Individual Differences* (Vol. 65), with no fewer than seven articles devoted to TEI, is a testament to the continued popularity of the construct in the personality psychology literature. Notwithstanding this interest and an expanding body of applied research demonstrating the importance of TEI to various substantive criteria (e.g., academic and occupational success, psychological well-being, relationship satisfaction; Malouff, Schutte, & Thorsteinsson, 2014; Martins, Ramalho, & Morin, 2010; Perera & DiGiacomo, 2013), there remain concerns about the validity and measurement of the affective construct. One such concern is the latent structure of item response data derived from measures of TEI (Parker, Keefer, Wood, 2011).

An important starting point in the examination of any novel construct is the development of a measure based on rigorous and testable theory, and underpinned by evidence for factorial and construct validity. Although there are several instruments in the psychological literature purporting to measure TEI, many of these measures have under-theorized conceptual bases and inadequate psychometric properties (Petrides, 2009a). One promising set of measures is the family of TEIQue instruments, which are predicated on Petrides's (2011) model of TEI. These measures have been shown to produce internally consistent and temporally stable scores (Petrides, 2009a, 2009b); yet, the factorial structures of these instruments have not been established with a high degree of fidelity. This is because most existing analyses of the factor structures of the TEIQue instruments have not been conducted on item-level data but, rather, facet or subscale scores (e.g., Freudenthaler, Neubauer, Gabler, & Scherl, 2008; Mikolajczak, Luminet, Leroy, & Roy, 2007; Petrides, 2009a, 2009b). The analysis of sum-responses, even those based on a priori scoring keys, may mask the presence of item cross-loadings, residual covariances and other sources of potential model misspecification given the typical construct relevant and irrelevant multidimensionality of personality test items designed to measure multifactorial constructs (Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin, Arens, & Marsh, accepted). The failure to account for these sources of multidimensionality in item-level responses may obscure the true measurement structure underlying the acquired data, potentially leading to erroneous inferences about the latent structure of the construct under scrutiny and biases in relations with other substantively important constructs (Marsh, Lüdtke et al., 2013). Accordingly, existing validation work on the TEIQue measures may be contaminated to the extent that these item-level complexities have been ignored.

The present investigation is designed to redress these limitations in the extant TEI validation literature by examining the internal structure of one of the most widely used measures of TEI—the TEIQue-SF (Petrides & Furnham, 2006), at the item level. As mentioned by Parker et al. (2011), advances in EI-related research hinge on the availability of measures that are psychometrically robust. One property of a psychometrically sound measure is a theoretically meaningful and empirically supported factorial structure. Accordingly, this study first examines the factorial structure of the TEIQue-SF in line with the theoretical expectations implied by the a priori scoring key as well as theoretically plausible alternative measurement structures. The study then tests the measurement and structural invariance of TEIQue-SF item data across gender. Importantly, the current investigation harnesses the power and flexibility of the evolving exploratory structural equation modeling (ESEM) methodology given the known factorial complexity of the TEIQue-SF items, which, like most personality test items, are not pure unidimensional indicators of the construct they are purported to measure (Morin et al., 2014). In this regard, the investigation is a substantive-methodological synergy (Marsh & Hau, 2007).

TEI: Theoretical Grounding

The most important development in the EI literature in the past two decades has been Petrides and Furnham’s (2001) conceptual bifurcation of EI based on divergent approaches to psychometric measurement, resulting in two distinct perspectives on EI: ability EI and TEI. The ability EI perspective conceptualizes EI as a constellation of cognitive-emotional abilities located in extant frameworks of human intelligence (Petrides, 2011). This ability-based approach concerns the actual cognitive processing of emotional information as measured through maximal performance tests (Mayer, Salovey, & Caruso, 2008), in which participants rate the emotional content of various stimuli (e.g., faces) and solve problems involving emotional understanding and reasoning (e.g., MacCann & Roberts, 2008; Mayer, Salovey, & Caruso, 2002). Contrariwise, the TEI perspective conceptualizes EI as a collection of emotional dispositions and self-perceptions located at the lower stratums of existing personality hierarchies (Petrides, 2011; Petrides & Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). Dissimilar to the measurement of ability EI via maximal-performance, TEI is appraised via typical-performance measures (e.g., self or peer-report) akin to other personality constructs (Petrides, 2011; Pérez, Petrides, & Furnham, 2005). Although both perspectives on EI draw on overlapping affective content (e.g., emotion perception, expression and regulation), they are conceptually and empirically distinct constructs (Brackett & Mayer, 2003; Parker et al., 2011; Warwick & Nettlebeck, 2004). The present investigation is concerned with TEI.

TEI Models

Numerous theoretical models have been proposed to describe the construct of TEI. Among the most prominent is the Petrides (2010, 2011) model known as TEI theory. TEI theory aims to organize into a unifying framework all the affect-related aspects of personality, thereby serving an integrative function in the conceptualization of TEI (Mikolajczak et al., 2007). The Petrides model conceptualizes TEI as a multidimensional construct with a comprehensive construct content domain (Petrides, 2011). This content domain was derived from a content analysis of earlier models of EI and cognate affective-motivational constructs, such as alexithymia, empathy, optimism and self-motivation. From this theoretical perspective, TEI refers to a collection of relatively enduring affective-motivational personality traits. These traits reflect typical patterns of feelings, thoughts and behaviors related to the perception, regulation, management and expression of emotion-related information as well as dispositional tendencies towards sociability, positive emotionality, self-control, self-motivation, and holding generalized favorable outcome expectancies (Perera & DiGiacomo, 2013). The present research conceptualizes TEI in line with the TEI theory on which the TEIQue-SF is predicated.

The Structure of TEI

There are important assumptions about the structure of TEI from the TEI theory perspective that have not been sufficiently examined. TEI theory posits a hierarchical representation of TEI with a global construct at the apex of the hierarchy, encompassing interrelated sociability, self-control, emotionality and well-being dimensions at the first-order level, and finite affective-motivational dispositions at the base of the hierarchy (Petrides, 2009a). Notwithstanding this well-elaborated hierarchical latent structure, the current a priori scoring key for the TEIQue-SF implies a fully unidimensional structure of TEI, positing only one common source of variation in test items (Petrides & Furnham, 2006). As such, a common practice in the TEI literature is the aggregation of TEIQue-SF items to form a single composite or global TEI score (see e.g., Ali, Amorim, & Chamorro-Premuzic, 2009; Ferguson & Austin, 2010). Although a unidimensional item response theory model has been shown to fit TEIQue-SF data reasonably well and exploratory factor analyses (EFA) have yielded tentative support for a dominant TEI factor (Cooper & Petrides, 2010), this evidence for unidimensionality does not preclude the possibility of alternative, potentially better-fitting, measurement structures underlying the data, including a hierarchical representation as per TEI theory. Furthermore, it is widely recognized that unidimensional structures for psychological measures of high bandwidth constructs, such as TEI, are simply unrealistic (Marsh, Lüdtke et al., 2013). It would seem, then, that a comparison of the competing unidimensional and hierarchical representations of TEI is crucial to clarifying the latent structure underlying TEIQue-SF data.

