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Psychometrics of the Emotional Intelligence Scale in Elite, Amateur and Non-athletes

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Abstract

The purpose of this study was to assess the psychometrics properties of the Emotional Intelligence Scale (Schutte et al., 1998) and assess the measurement invariance across elite (n = 367), amateur (n = 629) and non-athletes (n = 550). In total, 1,546 participants from various sports completed the emotional intelligence scale. Several competing models were compared through exploratory structural equation modelling. The analyses were performed on the whole sample before subsequent invariance testing between athletic groups. The internal consistency of the scale was tested through Omega for the total scale and relevant subscales, which indicated largely unacceptable levels of stability. Results failed to support the purported unidimensional or four factor models proposed in the literature. However, a six-factor model provided the best fit to the data. Nonetheless, there was no evidence for weak or strong invariance suggesting that the scale may not be appropriate for use within athletic samples.

Key Words: *Trait Emotional Intelligence; Exploratory Structural Equation Modeling; Psychometrics; & Elite Athletes*.

Introduction

Research has had a longstanding interest in how emotions affect sport performance (Hanin, 2007). Emotion has typically been conceptualised at the state level, however it should also be considered at a trait level in order to better understand its influence in sport (Lazarus, 2000). One conceptualisation of emotion at the trait level is Trait Emotional Intelligence (TEI). Trait emotional intelligence is often described as an individual's capacity to recognise and utilise emotional states to change intentions and behaviour (Schutte et al., 1998). Research has reported that this stable disposition reflects emotional competence which explains performance variation in sport e.g. regulate emotion to optimal states for athletic performance, facilitate the use of psychological skills, pitching performance in baseball, and more adaptive coping strategies (Lane et al., 2010; Lane, Thelwell & Devonport, 2009; Lane, Thelwell, Lowther & Devonport, 2009; Zizzi, Deaner & Hirschorn, 2003). Furthermore, several debates exist in the literature surrounding TEI theory and measurement (Laborde & Allen, 2016; Petrides et al., 2016). In order to substantiate findings researchers must utilise reliable and valid measures (Asparouhov & Muthen, 2009; Marsh et al., 2011). As a result, validation of existing measurement should be the first stage of the research process (Marsh et al., 2011). Despite the importance given to TEI in sport, research assessing the variance between elite, amateur and non-athletes is scarce and inconsistent (Laborde, Dosseville & Allen, 2016). This may be due to misinterpretation of items of scales with weak theoretical underpinnings (Gignac, 2009; Meyer & Fletcher, 2007; Meyer & Zizzi, 2007). Therefore, this paper aims to fill this gap by assessing the psychometrics and invariance of a current TEI scale across sport expertise levels.

The Emotional Intelligence Scale

Schutte et al. (1998) validated a theory of TEI based on the ability model of emotional intelligence which consisted of four components e.g. managing emotion, understanding emotion, facilitating thought with emotion and perceiving emotion (Mayer, Salovey & Caruso, 2008). These four factors were previously conceptualised as six individual components, however a large degree of overlap between some factors resulted in two being dropped from the model (Salovey & Mayer, 1990). Schutte and colleague's claimed that higher scores of TEI represented competencies in emotional facilitation, management, perception, and understanding that are divergent from the major personality dimensions such as extraversion. As most existing theories had a large degree of overlap with personality traits, the model developed by Salovey and Mayer (1990) was unique and had a sound theoretical basis which resulted in increased attention amongst researcher's (Gardner & Qualter, 2010; Schutte et al., 2007). With this, Schutte et al. developed the Emotional Intelligence Scale (EIS) to operationalise their model. Sixty-two items were generated from the Salovey and Mayer (1990) ability model and was subjected to principle components analysis. Their results produced an ostensible factor structure consisting of one large factor and three progressively smaller factors. Schutte et al. suggested that the first factor sufficiently represented the four components of the ability model as the additional factors offered little conceptual uniqueness. Therefore, the additional factors were removed and the remaining 33 items represented a unidimensional measure of TEI (Schutte et al., 1998).

The scale was deemed reliable with internal consistency reported at α = .87 and a test-retest coefficient of α = .78. Additional research has largely supported the reliability of the unidimensional scale with internal consistency coefficients ranging from α = .93 - .76 (Austin, Saklofske, Huang & McKenney, 2004; Saklofske, Austin & Minski 2003; Stough et al., 2009). In general, research has utilised the EIS as a unidimensional scale, as a consequence there is little consistent evidence of the scales stability at the subscale level. Research has reported subscale internal consistency coefficients ranging from α = .58 - .77, with some research failing to report estimates of the scales' stability (Stough, Sakolfske &

Parker, 2009). Moreover, Schutte et al. never published the initial 62-item set or the factor loadings at any stage of the EIS's development. This resulted in confusion within the literature regarding the scale's factor structure and composite measures (Gignac, Palmer, Manocha & Stough, 2005).

Researchers have attempted to reconceptualise the scales factor structure, however the majority of research has been conducted outside of the sporting context. For example, Petrides and Furnham (2000) failed to support the unidimensional structure using confirmatory factor analysis (CFA), and offered an alternative conceptualisation by re-examining the data using exploratory factor analysis (EFA). The results indicated that a four-factor solution explained a satisfactory amount of variance representative of the Mayer et al. (2008) ability model, however not identical: Optimism/Mood Regulation, Appraisal of Emotions, Social Skills, and Utilisation of Emotions. This four-factor model has received support (Ciarrochi, Deane & Anderson, 2002; Saklofske et al., 2003) and criticism (Austin et al., 2004; Brackett & Mayer, 2003) with some studies providing alternative conceptualisations of the four factors e.g. self-management of emotions, social skills, empathy, and utilisation of emotions (Chan, 2003).

Research has postulated several reasons for the lack of consistency regarding the scale's structure and stability such as lack of reverse keyed items. To investigate this, Austin et al. (2004) revised the EIS adding 8 items and increased the reverse coded items. However, results of EFA still failed to replicate the four-factor model. The authors concluded that the 41-item EIS did not improve the scales reliability or validity. Moreover, Gignac et al. (2005) asserted that previous research did not consider the conceptual origins of the EIS (e.g. the original 62-item set was based on six factors). Although, Schutte et al. failed to replicate the six-factor model in their data, this may still provide the most parsimonious representation of the EIS. Therefore, Gignac et al. tested the unidimensional, four and a theoretical six factor nested model based on their interpretation of Salovey and Mayer's model. Results of CFA did not provide support for the unidimensional or four factor models, and only partially supported the six-factor nested model in the data. The analysis was then repeated after dropping the poor loading items, and revealed an adequate fit of the four-factor model on the resulting 21 items. Ng, Wang, Kim and Bodenhorn (2010) provided partial support for Gignac and colleague's four factor model. However, a two-level nested model which reintroduced all 33 items provided marginally better fit than Gignac et al.'s model. Therefore, no accepted conceptual basis for the EIS has been provided in the general domain.

