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Using exploratory structural equation modelling to examine the psychometric properties of the 10-item Perceived Stress Scale

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Abstract

Investigators frequently use the Perceived Stress Scale (PSS-10) to evaluate the extent to which external demands exceed perceived capacity to manage pressure. Analysts utilizing confirmatory factor analysis (CFA) assert that a bifactor model best fits PSS-10 data, though support exists for a two-factor conceptualisation. Since theorists contend that CFA has limitations, this paper assessed whether exploratory structural equation modelling (ESEM) provided a superior factorial solution. Accordingly, this research assessed the adequacy of two-factor vs. bifactor models using CFA and ESEM. Additionally, analyses tested convergent validity, invariance, and predictive validity in relation to well-being outcomes (Life Satisfaction and Somatic Complaints). In Study 1, 1556 (802 males, 754 females) UK-based participants completed the PSS-10 at time points six months apart. In Study 2, 1630 (838 males, 784 females, eight non-binary) UK-based participants completed the PSS-10 alongside measures of Life Satisfaction and Somatic Complaints. Study 1, using latent modelling, found that the two-factor ESEM model (containing Distress and Counter-Stress factors) produced superior fit (vs. CFA and bifactor solutions). In Study 2, structural equation modelling revealed acceptable predictive validity for the two-factor solution; Distress predicted Somatic Complaints and Counter-Stress predicted Life Satisfaction. Gender (Study 1 and 2) and time (Study 1) demonstrated measurement invariance. Latent means across studies indicated that females (vs. males) scored higher on Distress. Overall, ESEM estimated the PSS-10 more accurately. Findings supported the utility of Distress and Counter-Stress factors for predicting well-being indicators. Future research is necessary to consider this distinction in relation to allied health outcomes.

Keywords Perceived stress scale · Stress · Exploratory structural equation modelling · Measurement invariance · Psychometric properties

Introduction

The Perceived Stress Scale (PSS; Cohen et al., 1983) is a widely used, psychometrically validated, self-report instrument that evaluates the degree to which individuals feel life is unpredictable, uncontrollable, and overloading (Denovan et al., 2019). Development of the PSS drew on the transactional model (Lazarus & Folkman, 1984), which proposes that stress arises from individual appraisals of situational demands and perceived ability to cope (Cohen et al., 1983). Central personal cognitions being negative evaluations stemming from the perceived effect of stressors on well-being (primary appraisal) and ability to manage the resulting demands (secondary appraisal). In this context, individuals feel stressed when they believe a situation/event is threatening and/or fail to initiate an appropriate response (Lazarus & Folkman, 1984). If the stressor persists and remains unresolved then risk of adverse outcomes (i.e., reduced well-being, illness, and disease) increases over time (Cohen & Williamson, 1988).

Researchers have employed three versions of the PSS comprising different item numbers (i.e., PSS-14; PSS-10; and PSS-4). The original version is the PSS-14, which contains seven positively (e.g., 'How often have you been upset because of something that happened unexpectedly?') and seven negatively (e.g., 'How often have you dealt

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successfully with day-to-day problems and annoyances?') phrased items. Ensuing scale evaluation resulted in the psychometrically superior PSS-10, which possesses enhanced factor structure and internal consistency (Cohen & Williamson, 1988). Since the PSS-4 provides only a snapshot of perceived stress, assesses less construct domain than longer versions, and demonstrates higher measurement error, investigators typically only use the instrument in constrained testing situations (telephone interviews, time concerns to avoid respondent fatigue, etc.).

This paper accordingly focused on the PSS-10, which has become the predominant construct measure. Such is the instrument's popularity and prominence, researchers have translated the PSS-10 into multiple languages (e.g., Spanish, Turkish, Arabic, and Chinese) (Lee, 2012). The PSS-10 comprises six positively worded items assessing stress reactivity (e.g., "How often have you been upset because of something that happened unexpectedly?") and four negatively phrased items measuring stress resistance (e.g., "How often have you been able to control irritations in your life?").

Despite being the prevailing measurement instrument, uncertainties about PSS-10 factorial structure persist. These date back to PSS validation, when Cohen et al. (1983) failed to examine the scale's factorial composition. Subsequently, Cohen and Williamson (1988), using principal components analysis, identified a two-factor, inversely related structure composed of positive and negatively phrased items. Noting that factors arose from item polarity and were conceptually irrelevant, Cohen and Williamson (1988) recommended that researchers use total rather than factor scores (Golden-Kreutz et al., 2004). Proceeding multiple studies employing factor analysis produced equivalent two-factor solutions (e.g., Golden-Kreutz et al., 2004; Roberti et al., 2006).

More recently, studies using confirmatory analyses have demonstrated the psychometric superiority of the two-factor model (e.g., Mondo et al., 2021; She et al., 2021) (see review by Yılmaz Koğar, & Koğar, 2024). Concomitantly, academics such as Golden-Kreutz et al. (2004) and Roberti et al. (2006) have questioned Cohen and Williamson's (1988) conclusion that the two-factor solution was theoretically unimportant (Reis et al., 2019). Illustratively, Golden-Kreutz et al. (2004) proposed that the factors represent distinctions between stress (negative consequences) and counter-stress (positive responses). Golden-Kreutz et al.'s (2004) operationalisation was conceptually significant because it aligned with archetypal positive and negative states experienced during stress (Folkman, 1997).

Following replication of the two-factor solution, using exploratory factor analysis and confirmatory factor analysis, Roberti et al. (2006) labelled PSS-10 dimensions Perceived Self-Efficacy and Perceived Helplessness. These titles reflected the role that each factor played in stress processing and regulation (Schneider et al., 2020). The fact that the Roberti et al. (2006) study featured a nonclinical sample (United States college students) increased the generality of their conclusions. By reproducing the two-factor correlated structure, following studies supported the conclusions of Roberti et al. (2006) (e.g., Lee & Jeong, 2019; Michaelides et al., 2016).

Overall, comparisons of factorial models indicate that a unidimensional PSS-10 solution is psychometrically and conceptually problematic. Hence, investigators have adopted analogous two-factor solutions to Roberti et al. (2006), where positive items designate agency and mastery (i.e., efficacy, control, and counter-stress) and reversed items denote negative reactions (i.e., helplessness and discomfort) (Lee, 2012).

In addition to two-factors, some studies advance a general factor (e.g., Dominguez-Lara et al., 2022; Park & Colvin, 2019). Inclusion of a global factor alongside the established factors, produces a bifactor solution (Reise et al., 2010), which conceptualises perceived stress as a global factor encompassing discrete negative and positive dimensions (see Denovan et al., 2019; Lee & Jeong, 2019). Investigators evaluating bifactor models (vs. alternatives) report superior fit (Koğar & Koğar, 2023). In their review of studies using the PSS-10 and PSS-14, Koğar and Koğar (2023) identified three bifactor model variations: general factor with positive and negative subscales, incomplete without negative subscale, and incomplete without positive subscale.

Koğar and Koğar (2023) also reported that PSS evaluation has on occasion identified three-factor solutions (i.e., Bradbury, 2013: correlated three-factor model comprising distress, coping, and emotional reactivity factors; and Pangtey et al., 2020: perceived helplessness, perceived distress, and self-efficacy). However, since such instances are rare and the three-factor model is conceptually inconsistent with Lazarus and Folkman (1984), there is little academic support for that solution.

Noting the existence of alternative PSS-10 models, Denovan et al. (2019) compared factorial solutions using confirmatory analysis (CFA). Analysis found that a bifactor model (vs. one-factor, two-factor, and three-factor alternatives) consisting of PS Total, Distress, and Coping produced best data fit. While these outcomes furthered psychometric and conceptual understanding of the PSS-10, it is necessary to view the findings in the context of CFA constraints. Although an established technique with extensive modelling capabilities, CFA still has limitations (Asparouhov & Muthén, 2009; Grugan et al., 2024). A particular concern is cross-loading, which CFA restricts to zero. This is problematic because items are rarely exclusive indicators of assigned factors (Alamer, 2022). Moreover, bifactor CFA consistently produces greater fit because the technique accommodates 'nonsensical' response patterns (Gomez et al., 2020).