Another theoretically plausible alternative measurement structure that is potentially applicable to TEIQue-SF responses is the correlated traits structure. The correlated traits model assumes that the first order primary traits are sufficiently distinct to be regarded as separate constructs (Reise, Moor, & Haviland, 2010), thereby precluding the aggregation of test items to form composite or global scores. As a high bandwidth construct that crosses several psychological systems (Parker et al., 2011), including emotions, cognitions and motives, and encompasses several interrelated, yet distinct, affective-motivational personality traits (Petrides, 2011), this multifactorial correlated traits structure may be most reasonable. Indeed, although predicated on a different theoretical model of TEI, Parker et al. (2011) found that a correlated factors representation of the Emotional Quotient Inventory: Short-Form (EQ-i:S) fit the sample data better than competing single-factor and higher-order models. Furthermore, there is increasing recognition that working with TEI at the global level, given the conceptual heterogeneity of the construct, may obscure the true nature of the construct and meaningful links with substantive outcomes (Downey, Johnston, Hansen, Birney, & Stough, 2010; Parker et al., 2011; Perera & DiGiacomo, 2013; Zeidner, Matthews, & Roberts, 2012). For example, it is unlikely that emotionality dispositions (e.g., emotion perception) will be implicated in primary-control engagement coping efforts to the degree of self-control dispositions (e.g., low impulsivity). It is also entirely possible that some dimensions (sociability vs. self-motivation) are associated with substantive criteria (e.g., achievement) in opposite directions (Chen, Hayes, Carver, Laurenceau, & Zhang, 2012). Thus, quite apart from the potential for the better fit of a correlated traits model to TEIQue-SF data, this measurement structure may be more theoretically informative and enhance fidelity.

In summary, three competing measurement structures may account for the dimensionality of TEIQue-SF data: (a) a unidimensional model in which variation in TEIQue-SF items is attributable to only latent TEI and no other substantive common construct; (b) a higher-order model in which TEIQue-SF item variance is due to a weighted combination of first-order factors reflected in a higher-order TEI factor; and (c) a correlated traits model positing sufficiently distinct, yet related, well-being, sociability, emotionality and self-control factors. Clarifying the factorial structure of the TEIQue-SF is a crucial first step in determining the psychometric robustness of the measure. Thus, these three competing measurement structures are tested and compared in the present investigation.

Psychometric Multidimensionality and the Appropriateness of ICM-CFA

An important issue in examining the latent structure of any item response data is the appropriateness of the conventional independent clusters model of confirmatory factor analysis (ICM-CFA). When seeking to examine a priori factor structures, researchers typically proceed with conventional CFA tests that are predicated on an independent clusters model in which each item is postulated to load on only one factor, with item cross-loadings (i.e., non-target loadings) constrained to zero (Marsh et al., 2010; Morin, Marsh, & Nagengast, 2013). Notwithstanding the wide use of this analytic formulation for testing a priori factorial structures, it has been recognized, at least for the past two decades, that the ICM-CFA specification may be too restrictive for data acquired from multidimensional personality instruments (Church & Burke, 1994; Marsh et al., 2010; McCrae, Zonderman, Costa, Bond, & Paunonen, 1996). This is because personality test items are often imperfect indicators of the single construct they are purported to measure and will show some systematic association with non-target constructs (Hopwood & Donnellan, 2010). This source of construct-relevant psychometric multidimensionality in personality items tends to be amplified in measures of theoretically complex constructs, such as TEI, comprising multiple conceptually-related dimensions, with such complexity manifested in item multidimensionality (Morin et al., 2014). For these measures in particular, ICM-CFA assumptions might be too restrictive to adequately account for the fallibility of items, which, when allowed to do so, will systematically associate with constructs other than those they were intended to measure. In EFA, this source of psychometric multidimensionality can be sufficiently accounted for via item cross-loadings; however, in ICM-CFA, these cross-loadings are constrained to zero.

The failure to specify these secondary loadings in ICM-CFA tests typically manifests as model-data misfit and inflated factor correlations. Several recent investigations have found that widely-used personality inventories, such as the NEO FFI (Marsh et al., 2010; Rosellini & Brown, 2011), NEO PI-R (Furnham et al., 2012) and HEXACO-PI (Hopwood and Donellan, 2010), though showing acceptable fitting ESEM/EFA structures underlying the data, have not been supported under the assumptions of ICM-CFA. This model misfit is a function of error propagation generated by the misspecification of zero cross-loadings in the ICM-CFA framework. In addition to model misfit, the constraint of secondary loadings to zero assumed in the ICM-CFA can lead to inflated factor correlations, resulting in erroneous inferences about the discriminant validity of factors, the tenability of higher-order representations and even direct structural relationships between constructs in latent space (Morin et al., 2013; Marsh, Morin, Parker, Kaur, 2014). This is because a true relation between an item and non-target factor that should be accounted for through a cross-loading can only be expressed as a factor correlation in the ICM-CFA (Marsh et al., 2010). The higher the true item cross-loading, the greater the inflation of factor correlations when the non-target loading is constrained to zero.

As the TEIQue-SF is a multidimensional personality inventory comprising 30 seemingly dimensionally complex items that aim to appraise four conceptually-related, but distinct, constructs, the ICM-CFA may not be an appropriate analytic model for examining the latent structure underlying the instrument's data. Indeed, a cursory inspection of the TEIQue-SF item content provides good reason to expect construct-relevant item multidimensionality, which may be reflected in non-trivial cross-loadings. Take, for instance, Item 28 ("I find it difficult to bond well even with those close to me”), which is postulated to primarily load on emotionality. This item will also likely non-trivially load on sociability, reflecting social sensitivity and a preference for social interaction. Likewise, Item 19 (“I’m usually able to find ways to control my emotions when I want to”), which is designed to measure self-control may also tap lower emotionality, which is concerned, in part, with the expression of emotions. Yet another example is Item 15 (“On the whole, I am able to deal with stress”), which is designed to measure self-control. This item will also likely non-trivially load on the dispositional well-being factor, reflecting generalized wellness. An alternative analytic approach to the ICM-CFA that accounts for this presumed psychometric multidimensionality due to item fallibility may thus be required to sufficiently examine the latent structure underlying TEIQue-SF item data. Indeed, it has increasingly been recognized that items with no cross loadings or other sources of psychometric multidimensionality (e.g., method effects), especially those from multi-item, multidimensional instruments, are a “convenient fiction” (Morin et al., 2014, p. 32; see also Marsh et al., 2014). Statistical models must then be sufficiently accommodating to account for this psychometric complexity in items.

ESEM is an alternative analytic framework for examining the latent structure underlying data derived from multifactorial personality measures. The ESEM approach differs from the standard ICM-CFA approach to the extent that (a) all primary and non-target loadings are freely estimated, conditional on the imposition of minimal identifying restrictions, and (b) EFA factors can be rotated (Morin et al., 2013; Marsh et al., 2014; see Asparouhov & Muthén, 2009 for technical details). In this regard, ESEM provides a less restrictive framework for examining the latent structure underlying data, which can sufficiently account for the factorial complexity of multidimensional test items. As ESEM represents an integration of EFA within a general structural equation modeling (SEM) framework, the statistical features of SEM, including, but certainly not limited to, SEM parameter estimates, standard errors, fit indices, the modeling of error covariances, and tests of invariance between groups and across time are also available in the ESEM framework (see Morin et al., 2013; Marsh et al., 2014). ESEM, then, may be a particularly relevant analytic approach for investigating the latent structure of TEIQue-SF item response data given the assumed construct-relevant psychometric multidimensionality of the constituent items.

