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Psychometric Evidence of the 10-Item Connor-Davidson Resilience Scale (CD-RISC10, Greek Version) and the Predictive Power of Resilience on Well-Being and Distress

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Abstract

The purpose of this study was to evaluate the construct validity of CD-RISC10 in a sample of 1089 Greek adults of the general population. The CD-RISC10 factor structure was evaluated first with EFA in a 20% subsample and confirmed with CFA (CFA1) in a different 40% subsample. A cross-validation CFA followed (CFA2) in a third 40% subsample (i.e. of equal power with CFA1). Model fit comparison using −2ΔLL difference test suggested a bidimensional structure but bifactor ancillary measures indicated that multidimensionality was weak to exclude the unidimensional structure. Full weak measurement invariance across gender for this unidimensional model was successfully established in the entire sample. Partial strong measurement invariance was established after freeing intercepts of 2 items and partial strict after freeing the error variance of 1 item. Internal consistency reliability (α) was equal to three different model-based reliability calculations (CR) at adequate levels (.85), corroborating one another, although CD-RISC10 was not tau-equivalent. The average variance extracted was .37 to evaluate model-based convergent validity. Convergent and discriminant validity were evaluated further with correlation analysis with a resilience measure, life satisfaction, affectivity, depression, anxiety, and stress with all associations to the expected direction. The predictive validity of CD-RISC10 was evaluated with a SEM model of resilience regressed on two higher-order latent factors of subjective well-being (SWB) and psychological distress, yielding significant strong positive and negative effects respectively. Male scored significantly higher than females thus, normative data were calculated over the total sample and also separately by gender.

Keywords

Resilience, CD-RISC10, Factor Analysis, Validation, Bifactor, CFA, EFA, SEM, Normative Data

1. Introduction

Strangely, about a third of the animals and people who experience inescapable shocks or noise resist helplessness. Why they are so resilient? (Seligman, 2011). Resilience is a dynamic, multifaced process of positive adaptation when facing adversity, stress or trauma (Campbell-Sills & Stein, 2007). Resilience reliably mirrors how capable one is to handle stress (Aloba et al., 2016). It is one of the treatment outcomes in anxiety, depression, and stress responses (Connor & Davidson, 2003), encompassing attitudes and behaviours that foster adaptive coping strategies during stressful circumstances (Burns & Anstey, 2010).

When dealing with adversity, resilient individuals use internal personal resources—genetic, biological, psychological—as well as external—interpersonal and environmental (Campbell-Sills & Stein, 2007; Cheng, Dong, He, Zhong, & Yao, 2020; Connor & Davidson, 2003). A meta-analysis (Hu, Zhang, & Wang, 2015) showed that resilience contributed to sustaining mental health and preventing mental distress. Resilient individuals cope with stressors, a process associated with psychological well-being, life satisfaction, positive emotions, and negatively associated with emotional and behavioral problems (Kavčič, Kocjan, & Dolenc, 2021).

Windle, Bennett, & Noyes (2011) and Salisu & Hashim (2017) reviewed resilience measures, ranking CD-RISC10 (Campbell-Sills & Stein, 2007), among the most popular with good psychometric qualities.

1.1. Connor-Davidson Resilience Scale, 10-Item Version (CD-RISC10)

The stability of the CD-RISC25 structure (Connor & Davidson, 2003) was questionable due to varying items (21 - 22) and/or factors (1 - 6), see Nartova-Bochaver, Korneev and Bochaver (2021). Other questionable issues during the CD-RISC25 development involved: 1) inconsistent loadings across Exploratory Factor Analyses (EFAs); 2) an item with no salient loading and 3) factors containing too few items or disparate theoretical underpinning (Campbell-Sills & Stein, 2007). These controversies led to shorter CD-RISC versions with 10 items (Campbell-Sills & Stein, 2007) or 2 items (Vaishnavi, Connor, & Davidson, 2007; out of the scope of this study).

Campbell-Sills and Stein (2007) proposed a unidimensional version of the CD-RISC, keeping 10 items measuring tolerance of negative experiences, pressure, change, personal problems, and painful feelings, reflecting a cognitive dimension of resilience (Madewell & Ponce-Garcia, 2016).

For the CD-RISC10 development, Campbell-Sills and Stein (2007) used three undergraduate samples, including a subsample of 131 individuals who self-reported childhood trauma and psychiatric symptoms to evaluate construct validity. In the first two samples Exploratory Factor Analysis (EFA) was carried out, and in the third Confirmatory Factor Analysis (CFA). The EFAs showed an unstable factor structure. Based on CFA, empirically-driven exclusion of items followed, proposing a unidimensional scale, preferred over a two-dimensional alternative with hardiness and persistence factors. The unidimensional CD-RISC10 had good internal consistency (.85) and construct validity verifying that resilience moderated the impact of childhood maltreatment on current psychiatric symptoms.

Currently, there are more than 80 translations of the CD-RISC (Nartova-Bochaver et al., 2021), including Malayalam (Aswini & Deb, 2019), Peruvian (Levey et al., 2021) and Russian (Nartova-Bochaver et al., 2021) and numerous validations of the scale both in the general population and special samples.

Furthermore, in consistency with the resilience literature (see Singh et al., 2016) a meta-analysis reported that gender significant moderates the association of resilience with mental health (Hu et al., 2015). Campbell-Sills, Forde and Stein (2009) also found that females of the general population scored significantly lower than males on the CD-RISC10. This finding was replicated, e.g. with medical students from Canada (Rahimi, Baetz, Bowen, & Balbuena, 2014), elderly (Meng et al., 2019), undergraduates, and depressive patients from China (Cheng et al., 2020), youngsters from Russia (Nartova-Bochaver et al., 2021), or public accountants from the US (Smith et al., 2018).

1.2. CD-RISC10 Validation Studies

Regarding the factor structure, validation studies on the general population confirmed the unidimensional structure for the versions from Australia (Burns & Anstey, 2010), Germany (Wollny & Jacobs, 2021), Russia (Nartova-Bochaver et al., 2021), Slovenia (Kavčič et al., 2021), China (Cheng et al., 2020) and Spain (Notario-Pacheco et al., 2011). Equally, a large body of literature on special populations also supported the unidimensional structure, i.e. US distance runners (Gonzalez et al., 2016), US college students with stress or trauma (Madewell & Ponce-Garcia, 2016), Chinese parents of children with cancer (Ye et al., 2017), Chinese elderly (Meng et al., 2019), or Chinese undergraduates and depressive patients (Cheng et al., 2020), and Spanish non-professional caregivers (Blanco et al., 2019). Conversely, a few validation studies on special populations proposed a bidimensional structure, i.e. nursing students from Nigeria (Aloba et al., 2016), or accounting/business students from the US (Smith et al., 2019), the later proposing a second order bidimensional structure. Lastly, a study on elderly from Finland suggested that CD-RISC was unidimensional for ages < 75 years and bidimensional for ages ≥ 75 (Tourunen et al., 2021).

The internal consistency reliability of the CD-RISC10 was adequate across studies. Specifically, for the studies in the general population Cronbach's alpha was .81 in the German sample (Wollny & Jacobs, 2021), .84 in the Russian sample (Nartova-Bochaver et al., 2021), .85 in the Spanish sample (Notario-Pacheco et al., 2011) and > .76 in the Slovenian sample (Kavčič et al., 2021).

Furthermore, several studies tested full and partial measurement invariance of the CD-RISC10 across gender. For example, measurement invariance was evaluated in Australian distance runners (Gonzalez et al., 2016), or Australian community sample (Burns & Anstey, 2010), US public accountants (Smith et al., 2018), or US business and accounting students (Smith et al., 2019), Chinese undergraduates and depressive patients (Cheng et al., 2020), Chinese older adults (Meng et al., 2019), Colombian vulnerable adolescents (Guarnizo Guzmán et al., 2019), and a Slovenian community sample (Kavčič et al., 2021).

1.3. The Present Study

Note that the CD-RISC10 validation studies in the general population are relatively fewer than those in special populations. Therefore, useful additions to the CD-RISC10 validation literature would be validation in the general population considering the following: 1) given the structural instability whether CD-RISC10 is unidimensional or bidimensional, after evaluating all alternative models proposed in the literature (i.e. unidimensional, bidimensional, bidimensional higher-order), and some untested alternatives (bidimensional bifactor) to gain insights on the scale dimensionality versus multidimensionality (c.f. Hammer & Toland, 2016); 2) given the gender differences in scoring, and the limited measurement invariance studies for the general population; whether CD-RISC10 items measure resilience invariantly across gender and 3) given the potential gender differences to provide normative data both for the general Greek population and for each gender separately.

Therefore, extending the CD-RISC10 validation studies for the general population with this validation in the Greek context adopted a cross-sectional design with the following objectives: (a) to evidence the construct validity of the CD-RISC10, using a multistage validation process testing alternative models (Kyriazos, 2018a); (b) to test the measurement invariance across gender; (c) to test the internal consistency reliability and the model-based reliability; (d) to test the convergent and discriminant validity; (e) to test the predictive validity of resilience on psychological distress and subjective well-being; (f) to provide professionals with normative data for the general Greek population, and for each gender.