Acknowledging these issues, theorists have increasingly advocated the use of exploratory structural equation modelling (ESEM). Since ESEM captures components of exploratory factor analysis (EFA) and CFA and combines the benefits from both approaches (e.g., uses fit indices, models item-specific error, and permits cross-loadings) statisticians regard it as a superior technique. Illustratively, target rotation within ESEM enables researchers to implement an a priori assessment of factorial models, whilst limiting cross-loadings to be close to zero. This facilitates the application of confirmatory tests of measurement structures with factor structures resemblant of EFA (Morin et al., 2020).

In the context of the PSS-10, application of CFA necessitates treating Distress and Coping factors as discrete factors. This is theoretically inconsistent with the notion that individuals high in Distress possess corresponding Coping ability and assumes that Distress items do not load on the Coping factor (and vice versa). Realistically, items assessing features of distress are likely to present weaker, but still meaningful, associations with coping ability. Therefore, cross-loadings are likely to occur. Using CFA for the PSS-10 is problematic because unmodelled cross-loadings can lead to biased parameter estimates and model misfit. When a PSS-10 indicator (item) loads significantly onto multiple factors, it reflects influence from more than one latent construct, which violates the assumption of simple structure. This assumption forms the foundation of CFA, requiring each indicator to measure only one specific factor. If researchers ignore cross-loadings, they risk misspecifying the model, which can lead to poor model fit (Bollen, 2020).

The presence of cross-loadings can also make it challenging to interpret the meaning of the factors and their relationships with the indicators, potentially leading to misinterpretations of the scales and the underlying constructs. This can produce poor fit indices and difficulties in interpreting the model. Cross-loadings can furthermore result in difficulty establishing discriminant validity, as indicators may be measuring constructs that are more closely related than initially hypothesized. This can distort factor correlations, structural parameter estimates, and overall model fit, making it difficult to interpret the relationship between the factors and their indicators (Ximénez et al., 2022). Indeed, even well-fitting CFA models (such as those observed within the PSS-10 literature), are likely to suffer from misspecifications arising from restrictive CFA assumptions. CFA effectively 'absorbs' unspecified cross-loadings by inflating correlations between factors (i.e., when items cross-load, the only mechanism for expression is through inflating factor associations) leading to biased estimates of factor correlations and structural parameters (Morin et al., 2016). Cross-loadings in CFA can undermine the validity and reliability of model interpretation and conclusions. As a result, CFA imposes overly restrictive assumptions that fail to capture the complexity of perceived stress, reducing the measure's validity.

ESEM, by virtue of being more flexible, permits cross-loadings. This acknowledges that multiple latent variables may influence items and avoids forcing them to load solely on one factor (Prokofieva et al., 2023). Specifically, it can assess whether items capture specific factor contact (e.g., Distress, inability to cope), while concurrently tapping into the other factor (i.e. Coping, ability to counter stress). It facilitates this by allowing items to load on multiple factors. Items' cross-loadings can be as low as 0.10, thus limiting inaccurately inflated parameters or distorted data-fit from restricting cross-loadings to zero. ESEM with target rotation allows researchers to apply a predefined factor structure, while permitting cross-loadings to be estimated freely but kept as close to zero as possible. For example, when estimating a Distress factor based on stress-related items (e.g., 'How often have you felt nervous and stressed?'), the model specifies that coping-related items should load near zero. This approach supports a more theoretically accurate evaluation of latent composition and accounts for the limitations of CFA by permitting cross-loadings. This helps to reduce bias impacting parameter estimates, resulting in a more precise estimation of factor correlations (Asparouhov et al., 2015). Precisely, ESEM helps to guard against concerns of restricting cross-loadings when they exist, including inflated factor correlations, biased parameter estimates, and model misspecification. See Fig. 1 for a schematic of how ESEM handles cross-loadings vs. CFA.

Regarding the PSS-10, mixed outcomes produced using CFA indicate that ESEM will yield superior solutions (Koğar & Koğar, 2023). In addition, Barbosa-Leiker et al. (2013) reported an instance of content overlap, which suggests cross-loading. In this context, ESEM is appropriate as it provides a less rigid evaluation of latent structure. Despite this, few analysts have thoroughly examined the PSS-10 using ESEM. A recent ESEM-based paper by Dominguez-Lara et al. (2022) found support for a two-factor model but failed to assess a bifactor solution.

In addition to assessing PSS-10 structure using ESEM, the present study tested gender and time invariance. Invariance is important because it demonstrates the consistency of PSS-10 measurement across distinct groups. While studies have previously evaluated differences over time (e.g., Ostwald et al., 2009), despite investigators administering the PSS-10 to different age groups (e.g., university students, Denovan et al., 2019; older adults, Park-Lee et al., 2009; adolescents, Austin et al., 2009), concurrent consideration of time and gender has remained limited. Indeed, to the

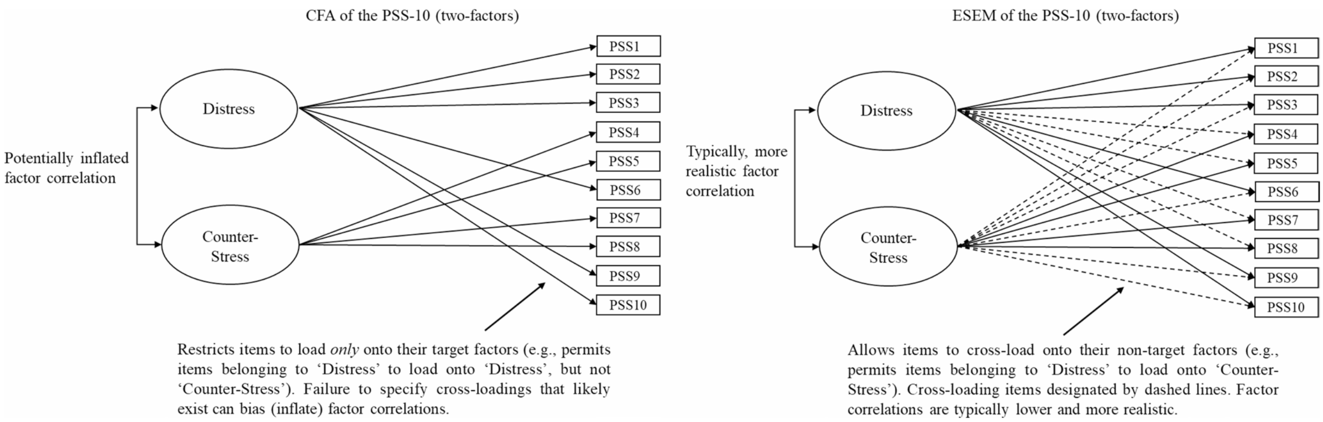

Fig. 1 Schematic of how ESEM handles cross-loadings vs. CFA

knowledge of the authors only one prior study has simultaneously examined PSS-10 gender and time invariance. Within this, Barbosa-Leiker et al. (2013) supported invariance, but employed CFA modelling. Hence, to compare separate groups on a latent construct (Chen et al., 2005), and means over time (Brown, 2006) it is necessary to establish group-level and longitudinal invariance using ESEM.