Gender Differences in TEI

There have been some gender differences observed in TEI. A relatively consistent finding is that women score higher than men on the emotionality factor (Mikolajczak et al., 2007; Petrides, 2009a; Petrides & Furnham, 2000). There is also some evidence that men score higher than women on the sociability and self-control factors, and that no gender differences exist on the dispositional well-being factor (Petrides, 2009a; Mikolajczak et al., 2007). For the gender differences observed, effect sizes tend to be small to medium, ranging from d = 0.30 for emotionality and d = 0.37 for sociability to d = 0.57 for self-control (Petrides, 2009a).

One limitation that may undermine inferences about true mean differences across gender in TEI drawn from these results is that they are based on manifest-variable analytic approaches (e.g., t-tests). These approaches do not explicitly test for, yet assume, that the measurements of TEI across gender are factorially invariant (Marsh et al., 2014; Meredith, 1993). If the quality of the TEI factor is not equivalent across gender (i.e., the construct is qualitatively different), mean differences between men and women in TEI are largely unintelligible (Marsh et al., 2010). Furthermore, even when equivalence of the factorial structures is demonstrated across gender (e.g., Tsaousis & Kazi, 2013), reliance on ICM-CFA evidence for this determination of factorial invariance may be problematic. This is because ICM-CFA measurement structures with misspecified zero secondary loadings can lead to distorted factors and inflated factor correlations (Morin et al., 2013), thereby potentially obfuscating inferences regarding the equivalence or non-equivalence of factor variances and covariances and latent means across gender. In the present investigation, the complete measurement and structural invariance of TEIQue-SF data across gender is tested, with a focus on factor mean differences, based on the retained measurement solution.

The Present Study

The present research is centrally concerned with evaluating the internal structure and complete factorial invariance (across gender) of TEIQue-SF data. To this end, the study first examines competing unidimensional, correlated-traits and higher-order structural representations of the TEIQue-SF using both CFA and ESEM analytic approaches. The assumption that ESEM models fit the sample data better than CFA analogues is examined given the expected construct-relevant psychometric multidimensionality of the TEIQue-SF items due to their fallibility as indicators of single constructs. The retained solution is then subject to tests of measurement and structural invariance across gender.

Method

Participants and Procedure

Participants were 496, predominantly freshman (95%), students enrolled in a metropolitan university in eastern Australia. The mean age of the participants was 17.87 years (*SD* = .89; range 16 – 23), and 62.3% (*n* = 309) of the sample was female (one student did not report their gender). Students were recruited by research assistants during orientation-week activities, and also via instructor announcements at introductory coursework lectures, as part of a larger study on the "adjustment experiences of new undergraduates". Students were advised that participation required the provision of consent to partake in the research and the completion of online batteries of questionnaires over the autumn semester. TEI data were collected during the first week of the semester.

Measure

TEI. The TEIQue-SF (Petrides, 2009a; Petrides & Furnham, 2006) provides a rapid assessment of TEI predicated on Petrides's (2011) theoretical model of TEI. The measure comprises 30 items, responded to on a seven-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The TEIQue-SF was designed to primarily yield a global index of TEI via the aggregation of the 30 constituent items. However, an alternative scoring key exists that allows for the computation of subscale scores. According to this alternative approach, 26 of the 30 items are assigned to one of the following four subscales: Emotionality (eight items); Sociability (six items); Self-control (six items); Well-being (six items). The four remaining items contribute to only the cumulative TEI score. In the present sample, the coefficient alpha reliability for the total TEIQue-SF score was .88, which converges with internal reliabilities reported by Petrides (2009a) and Petrides et al. (2010) in validation work.

Statistical Analysis

Analyses were conducted in two phases in line with the study aims. In the first phase, ICM-CFA and ESEM analyses of responses to the TEIQue-SF were conducted to test the absolute and relative fit of the unidimensional, second-order and correlated-traits measurement structures. Of particular focus is the comparison of the complex ESEM solutions with their more parsimonious CFA analogues. The reader should note that, in the case of a one-factor model (i.e., the unidimensional model in the present study), the ESEM specification is equivalent to the ICM-CFA representation.

One complication in specifying the correlated-traits CFA and ESEM structures is the treatment of Items 3, 14, 18 and 29 of the TEIQue-SF. Because these items do not index any TEI subdimension, contributing to only the general TEI score, it is unclear how they should be modeled in the correlated-factors structure. Previous CFAs of TEIQue data have simply omitted these items from correlated-factors models (e.g., Freudenthaler et al., 2008); however, this approach does not provide a true test of the internal structure of TEIQue-SF responses to the extent of item omission, and precludes nested model comparisons with the alternative measurement structures. To accommodate the full 30 items in the correlated-traits CFA and ESEM models, these four items were simply specified to correlate with each other and with the four first-order factors.

A second specification complexity concerns the ESEM representation of the higher-order model. Current operationalizations of ESEM in statistical software programs do not allow for the specification of higher-order models. To circumvent this limitation, Marsh, Nagengast and Morin's (2013) ESEM-within-CFA (EwC) approach was used. EwC involves importing a rotated ESEM measurement structure into a conventional CFA framework, thereby allowing for full CFA functionality with ESEM factors (Marsh, Nagengast et al., 2013; Marsh et al., 2014; Morin et al., 2013). Consistent with the EwC approach, final rotated estimates of factor loadings and residual variances from a correlated-factors ESEM solution were used as starting values for the first-order factors in a conventional CFA environment subject to m^2 identification restrictions, where m is the number of factors. A higher-order general factor was then fit onto the four first-order factors. In the EwC specification, the m^2 identification constraints can be achieved by (a) fixing the first-order factor variances to 1.0 and (b) constraining the cross-loadings of one-item per factor to be equal to their values from the ESEM solution (see Morin et al., 2013 for further details). Typically, the primary loading for the target item should be high and the cross-loadings small.

For all three measurement structures, across both CFA and ESEM specifications, several sets of correlated residuals were specified a priori. In developing the TEIQue-SF, Petrides (2009a) selected two items from the full form TEIQue, measuring each of the fifteen TEI facets, based on their item-facet-score correlations. Although the TEIQue-SF is not designed to measure these TEI facets, it is likely that any two items from the same facet have higher correlations than those from different facets, by virtue of their high content overlap, with potentially some systematic common variance unexplained by the factors. In the present study, this presumed intradimensional local dependence due to facet clusters was accounted for by specifying 15 correlated residuals linking each pair of items from the same facet. The failure to specify these sources of common variation can lead to inflated factor correlations (Marsh et al., 2010). For the unidimensional and higher-order model specifications, all 15 correlated residuals were freely estimated. For the correlated-traits models, only 13 of the 15 correlated residuals were estimated. The correlated uniquenesses for Item 3 with Item 18 and Item 14 with Item 29 could not be specified because these items have no residual components in the correlated-factors structure.