2. Methods

2.1. Participants and Procedure

Inclusion criteria were age ≥ 18 years, and absence of mental illness or insufficient cognitive ability. The sample involved 1089 Greek adults (65% females). About one in five (19%) were from 18 - 20 years, 29% from 21 - 30 years, 16%

from 31 - 40, 20% from 41 - 50 years, 14% from 51 - 60 years and 2.5% were > 60 years. More than one in two respondents were never married (55%), married (38%) or other (7%). Most were employees (50%), self-employed (17%), university students (16%), unemployed (8%), other (10%) with either a tertiary level education or higher (78%), or a secondary level education or lower (22%).

The questionnaire was administered online, after obtaining informed consent. Data were collected with the network sampling method. Psychology students (2018-2019) voluntarily recruited participants of their social environment, receiving extra course credit. Recruitment rules permitted students to recruit at least 10 non-student participants each, without taking the questionnaire themselves.

2.2. Sample Power Analysis

A priori power analysis based on the RMSEA (MacCallum, Browne, & Sugawara, 1996) for the unidimensional CD-RISC10 model (Campbell-Sills & Stein, 2007) suggested that a sample of $N = 279$ was required for achieving a power of approximately 80% to reject a wrong model ($df = 35$, RMSEA = .05, alpha = .05). See Results for post hoc power analysis.

2.3. Measures

2.3.1. Connor-Davidson Resilience Scale, 10-Item Version (CD-RISC10)

CD-RISC10 (Campbell-Sills & Stein, 2007) is a short version of the original CD-RISC (Connor & Davidson, 2003). It is a self-report, measure of resilience with 10 items (e.g. "Coping with stress can strengthen me") rated on a 5-point scale (0 = *Not True at All*; 4 = *True Nearly All of The Time*). The possible score ranges from 0 (minimum resilience) to 40 (maximum resilience).

2.3.2. Brief Resilience Scale (BRS)

BRS (Smith, Dalen, Wiggins, Tooley, Christopher, & Bernard, 2008) is a brief resilience measure with 6 items (e.g., "I usually come through difficult times with little trouble") rated on a 5-point Likert scale from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). Smith et al. (2008) reported internal consistency reliability of $\alpha = .80 - .91$, and in a Greek sample (Kyriazos, Stalikas, Prassa, Galanakis, Yotsidi, & Lakioti, 2018) it was $\alpha = .80$. In this study, internal consistency reliability was $\alpha = .73$.

2.3.3. Scale of Positive and Negative Experience 8 (SPANE-8)

SPANE-8 (Diener et al., 2010; Kyriazos, Stalikas, Prassa, & Yotsidi, 2018a) is a shorter version of SPANE-12, containing 1 general experience per factor instead of originally 3 (Diener et al., 2010: p. 145). Items are rated on a 5-point Likert scale (1 = *Very Rarely or Never* to 5 = *Very Often or Always*). Internal consistency reliability for SPANE-P and SPANE-N were .90 and .85 respectively in a Greek sample (see Kyriazos et al., 2018a). In this study, it was $\alpha = .86$ (SPANE-P) and .79 (SPANE-N).

2.3.4. Depression Anxiety Stress Scale, 9 Item Version (DASS-9)

This is a shorter version of DASS-21 (Lovibond & Lovibond, 1995; Yusoff, 2013; Kyriazos, Stalikas, Prassa, & Yotsidi, 2018b) with 3 items per factor instead of 7 in the original. Kyriazos et al. (2018b) reported internal consistency reliability of α = .79 (Depression), .77 (Anxiety), and .73 (Stress) in a Greek sample. In this study, internal consistency reliability was α = .70 (Depression), .78 (Anxiety), and .62 (Stress).

2.3.5. Satisfaction with Life Scale (SWLS)

The SWLS (Diener, Emmons, Larsen, & Griffin, 1985) measures perceived global life satisfaction (e.g. "I am satisfied with my life") on a 7-point scale, from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*), midpoint = *Neither Agree nor Disagree*. Diener et al. (1985) reported that Cronbach's alpha was .87 and in a Greek sample it was .87 (Kyriazos, Galanakis, Karakasidou, & Stalikas, 2021a). In this study, Cronbach's alpha was .88.

2.3.6. Data Diagnostics and Analytic Strategy

Note that in all instances MLR estimator was used to estimate the CFA and SEM models, treating data as continuous. CD-RISC10 is rated on a five-point scale, which is a "grey zone", heavily debated whether it is continuous (Li, 2016; Raykov, 2012; Rigdon, 1998) or ordinal (Kline, 2016). However, in practice, empirical researchers suggested using MLR in CFA models when the number of response categories was ≥ 5 (Li, 2016). Data was also treated as continuous because treating variables in the CFAs and SEM as ordinal would mean that every other analysis on the same variables should also treat them as ordinal, thus affecting correlation coefficients, mean comparisons, and even reliability coefficients (see Gadermann, Guhn, & Zumbo, 2012). It would also be unfamiliar to the reader, generating incomparable results to existing validation studies. Data were analyzed with R software (R Development Core Team, 2021).

The sample was randomly divided into three (20%, 40%, 40%) to carry out EFA (20%), an initial CFA1 (40%) and cross-validating CFA2 (40%) in three different subsamples: i.e. EFA followed by two CFAs of equal sample power, in a multistage validation process (3-*faced construct validation method*, Kyriazos, 2018a).

The assumption of univariate and multivariate normality was examined in the whole data set and in the three subsamples separately. Multivariate outliers were evaluated using Mahalanobis distance at α = .001 for the critical χ^2 value (Tabachnick & Fidell, 2013).

Initially, EFA was performed in the 20% subsample to establish a structure. The number of factors to retain was examined with Parallel Analysis (PA; Horn, 1965), Very Simple Structure (VSS; Revelle & Rocklin, 1979), Minimum Average Partial Correlations (MAP; Velicer, 1976) and Bayesian information criterion (BIC). The goodness of the EFA model fit was evaluated with the Root Mean Square Error of Approximation (RMSEA), Root Mean Square of Residuals (RMSR), Tucker-Lewis Index (TLI). Fit criteria adopted were RMSEA ≤ .06 [90% CI], TLI ≥ .95 (Hu & Bentler, 1999), lowest possible BIC (Mair, 2018), and

RMSR ≤ .0448 (Kelley's criterion; Kelley, 1935).

Then the CFA1 followed in a different 40% subsample. CFA goodness of fit was evaluated with RMSEA (≤.06, 90% CI), SRMR (≤.08), CFI (≥.95), TLI (≥.95), (Hu & Bentler, 1999), the normed chi-square ratio (χ^2/df) ≤ 3 (Carmines & McIver, 1981), Akaike information criterion (AIC) and BIC (the lower the better; Mair, 2018). Bifactor ancillary measures were ECV ≥ .85 suggesting a sufficiently unidimensional instrument (Stucky et al., 2014), PUC < .80, ECV-Gen > .60 and ω_h > .70 also suggesting not severe multidimensionality to exclude unidimensional interpretations (Reise, Bonifay, & Haviland, 2013: p. 22). All the alternative models of CFA1 were compared with the likelihood ratio test (−2ΔLL MLR rescaled version; Satorra & Bentler, 2010). A cross-validating CFA (CFA2) followed in a different 40% subsample to validate the optimal model of CFA1. A priori and post hoc power analysis based on the RMSEA (MacCallum et al., 1996) on the CFA2 results were calculated to estimate the power to reject a wrong model on RMSEA = .05, and alpha = .05. Then two trial CFAs were carried out (with vs without outliers) to test if outliers influenced results (Tabachnick & Fidell, 2013).

Additional analyses were performed in this the successfully cross-validated CFA 2 model over the entire sample: 1) We examined measurement invariance of the optimal CFA2 model across gender with difference test criteria $|\Delta\text{CFI}| < .010$ (Cheung & Rensvold, 2002), $|\Delta\text{RMSEA}| < .010$ (Chen, 2007). 2) Internal consistency reliability, the greatest lower bound (Jackson & Agunwamba, 1977), model-based reliability (Mair, 2018) and model-based convergent validity (Hoque et al., 2017). Model-based reliability and convergent validity were estimated with Composite Reliability (CR; Werts, Linn, & Karl, 1974) and Average Variance Extracted (AVE; Fornell & Larcker, 1981) respectively. CR was calculated with the standardized factor loadings (see Raykov, 2004), using three alternative calculations, proposed by Bollen (1980), Bentler (2009) and McDonald (1999: i.e. ω_t), see Kyriazos (2017) after testing tau equivalency of the optimal CFA1 model. 3) Additionally, convergent and discriminant validity were examined further with correlation analysis.

Subsequently, predictive validity was estimated by specifying a SEM model with CD-RISC10 regressed on two higher-order latent factors of Subjective-wellbeing (SWB; Diener et al., 1999) and Psychological Distress. SWB comprised the latent factors of life satisfaction (SWLS, Diener et al., 1985), and affectivity (SPANE-8 (Diener et al., 2010; Kyriazos et al., 2018a), and Psychological Distress comprised the latent factors of Depression, Anxiety, and Stress (DASS-9; Lovibond & Lovibond, 1995; Kyriazos et al., 2018b) to examine the effects of resilience.