The PSS-10 measures primary (relevance to personal wellbeing) and secondary appraisals (capacity to overcome ensuing demands) (Lazarus, 2006). Research consistently indicates these appraisals predict (directly and indirectly) well-being-related factors including lower life satisfaction (e.g., Abolghasemi & Varaniyab, 2010; Cho & Kim, 2014; Yang & Kim, 2016) and greater somatic complaints/problems (e.g., Verkuil et al., 2012). This designates PSS measurement validity. However, studies typically use total scores, created by adding perceived stress to reverse-score coping-related items (e.g., Lee et al., 2016). This is problematic because the scale's underlying multidimensionality and the practice of reversing items may produce unnecessary variance, which is detrimental to construct validity (Reise et al., 2016). Moreover, the variable-centred approach lacks assessment of item-specific variance/error.

The present paper

This study evaluated the factorial structure of the PSS-10 using CFA and ESEM (Study 1) and examined the predictive validity of the PSS-10 in relation to frequently assessed well-being criteria (somatic complaints and life satisfaction) (Study 2). Studies utilised independent, nonclinical adult samples as the researchers wished to establish, commensurate with prior investigations, that the PSS-10 is appropriate for use with general populations. Moreover, the non-clinical sample groups in this study acted as significant comparison groups for clinical samples. Assessment of factorial structure included tests of invariance across gender and time. Study 1 was necessary to advance understanding of the PSS-10's measurement properties. Also, latent mean contrasts across gender and time provided information on distress and counter-stress (coping) frequency levels. Study 2 assessed the predictive capacity of the PSS-10 relative to frequently studied wellbeing outcomes. Finally, performing analysis in a latent modelling context, facilitated explicit assessment of measurement error (Byrne, 2013).

Specific research objectives were to: (1) Determine whether factor analytic results best supported a two-factor or two-factor bifactor PSS-10 model; (2) Evaluate the effectiveness of CFA and ESEM estimation approaches; (3) Establish PSS-10 performance across gender and time; and (4) Assess whether the PSS-10 demonstrated satisfactory predictive validity relative to well-being criteria.

Achievement of Objectives 1 and 2 was via comparison of competing models (Study 1, establishment; and Study 2, replication). Objective 3 required invariance testing (Study 1 and 2). Objective 4 necessitated scrutiny of a latent model (Study 2). Figure 2 presents a schematic representation of the research tasks. This research adopted a correlational approach for examining the objectives, focusing on regression-based predictive relationships alongside psychometric scrutiny.

Study 1

Method

Participants

A sample of 1556 (802 males, 52%; 754 females, 48%) UK-based participants completed study measures at two time points (Time 1 and Time 2) six months apart. At Time 1, *Mean* age = 51.91 (*SD* = 14.93, range of 18 to 88). The *Mean*

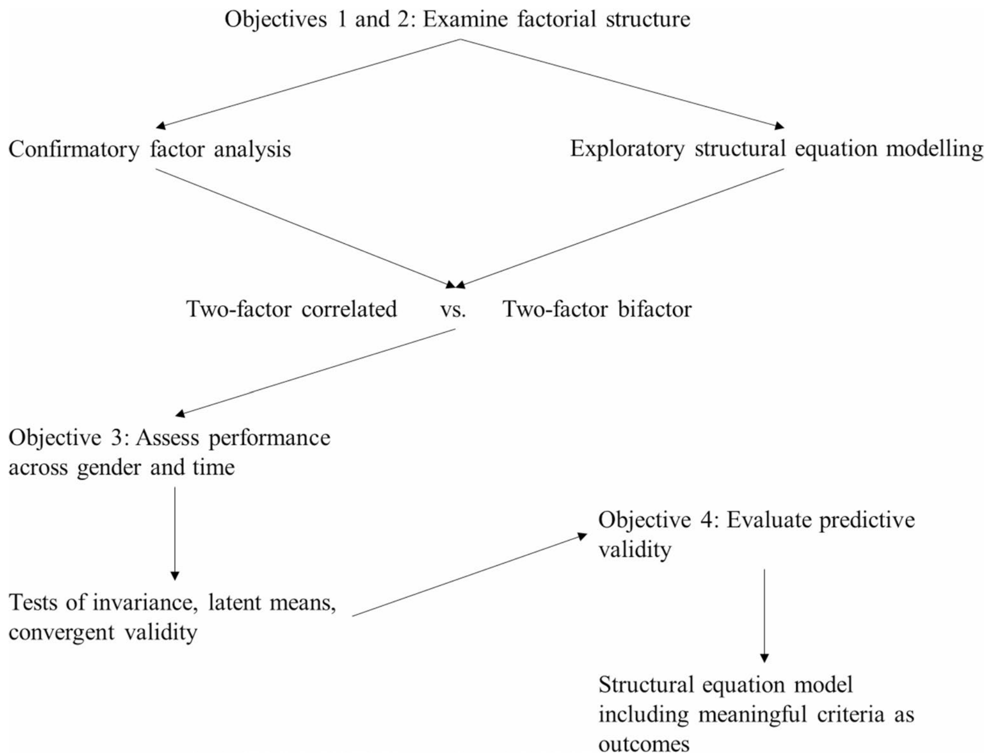

Fig. 2 Flowchart depicting the research objectives

age at Time 2 (*Mean* age = 51.98, *SD* = 14.91). The researchers instructed Bilendi to deliver a general, representative UK-based sample comprising equal distributions of gender and a range of ages.

Measure

The PSS-10 is a 10-item self-report instrument that measures the extent to which respondents feel their life over the past month was unpredictable, uncontrollable, and overloaded (Cohen & Williamson, 1988). Items appear as statements and participants record responses on a five-point response scale: 0 (*never*) to 4 (*very often*). The measure comprises two subscales, Distress (e.g., *'How often have you felt difficulties were piling up so high that you could not overcome them?'*), and Coping/counter-stress (e.g., *'How often have you been able to control irritations in your life?'*). Distress assesses negative features of stress and Counter-Stress the ability to manage stress. Denovan et al. (2019, 2024) reported satisfactory internal reliability for the total scale, in addition to the Distress and Counter-Stress subscales.

Procedure and ethical approval

The investigators recruited participants via Bilendi Ltd., who are a recognised provider of quality online samples for research purposes (see Dagnall et al., 2022; Drinkwater et al., 2021). Potential participants received a weblink to the online survey, which contained an information sheet and a consent form detailing study procedures and participant rights. Participants who indicated consent by ticking a box progressed to the survey. Prior to accessing the PSS-10, participants completed a brief demographic section. Following conclusion of the survey, participants received the study debrief, which re-iterated the study purpose and their rights. The Manchester Metropolitan University Research Ethics Committee provided ethical approval.

Analysis

Data screening occurred prior to model testing. Confirmatory factor analysis (CFA) and exploratory structural equation modelling (ESEM) assessed fit. Analysis tested a series of models: correlated two-factor and bifactor solutions (comprising Distress and Counter-Stress factors), and separate analysis for males and females at each time point. Following identification of the superior solution, analysis estimated CFA and ESEM models for the sample at each time point. To avoid confounding the Counter-Stress factor PSS-10 items were not reverse-coded (Barbosa-Leiker et al., 2013). Analyses used Mplus v8 (Muthén & Muthén, 2018).

The Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Standardized Root-Mean-Square Residual (SRMR), and the Root-Mean-Square Error of Approximation (RMSEA) determined model fit. CFI and TLI are relative fit indices. Relative fit examines the relationship between a proposed model's chi-square and the chi-square of a null/

baseline model (i.e., one in which all relationships among variables are zero). Hence, fit specifies the degree to which a model corresponds to a null model. CFI and TLI account for model complexity, penalizing overly complex models that do not improve fit. CFI and TLI ≥ 0.95 indicate ideal fit, with values ≥ 0.90 satisfactory. RMSEA estimates the discrepancy between the sample/population covariance matrix and the model-implied covariance matrix per degree of freedom, making it sensitive to model parsimony. RMSEA computes the difference between the covariance matrix of a population/sample and a reproduced covariance matrix and accordingly determines how 'far' a proposed model is from a perfect model. RMSEA uses a 95% Confidence Interval, which provides an indication of model fit precision. Cutoff values advise that RMSEA ≤ 0.05 indicates close fit, ≤ 0.08 acceptable fit, and ≥ 0.10 poor fit (Browne & Cudeck, 1992).