The second phase of the analytic protocol involved tests of measurement invariance of the retained factorial solution across gender. These multigroup tests were conducted in line with Marsh et al's (2009) taxonomy of invariance tests for ESEM. This taxonomy comprises 13 partially nested models ranging from the least restrictive model of configural invariance, comprising no invariance constraints, to a model of complete factorial invariance, including invariances of the factor loadings, item intercepts, item uniquenesses, factor variances-covariances, and factor means. Although complete factorial invariance is tested in the present study, the primary interest is in comparing latent means across gender; thus, only strong factorial invariance is required in principle (Morin et al., 2013).

Analyses in the present investigation were conducted using Mplus 7.2 (Muthén & Muthén, 1998 – 2012). All CFA and ESEM solutions were estimated using robust maximum likelihood estimation, operationalized as the MLR estimator in Mplus, which (a) produces standard errors and tests of model fit that are robust to nonnormality of the observed data and (b) implements full information maximum likelihood to account for missing data (Muthén & Muthén, 1998 – 2012). This estimation routine is appropriate when there are at least five response categories characterizing the sample data (Rhemtulla, Brosseau-Liard, & Savalei, 2012). The ESEM analyses were carried out using target rotation, which is suitable when there is at least some knowledge of the a priori factor structure as in the present case (Browne, 2001; Marsh et al., 2014). Specifically, all cross-loadings—that is, loadings of items on factors they were not designed to primarily index as per the a priori scoring key—were "targeted" to be approximately zero, whereas the primary loadings were freely estimated. This gives a somewhat confirmatory "flavor" to the ESEM analyses as it fosters the pre-specification of target and non-target loadings (Morin et al., 2014). It should be noted that, in target rotation, though loadings specified to be approximately zero are forced to be as close to zero as possible, they are not constrained to zero as in the ICM-CFA. Indeed, in principle, cross-loadings targeted to be zero can result in appreciably different values if the zero specification is not suitable (Asparouhov & Muthén, 2009). This should be particularly advantageous in controlling for psychometric multidimensionality due the fallibility of indicators (Morin et al., 2014).

Given the sample size dependency of the chi-square statistic and its restrictive hypothesis test (i.e., exact fit), the fit of the alternative measurement structures was evaluated in line with the approximate fit approach using both common goodness-of-fit indices and information criteria. Specifically, the fit assessment relied on the widely-used comparative fit index (CFI), Tucker-Lewis index (TLI), standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA) with associated 90% confidence intervals, Akaike Information Criterion (AIC; Akaike, 1987), the Bayesian Information Criterion (BIC; Schwartz, 1978), and sample-size adjusted BIC (saBIC; Sclove, 1987). For the goodness-of-fit indices, the following guidelines were employed to determine the degree of model fit: CFI > .90, TLI > .90, RMSEA < .08, SRMR <.10 for acceptable fit; and CFI > .95, TLI > .95, RMSEA < .05, SRMR < .08 for excellent fit (Browne & Cudeck, 1993; Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004). Comparisons of measurement structures were based on changes in not only the CFI (ΔCFI) with decreases of less than .01 indicating support for the more parsimonious model (Cheung & Rensvold, 2002), but also the information criteria, with lower values indicative of better fit to the data (Morin et al., 2014).

Results

TEIQue-SF Factor Structure

Diagnostic analysis. Twenty cases were identified as multivariate outliers on the TEIQue-SF indicators via inspection of squared Mahalanobis distance statistics (> $D_c^2(30) = 60.08$, $p < .001$). Additionally, Cook's D and log likelihood contribution statistics showed these cases to contain influential observations. Thus, the 20 cases were removed from the data set, leaving 476 cases available for further analysis. Across the remaining cases, there was nearly complete data on the TEIQue-SF (< 1% missing). FIML estimation was used to account for this trivial missingness (Enders & Bandalos, 2001). Finally, Mardia's normalized multivariate kurtosis estimate of 27.15 and Yuan, Lambert and Fouladi's (2004) normalized coefficient of multivariate kurtosis of 108.41 exceeded the recommended cut-off of 3.29. This suggests a joint distribution of the TEIQue-SF responses data that departs from normality, thereby necessitating the use of robust ML. The FIML correlation matrix of the 30 TEI indicators, with means and standard deviations, can be obtained from the author upon request.

Primary analysis. Results of the fit of the measurement structures are shown in Table 1. The unidimensional solution that is common to both the ICM-CFA and ESEM specifications did not provide an acceptable fit to the sample data. Similarly, the tests of the ICM-CFA higher-order and correlated-traits models resulted in an unacceptable fit to the data. On the contrary, the higher-order and correlated-traits ESEM models provided an acceptable fit to the data. In relative terms, the higher-order and correlated traits ESEM solutions provided an appreciably better fit to the data than their ICM-CFA analogues according to both the goodness-of-fit indices and information criteria.

INSERT TABLE 1 ABOUT HERE

A comparison of the estimates obtained from the ICM-CFA and ESEM solutions is informative. For the higher-order structure, the pattern of first order factor loadings was similar across ICM-CFA and ESEM solutions (profile similarity index [PSI] = .710). ICM-CFA first-order factor loadings (median [*Mdn*] = .518) were only marginally stronger than corresponding ESEM target loadings (*Mdn* = .502). On the contrary, the ICM-CFA second-order loadings (*Mdn* = .815) were substantially higher than those obtained from the ESEM solution (*Mdn* = .550). Notably, the standardized second-order loading of emotionality on global TEI, which was strong and statistically significant in the ICM-CFA solution ($\lambda = .751$, $p < .001$), was much smaller and non-significant in the ESEM solution ($\lambda = .22$, $p > .05$). In the correlated traits solution, though the pattern of factor loadings was similar across ICM-CFA and ESEM models (PSI = .708), ICM-CFA correlations (*Mdn* = .664) were systematically stronger than those observed in the ESEM solution (*Mdn* = .276). Given not only the theoretical consistency of the factor correlations obtained in the ESEM solution, in terms of support for the multidimensionality perspective underlying TEI (Parker et al., 2011), but also the superior fit of the ESEM structures to the sample data, these measurement solutions were preferred to the ICM-CFA structures.

The higher-order and correlated traits ESEM measurement structures were compared to determine the best-fitting solution. Although both solutions showed reasonable absolute fit to the sample data, the correlated traits model provided a superior fit relative to the higher-order structure in terms of changes in the fit indices and information criteria (see Table 1). Furthermore, from a substantive standpoint, the higher-order solution is unappealing because the second-order loading of emotionality on the global TEI factor was small and non-significant, indicating a partial collapsing of the higher-order factor. On these bases, the correlated traits model was retained as the best representation of the latent structure underlying TEIQue-SF responses. Standardized factor loading and factor correlation estimates from the retained ESEM correlated traits model are shown in Table 2. Twenty-one of the 26 target factor loadings were statistically significant (at $p < .05$); only the target loadings for one indicator of self-control (Item 30) and four indicators of emotionality (Items 2, 17, 8 and 23) were non-significant. Importantly, the target factor loadings (*Mdn* = .421) were systematically larger than the non-target loadings (*Mdn* = .068). In the final solution, the four factors were positively and statistically significantly correlated; however, the magnitudes of these associations are well below current and previous estimates based on the ICM-CFA specification and much more consistent with the construct's purported conceptual multidimensionality (see Table 2). Furthermore, as shown in

Table 2, there was a good deal of distinctiveness across the ESEM and CFA solutions in the content of the self-control, emotionality and sociability factors, though not the well-being factor, as indexed by factor score correlations. Finally, it is instructive to note that nine of the 13 estimated a priori correlated residuals were statistically significant in this solution.