Finally, the scores of males and females were compared using Mann-Whitney-Wilcoxon test, and assuming a significance at $p < .001$. The effect size was calculated with Vargha and Delaney (2000) interpretations (A estimate). Then normative data were calculated by converting raw scores to percentiles for the total sample and per gender separately.

See all the steps of the Analytic Strategy in **Table A1** (**Appendix**).

3. Results

3.1. Data Diagnostics & Sample Slitting

There were N = 1089 cases in the total sample. There were no missing values because all the fields of the digital survey were set as "required" (Kyriazos, 2018b). Out of the 1089 cases, there were 32 multivariate outliers, $\chi^2(10) = 29.59$, $p < .001$ for Mahalanobis. However, outliers were not data entry errors, therefore exclusion was unsupported, final N = 1089. The total sample (N = 1089) was randomly divided into three subsamples (20%, 40%, and 40%) to carry out the EFA, initial CFA (CFA1) and the cross-validating CFA (CFA2), see Kyriazos (2018a).

3.2. Univariate and Multivariate Normality

The assumption of univariate normality was examined in the whole data set (N = 1089), and of multivariate normality in the three samples separately ($n_{\text{EFA}} = 220$, $n_{\text{CFA1}} = 435$, $n_{\text{CFA2}} = 434$). All normality tests were significant, $p < .001$, see **Table A2** in the **Appendix**.

3.3. Exploratory Factor Analysis ($n_{\text{EFA}} = 220$)

The EFA, was carried out in the EFA subsample (20%, $n_{\text{EFA}} = 220$). Kaiser-Meyer-Olkin measure of sampling adequacy was .88, and MSA for items 1 - 10 ranged from .84 - .91 (see **Table 1**). Bartlett's test of sphericity was significant, $\chi^2(10) = 626.60$, $p < .001$. All items correlated at ≥ .22 with at least a second item (range from .22 - .50). The largest Squared Multiple Correlation was .44 (range from .21 - .44), see **Table 1**. The R determinant was 2.045828E+34 and the

Table 1. Factor loadings (λ), communalities (h^2), uniquenesses (u^2) and item-level MSA for the 10 CD-RISC10 items from the EFA performed in the 20% subsample ($n_{EFA} = 220$).

Item	λ	h^2	u^2	*MSA*
ITEM 1	.53	.28	.72	.87
ITEM 2	.69	.47	.53	.86
ITEM 3	.44	.20	.80	.84
ITEM 4	.40	.16	.84	.84
ITEM 5	.63	.40	.60	.91
ITEM 6	.67	.45	.55	.88
ITEM 7	.49	.24	.76	.88
ITEM 8	.65	.42	.58	.90
ITEM 9	.70	.49	.51	.90
ITEM 10	.66	.43	.57	.89

Note. Extraction = Principal Factor (fm = "pa"), No rotation.

anti-image correlation matrix diagonals were > .50 (=1,1,1,1,1,1,1,1,1,1). Therefore, EFA was carried out with all ten items. A single factor was extracted, (PAF extraction). Parallel analysis suggested 1 factor (see scree plot in **Figure 1**) and the Velicer MAP achieved a minimum of .02 with 1 factor. VSS complexity 1 also achieved a maximum of .79 with 1 factor and BIC was minimized (−118.75) with 1 factor. This single-factor structure had adequate fit, RMSR = .06, TLI = .922, RMSEA = .067 [90% CI .044, .091], explaining 35.4% of the variance. The factor score was adequately correlated with its regression score at .93. **Table 1** contains the factor loadings, communalities, uniquenesses, and MSA for each item.

3.4. Confirmatory Factor Analysis (CFA1, n_{CFA1} = 435)

The CFA was performed in a different subsample (40%, n_{CFA1} = 435). Four alternative CFA models were tested (**Table 2**). MODEL A was the original single-factor model (Campbell-Sills & Stein, 2007), emerging from the previous EFA. MODEL B was a 2-factor model proposed by Smith et al. (2019). The first factor (Toughness) comprised items 5 - 10 and the second factor (Motivation) comprised items 1 - 3. MODEL C was a different 2-factor model proposed by Tourunen et al. (2021), with the first factor containing items 2, 5 - 10 and the second-factor items 1, 3, 4, 7, that is, item 7 was specified to load on both factors as proposed by Tourunen et al. (2021: p. 5). MODEL D was a Bifactor model (Harman, 1976), containing 2 specific factors (Toughness and Motivation like MODEL B), tapping simultaneously a general resilience factor. The Bifactor

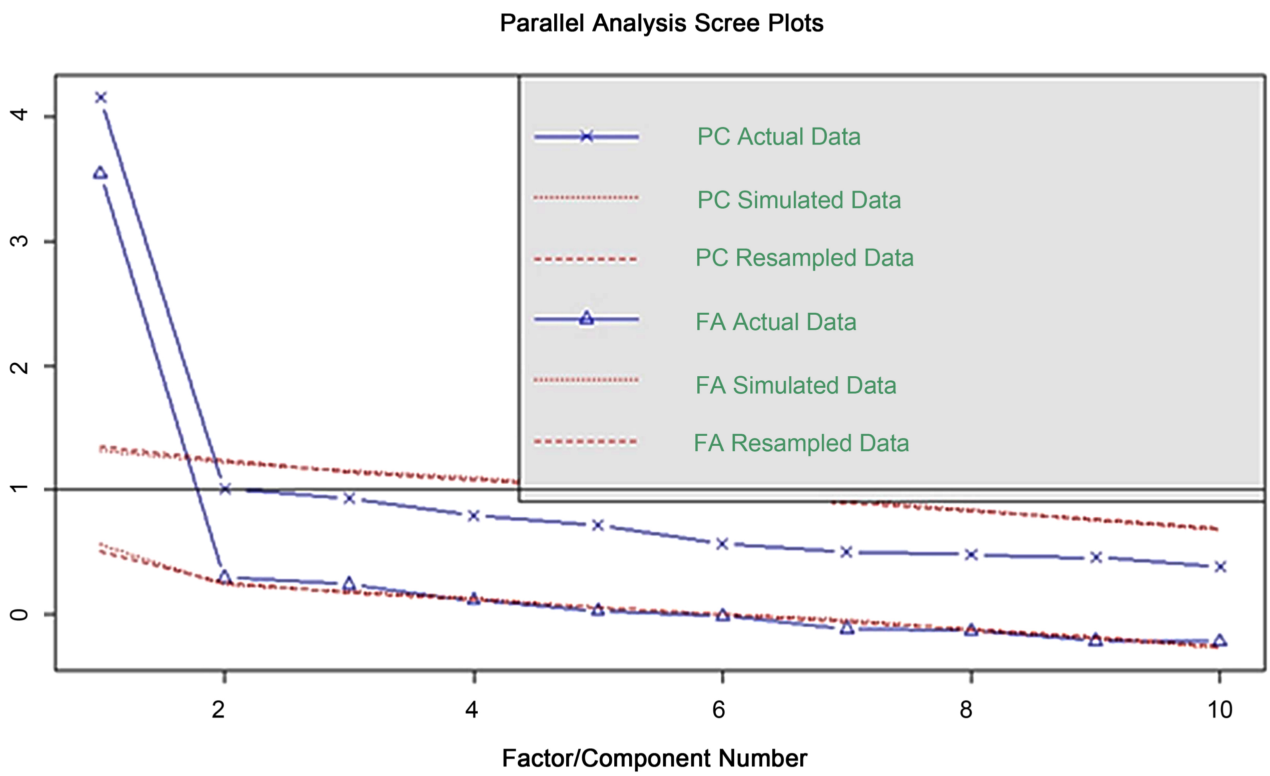

Figure 1. Parallel analysis scree plot suggesting a single factor, based on the EFA performed in the 20% Subsample (N_{EFA} = 220).

Table 2. Goodness of fit, factor loadings and inter-correlations for the alternative CD-RISC10 models specified in the CFA1, Carried out in the first 40% subsample ($n_{CFA1} = 435$).

Model fit Indicator	Models Tested			
	MODEL A 1-factor (Campbell-Sills & Stein, 2007)	MODEL B[a] 2-factor (Smith et al., 2019)	MODEL C[b] 2-factor (Tourunen et al., 2021)	MODEL D[c] 2-factor Bifactor
χ^2	82.42	7.25	75.44	87.42
df	35	34	33	25
χ^2/df	2.35	2.07	2.29	3.5
CFI	.944	.957	.95	.962
TLI	.928	.943	.932	.931
RMSEA	.056	.05	.054	.055
Low 90% CI	.043	.035	.041	.038
High 90% CI	.069	.064	.068	.072
SRMR	.045	.041	.042	.035
BIC	11,027.26	11,015.6	11,028.84	11,044.41
AIC	10,945.76	10,927.98	10,939.18	10,922.15
Loadings per Factor	.498 - .706	F1 = .497 - .720 F2 = .532 - .715	F1 = .570 - .713 F2 = −.048 - .592	F1= −.178 - .459 F2 = −.174 - .568 G = .478 - .719
Factor Inter-Correlation	-	.862	.871	-

Note. Estimator = MLR; CFI = Comparative Fit Index; TLI = Tucker-Lewis index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion. F1 = Factor 1, F2 = Factor 2. [a]Factor 1 (Toughness) = items 5 - 10 and Factor 2 (Motivation) = items 1 - 3. [b]Factor 1 = items 2, 5 - 10 and Factor 2 = items 1, 3, 4, 7. [c]Specific Factor 1 (Toughness) = items 5 - 10, Specific Factor 2 (Motivation) = items 1 - 3, G = general resilience factor.