The Emotional Intelligence Scale in Sport

To date only one study has examined the psychometrics of the EIS in sport (Lane et al., 2009). Lane and colleague's built on previous psychometric work by gauging the unidimensional model proposed by Schutte et al. and a theoretical six factor model based on the original Salovey and Mayer (1990) ability model. The six-factor model was developed by a panel of emotional intelligence experts (n = 9) through content analysis of the original 33 items. The analysis indicated that a six-factor model was the most appropriate representation of Mayer et al.'s model, which is similar to Gignac et al.'s interpretation, containing appraisal of own emotions (items 9, 19, 22, 15 & 2), regulation of own emotions (items 21, 14, 6, 23 & 1), utilisation of own emotions (items 7, 12, 17, 20, 27, 31 & 16), optimism (items 8, 28, 3 & 10), social skills (items 11, 13, 30, 4 & 24) , and appraisal of others emotions (18, 26, 29, 33, 32, 5 & 25). However, optimism and social skills were unique to Lane et al.'s content analysis. Results of CFA on data from 1,681 athletes provided no support for the unidimensional or six factor models. The data was reanalysed after removing 14 items that lacked emotional content, 13 of which Lane et al. reasoned that there was no direct reference to emotional experiences, and the remaining one was removed as it was represented optimism as a single item factor thus lacked content validity. The 19-item unidimensional and five factor models indicated significantly improved levels of fit, however still inadequate based on many recommended cut-offs (Hu & Bentler, 1999). Lane et al. attributed the poor fit to the reverse coded items which have been shown to distort single factor models (Woods, 2006), and particularly problematic with athletic samples (Lane, Sewell, Terry, Bartram & Nesti, 1999). Lane et al. called for further validation work with the EIS in sport specific samples.

Exploratory Structural Equation Modeling

Construct validation should be viewed as a continuing process with measures periodically subjected to thorough psychometric examination in order to substantiate their reliability and validity (Hopwood & Donnellan, 2010). In order to establish the EIS as a robust operationalisation for TEI research, a substantial body of research supporting the dimensionality of the scale must be collected. Re-examination of the scales psychometrics is therefore important in order to corroborate the findings and conclusions of TEI research. Research that has subjected the EIS to rigorous psychometric examination in sport is scarce (Lane et al., 2009). Marsh et al. (2011) warn that the widespread use of a measure before establishing its properties can lead to in-construct problems that characterise many psychological measures. Nonetheless, research that adopts CFA findings as definite measures of psychometric quality have been criticised on the basis of the Henny Penny Problem (Hopwood & Donnellan, 2010). For example, Hopwood and Donnellan argued that one poor CFA result is not a legitimate reason to discredit all previous findings using the measure, and that a measure should be evaluated equally by confirming and falsifying results.

Therefore, this research will utilise a more flexible approach to psychometric evaluation by adopting the Exploratory Structural Equation Modelling (ESEM) technique. Exploratory structural equation modelling is a relatively new methodological approach that combines the strengths of both CFA and EFA (see Marsh et al., 2013). For example, avoiding the strict requirements of CFA (e.g. only certain items can load onto certain factors) by allowing cross correlation between all common factors like in EFA, and providing robust indicators of model fit (e.g. goodness-of-fit statistics) that are available with CFA procedures. Recent research has advocated the use and benefits of ESEM over CFA as it provides improved accuracy in the model as is less likely to distort model adequacy through constraining loadings to zero (Marsh et al., 2011). The ESEM approach is particularly useful in sport where previous validations were based on limited factor analytic techniques of incomplete substantive measurement theory (e.g. high degrees of random error), thus of specific relevance regarding the EIS (Myer, Chase, Pierce & Martin, 2011).

Measurement Invariance of the EIS

Research examining differences between elite, amateur and non-athletes on psychological variables is difficult due to inconsistency in definition (e.g. what is elite), and comparability between studies (e.g. skilled vs non-skilled, professional vs amateur, and etc.) and so forth (Swann, Moran & Piggott, 2015). Swann et al. provided a framework for establishing sport expertise where athletes had to satisfy predetermined criteria to be classified as elite (e.g. competing at the highest available level in their given sport). Comparison between sub-groups or exploring previously understood phenomena in a new context offers an important extension to the understanding of elite level performance and expertise (Moran, 2012; Williams & Ford, 2008).

Furthermore, the utility of self-report measures such as the EIS to predict sport performance may be located at different levels. First, given it represents a trait, this is to say stable patterns, links are to be expected with sport performance considered on a long-term perspective, like season performance indicators (Laborde, et al., 2014; Perlini & Halverson, 2006). Interestingly, links can also be found with performance on a short-term perspective, via mediating mechanisms, such as impacting cortisol secretion (Laborde, Lautenbach, Allen, Herbert, & Achtzehn, 2014) or heart rate variability (Laborde, Brüll, Weber, & Anders, 2011;

Laborde, Lautenbach, & Allen, 2015) during stressful situations, or impacting the maximal voluntary contractions of muscles (Tok, Binboğa, Guven, Çatıkkas, & Dane, 2013).

To date no empirical study has directly examined whether TEI differed on a function of sport expertise using the EIS. Nonetheless, research has speculated that athletes will demonstrate higher mean TEI compared to non-athletes due to the requirements of competitive sport (Costarelli & Stamou, 2009; Meyer & Fletcher, 2007; Meyer & Zizzi, 2007). However, a systematic review of emotional intelligence in sport reported that mean TEI scores did not differentiate between athletes with different levels of expertise (Laborde et al., 2016), despite a positive relationship with physical activity levels and sport performance (Saklofske, Austin, Rohr, & Andrews, 2007; Zizzi et al., 2003). It should be noted that the failure to differentiate TEI across athletes may have been due to the difficulties in operationalising TEI with no agreed measure of TEI established (Laborde & Allen, 2016; Mayer et al., 2008). There are theoretical and practical advantages for using the same scale across different groups e.g. the ability to compare TEI scores across studies thus of importance to TEI research (Marsh et al., 2013). Therefore, additional research is required to understand whether athletes and non-athletes do not differ in TEI or whether results were distorted due to measurement. An implicit assumption underlying previous research is that the same test items are appropriately interpreted across athletic groups i.e. whether TEI retains its meaning across groups. To our knowledge, no study to date has rigorously tested the assumption that responses to the EIS are reasonably invariant over sport expertise. In order to corroborate previous conclusions based on sport expertise it is important to clarify that mean differences are attributable to theoretical rather than methodological reasons (Marsh et al., 2013).

The Current Study

Considering the lack of clarity regarding the EIS's development, such as the scarce relevant evidence available in sport, and the importance that validation of existing measurement has in progressing TEI research in sport, it appears relevant to examine the reliability and validity of the EIS in athletic samples. Therefore, the aim of this study is to re-examine the psychometrics of the EIS using robust flexible methods in a sample of athletes and non-athletes in order to determine the utility of the scale in sport and for the purpose of comparison with other domains. We will examine the unidimensional, four and six factor models proposed in the literature, as well replicating Lane et al.'s reduced item iteration. Furthermore, invariance testing will assess the differences in TEI across elite, amateur and non-athletes following the recommendations of Swann et al. (2015), and the utility of the scale to differentiate between levels of sport expertise. To our knowledge, no study to date has examined the scale using ESEM or across sport expertise. Due to a lack of relevant previous research no predictions are made regarding the psychometrics of the EIS across athlete groups and non-athletes.

Methods

Participants

The sample consisted of 1,546 participants (541 males & 1005 females) aged 18 - 57 (M = 23.97 & SD = 8.23). A wide range of elite (n = 367), amateur (n = 629) and non-athletes (n = 550) from various team and individual sports such as soccer, rugby, volleyball, hockey, athletics, and tennis, completed the questionnaire. Classification of athlete status was based on Swann et al.'s (2015) inclusion criteria from a review of 91 studies on elite sports performance. For example, to be classified as 'elite' athletes had to have met the criteria of participation within an international competition or in an internationally recognised sport for more than 8 years (for a breakdown see supplementary material). Myers, Ntoumanis, Gunnell, Gucciardi and Seungmin (2017) recommend the use of Monte Carlo simulation for estimation of sample size in structural equation modelling, however no guidelines exist for parameter estimation in ESEM. Applying CFA estimations with no missing data, standard error biases that do not exceed 10% and coverage of confidence intervals set at 95% indicated that sufficient power (i.e. .80) could be achieved with a sample size of 950. Furthermore, general 'rules of thumb' regarding minimum sample sizes for factor analysis were used as guidelines for recruitment in this research. Research suggests that a minimum of 1000 cases was required for an 'excellent' factor analysis (MacCallum, Widaman, Preacher, & Hong, 2001).

