Psychological trait resilience within ecological systems theory: The Resilient Systems Scales.

In Press: Journal of Personality Assessment

Author Copy: Final version as submitted, pre-proofing

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Abstract

The current project describes the development of the Resilient Systems Scales to address conceptual and methodological ambiguities in assessing the ecological systems model of resilience. Across a number of samples (total *n* = 986), our findings suggest that the Resilient Systems Scales show equivalence to a previously reported assessment (Maltby, Day, & Hall, 2015) in demonstrating the same factor structure, adequate intra-correlation between the two measures of resilience, and equivalent associations with personality and well-being. The findings also suggest that the Resilient Systems Scales demonstrate adequate test re-test reliability, compare well with other extant measure of resilience in predicting well-being, and map, to varying degrees, onto positive expression of several cognitive, social, and emotional traits. The findings suggest that the new measure can be used alongside existing measures of resilience, or singly, to assess positive life outcomes within psychology research.

Psychological trait resilience within ecological systems theory: The Resilient Systems Scales

The current understanding of psychological resilience focuses on two general frameworks. First, a *buffering approach* considers resilience the opposite of risk, i.e. how psychological processes interact with negative events to lessen their impact. In contrast, the assessment of *trait resilience* examines how people characteristically respond to and approach negative events. Both frameworks are criticised for their ambiguity regarding what comprises resilience. With the buffering hypothesis, this arises because any variable can be labelled a resilient factor so long as it alleviates the impact of a negative event. With the assessment of trait psychological resilience, there are over 25 resilience measures, with resilience encompassing many constructs, including hardiness, coping, optimism, perseverance, impulse control, and self-efficacy (Pangallo, Zibarras, & Lewis, 2015; Windle, Bennett, & Noyes, 2011). Furthermore, this ambiguity extends to the consideration of childhood resilience factors. Rutter (2013) identified eight conceptual frameworks that cover childhood resilience, including risk, inoculation effects of risk, mental attributes, biological features, and the effects of social relationships. Therefore, the existing literature provides researchers and practitioners with a rich list of possible definitions that could be used for describing psychological resilience; however, this does not translate into clear strategic approaches for considering resilience in children due the relatively large number of conceptual approaches that may be drawn upon (Rutter, 2013).

To address this research gap in how to best define resilience, Maltby, Day, and Hall (2015) introduced a new trait resilience assessment derived from three common mechanisms identified in ecological systems theory (Holling, 1973, 1978, 2006; Walker, Holling, Carpenter, & Kinzig, 2004). The first is *engineering resilience*, an ability, in terms of the speed and ease of the system, to recover to a stable equilibrium following disturbance. The second is *ecological resilience,* an ability to absorb or resist disturbance, whilst maintaining a

stable state and making necessary changes to one's own functioning. The third is *adaptive capacity,* an ability to vary functions and processes continually so as to be prepared to adapt to a disturbance.

Maltby et al. (2015) examined the underlying structure of the 115 items from the five most cited trait resilience scales in the literature (the *Hardiness Scale* [Bartone, Ursano, Wright, & Ingraham, 1989], the *Ego Resiliency Scale* [Block & Kremen, 1996], the *Psychological Resilience Scale* [Wagnild & Young, 1993], the *Connor-Davidson Resilience Scale* [Connor & Davidson, 2003] and the *Brief Resilience Scale* [Smith et al., 2008]). These scales embrace a series of theoretical resilience perspectives, such as the capacity to display controlled responses to environmental demands, a personality approach encapsulating emotional, cognitive, and behavioural traits, a "resilience core" reflecting general psychological and physical resilience, treatment contexts, and ability to effectively recover from adversity (Bartone et al., 1989; Block & Kremen, 1996; Smith et al., 2008; Wagnild & Young, 1993). Maltby et al. (2015) found that the three ecological systems theory resilience mechanisms emerged as the strongest latent factors. They thus developed a 12-item measure of the three dimensions of resilience based on the four highest-loading items on each of the latent factors, combining items from all of the five existing resilience scales.