INSERT TABLE 2 ABOUT HERE

Measurement and Structural Invariance

The measurement and structural invariance of the retained correlated traits ESEM structure across gender was tested, with a specific focus on examining latent mean differences.[1] One case had no data on gender and was omitted from the invariance tests, leaving 475 cases available for analysis. As shown in Table 3, the configurally invariant model (MGM1) with no parameters constrained to equality across groups provided a marginally acceptable fit to the data, indicating a reasonably similar pattern of target and non-target item-factor loadings across groups. This baseline model was compared to the more restrictive weak factorial invariance model (MGM2) in which factor loadings were constrained to be equal across groups. The weak invariance model did not result in a decrease in fit relative to the configural model, suggesting that the factor loadings were equivalent for males and females. In fact, the TLI (ΔTLI = .038) increased and the RMSEA (ΔRMSEA = .008) decreased, which is not entirely unexpected given that each of these fit indices incorporates a parsimony correction (West, Taylor, & Wu, 2012).

[1] Although the correlated traits ESEM model was retained in the present study and subjected to tests of invariance, because the higher-order model is the most prevalent structure of TEI in the literature, it is informative to summarize results of invariance tests of the higher-order ESEM structure. These equality analyses were conducted in accordance with the taxonomy of invariance tests for second-order factor models proposed by Chen, Sousa and West (2005), adapted for ESEM in an EwC framework. Marginal support was found for the configurally invariant higher-order model (model 1). In addition, evidence was obtained for the invariance of first-and-second-order factor loadings (models 2 and 3, respectively), intercepts of the observed indicators (model 4) and intercepts of first-order factors (model 5), though, for the latter model, the decrement in the CFI approached one (ΔCFI = –.009). Support was also found for the equality of item uniquenesses (model 6), first-order factor disturbances (model 7) and item correlated uniquenesses (model 8). Finally, evidence was obtained for the invariance of the second-order factor variance (model 9) and mean (model 10). Although the absence of appreciable changes in fit between models 9 and 10, with and without latent means constrained to equality, respectively, is indicative of the invariance of the higher-order factor mean, it is instructive to note that the inspection of model 9 revealed that men had trivially higher levels of GTEI than women (d = .175). However, caution is urged in the interpretation of these invariance tests, particularly those concerning model 5, as the CFI, used in the present study to detect appreciable differences between nested models, has been reported to be insensitive to mean structures, such that differences in the intercepts of observed and latent variables may not be detected (Chen et al., 2005). This may, in turn, obfuscate conclusions regarding the invariance of the higher-order latent mean. Complete results of the higher-order invariance tests may be obtained from the author by request.

The weak factorial invariance model was compared to an even more restrictive model of strong measurement invariance (MGM3) in which the item intercepts, as well as factor loadings, were constrained to equality across groups. This is a particularly important test of invariance as findings of intercept nonequivalence would be suggestive of differential item functioning, thereby precluding the comparison of latent means. MGM3 provided an acceptable fit to the data in absolute terms. Furthermore, this model did not result in a decrement in fit relative to the less restrictive weak factorial invariance model (ΔCFI = .000), indicating the equivalence of indicator intercepts over gender.

Next, strict measurement invariance was tested, which assumes the additional equivalence of item uniquenesses. Although strict factorial invariance is not a necessary assumption for the examination of differences in latent means, it is a prerequisite to the comparison of manifest scale mean scores that contain measurement error. The test of this model (MGM4) resulted in an acceptable fit to the data (see Table 3), and no decrement in fit relative to the less constrained MGM3. These findings support the generalizability of TEIQue-SF residual item variances across gender. A second model of strict measurement invariance (MGM5) was tested in which additional equality constraints were imposed on the 13 a priori specified correlated uniquenesses. This model provided a near identical fit to the sample data as the initial strict factorial invariance model, indicating the equivalence of correlated uniquenesses across gender.

The model of strict factorial invariance with added equality constraints on the correlated residuals was compared to an even more restrained model (MGM6) postulating the additional equivalence of the factor variance-covariance matrix. Although the tenability of the assumption of equivalent variance-covariance structures is not required for comparing factor means, this test is important in its own right to the extent that differences in the pattern of factor covariances across gender may hold implications for the discriminant validity of multifactorial constructs. The test of this model resulted in an acceptable fit to the sample data (see Table 3), and did not result in a decrement in fit relative to MGG5. These findings provide support for the invariance of the TEIQue-SF factor variance-covariance matrix.

The final model (MGM7) constrained the factor means to equality across groups in combination with the factor loadings, item intercepts, item uniquenesses, correlated residuals, and factor variances and covariances. This test of full measurement invariance resulted in an acceptable fit in absolute terms (see Table 3); however, the model led to a non-trivial decrement in fit (e.g., ΔCFI = –.011) relative to MGM6 with factor means free to vary between groups. Thus, MGM7 with the factor means constrained to equality was rejected in favor of MGM6. Evaluation of the group factor means based on the retained solution revealed some gender differences. As expected, women scored higher than men on emotionality, though this effect was small (d = .300); men scored moderately higher than women on both self-control (d = .491) and sociability (d = .483); and there were no statistically significant differences between men and women on well-being (d = .056).

INSERT TABLE 3 ABOUT HERE

Discussion

Notwithstanding the wide use of TEIQue instruments for the measurement of TEI, no studies have examined the factorial validity of these measures at the item-level using statistical methods appropriate for the assumed construct-relevant psychometric multidimensionality of the constituent items. The present study represents the first systematic attempt to evaluate the internal structure of TEIQue-SF item response data and examine the stability of the factorial structure over gender using the evolving ESEM methodology (Asparouhov & Muthén, 2009; Morin et al., 2013; Marsh et al., 2014). This analytic approach accounts for the dimensional complexity of multifaceted personality test items, which almost always load on more than one construct (Hopwood & Donnellan, 2010). The results of the present investigation suggest that TEIQue-SF item data are best represented by a multidimensional measurement structure that is invariant across gender; yet, important gender differences exist on mean levels of the TEI factors. The present study also illustrates some advantages of ESEM over conventional ICM-CFAs in examining the latent structure of multidimensional personality item data.

ESEM vs. ICM-CFA

On the basis of prior theory and research, three alternative measurement structures presumed to underlie TEIQue-SF data were tested using both ESEM and ICM-CFA approaches. No support was found for the unidimensional representation of TEI implied by the TEIQue-SF scoring key. Furthermore, no support was found for the conventional ICM-CFA specifications of the higher-order and correlated traits measurement models. On the contrary, the ESEM specifications of both the higher-order and correlated traits models were shown to be adequate structural representations of the TEIQue-SF data. The fit of these ESEM models was substantially greater than the fit of their ICM-CFA analogues, which is due primarily to the specification of non-zero item cross-loadings in the ESEM approach (Marsh et al., 2014). Indeed, the erroneous restriction of (non-zero) non-target loadings to zero is a major source of model misspecification inherent in CFAs of multifactorial personality measures that leads to model misfit (Marsh et al., 2010). The present research then provides another example of a multidimensional personality inventory that, although performs poorly when evaluated using conventional CFA, fits under the less restrictive assumptions of ESEM (see Marsh et al., 2010; Marsh, Nagengast et al., 2013 for examples). Thus, this research contributes to a bourgeoning literature suggesting that the ICM-CFA may be too restrictive for multidimensional personality item response data.