Model was tested to examine if CD-RISC10 was unidimensional, multidimensional, or somewhere in-between. We could not test a 2-factor, higher-order model (see Smith et al., 2019), because of the under-identification problems for all models with $m \leq 3$ (e.g. Wang & Wang, 2020). See the fit of all the models tested, the range of factor loadings, and inter-factor correlations in **Table 2**.

All models had a comparably good fit (**Table 2**). The results of the χ^2 difference test to compare the model fit (**Table 3**) of the single-factor model (MODEL A) vs the two-factor model (MODEL B) showed that the difference was significant, Scaled Δ in −2LL = 30.136, $\Delta df = 1$, $p < .001$. Equally, comparing the 2 bi-dimensional models (MODEL C vs. MODEL B) their χ^2 difference of was significant, Scaled Δ in −2LL = 4.821, $\Delta df = 1$, $p < .05$. The two comparisons suggested that the two-factor model described the data better (**Table 3**). See the path diagrams of MODEL A and MODELB in **Figure 2**.

However, the Bifactor Model tested ($\chi^2 = 87.42$, $df = 25$, RMSEA = .055, CFI = .962, TLI = .931, SRMR = .035), had an ECV ≥ .85, suggesting that CD-RISC10 was sufficiently unidimensional to warrant a single-factor model

Table 3. Tests of −2ΔLL difference to compare the model fit of the alternative models A-C specified in CFA 1 (n_{CFA1} = 435).

CFA 1 Models	H_0 LL	Scale Factor	Free Params	−2ΔLL	ΔScaling Correction	Scaled Δ in −2LL	Δ*df*	*P*
MODEL A	5452.878	1.3720	35					
vs MODEL B	5443.988	1.3950	34					
Test of Difference				17.780	.5900	30.136	1	.0000
MODEL C	−5447.589	1.3920	33					
vs MODEL B	−5443.988	1.3950	34					
Test of Difference				7.202	1.4940	4.821	1	.0281

Note. Estimator = MLR., H_0 LL = Log likelihood model (H_0), Scale Factor = H_0 LL Scaling correction factor, Free Params = Number of free parameters, Scaled Δ in −2LL = −2ΔLL/scaling correction, Δ*df* = Differences of number of free parameters.

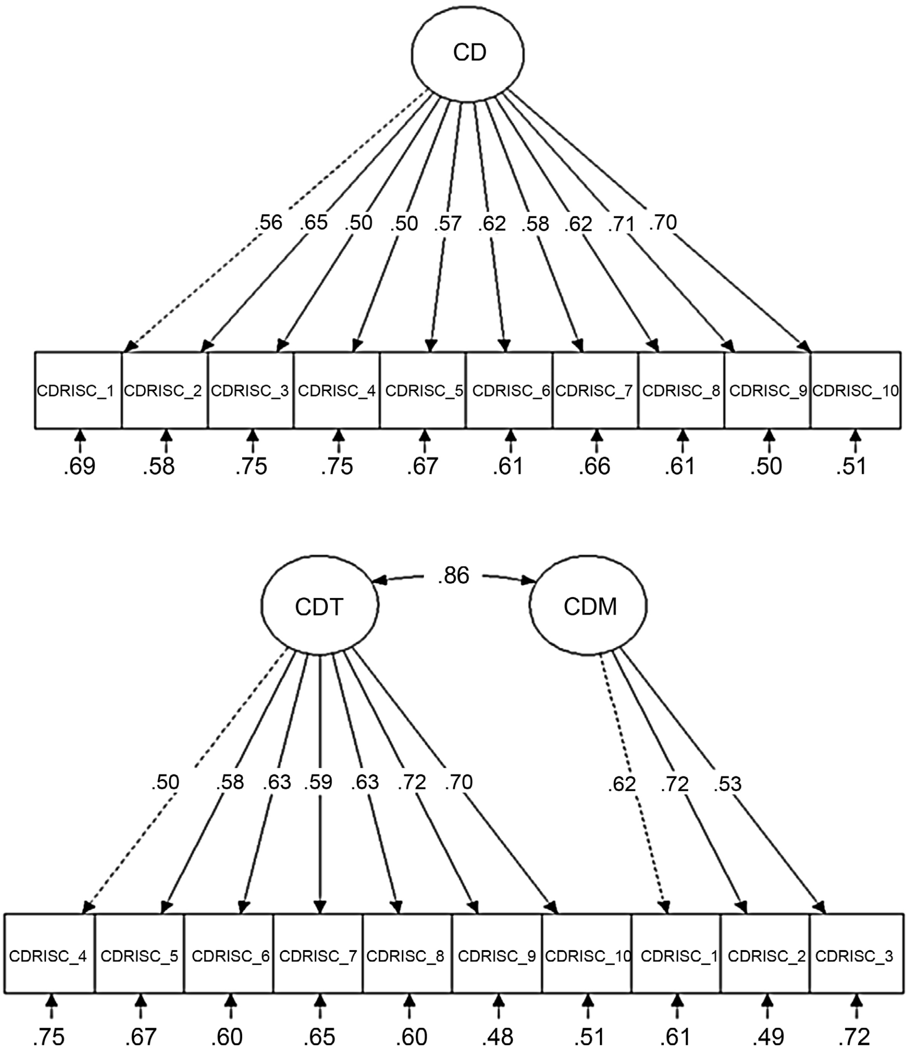

Figure 2. The path diagrams of the single-factor (upper part) and 2-factor model (lower part) specified in the CFA1 subsample (40%, N_{FA1} = 435). The χ^2 difference test (−2ΔLL) to compare the model fit suggested the fit of the 2-factor model was better however the bifactor model tested to examine unidimensionality vs multidimensionality suggested the CD-RISC10 was sufficiently unidimensional.

(Stucky et al., 2014). Additionally, PUC was < .80 (= .47), ECVGen > .60 (= .83) and ω_h > .70 (= .84), evidencing further that the presence of some multidimensionality is weak to reject the interpretation of CD-RISC10 as a primarily unidimensional measure (Reise et al., 2013). See bifactor metrics in **Table 4**.

Given the Bifactor results (**Table 4**), and considering jointly, model fit, factor loadings, inter-factor correlations (**Table 2**), and the χ^2 difference tests (**Table 3**) the single-factor model fit was considered more robust, $\chi^2(35) = 82.42$, RMSEA = .056 [90% CI .061, .086], CFI = .944, TLI = .928, SRMR = .045, BIC = 11,027.26, AIC = 10,945.76. All standardized factor loadings stayed above .40 (Brown, 2015) ranging from .498 - .706, $p < .001$ (**Table 2**).

Subsequently, 2 trial CFAs were carried out with and without multivariate outliers to test if outliers influenced the CFA1 model fit. The comparison of the model without outliers vs. the model with outliers suggested no significant fit difference, ΔCFI = −0.004 and ΔRMSEA = 0.002. See the model comparison in **Table A3** in the **Appendix**.

3.5. Cross-Validating Confirmatory Factor Analysis (CFA2, n_{CFA2} = 434)

The single-factor model (Model A) was crosschecked in a different subsample, of equal power (CFA2, n_{CFA2} = 434). The model showed good fit, $\chi^2(35) = 115.99$, χ^2/df = 3.31, RMSEA = .073 [90% CI .061, .086], CFI = .925, TLI = .904, SRMR = .049, BIC = 10,713.10, AIC = 10,632.53. All standardized factor loadings stayed above the threshold of .40 (Brown, 2015) ranging from .510 - .732, $p < .001$ (see **Figure 3**). Post hoc power analysis based on the RMSEA (MacCallum et al., 1996) of the single-factor model suggested that a sample size of n_{cfa2} = 434 was associated with a power > 94.81% to reject a wrong model (df = 35, RMSEA = .05, alpha = .05).

3.6. Measurement Invariance across Gender

We examined measurement invariance of the optimal single-factor model of CD-RISC10 across gender over the entire sample (N = 1089). When the single-factor model was tested separately for each gender (N_{males} = 383, $N_{females}$ = 706), it had an equally good fit for males, $\chi^2(35) = 84.72$, $\chi^2/df = 2.42$, RMSEA = .061

Table 4. Additional bifactor ancillary model fit measures for the 2-factor bifactor CD-RISC10 model specified in the CFA1 and carried out in the 40% of the subsample (n_{CFA1} = 435).