SRMR computes the square root of the divergence between a population covariance matrix and a model covariance matrix. Lower values reflect less deviation, with values ≤ 0.08 suggestive of good fit (Hu & Bentler, 1999). Since SRMR directly assesses the absolute discrepancy between observed and predicted correlations, it is useful in evaluating model misspecification. The selection of these criteria is appropriate for current data, as the models evaluated varied in complexity and dimensional structure (e.g., CFA, bifactor CFA, ESEM, and bifactor ESEM). Given that these models are not necessarily nested, consultation of the Bayesian Information Criterion (BIC) occurred for model comparison, as recommended (Lee, 2021). Lower BIC indicates superior fit.

Evaluation of bifactor models included Explained Common Variance (ECV), hierarchical omega (ω_h), and Item Explained Common Variance (IECV). ECV and $\omega_h > 0.80$ suggests that a general factor accounts for the majority of variance (vs. specific bifactors) and indicates scale unidimensionality (Rodriguez et al., 2016). IECV item values >0.80 signify that a specific item is a good representative candidate of a general factor, whilst limiting the impact of the specific bifactor. Thus, average (mean, M) IECVs >0.80 provide compelling evidence for scale items representing a general dimension rather than specific bifactors (Stucky & Edelen, 2015).

Following identification of optimal PSS-10 models for males and females and time points, invariance testing occurred. This involved assessing progressively restrictive models; test of form (configural), then factor loadings (metric), and finally intercepts (scalar). In the configural invariance model, the same item-factor assignment is imposed on all groups (gender and time) and thus, the number of factors is identical. Factor loadings, item intercepts, and factor means, however, can vary across groups. If configural invariance is supported, unstandardized loadings are restricted to equality across groups (metric invariance model). If metric model fit does not deteriorate when compared to the configural model, scalar invariance can be assessed by constraining item intercepts to equality. Scalar invariance allows for valid comparisons of latent group means. Then, users can validly compare manifest mean differences. A comparison of models used Chen's (2007) criteria, with invariance determined by a change in CFI ≤ 0.01, and a change in RMSEA ≤ 0.015. Satorra-Bentler chi-square also facilitated comparison among the nested models. If scalar invariance was satisfactory, Z-tests examined differences across gender and time.

Based on the final model, Average Variance Extracted (AVE) and Composite Reliability (CR) provided further evidence of the PSS-10's quality. AVE is the quantity of average variance accounted for in each item by the latent variable and helps to validate convergent validity. CR evaluates how consistent the items are with the latent factor. CR is a reliability test specific to a latent modelling context, and thus can provide important reliability information over and above omega. Theorists recommend AVE values >0.50 and CR >0.70 (Fornell & Larcker, 1981; Škerlavaj & Dimovski, 2009).

Results

Preliminary analysis

PSS-10 items evidenced multivariate non-normality (i.e., skewness, $b1p$, and kurtosis, $b2p$) at each time point using Mardia's test; Time 1 $b1p = 5.02$, $p < .001$, $b2p = 51.66$, $p < .001$; Time 2 $b1p = 4.80$, $p < .001$, $b2p = 50.59$, $p < .001$. Items varied in terms of skew directionality, but indicated negative kurtosis (however, values did not exceed the threshold of −1; Field & Miles, 2010). Estimation using maximum likelihood with robust standard errors (MLR) was thus necessary (Marsh et al., 2013). Omega reliability was good for Time 1 (total score $\omega = 0.85$, Distress subscale $\omega = 0.92$, Counter-Stress subscale $\omega = 0.86$) and Time 2 (total score $\omega = 0.84$, Distress subscale $\omega = 0.92$, Counter-Stress subscale $\omega = 0.86$).

Factor analysis

Table 1 shows the fit of the competing PSS-10 models for gender (males and females) at Time 1 and Time 2. All models demonstrated good fit across indices, specifically CFI and TLI ≥ 0.95, SRMR and RMSEA ≤ 0.08. In comparison, the bifactor ESEM solution exhibited the greatest data-model fit, based on the strongest fit indices and lowest BIC. However, scrutiny of bifactor-specific indices indicated that

Table 1 Fit indices of competing PSS-10 models in study 1

Model	Model Fit Indices													
Model	χ2	*df*	*CFI*	*TLI*	*SRMR*	*RMSEA (90% CI)*	*BIC*	χ2	*df*	*CFI*	*TLI*	*SRMR*	*RMSEA (90% CI)*	*BIC*
	Males							*Females*						
Two-factor CFA														
Time 1	144.17**	34	0.96	0.96	0.03	0.06 (0.05–0.07)	20571.054	82.47**	34	0.98	0.97	0.03	0.04 (0.03–0.05)	19358.185
Time 2	126.00**	34	0.97	0.96	0.03	0.05 (0.04–0.06)	20352.831	175.54**	34	0.95	0.94	0.04	0.07 (0.06–0.08)	19766.485
Bifactor CFA														
Time 1	71.61**	25	0.98	0.97	0.02	0.04 (0.03–0.06)	20511.623	52.50**	25	0.98	0.98	0.02	0.03 (0.02–0.05)	19343.232
Time 2	92.40**	25	0.98	0.96	0.02	0.05 (0.04–0.07)	20324.477	88.96**	25	0.97	0.96	0.03	0.05 (0.04–0.07)	19672.221
Two-factor ESEM														
Time 1	88.73**	26	0.98	0.97	0.01	0.05 (0.04–0.06)	20543.486	48.27**	26	0.99	0.99	0.01	0.03 (0.01–0.04)	19342.985
Time 2	80.44**	26	0.98	0.97	0.01	0.05 (0.03–0.06)	20332.121	129.50**	26	0.97	0.94	0.02	0.07 (0.06–0.08)	19743.622
Bifactor ESEM														
Time 1	48.80**	18	0.99	0.98	0.01	0.04 (0.03–0.06)	20508.474	28.80*	18	0.99	0.99	0.01	0.02 (0.01–0.04)	19338.933
Time 2	44.17**	18	0.99	0.98	0.01	0.04 (0.02–0.05)	20301.280	45.71**	18	0.99	0.98	0.01	0.04 (0.02–0.06)	19650.105
	Time 1							*Time 2*						
Two-factor CFA	185.04**	34	0.97	0.96	0.03	0.05 (0.04–0.06)	39880.635	261.98**	34	0.96	0.95	0.03	0.06 (0.05–0.07)	40072.347
Bifactor CFA	98.51**	25	0.99	0.97	0.02	0.04 (0.03–0.05)	39798.010	155.51**	25	0.98	0.96	0.03	0.05 (0.04–0.06)	39942.872
Two-factor ESEM	104.35**	26	0.99	0.98	0.01	0.04 (0.03–0.05)	39821.002	182.14**	26	0.98	0.96	0.01	0.06 (0.05–0.07)	40019.733
Bifactor ESEM	55.64**	18	0.99	0.98	0.01	0.03 (0.02–0.04)	39779.474	72.52**	18	0.99	0.97	0.01	0.04 (0.03–0.05)	39888.531

χ^2 chi-square; *df* degrees of freedom, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index, *SRMR* Standardized Root-Mean-Square Residual, *RMSEA* Root-Mean-Square Error of Approximation, *BIC* Bayesian Information Criterion; * χ^2 significant at $p<.05$; ** χ^2 significant at $p<.001$

this model did not possess a robust general factor for males at Time 1 (ECV = 0.27, $\omega_{h\,=}$ 0.36, *M* IECV = 0.26) and Time 2 (ECV = 0.35, $\omega_{h\,=}$ 0.41, *M* IECV = 0.34), or for females at Time 1 (ECV = 0.64, $\omega_{h\,=}$ 0.74, *M* IECV = 0.61) and Time 2 (ECV = 0.16, $\omega_{h\,=}$ 0.19, *M* IECV = 0.15). Similar results occurred when scrutinising the bifactor CFA for males at Time 1 (ECV = 0.55, $\omega_{h\,=}$ 0.74, *M* IECV = 0.55), Time 2 (ECV = 0.53, $\omega_{h\,=}$ 0.72, *M* IECV = 0.53), females at Time 1 (ECV = 0.60, $\omega_{h\,=}$ 0.79, *M* IECV = 0.61), and Time 2 (ECV = 0.36, $\omega_{h\,=}$ 0.50, *M* IECV = 0.32).