Quite apart from superior model fit, the ESEM approach has important advantages over the ICM-CFA approach in basic parameter estimation. Increasing empirical and simulation evidence shows that, even when ICM-CFA representations of multifactorial scale data fit the sample data, factor correlations can be upwardly biased (Marsh et al., 2009, 2010, 2011, 2014; Marsh, Lüdtke et al., 2013; Morin et al., 2013; Morin & Maïano, 2011). The data obtained in the present study is consistent with this evidence. Specifically, for the correlated traits model, the ESEM solution resulted in considerably less correlated factors (*Mdn* r = .276 vs. .664) that are in line with the non-homogeneity of the construct content domain (Parker et al., 2011; Petrides, 2011). Furthermore, for the higher-order model, second-order factor loadings, which are a function of first-order factor correlations, were substantially stronger in the ICM-CFA solution than the ESEM solution (*Mdn* λ = .815 vs .550). Except in the unusual case when non-target item loadings are uniformly zero across a multidimensional personality measure, ICM-CFA factor correlations will be inflated. This inflation may lead to erroneous conclusions about (a) the discriminant validity of the factors, (b) the tenability of higher-order representations, and (c) the predictive validity of the factors due to problems with multicollinearity (Marsh et al., 2014). These results also raise the possibility that existing estimates of TEI factor correlations in the extant literature based on the ICM-CFA and even manifest scale scores, in which items belong to only one scale, may be inflated (Lee & Ashton, 2007; Marsh et al., 2010). In the latter case, the degree of inflation may be obscured by any attenuation of correlations due to measurement unreliability.

ESEM may also enhance construct estimation. A notable set of findings in the present study is that the factor content of three of the four TEI factors varied appreciably across the CFA and ESEM analytic methods. Indeed, the proportion of shared variance between factor score estimates for self-control, emotionality and sociability derived from the CFA and ESEM solutions ranged from only 52% to 78%. This suggests that the cross-loadings loadings estimated under the ESEM model contribute non-trivially to the definition of these latent constructs (Booth & Hughes, 2014). For the self-control factor, substantive cross-loadings (i.e., those > .25 and theoretically meaningful) were observed for items from the sociability and emotionality subscales. The additional sociability item reflects the extent to which people are assertiveness, which is, notably, also reflected in the lower pole of self-control as a tendency for low scorers to avoid situations rather than directly deal with associated tensions. Additionally, the substantive emotionality item cross-loadings concern rumination and emotional knowledge, which may be related to the emotional control reflected in self-control. For the sociability factor, there were multiple substantive cross-loadings from items initially designed to measure all other factors. The cross-loadings of well-being items, which appear to tap the favorability of self-evaluations, may reflect the possibility that such evaluations tend to involve, at least in part, appraisals of personal strengths and qualities related to social relationships. Furthermore, the additional emotionality and self-control item loadings on sociability concern emotional expression, empathy and affect regulation that would seem central to the social awareness and communication that is involved in sociability (Matthews, Zeidner, & Roberts, 2012). Finally, for the emotionality factor, substantive cross-loadings were observed for two items—one designed to measure sociability and the other well-being. The additional sociability item loading concerns the degree of individuals’ assertiveness, which would seem to be involved in the expression of emotions, particularly in social settings, whereas the additional well-being loading concerns the absence of negative expectancies for future events, which may be related to one's sensitivity to their own emotional state (Beck, Weissman, Lester, & Trexler, 1974). Several further smaller, yet substantively meaningful, cross-loadings were observed for these factors. Taken together, the cross-loadings appear to allow for the estimation of the latent variables using all the available indicator-level information (Morin et al., 2014).

The finding of several appreciable and substantively meaningful cross-loadings raises the possibility that these parameters may have been specified a priori on the basis of theoretical expectations within a more parsimonious CFA framework (Booth & Hughes, 2014). As noted by Booth and Hughes (2014), the a priori specification of theoretically defensible cross-loadings in a CFA model should be preferred to the ESEM specification of all possible cross-loadings, some of which may be small, non-significant and substantively meaningless. This is for at least two reasons. First, any cross-loading specified a priori on the basis of substantive considerations that is supported by the data provides stronger evidence for the parameter as a true parameter by virtue of its hypothesis-driven orientation. Second, in the service of preserving scientific parsimony, the a priori inclusion of only theoretically defensible cross-loadings should minimize the estimation of trivial and atheoretical loadings that may reflect mere sampling idiosyncrasies (Booth & Hughes, 2014). Indeed, in the present study, though several appreciable and theoretically meaningful cross-loadings were found, a greater number of null or near null loadings were observed, which do not appear to contribute to the definition of the latent constructs. It is acknowledged, however, that, in highly complex multidimensional, multi-item instruments, not all construct-relevant psychometric multidimensionality due to item fallibility may be identified a priori. In these cases, ESEM with target rotation appears to be a reasonable analytic option as it is possible to specify hypotheses regarding the postulated factor structure (i.e., patterns of non-zero and approximately zero loadings) in a confirmatory fashion, but allow cross-loadings targeted to zero to deviate from zero should the initial null specification be unsuitable (Morin et al., 2014). Loadings targeted to zero that show substantial deviation from zero may then become the object of systematic inquiry for theoretical relevance and replicability.

The Multidimensionality of the TEIQue-SF

Although both the higher order and correlated traits ESEM solutions were found to be acceptable structural representations of the TEIQue-SF data in absolute terms, model comparisons using both approximate fit indices and information criteria revealed that the correlated traits model fit the sample data appreciably better. Furthermore, substantively, the higher-order solution is unappealing because the second-order loading of emotionality on global TEI was small and non-significant. Given the centrality of the emotionality dimension to TEI from the perspective of TEI theory, the high-order solution seems theoretically untenable. On these bases, the correlated traits model was retained as the preferred factorial solution. This result is in line with the recent work of Parker et al. (2011) who found support for a correlated factors representation of TEI based on data from the EQ-i:S, and has important implications for TEI theory and measurement. Although TEI theory posits a hierarchical structure of TEI (Petrides, 2009a), as a high bandwidth meta-construct with a content domain that spans multiple psychological systems and comprises diverse affect-motivational traits (Petrides, 2011), a higher-order representation of TEI, with a single, global TEI factor at the apex of the hierarchy, is unlikely to adequately reflect the theoretical complexity of TEI. Indeed, the findings of largely weak to moderate factor correlations in the retained correlated traits solution may be indicative of insufficient common variation among the TEI subfactors to infer the presence of some shared underlying trait. The correlated traits structure may, then, be more in line with the conceptual heterogeneity of TEI (Parker et al., 2011).