Using the items in this manner proved useful in terms of the conceptualisation and value of ecological systems theory within wider trait and well-being psychology. This was illustrated through the reporting of a stable three-factor structure in US, Japanese, and Polish samples, demonstrating positive associations with adaptive expressions of the traits of the five-factor personality model, and through the making of a positive contribution to clinical and non-clinical psychological health states, after controlling for personality and coping, and over time (Maltby, Day, & Hall, 2015; Maltby et al., 2016). This ecological systems model of resilience is aligned with biological and ecological resilient systems, hence representing a

positive manifestation of positive traits and outcomes through adaptive expressions of trait and well-being psychology.

However, though the 12 items presented by Maltby et al. (2015) demonstrate reliability and validity, there are four main reasons why their continued use is not constructive for the literature. First, though the borrowed items do demonstrate face validity in terms of reflecting Holling's theoretical descriptions of resilience based on emerging latent factors (Maltby et al., 2015, 2016), the current measures use items that were not written with Holling's descriptions of resilience systems in mind (e.g. Holling, 1973, 1978, 2006). Therefore, it may be advantageous to develop items more attuned to those descriptions, which emphasise particular dynamics underpinning each aspect of resilience, such as speed and ease of recovery, more attuned to a normal state for engineering resilience, and more attuned to the ability to function while withstanding disturbance, for ecological resilience. Second, the items from the existing 12-item scale, since they are borrowed from other scales, will always overlap with the existing measures of resilience. This hinders researchers, rendering them unable to operationalise the ecological systems theory alongside other theories of resilience, because it is difficult for these resilience assessments to be used together without the same items being used to measure different constructs. Third, some of the items borrowed from the Connor-Davidson Scale are not free to use, which makes the scale potentially prohibitive when individuals are not able to accommodate the cost (e.g. in schools) or within large samples. Fourth, two of the borrowed items use colloquialisms, with reference to "roadblocks" and "set-backs", and therefore the items may not meet the criteria of not using jargon and not being culturally specific, potentially making them inappropriate for use among some intended audiences (Kline, 1999). For these reasons, it would be fruitful to develop a set of equivalent items, forming a measure of the three resilience systems that maps directly onto

Holling's descriptions of resilience systems, can be employed alongside other measures of resilience, is free to use, and avoids colloquialisms.

Therefore, the aim of the current study was to examine whether we could develop reliable and valid alternative items to assess engineering, ecological and adaptive resilience, that avoided colloquialisms, were free to use, and were written in the theoretical context of Holling's descriptions of resilience systems, so that they might be used alongside other measures of resilience.

Method

Sample

Three samples of data were collected.

Sample 1 comprised 444 US adult respondents (264 males, 180 females), aged from 18 to 69 years (*M* = 32.04, *SD* = 11.01 years). Respondents were predominantly of white ethnicity (80.0%), with Asian (7.2%) and Black (6.57%) being the next most frequently reported ethnicities. The most frequently reported "highest level of qualification" was undergraduate degree (37.8%), followed by high school diploma (31.1%). The most reported income level was $0-10,000 per year (14.4%), followed by $20,000-$30,000 (14.2%). Most of the respondents reported being employed for either 40 or more hours per week (50.2%), or for 1-39 hours per week (26.1%), with 21.8% of the sample being below retirement age and unemployed, either looking or not looking for work. The employed respondents were drawn from a number of occupations, the highest frequencies being for computer-based or mathematical occupations (13.5%) and office and administrative support (12.2%).

Sample 2 comprised 378 US adult respondents (187 males, 191 females), aged from 18 to 74 years (*M* = 35.32, *SD* = 11.22 years). Respondents were predominantly of white ethnicity (78.0%), with Black (7.7%) and Asian (6.3%) being the next most frequently reported ethnicities. The most frequently reported "highest level of qualification" was

undergraduate degree (39.9%), the next highest being high school diploma (29.9%). The most reported income level was $0-10,000 per year (15.6%), followed by $20,000-$30,000 (14.8%). Most of the respondents reported being employed for either 40 or more hours per week (52.1%), or 1-39 hours per week (23.3%), with 21.7% of the sample being below retirement age and unemployed, either looking or not looking for work. The employed respondents were drawn from several occupations, the highest frequencies being for office and administrative support (15.1%) and sales or related occupations (10.6%).

Both Samples 1 and 2 were recruited via the Amazon Mechanical Turk (MTurk) programme, with the recruitment process limited to US individuals. Respondents were paid a reasonable rate in compensation for their time.