Superior fit (vs. two-factor CFA), and the redundancy of the general factor in the bifactor models signified that the two-factor ESEM was the most appropriate solution. Comparing models for each time point using the total (male and female) sample BIC supported this conclusion (see Table 1). Specifically, bifactor ESEM Time 1 (ECV = 0.55, $\omega_{h\,=}$ 0.65, *M* IECV = 0.52), Time 2 (ECV = 0.22, $\omega_{h\,=}$ 0.26, *M* IECV = 0.21), bifactor CFA Time 1 (ECV = 0.57, $\omega_{h\,=}$ 0.76, *M* IECV = 0.58), and Time 2 (ECV = 0.32, $\omega_{h\,=}$ 0.45, *M* IECV = 0.29).

Factor loadings were high for the two-factor ESEM model across males, females, and time points, and exceeded the strict requirements of 0.60 by Hair et al. (2006). Small but significant cross-loadings occurred for most items (i.e., < 1.0) (see Table 2). Average target-factor loadings were good for both Distress (Time 1 females = 0.79, males = 0.81, Time 2 females = 0.80, males = 0.83, Time 1 overall = 0.82, Time 2 overall = 0.81) and Counter-Stress (Time 1 females = 0.77, males = 0.79, Time 2 females = 0.77, males = 0.79, Time 1 overall = 0.78, Time 2 overall = 0.78) factors. Small to medium significant inter-factor correlations existed between Distress and Counter-Stress (Time 1 females = 0.33, males = 0.27, Time 2 females = 0.25, males = 0.25, Time 1 overall = 0.30, Time 2 overall = 0.25).

Invariance

Results of invariance testing for the two-factor ESEM model at each time point across gender (male vs. female) are in Table 3. At Time 1 and Time 2 (comparing gender), models of equal structure (configural), factor loadings (metric), and intercepts (scalar) reported good fit and did not display significant decreases in fit when compared against less restrictive models. Explicitly, for Time 1 and Time 2 (males vs. females) all CFI and RMSEA changes were ≤0.01 and ≤0.015 respectively for each model comparison (i.e., configural vs. metric, metric vs. scalar), alongside non-significant differences in Satorra-Bentler chi-square. Similarly, invariance existed across time point (Time 1 vs. Time 2) using the combined samples from Time 1 and Time 2. CFI and RMSEA changes were ≤0.01 and ≤0.015, respectively. The scalar model did, however, report a significant Satorra-Bentler result, yet the deviations in fit remained small enough to not cause concern (Papageorgiou et al., 2022). Existence of scalar invariance permitted a comparison of latent means, firstly for gender and then for the time points.

Latent mean comparisons

Women exhibited significantly higher Distress at Time 1 than men (Z = 1.84, p = .033). No significant differences existed for Distress at Time 2 (Z = 0.73, p = .234), or for Counter-Stress at Time 1 (Z = 0.28, p = .390) and Time 2 (Z = 0.28, p = .389). Similarly, no significant differences occurred across time points for Distress (Z = 1.26, p = .103) or Counter-Stress (Z = 1.22, p = .111).

Convergent validity

For the final model (two-factor ESEM for each sample per time point), Fornell and Larckers' (1981) formula manually calculated AVE and CR. The Time 1 model evidenced AVE of 0.65 and CR of 0.92 for Distress, and AVE of 0.61 and CR of 0.86 for Counter-Stress. The Time 2 model exhibited AVE of 0.67 and CR of 0.92 for Distress, and AVE of 0.62 and CR of 0.87 for Counter-Stress. These results indicated good convergent and construct validity.

Conclusion

A two-factor ESEM solution (containing Distress and Counter-Stress factors) was superior across gender and time. Satisfactory psychometric properties existed, including invariance and convergent validity.

Study 2

Method

Participants and procedure

Study 2 comprised a sample of 1630 UK-based participants (*Mean* age = 52.04, *SD* = 14.79, range of 18 to 86), including 838 males, 784 females, and eight non-binary. Data collation involved an identical procedure to Study 1. The same ethical submission as Study 1, approved Study 2. To reduce potential common method variance arising from multiple self-report measures, the researchers implemented procedural remedies (Krishnaveni & Deepa, 2013). Particularly, to accentuate construct divergence, specific section instructions created psychological distance among measures.

Table 2 Parameter estimates (standardized factor loadings) of the two-factor ESEM model across gender and time

	Time 1 Males		Time 2 Males		Time 1 Females		Time 2 Females		Time 1 Overall		Time 2 Overall	
	Distress	Counter-Stress	Distress	Counter-Stress	Distress	Counter-Stress	Distress	Counter-Stress	Distress	Counter-Stress	Distress	Counter-Stress
Item 1	**0.83****	− 0.06**	**0.85****	− 0.06**	**0.79****	− 0.08*	**0.81****	− 0.04	**0.81****	− 0.07**	**0.83****	− 0.04*
Item 2	**0.83****	0.05*	**0.85****	0.03*	**0.82****	0.03	**0.80****	0.07*	**0.82****	0.04*	**0.82****	0.05*
Item 3	**0.82****	0.02	**0.85****	0.03*	**0.85****	0.03	**0.82****	0.05*	**0.83****	0.02*	**0.84****	0.04*
Item 6	**0.81****	− 0.01	**0.82****	0.02	**0.79****	0.03	**0.81****	− 0.03	**0.80****	0.01	**0.81****	− 0.01
Item 9	**0.78****	− 0.08**	**0.76****	− 0.08**	**0.75****	− 0.08**	**0.77****	− 0.10**	**0.77****	− 0.08**	**0.77****	− 0.09**
Item 10	**0.82****	0.07**	**0.84****	0.06*	**0.79****	0.06*	**0.82****	0.04	**0.80****	0.07**	**0.83****	0.04*
Item 4	− 0.01	**0.76****	− 0.01	**0.74****	0.04*	**0.75****	0.01	**0.73****	0.01	**0.76****	− 0.01	**0.74****
Item 5	− 0.06*	**0.77****	− 0.06*	**0.81****	− 0.06*	**0.79****	− 0.01	**0.77****	− 0.06*	**0.77****	− 0.03*	**0.79****
Item 7	0.01	**0.79****	0.02	**0.76****	− 0.02	**0.74****	− 0.06*	**0.76****	− 0.01	**0.77****	− 0.02	**0.76****
Item 8	0.07*	**0.82****	0.06*	**0.84****	0.04*	**0.79****	0.06*	**0.84****	0.06*	**0.81****	0.06*	**0.84****

Targeted loadings in bold; *significant at $p<.05$; **significant at $p<.001$

Measures

The PSS-10 was utilised, in addition to two criterion measures: Somatic Symptom Scale-8 (SSS-8; Gierk et al., 2014), and the Satisfaction with Life Scale (SWLS; Diener et al., 1985).

SSS-8

The SSS-8 assessed vulnerability towards somatic complaints. The scale includes eight items, which reflect common somatic ailments (e.g., 'Headaches', 'Dizziness') over the past seven days. Participants respond to each item using a five-point response scale (i.e., 0, not at all, to 4, very much). Preceding research has reported good internal reliability (Gierk et al., 2014).