Model Factors	ECV	Omega	Omega Hierarchical (ω_h)	PUC	IECV
Toughness	.072	.83	.01		
Motivation	.097	.68	.19	.47	.45 - .99
General	.83	.87	.84		

Note. Estimator = MLR., ECV = Explained Common Variance, PUC = Proportion of Uncontaminated Correlations, IECV = Individual Explained Common Variance, Toughness = items 5 - 10 and Motivation = items 1 - 3, General = general resilience factor.

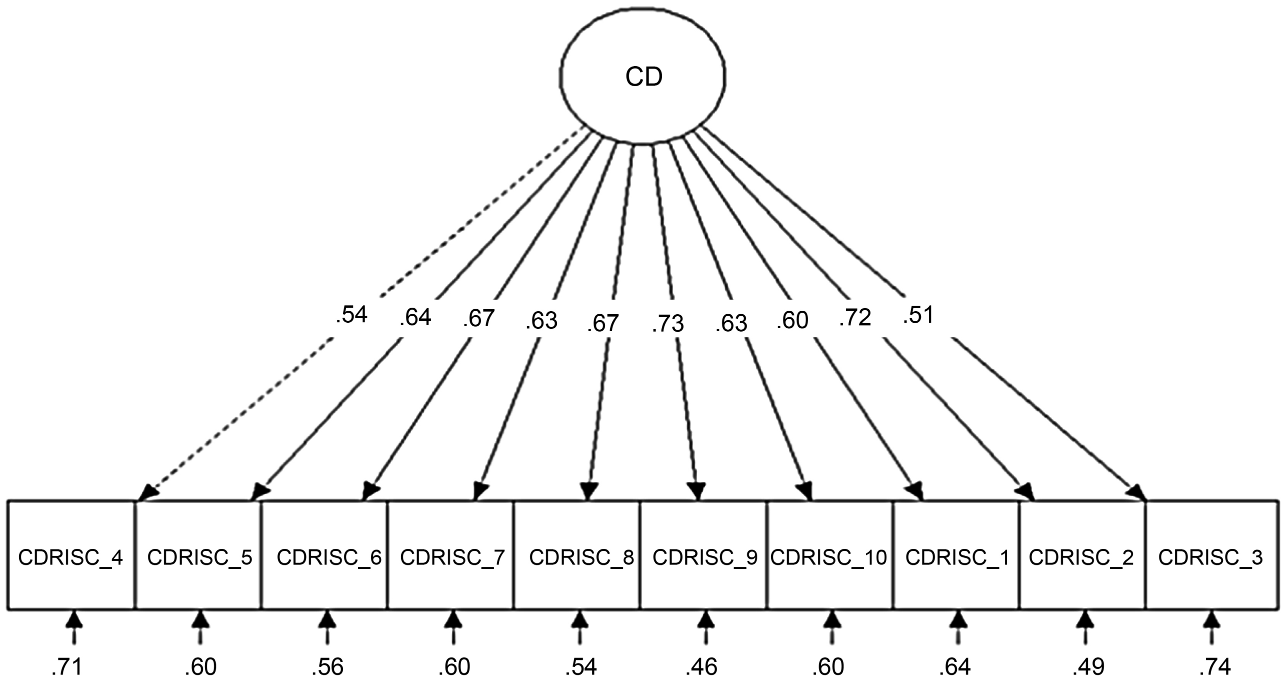

Figure 3. The path diagram of the single-factor model tested in the cross-validation CFA (CFA 2) subsample (40%, N_{CFA2} = 434).

[90% CI .047, .075], CFI = .945, TLI = .929, SRMR = .045, and females, $\chi^2(35)$ = 131.87, χ^2/df = 3.77, RMSEA = .063 [90% CI .053, .073], CFI = .933, TLI = .914, SRMR = .044.

After, testing the configural structure (Table 5), CFI and RMSEA suggested full weak invariance (Model 2 vs 1), but not full strong (Model 3 vs 2). Therefore, to achieve partial strong invariance, the intercepts of items 1 and 9 were freely estimated and ΔRMSEA and ΔCFI values (Model 4 vs 2) suggested partial strong invariance. To achieve partial strict invariance, the error variance of item 1 was freely estimated and ΔRMSEA and ΔCFI values (Model 5 vs 4) indicated partial strict invariance. All model comparisons are listed in Table 5.

3.7. Internal Consistency Reliability, Model-Based Reliability, and Convergent Validity

All reliability coefficients were calculated over the total sample (N = 1089). Before calculating reliability, Model A was tested for tau-equivalency. Model A was not tau-equivalent, F = 2.503, p < 0.001. However, the CD-RISC10 items were not homogeneous, F = 2.46, p < 0.001. Therefore, using ω coefficients to estimate reliability was more appropriate. Internal consistency reliability was α = .85 [95% CI .84, .87] and the greatest lower bound (Jackson & Agunwamba, 1977) was glb = .90 > α = .85 (see Mair, 2018). All three Composite Reliability coefficients were CR = .85 > AVE = .37.

3.8. Convergent, Discriminant Validity and Concurrent Validity with Correlation Analysis

Bivariate correlations (Spearman rho) of the CDRISC10 were calculated to test

Table 5. Goodness-of-Fit for the five nested CD-RISC10 models (M1 - M5) to test measurement invariance across gender (N_{males} = 383, $N_{females}$ = 706) in the total sample (N = 1089).

Nested Models of Measurement Invariance	χ^2	*df*	CFI	RMSEA	Model Comparison	Difference in fit	
						ΔCFI	ΔRMSEA
M1. Full Configural	215.76	70	.938	.062	-	-	-
M2. Full Weak	226.24	79	.937	.059	Model 2 vs 1	−.001	−.003
M3. Full Strong	258.55	88	.927	.060	Model 3 vs 2	−.010	.001
M4. Partial Strong[a]	245.86	87	.932	.058	Model 4 vs 2	−.005	−.001
M5. Partial Strict[b]	277.24	96	.923	.059	Model 5 vs 4	−.009	.001

Note. Estimator = MLR. [a]after freeing intercepts of items 1 and 9. [b]after freeing error variance of item 1.

the convergent validity with another resilience measure (BRS; Smith et al., 2008), discriminant validity with depression, anxiety and stress (DASS-9, Lovibond & Lovibond, 1995; Yusoff, 2013; Kyriazos et al., 2018b) and concurrent validity with affectivity (SPANE-8; Diener et al., 2010; Kyriazos et al., 2018a), and life satisfaction (SWLS; Diener et al., 1985). All relationships were significant at $p < .001$, in the expected direction (**Figure 4**), ranging from .59 (BRS resilience) to −.37 (depression).

3.9. Predictive Validity with a Structural Equation Model (SEM)

Predictive validity was examined by specifying a SEM model to test the predictive power of resilience measured by CD-RISC10 on two second-order factors: 1) a second-order latent factor of Subjective Well-being (SWB; Diener et al., 1999) containing life satisfaction, (SWLS) positive and negative affect (SPANE-8) and 2) a second-order latent factor of Psychological Distress (PD) containing Anxiety, Depression, and Stress (DASS-9). This model showed a very good fit, $\chi^2(455)$ = 1443.01, p = .000, CFI = .921, TLI = .914, RMSEA = .045 [90% CI = .042, .047], SRMR = .054 (calculated with bias-corrected and accelerated CIs, MLR estimator). All measured variables had statistically significant relationships with their latent variables ($p < .001$). The loadings of all first-order factors to SWB and PD either approximated or exceeded .70, suggesting robustness. Specifically, Life Satisfaction coefficient was .695, p = .000; positive affect coefficient was .766, p = .000; Negative affect coefficient was −.852, p = .000, Depression coefficient was .950, p = .000; Anxiety coefficient was .828, p = .000; and Stress coefficient was .889, p = .000. Crucially, the effect of resilience measured by CD-RISC10 (CD) on SWB was β = .538, $p < .001$, explaining 29% of the variance in SWB. The effect of resilience on PD was β = −.442, $p < .001$, explaining 20% of the variance in PD. The covariance of SWB with PD was −.750. **Figure 5** presents the path diagram of the SEM structural model and **Figure A1** in the **Appendix** the full SEM model.