Sample 3 comprised undergraduate students from a United Kingdom university experiment participation scheme, whereby students were given the option to take part in experiments in return for being able to recruit participants for their own research projects in their final year. With this sample there were two data collection points, just under three months apart. At Time 1, 310 students (47 males, 263 females; Mean age = 19.40, *SD* = 2.4 years) took part, with 164 of them (22 males, 140 females; Mean age = 19.62 years, *SD* = 3.01) participating at both time points. The study was advertised, and volunteers signed up and completed the study online via an electronic survey system. If participants withdrew from a single study or multiple studies under the scheme they did not jeopardise the reward (i.e., the opportunity to recruit participants for their own research projects). Data were matched across time points through a unique identifier allocated through the experiment participation scheme software account.

Procedure

Development of Items. A list of possible items was compiled through a focus group of eight students (two males, six females) aged 20 to 25 years (*M* = 20.87, *SD* = 1.7 years),

who were enrolled on a research project module, at either an undergraduate or postgraduate level, and were attending a class on item writing (Maltby, Day, & Macaskill, 2013). Respondents were provided with definitions of the three resilience dimensions, and the 12 items identified and borrowed from existing resilience scales by Maltby et al. (2015) to measure these dimensions of resilience (henceforth these items are referred to as "borrowed" items). The focus group was asked to write alternative items for the three definitions, using the original items from the established scales as an initial guide. However, the focus group was also asked to develop the items in such a way that they would map onto the dynamics emphasised by the theoretical descriptions of the three dimensions: engineering, items focusing on speed and ease of reaching an equilibrium; ecological resilience, items focusing on maintaining and altering functioning whilst demonstrating strength; and adaptive capacity, items focusing on a predisposition for change and the unpredictable. To tap directly into these resilience constructs, all items were written with a positive emphasis on engagement in resilience behaviours, with an emphasis on simplicity and suitability of language and meaning to promote clarity. The focus group then met again a week later, and after a couple of minor amendments, selected the eight items they felt best represented each dimension, with items selected if six out of the eight individuals agreed the item should go forward. These 24 "new" items are presented in Table 1.

Sample 1 and 2 measures. Respondents in Sample 1 were then provided with 36 resilience items (the 24 new items and the 12 items borrowed from existing resilience scales) and asked to indicate their agreement with each question (item) using a five-point response scale ranging from "1=Strongly Disagree" to "5=Strongly Agree". Respondents in Sample 2 were provided with 24 resilience items (12 "new" items and the 12 "borrowed" items), with the number of "new" items having been reduced following exploratory factor analysis that is detailed below. These 12 "new" items formed what are referred to henceforth as the Resilient

Systems Scales. In addition, the first sample completed the Ten-Item Personality Inventory (TIPI; Gosling, Rentfrow, & Swann, 2003), and the second sample the Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983) to facilitate comparisons between the new and old items in terms of the relationships between the latter, and personality and affect as reported in previous studies (Maltby et al., 2016, 2015). The TIPI comprises ten items, scored on a seven-point scale ("1=Strongly Disagree" to "7=Strongly Agree"), and used to assess emotional stability, extraversion, conscientiousness, agreeableness, and openness to experience. The HADS comprises two seven-item subscales, measuring anxiety and depression, and scored on a series of different four-point scales indicating degree of intensity or frequency of symptoms.

Sample 3 measures. Respondents in Sample 3 were given the Resilient Systems Scales at both administration points. In addition, at Time 1 (n = 310) respondents were administered a number of scales to examine the incremental validity of the Resilient Systems Scales against extant measures of resilience, in predicting well-being outcomes. In choosing these extant measures, we selected the four most cited measures of resilience within the Web of Science (MIMAS, 2017). The first chosen was the Connor-Davidson Resilience Scale (CD-RISC; Connor & Davidson, 2003), which had been cited 848 times. The CD-RISC is a 25-item measure of a series of trait characteristics that are thought to exemplify resilience via five factors: personal competence, trust in one's instincts, positive acceptance of change, control, and spiritual influences. Responses are scored on a five-point scale ranging from "0=Not at all true" to "4=True nearly all of the time".