SWLS

The SWLS measures a cognitive dimension of well-being (life satisfaction), by focusing on global judgements of how satisfied people are with their lives. Items appear as statements (e.g., 'In most ways my life is close to ideal', 'If I could live my life over, I would change almost nothing'), participants respond using a seven-point scale (i.e., 1, strongly disagree, to 7, strongly agree). The scale has demonstrated high internal consistency and temporal stability (Diener et al., 1985).

Analysis

Analysis for Study 2, by examining factor structure, invariance, convergent validity, and reliability, focused on verifying the supported model from Study 1. Additionally, the predictive validity of the superior model was scrutinised by specifying a structural equation model, which regressed the two-factor ESEM model onto Somatic Complaints and Life Satisfaction. Initially, in addition to testing the ESEM model, assessment of measurement models representing Somatic Complaints and Life Satisfaction occurred (Anderson & Gerbing, 1988). Fit indices of CFI, TLI, SRMR, and RMSEA determined data-model fit.

Results

Preliminary analysis

As with Study 1, alongside negative kurtosis multivariate non-normality existed for PSS-10 items; $b1p$= 5.17, p<.001, $b2p$= 48.31, p<.001. Good reliability was apparent for the total scale (ω= 0.86), Distress (ω= 0.92), and

Table 3 Study 1 PSS-10 invariance models

Model	χ^2	df	CFI	CFI difference	TLI	SRMR	RMSEA (90% CI)	RMSEA difference	ΔS–Bχ2 (df), *p*
Time 1 (Male vs. Female)									
Configural	134.07**	52	0.99		0.98	0.01	0.04 (0.03–0.05)		
Metric	152.13**	68	0.99	None	0.98	0.02	0.04 (0.03–0.04)	0.005	10.72 (16), 0.826
Scalar	159.87**	76	0.99	None	0.98	0.02	0.03 (0.02–0.04)	0.002	5.01 (8), 0.756
Time 2 (Male vs. Female)									
Configural	209.63**	52	0.98		0.96	0.01	0.06 (0.05–0.07)		
Metric	238.17**	68	0.97	0.002	0.97	0.02	0.05 (0.04–0.06)	0.005	17.07 (16), 0.380
Scalar	247.36**	76	0.97	None	0.97	0.02	0.05 (0.04–0.06)	0.003	4.05 (8), 0.852
Time (Time 1 vs. Time 2)									
Configural	286.53**	52	0.98		0.97	0.01	0.05 (0.04–0.06)		
Metric	316.68**	68	0.98	0.001	0.97	0.01	0.04 (0.04–0.05)	0.006	10.28 (16), 0.851
Scalar	341.34**	76	0.98	0.002	0.97	0.01	0.04 (0.04–0.05)	0.001	21.12 (8), 0.007*

χ^2 chi-square, *df* degrees of freedom, *CFI* Comparative Fit Index, *SRMR* Standardized Root-Mean-Square Residual, *RMSEA* Root-Mean-Square Error of Approximation, *S–Bχ2* Satorra-Bentler scaled chi-square; *χ^2 significant at $p<.05$; **χ^2 significant at $p<.001$

Table 4 Study 2 PSS-10 invariance models

Model	χ^2	df	CFI	CFI difference	TLI	SRMR	RMSEA (90% CI)	RMSEA difference	ΔS–Bχ2 (df), *p*
Male vs. Female									
Configural	188.58**	52	0.98		0.96	0.01	0.05 (0.04–0.06)		
Metric	216.28**	68	0.98	0.001	0.97	0.02	0.05 (0.04–0.06)	0.005	17.14 (16), 0.376
Scalar	239.79**	76	0.98	0.003	0.97	0.02	0.05 (0.04–0.05)	None	23.01 (8), 0.003*

χ^2 chi-square, *df* degrees of freedom, *CFI* Comparative Fit Index, *SRMR* Standardized Root-Mean-Square Residual, *RMSEA* Root-Mean-Square Error of Approximation, *S–Bχ2* Satorra-Bentler scaled chi-square, *χ^2 significant at $p<.05$; **χ^2 significant at $p<.001$

Counter-Stress ($\omega = 0.86$) subscales. SSS-8 and SWLS also exhibited good reliability ($\omega = 0.89$, $\omega = 0.81$ respectively).

Factor analysis

The two-factor ESEM model demonstrated good fit across indices, χ2 (26) = 168.39, $p<.001$, CFI = 0.98, TLI = 0.96, SRMR = 0.01, RMSEA = 0.05 (0.05, 0.06). Average target-factor loadings were high (Distress = 0.82, Counter-Stress = 0.78), and small but significant cross-loadings occurred for most items (i.e., < 1.0). The latent factors exhibited a small significant correlation, $r=.21$, $p<.001$. A one-factor model of the SWLS revealed good fit, χ2 (5) = 20.84, $p=.001$, CFI = 0.99, TLI = 0.97, SRMR = 0.01, RMSEA = 0.04 (0.03, 0.06). A high average factor loading existed (0.68). Comparable results occurred for the SSS-8, but with marginally acceptable RMSEA, χ2 (19) = 276.53, $p<.001$, CFI = 0.93, TLI = 0.90, SRMR = 0.04, RMSEA = 0.09 (0.08, 0.10). Average loading = 0.71.

Invariance and latent means

Invariance testing for gender (males vs. females) found good fit at the configural, metric, and scalar level for the two-factor ESEM. Moreover, no significant differences in CFI or RMSEA existed (Table 4). Latent mean comparisons revealed that females scored significantly higher than males on Distress ($Z = 6.11$, $p<.001$). No significant difference emerged for Counter-Stress ($Z = 1.24$, $p=.108$).

Convergent validity

AVE for the two-factor ESEM model in Study 2 was good. Specifically, 0.67 for Distress, and 0.61 for Counter-Stress. CR was additionally good, with results of 0.92 and 0.86 occurring for Distress and Counter-Stress, respectively.

Predictive validity

A model examining predictive relationships between the two-factor ESEM model and criterion variables of Somatic Complaints and Life Satisfaction (Fig. 3) revealed good fit, χ2 (216) = 1184.31, $p<.001$, CFI = 0.94, TLI = 0.92, SRMR = 0.04, RMSEA = 0.05 (0.05, 0.06). Distress predicted significantly greater Somatic Complaints, $\beta = 0.67$, $p<.001$, and Counter-Stress predicted significantly lower Life Satisfaction (due to retaining original PSS-10 scoring), $\beta = -0.25$, $p<.001$. Distress was not a significant predictor of Life Satisfaction, $\beta = -0.05$, $p=.160$, and Counter-Stress did not significantly predict Somatic Complaints, $\beta = -0.05$, $p=.061$. As thematically associated outcomes significantly predicted PSS-10 factors (i.e., Somatic Complaints by Distress, Counter-Stress by Life Satisfaction) these results suggested that the PSS-10 possessed satisfactory predictive validity. Moreover, the model explained 44% and 7%