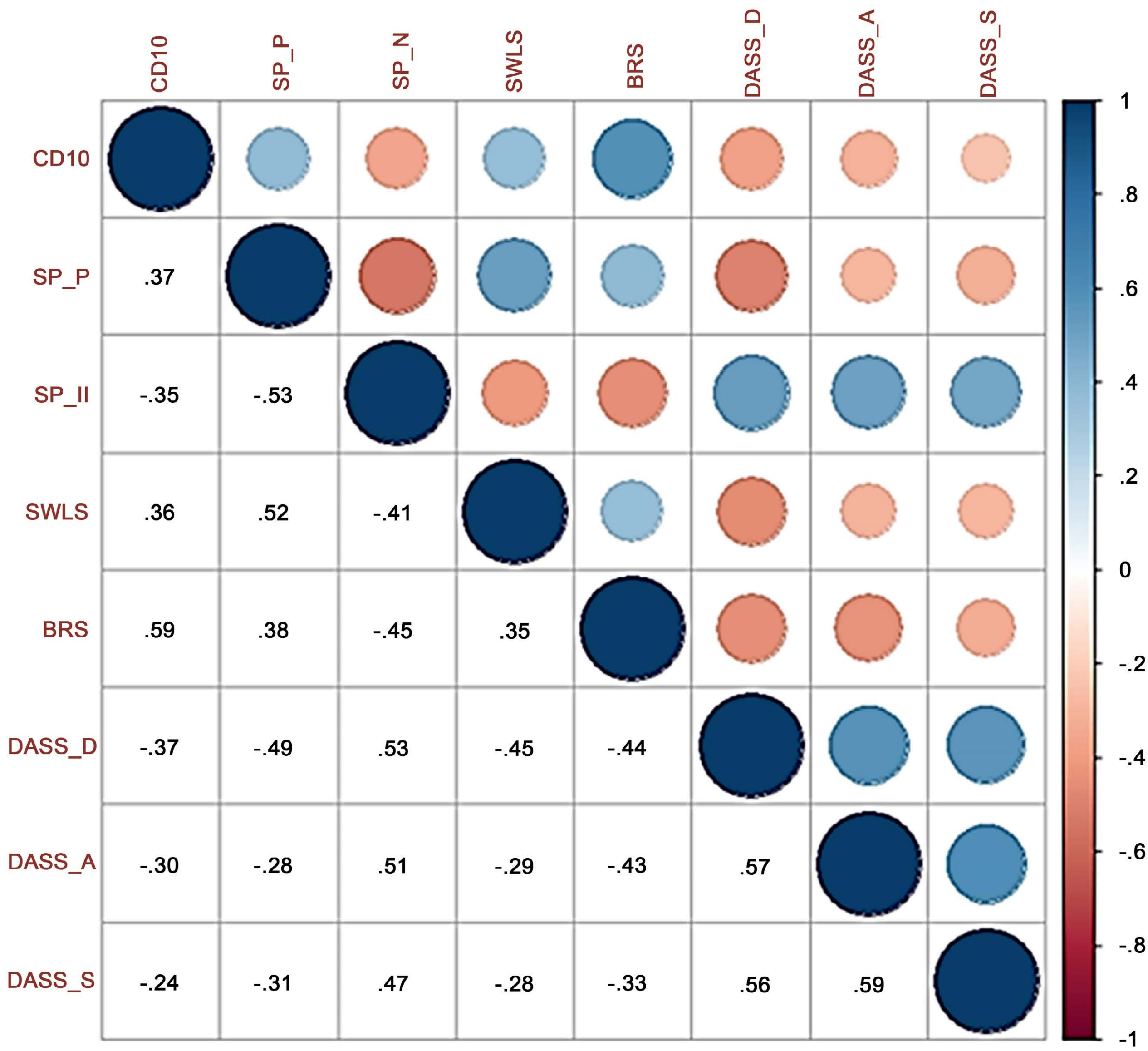

Figure 4. (1) Above the diagonal: Correlogram of the correlations (Spearman Rho) of CD-RISC10 with positive affect (SPANE-P or SP_P), negative affect (SPANE-N or SP_N), life satisfaction (SWLS), resilience (BRS), depression (DASS_D), anxiety (DASS_A) and stress (DASS_S) to evaluate convergent and discriminant validity. Positive correlations are displayed in blue and negative in red. The color intensity and the size of the colored circles are proportional to the magnitude of the correlation coefficients. The color legend in the right presents the colors corresponding to the magnitude of correlation coefficients. (2) Below the diagonal: a correlation matrix corresponding to the correlogram, with all values significant at $p < .001$.

3.10. Normative Data and Descriptive Statistics

CD-RISC10 score in the total sample ($N = 1089$) was $M = 28$ ($SD = 6.35$), $Mdn = 29$, ranging from 2 - 40. On absence of normality (Shapiro-Wilk at $p < .001$), a Mann-Whitney-Wilcoxon test indicated that CD-RISC10 scores were significantly higher for males ($N = 383$, $M = 29.31$, $SD = 6.21$, $Mdn = 30$) than for females ($N = 706$, $M = 27.28$, $SD = 6.32$, $Mdn = 28$), W = 161,468, $p = 0.000$, with small effect size (A = 0.60). Given the significant gender differences[1] raw scores

[1]Under the restrictions of the partial scalar invariance.

were converted to the 10th, 25th, 50th, 75th, and 90th percentiles for the total sample, and for males and females separately (**Table 6**). At item level, item 8 (*not easily discouraged by failure*) had the lowest mean (*M* = 2.5, *SD* = 1.06) and item 5 (*tend to bounce back after illness or hardship*) had the highest (*M* = 3.08, *SD* = .85), equal to somewhere between scale points *sometimes true* (2) and *often true* (3). See descriptive statistics for each item in **Table 6**.

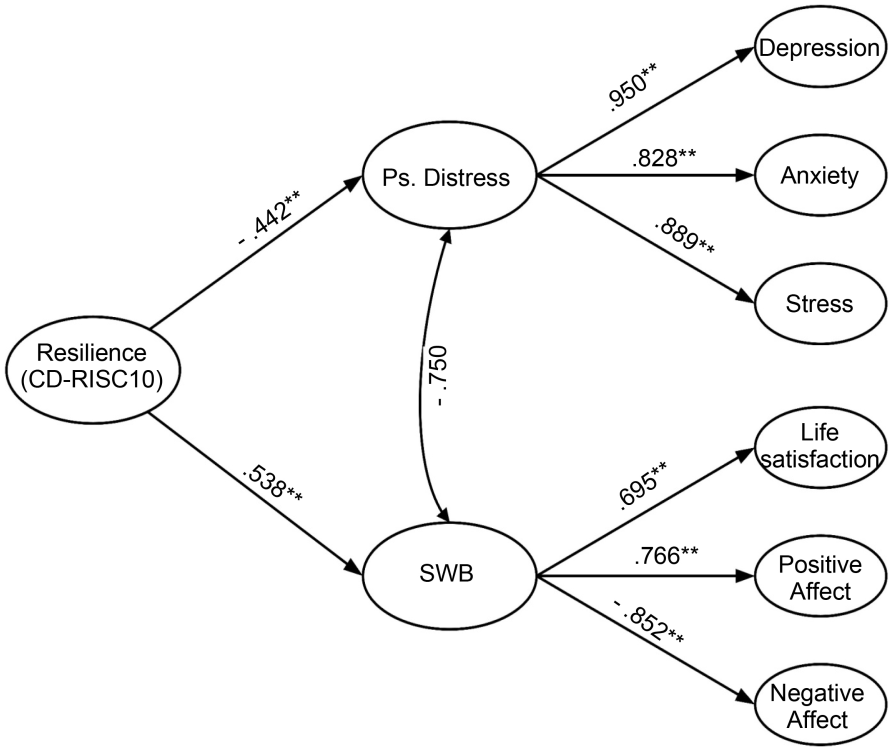

Figure 5. Path diagram with the structural paths of the higher-order SEM model to test the predictive power of resilience (CD-RISC10) on two second order factors, i.e. 1) a second-order factor of Subjective Well-being (SWB; Diener et al., 1999) comprised by life satisfaction (SWLS; Diener et al., 1985), positive and negative affect (SPANE-8; Diener et al., 2010; Kyriazos et al., 2018a) and 2) a second-order factor of psychological distress (DASS-9 Anxiety, Depression and Stress; Lovibond & Lovibond, 1995; Kyriazos et al., 2018b). All effects were significant at $p < .001$.

Table 6. CD-RISC10 scores converted to percentiles for the total sample (N = 1089), males (n = 303) and females (n = 706).

					Percentile				
Group	*Mdn*	*M*	*SD*	Min - Max	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Total sample	29.00	28.00	6.35	2.00 - 40.00	20.00	24.00	**29.00**	338.00	36.00
Males	30.00	29.31	6.21	2.00 - 40.00	21.00	26.00	**30.00**	34.00	37.00
Females	28.00	27.28	6.32	4.00 - 40.00	19.00	23.00	**28.00**	32.00	35.00

Note. Means are unrepresentative of the sample due to the violation of normality assumption.

4. Discussion

The purpose of this study was to evaluate: 1) the construct validity of the CD-RISC-10, Greek version in the general population testing alternative models and cross-validating them with a multistage process (Kyriazos, 2018a), 2) the measurement invariance across gender; 3) internal consistency reliability and the model-based reliability; 4) the convergent and discriminant validity; 5) the predictive validity of resilience on psychological distress and subjective well-being; 6) normative data for the entire sample, and for each gender separately.

4.1. Interpretation and Similarity of the Findings

To establish construct validity, we used a multistage validation (Kyriazos, 2018a), based on sample-splitting. Sample-splitting (Guadagnoli & Velicer, 1988) is a well-known cross-validation method with factor analysis because a hypothesized structure is replicated across subsamples (Byrne, 2012; DeVellis, 2017). Given the instability of the CD-RISC10 dimensionality across samples and sometimes within the same sample (e.g. Tourunen et al., 2021; Smith et al., 2019), cross-validation was essential to safeguard structural replicability. A multistage cross-validating procedure using 3 subsamples was also implemented during CD-RISC10 development (Campbell-Sills & Stein, 2007).