Materials

Trait Emotional Intelligence was measured using the EIS which theoretically taps the ability model (Mayer et al., 2008). Responses are made to 33 items (e.g. "I am aware of my emotions as I experience them"), on a 5-point Likert scale anchored from 1 (strongly disagree) to 5 (strongly agree), with scores polarised ranging from 33 (low) – 165 (high). Completion time of the scale ranged from 10 – 15 minutes (Stough et al., 2009). The scale utilises reverse scoring to combat acquiescent responding on 3 items (all item statements presented in Table 3).

Finally, demographic information was collected for descriptive and grouping purposes (e.g. age, sex, sport played, highest competition level, years spent playing sport, and success level).

Procedure

Ethical approval was granted from the Ethics Committee at a university in Northern Ireland. A request was made to sport coaches and lecturers for permission to attend training sessions and classes to ask for participants to take part. Data was collected at designated laboratories or training facilities using a questionnaire gauging biographical information and the EIS items. Participants were briefed prior to data collection and informed of their ethical rights e.g. anonymity, right to withdraw and etc. After completion participants were debriefed and thanked for their participation. Data collection was discontinued once the a priori numbers of cases were collected. All preliminary analyses were conducted on SPSSv23 and modelling techniques on Mplus 7.4 statistical analysis software programs.

Design & Data Analytic Strategy

The study adopted a cross-sectional design and utilised a purposive sampling technique. Data was screened for outliers and missing data, and checked for multivariate normality using Mardia skewness and kurtosis. Only a small number of cases (1.1%) contained random missing data therefore listwise deletion was employed in line with the recommendations of Tabachnick and Fidell (2007). Then descriptive statistics and internal consistency was computed for the overall scale and relevant subscales proposed in the literature (Lane et al., 2009). Cronbach's Alpha has recently received criticism due to biases of over and under estimation, unsuitability with non-unidimensional scales, and issues with error (Dunn, Baguley & Brunsden, 2014). On the other hand, omega (McDonald, 1999) is much more sensitive to multidimensional scales and more accurate at estimating internal consistency in the congeneric model where error variances are allowed to vary, ergo more suitable for data generated for psychological constructs (Dunn et al., 2014). Therefore, Omega will be used to calculate internal consistency with coefficients of .70 or higher required for stability (Tabachnick & Fidell, 2007).

The dimensionality of the scale was assessed using ESEM in order to obtain the most parsimonious model. Joreskog (1971) recommended establishing a baseline model before multi-group comparison. In order to determine the most appropriate baseline model, the initial analysis tested the 33-item unidimensional, four and six factor models, and the 19-item unidimensional and five factor models suggested in the literature (Lane et al., 2009; Petrides & Furnham, 2000; Schutte et al., 1998). Then measurement invariance with latent means analysis between elite, amateur and non-athletes in the best fitting baseline model. Measurement invariance can follow a subsequent taxonomy of 13 ESEM models (Marsh et al., 2009) to establish differences using the factor analytic technique. However, researchers have argued for a less demanding test of invariance in which a subset of parameters are not constrained to be invariant (Marsh et al., 2013). Therefore, the following research will test competing models in order to establish a well-fitting baseline measurement model which will then be subjected to successive equivalence constraints in the model parameters across groups until the most parsimonious fit is achieved. For example, measurement invariance will be tested using the Mplus procedure proposed by Muthen and Muthen (2014) where invariance is tested between the configural model, where the same pattern of factors and loadings across groups is established by enabling loadings and intercepts to correlate freely, the metric model which tests for weak invariance by holding loadings equal across groups, and then the scalar model which estimates strong invariance by constraining factor loadings and intercepts (Muthen & Muthen, 2014).

The analyses utilised the Robust Maximum Likelihood (MLR) extraction method which can handle lesser instances of missing data non-normality (Beauducel & Herzberg, 2006) and categorical variables when there are at least five response categories (Bandalos, 2014). As conflicting evidence exists regarding the factor structure of the EIS, a non-restrictive exploratory oblique geomin rotation was used to provide a comprehensive representation of how the test items and latent factors of the EIS are interrelated (Muthen & Muthen, 2014). An epsilon value of .50 was adopted which enables as many items as possible to be optimally identified within one component while minimising the potential number of doublets (King & Daniel, 1996). Model fit was determined by using a combination of absolute, incremental and parsimony-corrected fit indices in combination with the likelihood ratio statistic e.g. Chi-Square (χ^2), as suggested by Hu and Bentler (1999). A model is deemed acceptable if the Root Mean Square Error of Approximation (RMSEA) with 90% confidence intervals (CI) and Standardised Root Mean Residual (SRMR) is .06 and .05 or less respectively, and each of the Comparative Fit Index (CFI) and Tucker Lewis Index (TLI) is .90 or greater (Asparouhov & Muthen, 2009; Marsh, Hau, & Grayson, 2005; Marsh, Hau, & Wen, 2004). In order to select the most parsimonious model, the Bayes Information Criterion (BIC) and Akaike's Information Criteria (AIC) was used to compare competing models. The AIC and BIC assign a greater penalty to model complexity and therefore has a better propensity to select more efficient models. For example, a 10 point reduction in a BIC value represents a 150:1 likelihood that the model is statistically a better fit (Rafferty, 1995). Chen (2007) suggested that changes less than .01 and .015 in the CFI and RMSEA, respectively, would be supportive of an invariant model in relation to the previous model. Finally, due to the exploratory nature of ESEM standardised solutions were examined to evaluate the significance and strength of parameter estimates. Standardised factor loadings were interpreted using Comrey and Lee's (1992) recommendations (e.g. > .71 = excellent, > .63 = very good, > .55 = good, > .45 = fair, > .32 = poor).

Results

Preliminary Analyses

Descriptive statistics were tabulated for the total and subscale scores of the competing EIS models. The scores produced fall within the upper percentiles of the scale with no outliers. Multivariate skewness (-.903) and kurtosis (.855) indicated a slight negative skew with no significant departure from normality. Note, although the MLR technique can tolerate deviations from normality, it is important to assess multivariate normality during invariance testing, given it can be affected in skewed data (Muthen & Muthen, 2014). The internal consistency (Ω) for the EIS ranged from Ω = .51 - .73 for the EIS subscales, and Ω = .81 - .85

for the total scores. Therefore, indicating a good level of composite reliability for the total scores but less than satisfactory at the subscale level (see Table 1).

Insert Table 1 here

Exploratory Structural Equation Modeling

The first model assessed the unidimensional structure proposed by Schutte et al. (1998) on all 33 items and indicated a poor fit to the data.

The four-factor model proposed by Petrides and Furnham (2000) indicated substantially improved fit, albeit still inadequate on many of the cut-off criteria proposed (Hu & Bentler, 1999). Model fit was just below the suggested criteria and could have been achieved through modification (e.g. allowing 3 error terms to correlate). However, as the initial testing was aimed at identifying the most parsimonious baseline model these options were not explored.

The six-factor model again indicated improved fit and satisfied the pre-established cut-offs (see Table 3).

In order to determine whether a more parsimonious fit could be achieved, we reanalysed the data on the 19 items proposed by Lane et al. (2009) by examining a unidimensional and five factor model. However, model fit was significantly worse in both instances (Chen, 2007). Therefore, ESEM indicated that the six-factor model with all 33 items represents the best fit to the data (see Table 2).