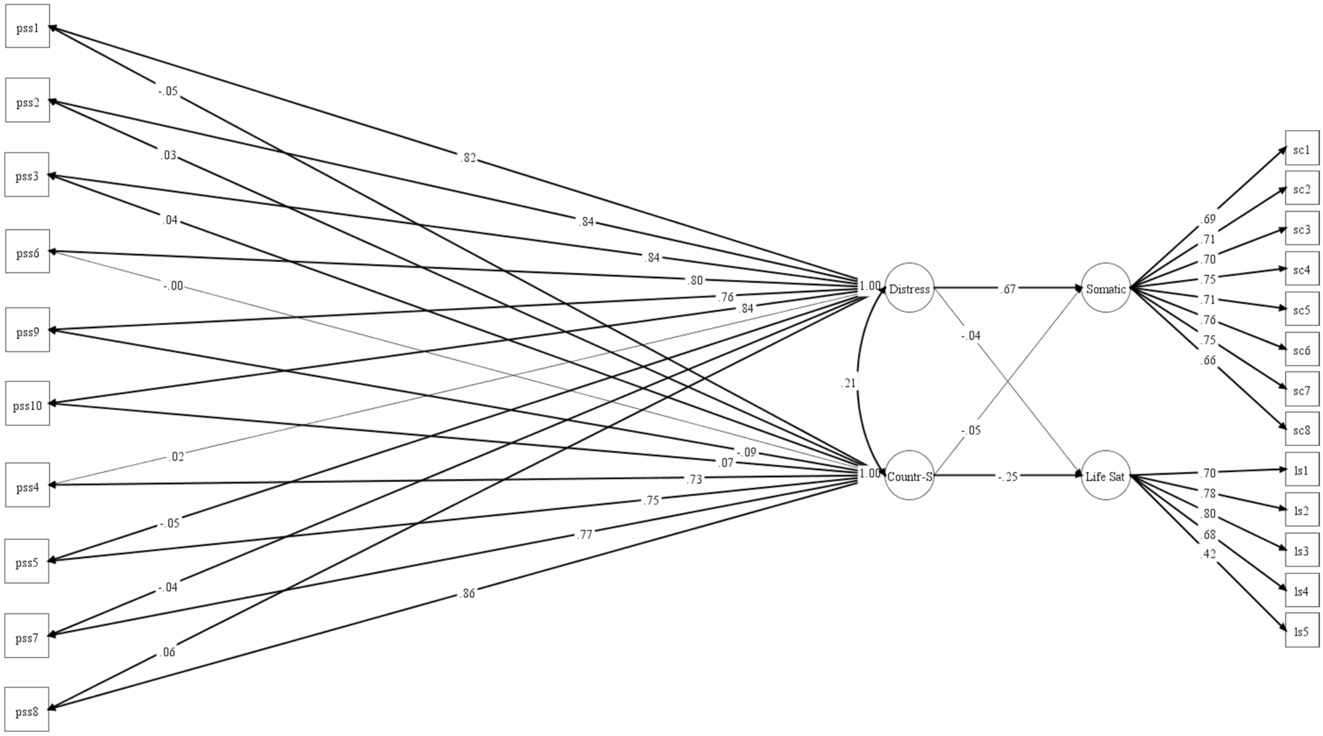

Fig. 3 Predictive validity of the two-factor ESEM model of the PSS-10. *Note.* Countr-S = Counter-Stress; Somatic = Somatic Complaints; Life Sat = Life Satisfaction. Latent variables represented by ellipses; measured variables represented by rectangles; error not shown but specified for all variables. Bold arrows depict significant loadings/relationships at $p<.05$; faded arrows depict non-significant loadings/relationships at $p>.05$. Standardised results displayed

of variance in Somatic Complaints and Life Satisfaction, respectively.

Conclusion

The PSS-10 performed well psychometrically. Moreover, Study 2 confirmed the two-factor ESEM model within an independent sample, where it significantly predicted Somatic Complaints (Distress factor) and Life Satisfaction (Counter-Stress factor).

Overall discussion

Study 1 revealed that the two-factor ESEM solution (containing Distress and Counter-Stress factors) produced superior fit to the alternative tested models (i.e., CFA and bifactor). Successful replication of the two-factor ESEM model occurred in Study 2. With regards to Objective 1 (determine whether factor analytic results best supported a two-factor or two-factor bifactor PSS-10 model), outcomes confirmed that this solution was most appropriate for the PSS-10, owing to the greater flexibility and less restrictive nature of ESEM (vs. CFA) (Morin et al., 2020). Consistent with previous research, permitting cross-loading, even small, as in this research, produced unbiased factor associations that accurately reflected data (Marsh et al., 2014). In relation to Objective 2 (evaluate the effectiveness of CFA and ESEM estimation approaches), findings supported greater ESEM effectiveness.

The fact that the general factor lacks conceptual coherence explained the poorer performance of the bifactor model. This interpretation aligned with research that attributes better bifactor model fit to the inclusion of less constrained parameters (Reise et al., 2016). Indeed, the principal argument for a PSS-10 bifactor model was the high covariance between Distress and Counter-Stress factors (i.e., > 0.50; Juárez-García et al., 2023). That noted, CFA can inflate factor correlations (Alamer, 2022). In contrast, ESEM identified weaker correlations between factors. Therefore, CFA produced biased inter-factor associations, and a two-factor approach provided a superior solution. By allowing users to interpret subscale scores reliably, avoid misclassification, and develop interventions based on a clearer representation of individuals' stress profiles, the distinction between Distress and Counter-Stress enhances PSS-10 practical utility.

Moreover, the two-factor solution is theoretically coherent. Particularly, commensurate with Lazarus and Folkman's stress model, which includes negative and positive psychological aspects (Folkman, 1997). The coexistence of negative and positive aspects is plausible and adaptive since it concurs with the notion that positive psychological states protect individuals by countering distress and discomfort (Folkman & Moskowitz, 2000; Steptoe et al., 2009). Additionally, the two-factor model agrees with Barbosa-Leiker et al. (2013), who contend that inclusion of differing appraisals (negative and positive) affords a theoretical basis for understanding divergent relations between stress and health-related outcomes.

Aligning with Objective 3 (establish PSS-10 performance across gender and time), PSS-10 invariance existed across gender (Study 1 and 2) and time (Study 1) designating that the Distress and Counter-Stress factors assessed men and women similarly. These findings resonate with the results of Barbosa-Leiker et al. (2013) and Denovan et al. (2019; albeit with a bifactor). Longitudinal stability of assessment over six months supported use of the PSS-10 for capturing changes in stress over time. This mirrors Barbosa-Leiker et al. (2013) and Reis et al. (2019), who observed stability over two years and eight weeks, respectively.

Latent means indicated that women scored higher than men on Distress. No significant mean differences existed over time, or for Counter-Stress. The observation of higher latent means for women (vs. men) was in line with myriad preceding papers (e.g., Barbosa-Leiker et al., 2013; Costa et al., 2021; Reis et al., 2019). Demonstration of gender invariance indicated that the PSS-10 is a useful tool for examining 'true' gender difference in stress perception.

Study 2 found the two-factor model demonstrated predictive validity, supporting Objective 4 (assess whether the PSS-10 demonstrated satisfactory predictive validity relative to well-being criteria). Distress significantly predicted Somatic Complaints, and Counter-Stress prognosticated Life Satisfaction. The observed Distress and Somatic Complaints relationship echoes findings from previous investigations (e.g., Verkuil et al., 2012) and somatisation research (Clarke et al., 2008). Indeed, somatic complaints represent an expression of individual distress. Noting the predictive relationship with Somatic Complaints, elevated Distress scores may serve as early warning signs for stress-related physical symptoms, warranting integrated physical-mental health approaches.

Analysis found the PSS-10 explained 7% of variance in Life Satisfaction. This was similar to the 12% of variance reported by Shi et al. (2015). The strong relationship between Counter-Stress (vs. Distress) and Life Satisfaction reflected thematic similarity. A common feature being self-perceived ability to cope (Veenhoven, 1996). Conversely, Life Satisfaction comprises features not represented within the PSS-10 (i.e., achieved goals, self-concepts, mood) (Diener et al., 2002). These divergences explain why the proportion of shared variance between Perceived Stress and Life Satisfaction was low. The observation that Counter-Stress did not predict Somatic Complaints further demonstrated factor dissociation.

Implications for research and practice

The confirmation of a two-factor structure within the PSS-10 comprising discrete subscales assessing Distress and Counter-Stress has important implications for clinical practice, applied settings and psychological research. Specifically, because the two-factor model specifies that stress perception encompasses emotional responses and cognitive appraisals it enables a more sophisticated appreciation of individual differences in stress perception. Accordingly, the distinction between distress and coping/counter-stress enhances the interpretive power of the PSS-10 and concomitantly informs the design and evaluation of psychological interventions.