The multidimensional representation of TEI implied by the correlated traits structure offers critical advantages to TEI theory development and empirical research. One criticism of the global TEI construct, represented in higher-order (and unidimensional) factor models, is its generality or high bandwidth (Landy, 2005; Mayer & Salovey, 2008; Perera & DiGiacomo, 2013), which may obscure meaningful links with substantive criteria. Take, for instance, the relationship between TEI and relationship satisfaction. At the global TEI level, it is unclear whether this association is attributable to the effects of emotionality (e.g., emotion perception), sociability (e.g., preference for social activity), self-control (e.g., low impulsivity) or well-being (dispositional positive affect). The correlated traits representation of TEI redresses the identified criticism by allowing researchers to work with the construct at lower levels of conceptual aggregation, thereby potentially enhancing predictive accuracy and clarifying the conceptual relationships with substantive outcomes. Indeed, there has been an increasing recognition over the past half-decade that working with TEI at the subfactor level is necessary to refine previous research and foster theory development (Downey et al., 2010; Matthews et al., 2012; Parker et al., 2011; Perera & DiGiacomo, 2013; Zeidner et al., 2012). It is noted, however, that the retention of the correlated traits model in the current study is based on an examination of fit indices, information criteria and parameter estimates for the models estimated on data from a single, moderate-sized, sample. Until such time as the present study findings are replicated or disconfirmed, it would be wise for applied researchers to consider both levels of conceptual aggregation in their analyses. Indeed, the global TEI factor retains much theoretical and practical attraction and appears integral to the scientific utility of the construct.

Notwithstanding the presumed benefits of examining TEI at the subfactor level, the scientific utility of TEI as a parsimonious representation of affect-motivational traits may be undermined by imposing a less restrictive correlated factors structure onto TEI data. This is because the scientific utility of TEI hinges on its integrative function, unifying the affective aspects of personality. This issue is somewhat reflective of the bandwidth-fidelity dilemma in the personality assessment literature in which the higher efficiency of broad-band global factors is set against the higher fidelity of narrow-band subfactors (Saucier & Goldberg, 2003; Saucier & Ostendorf, 1999). To the extent that global TEI is a higher-order, efficient representation of affective personality traits that are dispersed across existing personality and emotion frameworks, narrow-band subfactors may not be sufficiently independent of established traits to be scientifically useful. Thus, although the nature of TEI and its relations with substantively important criteria cannot be adequately understood if its multidimensionality is ignored, the utility of TEI is open to question if not conceptualized and operationalized at a global level.

An examination of the parameter estimates in the retained correlated traits ESEM solution revealed reasonably well-defined well-being, self-control and sociability factors, reflected in largely sizable target factor loadings; however, the emotionality factor was less well-defined. Although no studies have reported item-level factor analyses of the TEIQue-SF or other TEIQue forms, factor analyses of facet level scores obtained from the full-form show that, of the four factors, the least well-defined is emotionality (Petrides, 2009a). The present findings are consistent with this factor analytic evidence to the extent that four of the eight target emotionality items showed weak loadings and, notably, were found to load considerably better on the other factors. From the perspective of TEI theory, emotionality concerns trait empathy, emotion expression and perception and self-perceived relationship skills. As noted by Matthews et al. (2012), the common core of these facets may be the regulation of emotion in social contexts via the bidirectional flow of emotion-based information between social partners. Given that emotion regulation is also reflected in the self-control and sociability domains, it is perhaps not entirely surprising that these items largely shifted under the self-control and sociability factors in the present ESEM analyses. Future research would do well to examine the possibility of a cohesive emotion regulation factor in TEI factor space, indexed by existing empathy and emotion control, perception and expression items. Indeed, it has recently been recognized that the most unique scientific contribution of TEI to personality psychology may be in the conceptualization of a cohesive emotion regulation factor insofar as, of the TEI dimensions, the regulative traits tend to correlate least with existing dimension of personality (Matthews et al., 2012).

Invariance

The present study yielded strong support for the invariance of the TEIQue-SF factor structure. Evidence was obtained for the equivalence of factor loadings, item intercepts, item uniquenesses, item correlated uniquenesses, and the factor variance-covariance matrix. Notably, the invariance of TEIQue-SF item intercepts across gender is suggestive of the absence of differential item functioning, which is a core property of good psychological measurement (Meredith, 1993; Teresi & Fleishman, 2007). In addition, the finding of strict factorial invariance (i.e., equivalent item uniquenesses), including the equivalence of the correlated residuals, not only supports the generalizability of the complex measurement error structure across gender but also justifies tests of manifest mean invariance across gender (Morin et al., 2013). In this regard, the present result may be particularly important to a wealth of previous research reporting TEI manifest mean differences across gender exclusive of evidence for strict measurement invariance.

Although the TEIQue-SF showed strict measurement invariance and the equivalence of the factor variance-covariance matrix across gender, important gender mean differences were found on the TEI subfactors. The present study replicated previously reported gender differences in the TEI subfactors, with men scoring moderately higher than women on self-control and sociability and women scoring marginally higher than men on emotionality (Mikolajczak et al., 2007; Petrides, 2009a). As in previous research, the largest gender differences were for self-control followed by sociability and then emotionality, while no significant gender differences were found for well-being (Mikolajczak et al., 2007; Petrides, 2009a). Even though these results are consistent with prior work, the research is the first to examine TEI factor mean invariance across gender in the context of demonstrating the requisite standard of measurement invariance while using a data analytic model that accounts for the factorial complexity of TEI test items.

Limitations and Directions for Future Research

A few limitations of this research merit acknowledgement as they serve to guide the appropriate interpretation of the findings. First, although a complex structure of measurement error was specified in the present factor models, accounting for the presumed intradimensional local dependence of items generated by (unmodeled) TEI facets, it is possible that there are several other sources of systematic residual covariation that were unmodeled. One possibility is the presence of method effects due to common rater effects (e.g., self-report bias), item characteristic effects (e.g., homogenous item wordings) or response biases that, if not controlled, may lead to biased factor loading and factor correlation estimates (Podsakoff , MacKenzie, Lee, & Podsakoff, 2003). Future research would do well to identify further plausible sources of systematic error variance characterizing the TEIQue-SF and explicitly model these measurement error structures.

A second limitation concerns the apparent over-parameterization or lack of parsimony of the retained ESEM solution. As a considerably more complex model relative to the ICM-CFA, the ESEM model is more susceptible to over-parameterization. One condition in which an ESEM structure may result in over-parameterization is when cross-loadings are at or near zero (Marsh et al., 2014). An over-parameterized model is undesirable for at least two reasons. First, on a philosophical level, the over-parameterization of a model is inconsistent with one of the basic tenets of scientific pursuit, namely the determination of the most parsimonious, yet substantively meaningful, representation of population processes. Second, on an empirical level, an over-parameterized model may lead to less precision in parameter estimation relative to an equally well-fitting, yet more parsimonious, nested model (Bentler & Mooijaart, 1989). In the present study, though there was evidence of over-parameterization in the final solution, reflected in some zero and near-zero cross-loadings, several non-target loadings were non-trivial. Indeed, for each ESEM factor, at least three non-target loadings exceeded a standardized value .20. In cases where (a) large numbers of non-target loadings are non-trivial and significant, (b) the ESEM solution provides an appreciably better fit to the data than its ICM-CFA analogue, and (c) the ESEM solution yields smaller factor correlations than the ICM-CFA model that are theoretically meaningful, the ESEM model should be preferred notwithstanding its lack of parsimony (Marsh et al., 2011). On the contrary, when (a) ESEM and ICM-CFA models are equally well-fitting, (b) secondary loadings are largely zero or near-zero and (c) factor correlations are comparable across solutions, ICM-CFA solutions should be preferred on the basis of parsimony.