Insert Table 2 here

Analysis of the factor structure indicated that most items aligned to Lane et al.'s conceptualisation. However, some misspecification (e.g. poor and cross-loading items), was found thus questioning the viability of the six-factor model. For example, items 13, and 28 cross-loaded across three different factors, and items 4, 8 and 11, produced poor loadings (<.32) based on Comrey and Lee's (1992) recommendation (see Table 3). These misspecifications may be the result of the oblique rotation utilised. However, the degree of cross-loading is not considered problematic in ESEM (Perry, Nicholls, Clough & Crust, 2015) therefore we proceed to invariance testing.

Insert Table 3 here

Measurement Invariance

Measurement invariance was tested comparing the six-factor configural model with all parameters allowed to be unequal across groups to the metric model of weak invariance model e.g. by holding loadings equal across groups, and then the scalar model of strong invariance which imposed additional constraints e.g. by constraining factor loadings and intercepts across groups,. The configural model indicated acceptable absolute fit e.g. RMSEA = .065 with 90% CI (.067 - .062), however unacceptable levels of incremental fit e.g. CFI = 885. The metric invariance model produced fit that was significantly poorer ($\Delta\chi^2$ (324) = .2000.312, p = .001), as did the scalar invariance model ($\Delta\chi^2$ (378) = 2233.9915, p = .008) suggesting that measurement of the six-factor model differs across elite, amateur and non-athletes (e.g. participants interpretation of TEI differed across observed variables). Furthermore, the AIC and BIC produced lower values for the configural model indicating greater parsimony of the configural model. Nonetheless, all models produced inadequate fits to the data with significant changes in incremental fit as suggested by Chen (2007) e.g. ΔCFI > .01. Further invariance testing (e.g. invariance uniqueness) was not explored as the aim was to test invariance at the group level i.e. compare latent mean structures.

Parameter Estimates

The next stage of the analysis was to examine the factor structure of the six-factor model across elite, amateur and non-athletes (see supplementary material). The χ^2 contribution for each group was significant (elite χ^2 = 1062.130, amateur χ^2 = 897.574 & non-athlete χ^2 = 1360.978) and in line with the summative baseline value (χ^2 = 1919.710) in the more freely estimated six-factor model. The analysis of the latent means across groups were all freely estimated and produced factor matrixes which were not representative of Lane et al.'s (2009) six factor model. The factor solutions contained at least two misloading items and two cross-loading items in each factor. As a result, none of the factor structures could be deemed proper. Although the residual variance was high across groups some items loaded poorly across all factors e.g. items 8, 10, 20, 27, 28 and 31 < .32 (Comrey & Lee). The latent factor correlations (see supplementary material) largely indicated independence amongst the subscales (*r* = .46 - -.01) with the factors purporting to be utilisation and optimism displaying the weakest correlations in the athlete groups. Thus, the six-factor model could not be identified nor differentiated across elite, amateur and non-athletes.

Discussion

Summary

The aim of this research was to assess the psychometric quality and measurement invariance of the EIS in a sample of elite, amateur and non-athletes. The findings indicated that the scale possessed unsatisfactory levels of internal consistency for all EIS models incorporating subscales e.g. four-factor model (Petrides & Furnham, 2000). Conversely, both the 33 and 19-item unidimensional models indicated good levels of stability. This may be a result of the increased number of items within the unidimensional models which inflates inter-item correlation, however omega isn't as susceptible to this compared to other estimates e.g. Cronbach's alpha (Dunn et al., 2014). Results from ESEM indicated that the six-factor model produced acceptable and a better fit to the data compared to the four and unidimensional factor models proposed in the literature (Petrides & Furnham, 2000; Schutte et al., 1998). Moreover, similar to previous research the results indicated that the unidimensional and four-factor model did not produce acceptable fit to the data (Ng et al., 2010; Gignac et al., 2005). Finally, measurement invariance was tested on the six-factor model following the procedures proposed by Muthen and Muthen (2014), assessing fit between a freely estimated model and a subsequently more restricted model after establishing a well-fitting baseline model. The configural model indicated the best fit to the data indicating measurement invariance, however all subsequent invariance models produced inadequate fit to the data. The factor matrixes produced for all groups were not representative of Lane et al. (2009) findings, with several examples of misspecification in the factor structure. Therefore, interpretation of the EIS items differed across sport expertise. This is the first study to examine the EIS using robust statistical measures and its measurement invariance across sports expertise, thus offering a possible rationale for inconsistencies in the literature regarding differences across athlete and non-athletes.

Evaluation of Lane et al.'s Six Factor Model

The six-factor model produced a good fit to the data and analysis of the factor loadings indicated a reasonable replication of Lane et al. (2009) model prior to invariance testing. For example, both appraisal factors contained all pre-specified items, whereas the optimism and social skills factors contained some misplaced items and some poor loadings < .32, albeit not problematic in an ESEM framework (Perry et al., 2015). Regarding the cross loadings, items 13 (e.g., “I arrange events others enjoy”) and 28 (e.g., “When I am faced with a challenge, I give up because I believe I will fail”) there appears to be no systematic rationale for their misspecification. However, item-13 contains wording which refers to ‘others’. This may highlight a weakness in the initial item generation whereby the items are poor representations of their hypothesised factor. The scale development literature advocates structure, clarity, brevity and specificity in item development (MacKenzie, Podsakoff, & Podsakoff, 2011). Therefore, it is possible that item-13 lacks specificity and therefore is a poor operationalisation of social skills. Similarly, item 28 cross-loads on the utilisation and regulation factors. Analysis of the item wording indicates little reference to optimism, possibly due to its reverse coding, a problem identified in previous research (Austin et al. 2004; Gignac, 2009; Lane et al., 2009).

Moreover, analysis of the invariance models produced improper factor structures e.g. all factors contained misspecification with items failing to rotate onto their intended factors and poor loadings. Furthermore, the invariance models produced unacceptable levels of fit suggesting that participant's interpretation of TEI may have differed due to something other than as a function of sport expertise. The failure to provide scalar invariance is a cause for concern for TEI research. For example, scalar (i.e. strong) invariance, which requires item loadings, intercepts, and residuals to be equal across groups, is necessary to make meaningful, unbiased comparisons across groups (Muthen & Muthen, 2014). Failure to do so questions the consistency in direction and magnitude of the individual scale items and as a consequence the latent constructs they measure. Equally, the inability to claim metric (i.e. weak) invariance is also concerning for cross-sectional research correlating EIS scores with other construct scores as it directly pertains to the factor loadings. If the manifest variables are unequally loaded, then the researcher cannot be confident in the accuracy of measurement (Marsh et al., 2013). Thus, the current findings advocate caution when interpreting conclusions of previous research and question the scales utility in sport.

Application of the Emotional Intelligence Scale in Sport

These findings are in line with much of the previous research assessing the psychometrics of the EIS which failed to support the scales dimensionality (Gignac et al., 2005; Lane et al., 2009; Ng et al., 2010). The results of this research coincide with the literature suggesting that the Schutte et al. (1998) model of TEI requires clarification and refinement as the data did not fit the unidimensional or four-factor models. These findings raise concern at two levels, first, the inability to fit the hypothesised unidimensional or four-factor model and two, the inconsistency in the factor structures across elite, amateur and non-athletes. Research has cautioned the use of CFA techniques as a singular method for determining the psychometrics of a measure (Marsh et al., 2011). However, it is believed that establishing factorial validity should be critical in assessing the robustness of a measure as this will provide evidence for a strong theory operationalisation (Marsh et al., 2011). Exploratory structural equation modeling adopts a flexible approach to instrument evaluation however, as in all EFA techniques, its rotation procedures are numerically driven and negate theory, and different rotation procedures may produce different factor solutions but similar fit statistics (Asparouhov & Muthen, 2009). Nonetheless, the inconsistencies in previous research may be attributed to the misapplication of statistical techniques adopted e.g. the unidimensional structure of the EIS suggests that the items would be oblique rather than orthogonal (Brackett & Mayer, 2003), of which this research counters. Therefore, additional research may be required adopting similar techniques to the current research before the EIS can be discredited as a viable measure of TEI.