The second chosen was the Psychological Resilience Scale (PRS; Wagnild & Young, 1993), which had been cited 635 times. This 25-item scale measures resilience via the capacity to withstand stress and create meaning from challenges. Responses are scored on a seven-point scale ranging from "1=Disagree" to "7=Agree". In its original form, the PRS

comprises two factors: Personal Competence and Acceptance of Self and Life. The third chosen was the Ego Resiliency Scale (ER-89; Block & Kremen, 1996), which had been cited 438 times. This 14-item scale assesses a global ability to adapt to a stressful experience and return to individual characteristics afterwards. Responses are scored on a seven-point scale, from "1=Does not apply at all" to "7=Applies very strongly". The fourth chosen was the Hardiness Scale (HS; Bartone et al., 1989), which had been cited 270 times. This scale comprises 45 items designed to measure dispositional resilience, presented as three factors: commitment, control, and challenge. Responses are scored on a four-point scale ranging from "0=Not at all true" to "3=Completely true".

In addition to the resilience scales administered at Time 1, to assess well-being outcomes, we concentrated on two measures that reflect overall positive functioning: physical health and eudemonic well-being. To measure well-being in terms of physical health, we used the Physical Health Questionnaire (PHQ; (Schat, Kelloway, & Desmarais, 2005). This 14-item scale assesses a range of somatic symptoms, across gastrointestinal problems, headaches, sleep disturbances, and respiratory illness. Responses are scored on a seven-point scale from "1=Not at all" to "7=All of the time". For the purposes of this study, we computed an overall physical health score, with higher scores indicating lower levels of physical health. We assessed eudemonic well-being because it represents psychological health in terms of longer-term engagement and meaning derived from life challenges. To measure eudemonic well-being, we used the 18-item Scales of Psychological Well-being (Ryff & Keyes, 1995) that encompasses six dimensions of psychological well-being (autonomy, environmental mastery, positive relations with others, personal growth, purpose in life, and self-acceptance). Responses are scored using a six-point Likert scale ranging from "1=Strongly disagree" to "6=Strongly agree".

At Time 2, respondents (*n* = 164) were given a series of scales to add to the convergent validity of the scales. We largely based this on the adaptive assumptions underpinning resilient systems theory and the idea that resilience should be associated with a number of adaptive expressions of cognitive, social, and emotional psychological traits (Maltby et al., 2015). In selecting our measures, we included assessments of executive functioning and emotional intelligence, given that these are indicative of wider adaptive cognitive and emotional ability traits (Cooper & Petrides, 2010; Wilson, Evans, Emslie, Alderman, & Burgess, 1998), and measures of self-esteem and self-efficacy, as these are indicative of adaptive expressions of self-concept and self-competence (Chen, Gully, & Eden, 2001; Rosenberg, 1965). Specifically, we administered four measures, described next.

The first measure was the Dysexecutive Functioning Questionnaire (DEX; Wilson et al., 1998). The scale comprises 20 self-report items that cover a range of dysexecutive symptoms around inhibition, intention, social regulation, and abstract problem solving. Each item is scored on a five-point scale from “0=Never” to “4=Very often”. Research suggests that these dysexecutive problems are best described within one underlying factor (Gerstorf, Siedlecki, Tucker-Drob, & Salthouse, 2008); therefore, we computed an overall score for the scale, wherein higher scores represented higher levels of dysexecutive symptoms. The second measure was the Trait Emotional Intelligence Questionnaire-Short Form (TEIQue-Short Form; Cooper & Petrides, 2010; Petrides & Furnham, 2006), which assesses a global level of trait emotional intelligence across 15 facets of emotional intelligence (e.g. well-being, self-control, emotionality, sociability). Items are scored on a seven-point Likert-type scale ranging from “1=Completely disagree” to “7=Completely agree”. As the measure assesses global levels of trait emotional intelligence, we computed an overall score for the scale, wherein higher scores represented higher levels of emotional intelligence. Third, we used overall scores from the ten-item Rosenberg Self-Esteem Scale (Rosenberg, 1965) to assess overall

subjective emotional evaluation of one's own worth. Items are scored on a four-point Likert-type scale ranging from "1=Strongly disagree" to "4=Strongly agree". Fourth, overall scores from the eight-item New General Self-Efficacy Scale (Chen et al., 2001) were used to assess self-efficacy as a belief in the competence to attain the required performance across a variety of achievement situations. In it, items are scored on a five-point Likert-type scale, ranging from "1=Strongly disagree" to "5=Strongly agree".