In clinical settings, practitioners can use the Distress subscale to assess the intensity of emotional discomfort experienced in response to perceived demands, and the Counter-Stress subscale to evaluate individual sense of control/confidence to address those demands. This information can then inform the development of individualised treatment strategies. For instance, clients with elevated distress scores will benefit from interventions designed to improve emotional regulation (e.g., mindfulness-based stress reduction; Aghamohammadi et al., 2022), whereas individuals reporting lower coping will gain from targeted skill-building in domains such as social support engagement and adaptive thinking (Rodríguez Villegas, & Salvador Cruz, 2015). These examples illustrate how the two-factor structure can help practitioners to identify therapeutic goals and employ interventions that address the root causes of individual stress-related difficulties.

In addition to treatment shaping, adoption of the two-factor model advances the ability to monitor progress following treatment. Explicitly, independent assessment of distress and counter-stress reveals shifts in emotional burden and coping capacity over time that can inform real-time care adjustments. Illustratively, a treatment might reduce distress without improving coping skills, indicating the need for additional support to maintain long-term stress resistance. Likewise, a program that successfully increases coping confidence may not reduce distress immediately but can still effectively prepare individuals to manage future stressors. This nuanced level of insight, which total scores do not provide, creates a detailed feedback loop that allows for more accurate assessment of intervention impact and can guide continuous improvement in program design.

The two-factor model likewise has practical value in non-clinical applications. This is true within organisational settings where subscale scores can inform wellbeing policies by identifying employees who, despite not displaying signs of distress, lack adequate coping resources to deal with sustained and/or unanticipated work-related pressure. Hence, via consideration of subscale scores employers can implement targeted wellness programs that address emotional strain and build hardiness and resilience. Similarly, in educational settings, subscale scores can help teachers and support staff identify students who would benefit from stress management coaching. In this context, subscale scores can help to prospectively identify individuals who will benefit from support and/or early interventions. Thus, the enhanced interpretability provided by subscale scores enhances the diagnostic and evaluative sensitivity of the PSS-10. Particularly, by differentiating between emotional burden and perceived coping, real-world users can evaluate stress management capabilities.

From the perspective of researchers, the two-factor model enhances conceptual clarity and methodological precision. Moreover, treating Distress and Counter-Stress as distinct but related constructs aligns with contemporary stress models (e.g., transactional model, Lazarus & Folkman, 1984). Indeed, the coping (i.e., Counter-Stress) subscale, reflects elements of positive psychological functioning that align with resilience and perceived control. Specifically, this corresponds with central positive psychology constructs such as optimism, cognitive reappraisal, and self-efficacy. These traits buffer against adversity and support adaptive stress responses (Denovan et al., 2023). Correspondingly, researchers can confidently use subscale scores to explore how these stress components differentially relate to affiliated psychological variables (e.g., anxiety, depression, burnout, and subjective well-being). This approach affords deeper theoretical insights, which will assist investigation of stress across diverse settings and populations.

The ability to disaggregate PSS-10 scores also increases detection of stress profiles within certain contexts. For example, in healthcare settings, workers may report high coping scores despite ongoing distress, reflecting professional resilience amid chronic occupational strain. Conversely, students entering university may exhibit low distress concurrent with low coping, highlighting potential stress vulnerability. These examples highlight how the two-factor model can recognise meaningful variations and inform the development of specific interventions.

In conclusion, the confirmation of Distress and Counter-Stress as distinct components extends the theoretical foundations of the PSS-10 and increases the instrument's clinical and practical utility. Specifically, the two-factor model allows practitioners to deliver personalised guidance, researchers to conduct precise analyses, and organizations and educational institutions to implement targeted, evidence-based stress support.

Limitations

The investigators did not collate data on ethnicity. Research has consistently reported that ethnic groups experience and score stress differently (Brown et al., 2020; Trepasso-Grullon, 2012; Williams, 2018). The sample was also nonclinical, which is an important consideration as researchers extensively use the PSS-10 in clinical settings (Barbosa-Leiker et al., 2013). Accordingly, lack of demographic information potentially restricts generalizability and replicability. To address this, future investigations could employ stratified sampling to ensure representation across ethnic groups, enhancing generalizability. Additionally, subsequent studies should replicate analyses with distinct samples that vary in terms of ethnicity and health status. Longitudinal invariance existed over a six-month period, which is limiting for exhibiting measurement stability over a longer duration. Furthermore, the cross-sectional nature of Study 2 limited causal inferences, and the samples included UK-based participants, which restricts applicability of the findings to other nations.

Arising as a function of using self-report measures, this study shared often cited limitations with much published research. Particularly, potential occurrence of social desirability effects, which can undermine accuracy and validity with health-based measures. Indeed, Latkin et al. (2017) reported that, in the context of mental health measures, individuals who tend to provide more socially desirable responses may underreport symptoms (e.g., distress) due to stigma surrounding mental health issues. Implementation of specific social desirability scales (e.g., short forms of the Marlowe-Crowne Social Desirability Scale, MCSDS; Fischer & Fick, 1993) limit the impact of social desirability within analyses. Hence, future studies could include the MCSDS alongside the PSS-10. Furthermore, reliance on self-report measures for stress assessment can impact validity because judgments derive from subjective interpretations (e.g., participants' opinions or beliefs, item perception). Acknowledging this, a mixed methods approach, integrating objective biomarkers (e.g., cortisol) and qualitative interviews, would yield a fuller picture of stress experiences. Besides, including additional objective measures, such as physiological assessments, alongside self-report scales would provide a more comprehensive assessment of PSS-10 validity since subjective interpretations do not influence objective measures that better reflect observed phenomena (Souza et al., 2021).

Regarding PSS-10 items, occurrence of non-normality was concerning, yet not atypical when examining psychosocial factors (Bono et al., 2017). Non-normality can arise from various sources, including non-normal distributions of the observed variables, or violations of the underlying assumptions of the model (e.g., homoscedasticity). This can produce biased standard error estimates, resulting in inaccurate significance tests and potentially incorrect conclusions (Enders, 2001). Within this research, negative kurtosis existed, indicating (vs. a normal distribution) flatter tails and less of a peaked centre. Consequently, fewer extreme scores occurred, which is likely due to recruiting a non-clinical sample. Indeed, this did not limit the findings because values fell within the tolerance threshold, and the use of MLR estimation attenuated the possible effects. Explicitly, MLR obtains standard errors using an approach that considers the potential for heteroscedasticity, resulting in more reliable significance tests and trustworthy model fit indices when non-normality exists (Benson & Fleishman, 1994).

Conclusions

The present research confirmed a two-factor ESEM model of the PSS-10 with two independent studies. Convergent validity and invariance (across gender and time) existed for this solution. Latent means revealed that women scored higher on Distress than men, consistent with previous research. The PSS-10 predicted theoretically linked variables (i.e., Distress → Somatic Complaints, Counter-Stress → Life Satisfaction), but Distress did not predict Life Satisfaction, and Counter-Stress did not predict Somatic Complaints. Also, analysis only accounted for a small proportion of variance in Life Satisfaction (see Shi et al., 2015). The use of ESEM provided a more realistic assessment of the PSS-10, and findings supported the utility of Distress and Counter-Stress factors for predicting well-being indicators. However, future work is necessary to examine this demarcation in relation to other health outcomes.

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Data availability The datasets generated during and/or analysed during the current research are accessible via Figshare: https://doi.org/10.6084/m9.figshare.26057860.v1.

Declarations

Ethical approval Approval was obtained from the Manchester Metropolitan University Ethics Committee. The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent Informed consent was obtained from all individual participants included in the research

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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