At a conceptual level, the current study offers partial support for the EIS as a general (six-factor) measure of TEI. This hypothesises that akin to other trait constructs such as perfectionism (Rasquinha, Dunn & Dunn, 2014), TEI may be domain specific and further research may wish to explore this avenue. However, it is noted that researchers may prefer a scale which is interpreted with the same meaning across groups in order to allow intergroup comparisons (Marsh et al., 2013). Furthermore, although the unidimensional models indicated good internal consistency, the poor fit of those models questions Schutte et al.'s (1998) assertion that TEI via the EIS can be measured as a unidimensional construct. Also, the majority of TEI theory suggests a multifactorial construct with measures which reflect as such e.g. the Trait Emotional Intelligence Questionnaire (Petrides, 2009). The EIS on the other hand indicates a deficit between theory and method which requires clarification in order to progress the research in the area. Until then, recommendations for future use of the scale are difficult.

Regarding the current findings, caution is warranted regarding use of the EIS with athletic samples. The results are limited in that ESEM failed to provide support for either strong or weak invariance across sport expertise. Therefore, it is not possible to conclude that TEI differs across sport expertise. Furthermore, the factor loadings and latent factor correlations of the utilisation of emotion and optimism factors suggest athletes interpret these items differently. For example, in both elite and amateur athletes these factors had the weakest item loadings and correlations with other latent variables. The utilisation of emotion is an important component of TEI, however it has not been well represented in factor analytic research (Ng et al., 2010). It is possible that athlete's self-perception of this trait is highly influenced by other factors e.g. mood regulation or emotional competence (Lane et al., 2009). Thus, this factor may form an underlying construct tapped indirectly by other items that manifests itself as a higher or lower order trait (Lane et al., 2009; Schutte et al., 1998).

In general, researchers have noted a limitation of TEI research in that there is no agreed measure of TEI (Laborde & Allen, 2016; Mayer et al., 2008). Considering that theoretical evidence of which all factor analysis should be based on (Hopwood & Donnellan, 2010), is often divided due to the multidimensional framework proposed for the EIS model e.g. confusion surrounding Schutte et al.'s attempts to map a four-factor structure using a unidimensional scale based on a six-factor model, it is not surprising that findings fail to substantiate this line of enquiry. Therefore, building a consensus on which model to progress is difficult and as a result understanding of TEI is limited. These inconsistencies may be partially due to the misapplication of the statistical techniques adopted. For example, the majority of previous research utilised principle components analysis which is often mislabelled as a factor estimation method, as it does not distinguish between unique and common variance. Thus, it is more appropriately used as a data reduction technique to condense the number of variables rather than accounting for the variance of the correlations among the observed variables (Joreskog, 1971). It is likely that Schutte et al. would have reported a different factor structure if EFA techniques were adopted.

Strengths and Limitations

A strength of the current research is the size and coverage of the sample which offers a comprehensive expression of TEI in sport with a range of sport expertise, sport type etc. examined thus generalisable across the domain. Furthermore, despite being calculated ex-post-facto the classification of elite status is based on Swann et al.'s (2015) pre-determined criteria thus avoiding social desirability.

Nonetheless, the current research findings are in light of several limitations. The cross-sectional design utilising self-report measures may be subject to additional sources of error and biases as opposed to longitudinal designs. Similarly, due to the nature of self-report measures (e.g. reliance on emotional self-perceptions), the EIS may be subject to increases in social desirability. For example, an individual with higher TEI will want to portray themselves in the best possible way (Schutte et al., 2007). Nevertheless, it should be noted that such limitations are common to all scales based on self-report measures, including personality assessment, and therefore should not prohibit the utility of self-report TEI measures (Davies, Lane, Devonport & Scott, 2010). Moreover, the influence of social desirability has received increased interest in sport psychology (Birch, Crampton, Greenless, Lowry, & Coffee, 2017). Future psychometric research should include measures of social desirability like the Marlowe-Crowne Social Desirability Scale (Crowne & Marlowe, 1964) to test this idea and to further validate utility of their scales. Although primarily considered a strength of the current research, the ESEM technique is not without limitation e.g. the cut-offs for the fit indices employed were recommended for CFA procedures with no ESEM specific indicators developed for multi groups or data sets. Also, ESEM doesn't enable the researcher to test for modification indices or other forms of guided parameter restraint (Marsh et al., 2011). Finally, ESEM models often require large numbers of free parameter estimates, and more parameters could lead to less precise estimates, particularly with smaller samples (Asparouhov & Muthén, 2009).

Conclusion

In conclusion, this study was the first to use ESEM to evaluate the dimensionality of the EIS. The findings extended the lack of consensus regarding the psychometrics of the EIS e.g. omega estimates failed to support the subscales stability. Furthermore, despite the advantages of ESEM over traditional CFA and EFA procedures, support for a unidimensional and four-factor model was not provided. Support for Lane and colleague's (1999) six factor model was provided, however the model is not appropriate for use with athletic samples with poor fit for both weak and strong invariance models. Thus, inability to detect differences across sports expertise may be a result of methodological rather than theoretical suppositions. Previous research has suggested alternative measurement models for the EIS, however we have not provided an alternative estimation of the model as this only adds to the lack of consensus in the literature (Gignac, 2009; Laborde & Allen, 2016; Mayer et al., 2008). Alternatively, we call interested researchers to clarify and refine the EIS conceptualisation, providing a clear rationale for the measure. The present findings suggest that the EIS is not a suitable measure of TEI in sport, and caution is warranted in future use with the scale.

References

Austin, E. J., Saklofske, D. H., Huang, S. H. S., & McKenney, D. (2004). Measurement of trait emotional intelligence: Testing and cross-validating a modified version of

Schutte et al.'s (1998) measure. *Personality and Individual Differences, 36*, 555 - 562. doi.org/10.1016/S0191-8869(03)00114-4

Asparouhov, T. & Muthen, B. (2009). Exploratory Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 16(3)*, 397 – 438. doi.org/10.1080/10705510903008204

Bandalos, D. L. (2014). Relative performance of categorical diagonally weighted least squares and robust maximum likelihood estimation. *Structural Equation Modeling, 21*, 102 – 116. doi.org/10.1080/10705511.2014.859510

Beauducel, A., & Herzberg, P. Y. (2006). On the performance of maximum likelihood versus means and variance adjusted weighted least squares estimation in CFA. *Structural Equation Modeling, 13*, 186 – 203. doi.org/10.1207/
s15328007sem1302_2

Birch, P.D. J., Crampton, S., Greenless, I., Lowry, R., & Coffee, P. (2017). The mental toughness questionnaire-48: A re-examination of factorial validity. *International Journal of Sport Psychology, 48(3)*, 331-355. doi.org/10.7352/IJSP.2017.48.331

Brackett, M. A., & Mayer, J. D. (2003). Convergent, discriminant, and incremental validity of competing measures of emotional intelligence. *Personality and Social Psychology Bulletin, 29*, 1147 - 1158. doi.org/10.1177/0146167203254596

Chan, D. W. (2003). Dimensions of emotional intelligence and their relationships with social coping among gifted adolescents in Hong Kong. *Journal of Youth and Adolescence, 32*, 409 - 418. doi.org/10.1023/A:1025982217398

Chen, F. F. (2007). Sensitivity of goodness of fit indices to lack of measurement invariance. *Structural Equation Modeling, 14*, 464 – 504. doi.org/10.1080/10705510701301834

Ciarrochi, J., Deane, F. P., & Anderson, S. (2002). Emotional intelligence moderates the relationship between stress and mental health. *Personality and Individual Differences, 32*, 197 - 209. doi.org/10.1016/S0191-8869(01)00012-5

Comrey, A. L., & Lee, H. B. (1992). *A First Course in Factor Analysis*. Hillsdale, NJ: Erlbaum.