Specifically, EFA indicated a single factor, using multiple methods to select the factors to retain (Horn, 1965; Revelle & Rocklin, 1979; Velicer, 1976). The emerging resilience factor had strong factor loadings (Costello & Osborne, 2005; Tabachnick & Fidell, 2013), explaining adequate total variance. This unifactorial structure was proposed by Campbell-Sills and Stein (2007).

Subsequently, two CFAs of equal sample power verified the EFA structure. In the first CFA four alternative models were specified, including a bifactor model to evaluate if CD-RISC10 was unidimensional, bidimensional, or somewhere in between (Hammer & Toland, 2016). This procedure (although overlooked by the CD-RISC10 validation studies) is pertinent here, because bifactor models may contribute uniquely to dimensionality conflicts (Hammer & Toland, 2016; McDermott, Levant, Hammer, Hall, McKelvey, & Jones, 2017), although they are most popular as an alternative higher-order specification (Brown, 2015). All the CFA1 models had a comparably good fit. The fit difference test comparing the fit of all the models suggested the two-factor model fitted the data better. Nevertheless, the ancillary bifactor fit measures suggested a weak presence of bi-dimensionality to reject a unidimensional interpretation. This unidimensional structure was also proposed by many studies in the general population of Germany (Wollny & Jacobs, 2021), Australia (Burns & Anstey, 2010), Russia (Nartova-Bochaver et al., 2021), Slovenia (Kavčič et al., 2021) or Spain (Notario-Pacheco et al., 2011). The same was true for most studies on special populations (Gonzalez et al., 2016; Madewell & Ponce-Garcia, 2016; Ye et al., 2017; Meng et al., 2019; Cheng et al., 2020; Blanco et al., 2019).

Further support for the robustness of the unidimensional model was the good model fit in the cross-validation CFA (CFA2) using a different subsample of equal power to CFA1. Note the model specified in CFA1 and CFA2 contained no error co-variances, although they would be plausible based on existing studies (Ye et al., 2017; Kavčič et al., 2021). We avoided error co-variances because this would most likely generate a solution difficult to replicate (Byrne, 2012) due to overfitting, possibly located at a local optimum. The a priori and post hoc statistical power of this model (MacCallum et al., 1996) suggested a subsample size of 1.6 times greater than the suggested minimum.

Next, we examined the measurement invariance of CD-RISC10 in the entire sample. The comparison of the nested models suggested that CD-RISC10 had fully configural and metric invariance but partial strong and strict, because items 1 and 9 were functioning differently in male and female respondents. Therefore, it is not possible to safely compare latent means across gender, since it is unknown if mean differences could be attributed to true population differences or to measurement bias (e.g. Fischer & Karl, 2019). Similarly, studies in the Australian general population (Burns & Anstey, 2010) also failed to establish full strong measurement invariance.

Note that male scores were significantly different and higher than female (keeping in mind the restriction of partial scalar invariance). Generally, women self-reported lower resilience than men in numerous CD-RISC10 studies (Cheng et al., 2020; Kavčič et al., 2021; Notario-Pacheco et al., 2011; Nartova-Bochaver et al., 2021). These gender differences might be attributed to some resilience qualities measured by CD-RISC10 that seem to be less pronounced in females under stress or adversity than males, e.g. internal control and personal competence (Cheng et al., 2020; Kavčič et al., 2021; Pulido-Martos et al., 2020; Taylor et al., 2000). Moreover, previous research reported higher resilience scores for adult males than females (Cheng et al., 2020; Kavčič et al., 2021; Nartova-Bochaver et al., 2021; Notario-Pacheco et al., 2011). However, for older adults, the results are inconsistent since Tourunen et al. (2021) reported no gender differences in CD-RISC10 scores an elderly from Finland but these findings were not replicated in the Chinese context (Meng et al., 2019). Therefore, normative data were calculated over the total sample and by gender. This could offer a benchmark for health professionals and numerous programs using resilience as an outcome measure.

Internal consistency reliability and all three model-based reliability estimates were equal, corroborating each other, and they stayed far above the .70 acceptability threshold (Hair et al., 2010). However, the optimal CFA1 model was not tau-equivalent, rendering alpha a somewhat undependable reliability evaluation for this 10-item measure (Brown, 2015: p. 338). In contrast, the greatest lower bound estimate managed to stay above the internal consistency reliability (Mair, 2018). Additionally, the greatest lower bound estimate was greater than the internal consistency reliability (Mair, 2018). CR was greater AVE with AVE marginally missing the .50 threshold (Fornell & Larcker, 1981). This might be an indication that CD-RISC10 items were sufficiently reliable, however, variance due to construct and the variance due to error of measurement is hard to distinguish (Santos et al., 2015). The reliability (both internal consistency and model-based) were generally comparable both to the original (Campbell-Sills & Stein, 2007) and to other studies to general populations, e.g. for a German (Wollny & Jacobs, 2021), Russian (Nartova-Bochaver et al., 2021), or Slovenian sample (Kavčič et al., 2021).

To evaluate convergent and discriminant validity further a correlation analysis followed. All the associations were highly significant of low to strong magnitude at the expected direction, i.e. positive with resilience, life satisfaction, and PA and negative with NA and distress. The existing CD-RISC10 literature corroborates these associations (e.g. Campbell-Sills & Stein, 2007; Wollny & Jacobs, 2021; Nartova-Bochaver et al., 2021; Kavčič et al., 2021; Kuiper et al., 2019; Tourunen et al., 2021). In fact, a large body of quality of life research generally views wellbeing as a state of prevalence of positive psychological traits including resilience (among others). In contrast, illbeing is viewed as a state of prevalence of negative psychological traits like negative effect, stress, pessimism, or hopelessness (see Sirgy, 2021).

Furthermore, to examine the predictive effect of resilience on subjective well-being and psychological distress a SEM model specified. The direct effects of resilience on SWB (Diener et al., 1999) and on distress were significant of strong magnitude, supporting the predictive validity of resilience operationalized by CD-RISC10. Therefore, high-resilient individuals were more likely to have increased subjective well-being and decreased psychological distress than low-resilient. The above findings were consistent with existing literature on the effects of resilience on SWB (e.g. Bajaj & Pande, 2016; Samani et al., 2007), affect (Gonzalez et al., 2016; Gucciardi et al., 2011) and distress (Campbell-Sills & Stein, 2007; Aloba et al., 2016).

4.2. Generalizability, Limitations, and Implications

The generalizability of the findings is rather safe due to the rigorous cross-validation process, the alternative models tested, concrete method of model comparison, high reliability, convergent and discriminant validity, and adequate sample power. Nonetheless, the interpretation should be cautious due to the non-probability sampling, and the cross-sectional study design, disallowing causal inferences regarding the SEM model (Kline, 2020), although such rigid views on causality are rather over-simplifications with SEM (Kline, 2020; Stalikas & Kyriazos, 2019). A limitation was the imbalanced sample in terms of gender. The study was also limited by its reliance on a monocultural sample, a single data collection procedure, and self-report measurement.

Future research directions could include measurement invariance of other demographics like age, or SES or the use of additional techniques to evidence construct validity like CFA MTMM or Multilevel CFA (see Kyriazos, 2018c; Kyriazos, 2019; Kyriazos & Stalikas, 2019a). It would be equally interesting to further evaluate in the Greek context the relationship of resilience with constructs associated with well-being like meaning in life (see Stalikas, Kyriazos, Yiotsidi, & Prassa, 2018), flourishing (e.g. Kyriazos, Stalikas, Prassa, Yotsidi, Galanakis, & Pezirkianidis, 2018), within different contexts like interpersonal relationships (e.g. Kyriazos & Giotsa, 2019), the COVID-19 pandemic (see Kyriazos, Galanakis, Katerelos, & Stalikas, 2021b) or positive psychology parenting (e.g. Kyriazos & Stalikas, 2019b; Kyriazos & Stalikas, 2018).

Conflicts of Interest

The authors declare no conflicting interests.

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Appendix

Table A1. Description of the analyses sequence performed.