Another issue to be considered in interpreting the present findings is the suitability of current standards of model fit assessment for ESEM structures. Current guidelines for the evaluation of model fit using fit indices are largely based on simulation work with either ICM-CFA population data-generating models or slightly more complex CFA models allowing a small number of cross-loadings (e.g., Hu & Bentler, 1999). Thus, it is not entirely clear how these fit indices behave in the ESEM framework. Of particular concern are indices that do not incorporate a parsimony correction (e.g., SRMR) and may favor a more complex ESEM structure by virtue of its increased complexity alone. More simulation work is needed on the behavior of fit indices in ESEM before guidelines can be considered suitable. Until then, it is wise to heed Marsh et al's (2010, p. 488) advice to use an "eclectic approach" to model fit assessment, comprising an evaluation of fit indices, parameters estimates, substantive hypotheses and alternative measurement structures as in the present study.

A final limitation concerns the extent of psychometric support for the TEIQue-SF obtained in the current study. Although evidence was obtained for the factorial validity and measurement invariance of the TEIQue-SF, this evidence should be considered a first step, and only a first step, in determining the psychometric robustness of the instrument. Future investigators are thus encouraged to use the present results, particularly those pertaining to the factorial structure of the TEIQue-SF, as the basis for further investigations into the psychometric properties of the measure. Profitable lines of future inquiry include replications of the factorial structure supported in the study and examinations of convergent, discriminant and criterion validities of the TEIQue-SF scores, ideally in a multitrait-multimethod framework.

In summary, the current research has been centrally concerned with evaluating the factorial structure and invariance of the TEIQue-SF item response data. The findings of the study indicate that the data obtained are consistent with a multidimensional measurement structure, as implied by the retained correlated traits factorial solution, which was found to be invariant across gender. Notwithstanding this support for the correlated-factor structure, investigators are urged to consider both global and subfactor levels of aggregation in applied studies of TEI until such time as these results are replicated or disconfirmed. The present research also replicates previously reported findings concerning gender differences, and the absence thereof, in mean levels of TEI subfactors. Finally, the current study also contributes to a growing methodological literature suggesting that ESEM may be a more appropriate analytic structure for data derived from multidimensional measures. Taken together, this research not only lays the foundation for further psychometric work on the TEIQue-SF but also demonstrates the utility of ESEM for personality assessment.

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Table 1

Model Fit Statistics for the ICM-CFA and ESEM Measurement Structures

Model	χ^2	*df*	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	AIC	BIC	saBIC
Independence model	4617.023	435								
Unidimensional	1281.330	390	.787	.762	.069	[.065, .074]	.068	48082.109	48519.478	48186.223
ICM-CFA										
Higher-order	1122.811	386	.824	.800	.063	[.059, .068]	.066	47912.150	48366.180	48020.229
Correlated traits	1022.976	368	.843	.815	.061	[.057, .066]	.064	47837.382	48366.390	47963.309
ESEM										
Higher-order[a]	674.860	320	.915	.885	.048	[.043, .053]	.042	47530.147	48259.095	47703.670
Correlated traits	569.962	302	.936	.908	.043	[.038, .049]	.035	47446.953	48250.879	47638.323

Note. *N* = 476. *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root-mean-square error of approximation; 90% CI = 90% confidence interval for the RMSEA; SRMR = standardized root-mean-square residual; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; saBIC = sample-size adjusted BIC. [a] The higher-order ESEM specification was conducted in an EwC framework.

Table 2

Factor Loadings from the retained ESEM Correlated Traits Model, and *Correlations from both the ESEM and ICM-CFA Solutions*

Item	Well-being	Self-control	Emotionality	Sociability
5	**.655**	.087	.157	−.131
20	**.854**	.073	.005	−.092
9	**.449**	.063	.029	.296
24	**.461**	.020	.057	.361
12	**.788**	−.079	.252	−.245
27	**.740**	.060	−.128	.014
4	.078	**.604**	−.024	.063
19	.246	**.311**	−.193	.310
7	−.092	**.518**	.140	.051
22	.008	**.365**	.235	−.071
15	.357	**.307**	−.166	.151
30	.218	**.069**	−.076	.252
1	.058	−.070	**.290**	.329
16	.092	−.056	**.589**	.037
2	.004	.170	**.135**	.052
17	.216	−.125	**.121**	.200
8	.115	.501	**.122**	.005
23	.092	−.395	**.184**	.264
13	.219	.147	**.384**	−.075
28	.077	−.011	**.615**	.132
6	.101	.135	.175	**.470**
21	.199	.009	.076	**.520**
10	−.083	.258	.305	**.337**

25	.004	.114	.198	**.189**
11	−.048	.009	−.077	**.683**
26	.029	.077	.218	**.392**
Factor correlations				
Well-being	.991	.771	.661	.649
Self-control	.345	.720	.534	.667
Emotionality	.291	.260	.850	.683
Sociability	.501	.116	.167	.884

Note. All factor loadings are standardized, and target loadings are shown in bold. Correlations above the diagonal are from the ICM-CFA solution whereas those below the diagonal are ESEM estimates. Correlations between factor scores of corresponding factors obtained from the CFA and ESEM solutions are shown on the diagonal. All factor correlations are significant at the < .05 level or better.

Table 3

Fit Statistics for Gender Invariance (IN) Models.

Model	χ^2	*df*	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR	AIC	BIC	saBIC
MGM1 (Configural IN)	1063.080	604	.894	.847	.057	[.051, .062]	.044	47483.183	49090.222	47865.115
MGM2 (IN FL)	1087.470	692	.909	.885	.049	[.043, .055]	.053	47417.325	48657.993	47712.185
MGM3 (IN FL + Inter)	1106.201	714	.909	.890	.048	[.042, .054]	.055	47397.230	48546.305	47670.322
MGM4 (IN FL + Inter + Uniq)	1122.884	740	.912	.896	.047	[.041, .052]	.059	47371.233	48412.062	47618.599
MGM5 (IN FL + Inter + Uniq + Corr Uniq)	1130.250	753	.913	.899	.046	[.040, .051]	.059	47359.557	48346.263	47594.060
MGM6 (IN FL + Inter + Uniq + Corr Uniq + FVCV)	1132.867	763	.915	.903	.045	[.040, .051]	.062	47346.475	48291.547	47571.083
MGM7 (IN FL + Inter + Uniq + Corr Uniq + FVCV + FM)	1180.761	767	.904	.892	.048	[.042, .053]	.068	47387.322	48315.742	47607.973

Note. *N* = 475. *df* = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; SRMR = standardized root-mean-square residual; MGM = multiple-group model; IN = invariance; FL = factor loadings; Inter = Intercepts; Uniq = uniquenesses; Corr Uniq = correlated uniquenesses; FVCV = factor variance-covariance matrix; FM = factor means.