Costarelli, V., & Stamou, D. (2009). Emotional Intelligence, Body Image and Disordered Eating Attitudes in Combat Sport Athletes. *Journal of Exercise Science & Fitness, 7(2)*, 104 – 111. doi.org/10.1016/S1728-869X(09)60013-7

Crowne, D. P., & Marlowe, D. (1964). *The approval motive: Studies in evaluative dependence*. New York: Wiley.

Davies, K. A., Lane, A. M., Devonport, T. J., & Scott, J. A. (2010). Validity and reliability of a brief emotional intelligence scale (BEIS-10). *Journal of Individual Differences, 31(4)*, 198 – 208. doi.org/10.1027/1614-0001/a000028

Dunn, T. J., Baguley, T., Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British Journal of Psychology, 105*, 399 – 412. doi.org/10.1111/bjop.12046

Gardner, K. J. & Qualter, P. (2010). Concurrent and incremental validity of three trait emotional intelligence measures. *Australian Journal of Psychology, 62*, 5 – 13. doi.org/10.1080/00049530903312857

Gignac, G. E. (2009). Psychometrics and the measurement of emotional intelligence. In C. Stough, D. H. Saklofske & J. D. A. Parker (Eds.), *Assessing emotional intelligence: Theory, research, and applications (pp. 9-42)*. New York: Springer

Gignac, G. E., Palmer, B. R., Manocha, R., & Stough, C. (2005). An examination of the factor structure of the Schutte self-report emotional intelligence scale via confirmatory factor analysis. *Personality and Individual Differences, 39*, 1029 – 1042. doi.org/10.1016/j.paid.2005.03.014

Hanin, Y. (2007). Emotions in sport: current issues and perspectives (pp. 31 – 58). In, G. Tenenbaum & R. Eklund (Eds.), *Handbook of Sport Psychology* (3rd ed.). New York: Wiley.

Hopwood, C. J. & Donnellan, M. B. (2010). How should the internal structure of personality inventories be evaluated? *Personality and Social Psychology Review, 14*, 332 – 346. doi.org/10.1177/1088868310361240.

Hu, L. T., & Bentler, P. M. (1999). Cut off criteria for fit indexes in covariance structural analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*, 1 - 55. doi.org/10.1080/10705519909540118

Joreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika, 36*, 409 – 426. doi.org/10.1007/BF02291366

King, D. A., & Daniel, L. (1996). Psychometric integrity of the Self-Esteem Index: A comparison of normative and field study results. *Educational and Psychological Measurement, 56(3)*, 537 – 550. doi.org/10.1177/0013164496056003016

Laborde, S., & Allen, M. S. (2016). Comment: Measurement and the Interpretation of Trait EI Research. *Emotion Review*, 8(4), 342 – 344. doi.org/10.1177/1754073916650498

Laborde, S., Brüll, A., Weber, J., & Anders, L. S. (2011). Trait emotional intelligence in sports: A protective role against stress through heart rate variability? *Personality and Individual Differences*, 51, 23-27. doi:10.1016/j.paid.2011.03.003

Laborde, S., Dosseville, F., & Allen, M. (2016). Emotional intelligence in sport and exercise: A systematic review. *Scandinavian Journal of Medicine & Science in Sports, 26(8),* 862 – 874. doi.org/10.1111/sms.12510

Laborde, S., Dosseville, F., Guillén, F., & Chávez, E. (2014). Validity of the trait emotional intelligence questionnaire in sports and its links with performance satisfaction. *Psychology of Sport and Exercise, 15,* 481-490. doi.org/10.1016/j.psychsport.2014.05.001

Laborde, S., Lautenbach, F., & Allen, M. S. (2015). The contribution of coping-related variables and heart rate variability to visual search performance under pressure. *Physiology & behavior,* 139, 532-540. doi:10.1016/j.physbeh.2014.12.003

Laborde, S., Lautenbach, F., Allen, M. S., Herbert, C., & Achtzehn, S. (2014). The role of trait emotional intelligence in emotion regulation and performance under pressure. *Personality and Individual Differences, 57,* 43-47. doi.org/10.1016/J.Paid.2013.09.013

Lane, A. M., Devonport, T. J., Soos, I., Karsai, I., Leibinger, E., & Hamar, P. (2010). Emotional intelligence and emotions associated with optimal and dysfunctional athletic performance. *Journal of Sports Science and Medicine, 9(3),* 388 – 392.

Lane, A. M., Meyer, B. B., Devonport, T. J., Davies, K. A., Thelwell, R. C., Gill, G. S., Diehl, C. D. P., Wilson, M., & Weston, N. (2009). Validity of the emotional intelligence scale for use in sport. *Journal of Sports Science and Medicine, 8*, 289 – 295.

Lane, A. M., Sewell, D. F., Terry, P. C., Bartram, D., & Nesti, M. S. (1999). Confirmatory factor analysis of the Competitive State Anxiety Inventory-2. *Journal of Sports Sciences 17,* 505 – 512. doi.org/10.1080/026404199365812

Lane, A. M., Thelwell, R. C., & Devonport, T. J. (2009). Emotional intelligence and mood states associated with optimal performance. *Electronic Journal of Applied Psychology, 5(1)*, 67 – 73. doi.org/10.7790/ejap.v5i1.123

Lane, A. M., Thelwell, R. C., Lowther, J., & Devonport, T. J. (2009). Emotional intelligence and psychological skills use among athletes. *Social Behaviour and Personality, 37*, 195 – 202. doi.org/10.2224/sbp.2009.37.2.195

Lazarus, R. S. (2000). How emotions influence performance in competitive sports. *The Sport Psychologist*, *14*, 229 – 252. doi.org/10.1123/tsp.14.3.229

MacCallum, R. C., Widaman, K. F., Preacher, K. J., & Hong, S. (2001). Sample size in factor analysis: The role of model error. *Multivariate Behavioral Research*, *36*, 611 – 637. doi.org/10.1207/S15327906MBR3604_06.

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N, P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly, 35*, 293-334.

Marsh, H. W., Hau, K. T., & Grayson, D. (2005). Goodness of Fit Evaluation in Structural Equation Modelling. In A. Maydeu-Olivares & J. McArdle (Eds.), Contemporary Psychometrics. *A Festschrift for Roderick P. McDonald* (pp. 275 - 340). Mahwah NJ: Erlbaum.

Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis testing approaches to setting cut-off values for fit indexes and dangers in over-generalising Hu & Bentler's (1999) findings. *Structural Equation Modeling*, *11*, 320 – 341. doi.org/10.1207/s15328007sem1103_2

Marsh, H. W., Liem, G. A. D., Martin, A. J., Morin, A. J. S., & Nagengast, B. (2011). Methodological measurement fruitfulness of exploratory structural equation modeling (ESEM): New approaches to key substantive issues in motivation and engagement.