N.	Description	Rationale
1	Data screening	To detect outliers with Mahalanobis distance critical value.
2	Univariate normality evaluation with multiple tests	To test for skewness, kurtosis and the univariate normality assumption with Kolmogorov-Smirnov (Lilliefors), Shapiro-Wilk, Shapiro-Francia, and Anderson-Darling tests.
3	Multivariate normality evaluation with multiple tests	To test for the multivariate normality assumption with Mardia's multivariate kurtosis and multivariate skewness tests, Henze-Zirkler's consistent test, Doornik-Hansen omnibus test, Energy test and Royston test.
4	Sample-splitting (20%, 40%, 40%)	To carry out EFA (20%), an initial CFA1 (40%) and cross-validating CFA2 (40%) in three different subsamples, the sample was randomly divided into three parts (20%, 40%, 40%). The two CFA subsamples (40%) were of equal power (3-Faced *Construct Validation Method*, Kyriazos, 2018a).
5	Exploratory Factor Analysis (EFA)	To establish a structure for CD-RISC10. The number of factors to retain was examined with Parallel Analysis (Horn, 1965), Very Simple Structure (Revelle & Rocklin, 1979), Minimum Average Partial Correlations (Velicer, 1976) and Bayesian information criterion (BIC).
6	Confirm the EFA results with a Confirmatory Factor Analysis (CFA 1)	The EFA structure of CD-RISC10 was confirmed with an initial CFA, to test alternative models including a bifactor model.
7	Tests of fit difference	To compare the model fit of all the alternative CFA1 models with the likelihood ratio test ($-2\Delta LL$ MLR rescaled version; Satorra & Bentler, 2010).
8	Evaluating the Bifactor model	To evaluate the bifactor model, using bifactor ancillary model fit measures (Reise, Bonifay, & Haviland, 2013).
9	Evaluating the influence of outliers on CFA1	To test if outliers influenced CFA1 model fit with 2 trial CFAs (in a subsample with vs without multivariate outliers; Tabachnick & Fidell, 2013).
10	Cross-validating the CFA1 optimal model with CFA2	To cross-validate the optimal CFA1 in a different subsample of equal power (CFA2).
11	A priori & post hoc power analysis of the CFA2 model	To evaluate the sample required for achieving a power of 80% to reject a wrong model. An alpha level of .05 was assumed with an RMSEA misspecification of .05 (MacCallum, Browne, & Sugawara, 1996).
12	Measurement invariance across gender to the strict level of the CFA2 model	To test if the cross-validated CFA2 model was invariant factors, factor loadings, intercepts, and error variances across gender.
13	Internal Consistency Reliability, Model-Based Reliability and Model-based Convergent Validity after testing tau-equivalency of the optimal model	To evaluate Cronbach's alpha [95% CI], and the greatest lower bound estimate (*glb*; Jackson & Agunwamba, 1977). To evaluate Composite Reliability (CR; Werts, Linn, & Karl, 1974) with the standardized loadings using 3 calculations (Bollen, 1980; Bentler, 1972; McDonald, 1999) and Average Variance Extracted (AVE; Fornell & Larcker, 1981), evidencing model-based reliability (see Mair, 2018) and convergent validity respectively (see Hoque et al., 2017).

Continued

14	Convergent, Discriminant Validity with correlation analysis	To test Convergent and Discriminant Validity with other constructs Spearman's rho correlation coefficient was estimated. An alpha level of .01 was assumed.
15	Predictive Validity with a Structural Equation Model (SEM)	To test the predictive power of resilience operationalized with CD-RISC10 on two second-order factors: (1) Subjective Well-being (Diener et al., 1999) and (2) Psychological Distress (Lovibond & Lovibond, 1995; Kyriazos et al., 2018b).
16	Differences in resilience across males and females	To test if there are differences in resilience across gender a Mann-Whitney-Wilcoxon test was calculated. The effect size was calculated with Vargha and Delaney (2000) interpretation (A estimate), assuming an alpha level of .01.
17	Normative Data and Descriptive Statistics	To convert raw scores to percentiles for the total sample and for males-females separately.

Note. Data was analysed with R software.

Table A2. Item descriptive statistics, univariate and multivariate normality tests for the total sample (N = 1089) and the 3 subsamples (n_{EFA} = 20%, n_{CFA1} = 40% and n_{CFA2} = 40%) for CD-RISC10.

ITEM	Descriptive Statistics				Univariate Normality Tests			
	M	*SD*	Skew	Kurtosis	KS*	SW*	SF*	AD*
ITEM 1	2.98	.89	−.76	.45	.26	.84	.84	66.79
ITEM 2	2.76	.87	−.46	.14	.25	.87	.87	61.47
ITEM 3	2.72	1.10	−.59	−.33	.21	.88	.88	48.21
ITEM 4	2.57	1.07	−.56	−.20	.23	.89	.89	46.62
ITEM 5	3.08	.85	−.75	.30	.24	.83	.83	73.06
ITEM 6	2.97	.80	−.63	.56	.27	.84	.83	75.02
ITEM 7	2.76	1.04	−.74	.11	.25	.87	.84	54.38
ITEM 8	2.50	1.06	−.45	−.40	.23	.90	.87	45.97
ITEM 9	2.98	.96	−.83	.31	.24	.84	.90	64.76
ITEM 10	2.67	1.00	−.53	−.09	.23	.88	.84	49.50

Multivariate Normality Tests

Sample	Multi-variate Outliers[a]	M-Skew*	M-Kurtosis*	Henze-Zirkler*	Doornik-Hansen (*df*)*	Energy*	Royston*
Total (*N* = 1089)	32	1361.04	4.00	2.29	495.30 (20)	1.89	1325.10
EFA (n_{EFA} = 220)	3	467.02	9.51	1.17	103.26 (20)	2.80	539.27
CFA 1 (n_{CFA1} = 435)	16	845.10	27.86	1.60	249.70 (20)	5.86	813.87
CFA 2 (n_{CFA2} = 434)	13	725.14	23.18	1.77	222.92 (20)	5.33	819.24

Note. KS = Kolmogorov-Smirnov (Lilliefors), SW = Shapiro-Wilk, SF = Shapiro-Francia, AD = Anderson-Darling, M-Skew = Mardia's Skew, M-Kurtosis = Mardia's Kurtosis. [a]Mahalanobis was 29.59 for the total sample and for all subsamples. $^{*}p < .001$.

Table A3. The fit of the single-factor model emerging from CFA1 was compared in the CFA1 subsample with outliers (MODEL 1, $n_{CFA1} = 435$) vs a subsample without outliers (MODEL 2, $n_{CFA1} = 416$) to evaluate the impact of outliers.

MODEL	*n*	χ^2	*df*	CFI	RMSEA	Model Comparison	ΔCFI	ΔRMSEA
MODEL 1 (WITH OUTLIERS)	435	82.42	35	.944	.056	-		
MODEL 2 (NO OUTLIERS)	419	84.89	35	.940	.058	MODEL 2 vs MODEL 1	−.004	.002

Note. Estimator = MLR, *df* = Degrees of freedom; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation

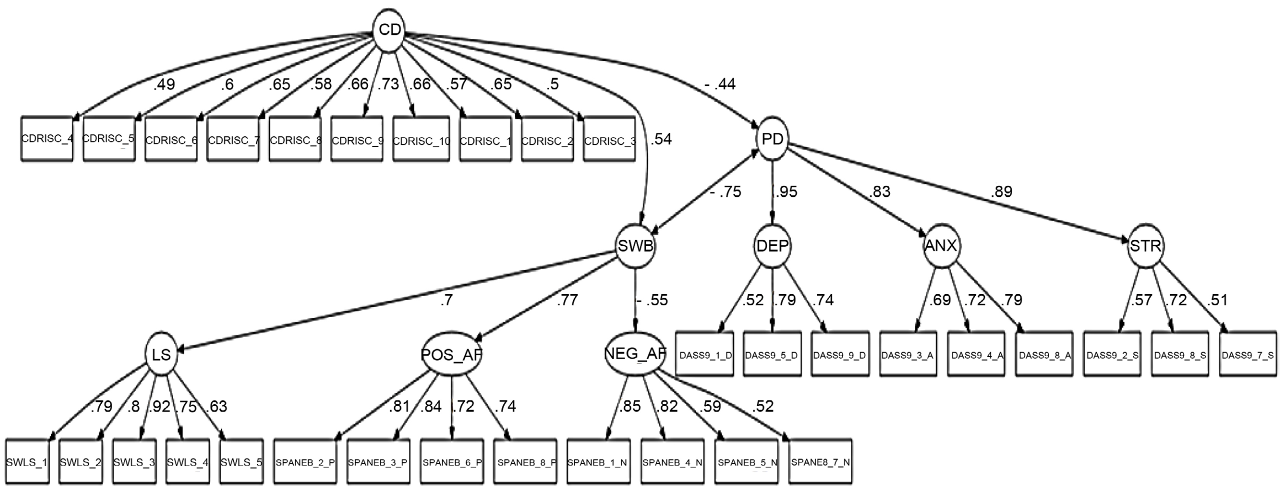

Figure A1. The full SEM model to test the predictive power of resilience operationalized with CD-RISC10 (CD) two second order latent variables of (1) subjective wellbeing (SWB; Diener et al., 1999) and (2) Psychological Distress (PD) with standardized coefficients ($p < .001$). *Note*: CD = CD-RISC10 (Campbell-Sills & Stein, 2007); LS = Satisfaction with Life Scale (SWLS, Diener et al., 1985); POS_AF = SPANE 8 Positive affect (Diener et al., 2010; Kyriazos et al. 2018a); NEG_AF= SPANE 8 Positive affect; DEP, ANX, STR = depression, anxiety and stress (DASS-9, Lovibond & Lovibond, 1995; Kyriazos, et al., 2018b).