Journal of Psychoeducational Assessment, 29, 322 – 346. doi.org/10.1177/0734282911406657

Marsh, H. W., Muthén, B., Asparouhov, T., Lüdtke, O., Robitzsch, A., Morin, A. J. S., & Trautwein, U. (2009). Exploratory structural equation modeling, Integrating CFA and EFA: Applications to students' evaluations of university teaching. *Structural Equation Modeling, 16*, 439 – 476. doi.org/10.1080/10705510903008220

Marsh, H. W., Vallerand, R. J., Lafreniere, M. K., Parker, P., Morin, A. J. S., Carbonneau, N., Jowett, S., Bureau, J. S., Fernet, C., Guay, F., Abduljabbar, A. S., & Paquet, Y. (2013). Passion: does one scale fit all? Construct validity of two-factor passion scale and psychometric invariance over different activities and languages. *Psychological Assessment*, *25*, 796 – 809. doi.org/10.1037/a0032573

Mayer, J. D., Salovey, P., & Caruso, D. R. (2008). Emotional intelligence: New ability or eclectic traits? *American Psychologist, 63(6)*, 503 – 517. doi.org/10.1037/0003-066X.63.6.503

McDonald, R. P. (1999). *Test theory: A unified treatment*. Mahwah, NJ: Lawrence Erlbaum.

Meyer, B. B., Fletcher, T. B. (2007). Emotional intelligence: A theoretical overview and implications for research and professional practice in sport psychology. *Journal of Applied Sport Psychology*, *19*, 1–15. doi.org/10.1080/10413200601102904

Meyer, B. B., Zizzi, S. (2007). Emotional intelligence in sport: conceptual, methodological, and applied issues. In Lane A. M. (Ed.), *Mood and Human Performance: Conceptual, Measurement, and Applied Issues (pp. 131–54)*. London: Nova Science Publishers.

Moran, A. P. (2012). *Sport psychology: A critical introduction (2nd ed.)*. London: Routledge.

Muthén, L. K. & Muthén, B. O. (2014). *Mplus User's Guide*. Los Angeles, CA: Muthén & Muthén.

Myer, N. D., Chase, M. A., Pierce, S. W., & Martin, E. (2011). Coaching efficacy and exploratory structural equation modeling: A substantive-methodological synergy. *Journal of Sport and Exercise Psychology, 33(6)*, 779 – 806. doi.org/10.1123/jsep.33.6.779

Myers, N. D., Ntoumanis, N., Gunnell, K. E., Gucciardi, D. F., & Seungmin, L. (2017). A review of some emergent quantitative analyses in sport and exercise psychology. International review of Sport and Exercise Psychology. doi: 10.1080/1750984X.2017.1317356

Ng, K. M., Wang, C., Kim, D. H., & Bodenhorn, N. (2010). Factor structure analysis of the Schutte self report emotional intelligence scale on international students. Educational and Psychological Measurement, 70, 695 – 709. doi.org/10.1177/0013164409355691

Perlini, A. H., & Halverson, T. R. (2006). Emotional intelligence in the National Hockey League. *Canadian Journal of Behavioural Science, 38*, 109-119. doi.org/10.1037/cjbs2006001

Perry, J. L., Nicholls, A. R., Clough, P. J., & Crust, L. (2015). Assessing Model Fit: Caveats and recommendations for confirmatory factor analysis and exploratory structural equation modeling. *Measurement in Physical Education and Exercise Science, 19(1)*, 12-21. doi.org/10.1080/1091367X.2014.952370

Petrides, K. V. (2009). *Technical manual for the trait emotional intelligence questionnaire (TEIQue)*. London, England: London Psychometric Laboratory.

Petrides, K. V., & Furnham, A. (2000). On the dimensional structure of emotional intelligence. *Personality and Individual Differences, 29*, 313 – 320. doi.org/10.1016/S0191-8869(99)00195-6

Petrides, K. V., Mikolajczak, M., Mavroveli, S., Sanchez-Ruiz, M.-J., Furnham, A., & Pérez-González, J. C. (2016). Developments in trait emotional intelligence research. *Emotion Review,* 8(4), 335 – 341. doi.org/10.1177/1754073916650493

Rafferty, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology, 25*, 111 – 163. doi.org/10.2307/271063

Rasquinha, A., Dunn, J. G. H., & Dunn, J. C. (2014). Relationships between perfectionistic strivings, perfectionistic concerns, and competitive sport level. *Psychology of Sport and Exercise, 15,* 659 – 667. doi.org/10.1016/j.psychsport.2014.07.008

Saklofske, D. H., Austin, E. J., & Minski, P. S. (2003). Factor structure and validity of a trait emotional intelligence measure. *Personality and Individual Differences, 34*, 707 - 721. doi.org/10.1016/S0191-8869(02)00056-9

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. *Imagination, Cognition and Personality, 9,* 185 – 211. doi.org/10.2190/DUGG-P24E-52WK-6CDG

Schutte, N. S., Malouff, J. M., Hall, L. E., Haggerty, D. J., Cooper, J. T., Golden, C. J., & Dornheim, L. (1998). Development and validation of a measure of emotional intelligence. *Personality and Individual Differences, 25(2)*, 167 – 177. doi.org/10.1016/S0191-8869(98)00001-4

Schutte, N. S., Malouff, J. M., Thorsteinsson, E. B., Bhullar, N., & Rooke, S. E. (2007). A meta-analytic investigation of the relationship between emotional intelligence and health. *Personality and Individual Differences, 42*, 921 – 933. doi.org/10.1016/j.paid.2006.09.003

Stough, C., Sakolfske, D. H., & Parker, J. D. A. (2009). *Assessing Emotional Intelligence: Theory, Research and Applications*. New York: Springer.

Swann, C., Moran, A., & Piggott, D. (2015). Defining elite athletes: Issues in the study of expert performance in sport psychology. *Psychology of Sport and Exercise 16(1)*, 3–14. doi.org/10.1016/j.psychsport.2014.07.004

Tabachnick, B.G., & Fidell, L.S. (2007). *Using Multivariate Statistics*. Boston: Allyn and Bacon.

Tok, S., Binboğa, E., Guven, S., Çatıkkas, F., & Dane, S. (2013). Trait emotional intelligence, the Big Five personality traits and isometric maximal voluntary contraction level under stress in athletes. *Neurology, Psychiatry and Brain Research, 19, 133-138*. doi:10.1016/j.npbr.2013.04.005

Williams, A. M., & Ford, P. R. (2008). Expertise and expert performance in sport. *International Review of Sport and Exercise Psychology, 1,* 4 – 18. doi.org/10.1080/17509840701836867

Woods, C. M. (2006). Careless responding to reverse-worded items: implications for confirmatory factor analysis. *Journal of Psychopathology and Behavioral Assessment 28*, 186 - 191. doi.org/10.1007/s10862-005-9004-7

Zizzi, S. J., Deaner, H. R., & Hirschhorn, D. K. (2003). The relationship between emotional intelligence and performance among college baseball players. *Journal of Applied Sport Psychology, 15*, 262 – 269. doi.org/10.1080/10413200390213371

Table 1

Means, Standard Deviations, and Reliability (Ω) Scores for EIS Total and Subscale Scores for One, Four, Five and Six Factor Models

Model (Items)	Subscale	M (SD)				Ω
		Total	Elite	Amateur	Non-Athletes	
Schutte et al., One Factor (33 item)	Total	123.15 (15.87)	130.13 (12.88)	123.94 (13.08)	117.60 (18.37)	.85
Petrides & Furnham Four Factor	Optimism/Mood Regulation	32.93 (5.43)	35.87 (4.28)	32.22 (7.02)	30.09 (8.61)	.71
(33 item)	Appraisal of Emotions	24.20 (5.38)	26.31 (6.54)	23.55 (8.25)	20.97 (10.38)	.70
	Social Skills	41.14 (5.60)	43.90 (6.24)	41.09 (7.33)	38.81 (9.65)	.73
	Utilisation of Emotions	14.88 (2.50)	15.41 (3.12)	14.80 (3.84)	12.92 (5.33)	.62
Lane et al., Six Factor (33 item)	Appraisal of own emotions	19.11 (3.34)	20.19 (4.15)	18.99 (4.51)	15.62 (6.91)	.65
	Regulation of own emotions	18.43 (3.38)	20.63 (3.82)	18.96 (4.39)	16.34 (7.23)	.63
	Utilisation of own emotions	21.82 (3.46)	24.37 (4.51)	22.90 (5.12)	20.52 (6.91)	.69
	Optimism	14.66 (2.07)	17.52 (3.60)	15.05 (4.12)	13.03 (6.63)	.57
	Social skills	18.88 (2.84)	20.07 (3.34)	19.45 (4.56)	16.82 (7.29)	.51
	Appraisal of others emotions	25.97 (4.13)	28.16 (4.22)	26.27 (5.57)	24.16 (8.37)	.69
Lane et al., One Factor (19 item)	Total	72.38 (9.01)	77.39 (7.58)	73.88 (9.89)	69.26 (13.18)	.81

Lane et al., Five Factor (19 item)	Appraisal of own emotions	11.56 (2.28)	13.57 (3.15)	11.11 (3.82)	9.69 (4.51)	.58
	Regulation of own emotions	11.05 (2.14)	12.56 (3.92)	10.26 (4.62)	8.83 (5.26)	.54
	Utilisation of own emotions	17.94 (3.07)	19.61 (3.85)	18.61 (4.48)	16.74 (5.60)	.65
	Social skills	10.74 (2.03)	13.95 (2.11)	11.02 (2.80)	8.98 (4.87)	.51
	Appraisal of others emotions	18.37 (2.91)	20.66 (3.13)	18.45 (3.77)	16.11 (5.32)	.61

Six Factor 33 item measure Lane et al., (2009), One Factor 19 item measure Lane et al., (2009), Five Factor 19 item measure Lane et al., (2009), Four Factor 33 item measure Petrides & Furnham (2000), One Factor 33 item measure Schutte et al., (1998). (N = 1546).

Table 2

Global Fit Indices of One, Four, Five and Six Factor EIS Invariance Models

Model	χ^2	***df***	**RMSEA**	**ULCI**	**LLCI**	**SRMR**	**TLI**	**CFI**	**AIC**	**BIC**
One Factor (33 item)	6523.281	495	.089	.092	.086	.074	.610	.634	127946.704	128475.703
Four Factor (33 item)	2885.510	402	.063	.066	.060	.037	.802	.849	124494.933	125520.871
Six Factor (33 item)	1919.710	345	.054	.057	.052	.028	.902	.920	123643.133	124973.646
One Factor (19 item)	4610.755	495	.104	.106	.101	.118	.331	.373	66788.394	67248.772
Five Factor (19 item)	1495.142	373	.062	.064	.059	.039	.758	.829	63916.781	64944.493
Six Factor (33 item) Configural	3320.682	1035	.065	.068	.062	.035	.823	.885	120866.811	124858.350
Six Factor (33 item) Metric	5320.994	1359	.075	.078	.072	.069	.748	.784	122219.123	124478.392
Six Factor (33 item) Scalar	5554.597	1413	.075	.077	.073	.071	.747	.774	122344.726	124316.450

Note. Number of items for each analysis denoted in parenthesis. χ^2 = Chi-Square, RMSEA = Root Mean Square Error of Approximation, ULCI = Upper Limit Confidence Interval, LLCI = Lower Limit Confidence Interval, SRMR = Standardised Root Mean Residual, Tucker Lewis Index, CFI = Comparative Fit Index, AIC = Akaike Information Criteria, BIC = Bayes Information Criterion. N = 1546.

Table 3

Parameter Estimates for Total Sample on the Six-Factor EIS Model

Items	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**
Appraisal of others emotions						
18. By looking at their facial expressions, I recognize the emotions people are experiencing	.01	**.65**	.18	.26	.30	.16
26. When another person tells me about an important event in his or her life, I almost feel as though I experienced this event myself	.13	**.58**	.07	.22	.12	.20
29. I know what other people are feeling just by looking at them	.22	**.69**	.15	.09	.24	.27
33r. It is difficult for me to understand why people feel the way they do	.21	**.62**	.03	.16	.27	.28
32. I can tell how people are feeling by listening to the tone of their voice	.09	**.64**	.30	.22	.01	.16
5r. I find it hard to understand the nonverbal messages of other people	.05	**.57**	.14	.22	.21	.03
25. I am aware of the nonverbal messages other people send	.12	**.63**	.06	.24	.13	.21
Appraisal of own emotions						
9. I am aware of my emotions as I experience them	**.67**	.06	.23	.04	.31	.05
19. I know why my emotions change	**.59**	.14	.05	.17	.21	.28

22. I easily recognize my emotions as I experience them	**.62**	.13	.18	.22	.03	.28
15. I am aware of the nonverbal messages I send to others	**.62**	.09	.30	.16	.26	.25
2. When I am faced with obstacles, I remember times I faced similar obstacles and overcame them	**.64**	.18	.25	.05	.23	.18
Regulation of emotions						
21. I have control over my emotions	.08	.16	.29	**.56**	.26	.04
14. I seek out activities that make me happy	.27	.15	.13	**.58**	.23	.02
6. Some of the major events of my life have led me to reevaluate what is important and not important	.03	.08	.14	**.62**	.15	.29
23. I motivate myself by imagining a good outcome to tasks I take on	.29	.16	.22	**.64**	.30	.04
1. I know when to speak about my personal problems to others	.18	.23	.07	**.69**	.24	.14
Social Skills						
11. I like to share my emotions with others	.02	.23	.21	.11	.08	**.30**
13. I arrange events others enjoy	.27	**.59**	.24	.17	.30	.54
30. I help other people feel better when they are down	.23	.26	.30	.06	.19	**.64**
4. Other people find it easy to confide in me	.21	.18	.23	.16	.03	**.31**

24. I compliment others when they have done something well	.06	.06	.19	.23	.28	**.66**
Utilisation of emotions						
7. When my mood changes, I see new possibilities	.30	.12	**.57**	.17	.26	.06
12. When I experience a positive emotion, I know how to make it last	.26	.16	**.54**	.01	.19	.24
17. When I am in a positive mood, solving problems is easy for me	.24	.20	**.63**	.18	.02	.12
20. When I am in a positive mood, I am able to come up with new ideas	.11	.01	**.61**	.22	.30	.25
27. When I feel a change in emotions, I tend to come up with new ideas	.10	.20	**.49**	.15	.17	02
31. I use good moods to help myself keep trying in the face of obstacles	.07	.19	**.58**	.31	.04	.15
16. I present myself in a way that makes a good impression on others	.16	.17	**.56**	.01	.24	.23
Optimism						
8. Emotions are one of the things that make my life worth living	0.8	.05	.17	.20	**.30**	.19
28. When I am faced with a challenge, I give up because I believe I will fail	.26	.15	.46	**.51**	.48	.01
3. I expect that I will do well on most things I try	.14	.25	.03	.30	**.68**	.21
10. I expect good things to happen	.08	.17	.01	.22	**.66**	.13

Note. r = reverse coded. Values in bold indicate highest loading on that factor. Values underlined are interpreted as a factor. N = 1546.