In addition, at Time 2, we specifically wished to test the Resilient Systems Scales' association with social desirability responding, with the prediction that there should be no association between the Resilient Systems Scales and a tendency among respondents to answer items on the Resilient Systems Scales in a manner that would be viewed favourably by others. Therefore, we also administered the six-item Lie subscale of the Abbreviated Form of the Revised Eysenck Personality Questionnaire - Short-Form (Francis, Brown, & Philipchalk, 1992). Items were scored on a "Yes" – "No" response scale and summed to assess overall social desirability.

Ethical Consent

The current study received ethical approval from a university psychology research ethics board.

Results

The data analysis strategy formed three stages: (1) factor analysis, (2) equivalence analysis, and (3) test re-test and comparison analysis.

Factor Analysis

In the factor analysis stage, Sample 1 was used for an exploratory factor analysis (EFA) and Sample 2 for a confirmatory factor analysis (CFA).

Exploratory Factor Analysis (EFA). First, the skewness (-1.34 to .44) and kurtosis (-1.27 to 1.95) statistics for the 36 items fell within the criteria for a normal univariate

distribution, with values within +/-1 representing "very good" symmetry and values within +/-2 representing "acceptable" symmetry, and skewness > 2 and kurtosis > 7 representing a concern around symmetry (Curran, West, & Finch, 1996; George & Mallery, 2010). Consequently, a maximum likelihood extraction method was used for the EFA. The second step of the analysis was to determine the factor structure of the items. The items were newly written, and consequently, to allow any potential factor structure to emerge among them, EFA was used in the first instance. The participants (444) to variables (36) ratio exceeded the recommended ratio for EFA, of 10 to 1 (with a minimum number of participants of 150) (Cattell, 1978; Gorsuch & Hillsdale, 1983). The Kaiser-Meyer-Olkin measure of sampling adequacy (.95) and Bartlett's test of sphericity (x^2=14192.36, df = 630, p < .001) suggested an adequate case-to-variable ratio for the analysis.

We considered three methods for assessing the number of factors to retain for the EFA: the K1 method (eigenvalues greater than one; Kaiser, 1960), a scree plot (Cattell, 1966), and parallel analysis using Monte Carlo simulations (Horn, 1965). The latter analysis compares the extracted eigenvalues of the EFA to those that might be expected from purely random data. Previous findings have suggested that parallel analysis is the most accurate method for determining the number of factors, comparing favourably to the other two methods, and demonstrating less variability (e.g. Fabrigar, Wegener, MacCallum, & Strahan, 1999; Glorfeld, 1995; Ledesma & Valero-Mora, 2007). Therefore, parallel analysis using Monte Carlo simulations was used to determine the number of factors. The fourth eigenvalue obtained using maximum likelihood extraction (eigenvalues 14.22. 5.46, 4.00, and 1.26) failed to exceed the fourth from the parallel analysis (eigenvalues 1.58, 1.51, 1.46, and 1.41), calculated from 1,000 generated datasets with 444 cases and 36 variables, thus suggesting a three-factor solution.

Given this, a three-factor solution (see Table 1) was explored, using a promax rotation (it was anticipated that the factors would be correlated), with delta set to 0. Meaningful loadings were assessed using the criteria of .32 ("poor"), .45 ("fair"), .55 ("good"), .63 ("very good"), and .71 ("excellent") (Comrey & Lee, 1992; Tabachnick, Fidell, & Boston, 2007). We have presented the items (with the items from existing scales italicised) in Table 1 in the order in which the factors loaded, and then according to the salience of each item to each factor.

- Insert Table 1 about here -

Looking at the table, all the items load singularly on a factor, with loadings ranging from .49 (above "fair") to .91 (above "excellent"). In terms of naming the factors, the pattern and values of the loadings indicate that the first factor is an "engineering resilience" factor, the second an "ecological resilience" factor, and the third an "adaptive capacity" factor. The newly written items can largely be found to load alongside the "borrowed" items, with at least four of the newly written items loading on each of the factors with a loading exceeding the criterion for "excellent" (.71). The factor correlations between the three factors were as follows: engineering/ecological, $r = .52$; engineering/adaptive capacity, $r = .35$; ecological/adaptive capacity, $r = .28$. These findings suggest the factors share no more than 27% of the variance.

Confirmatory Factor Analysis (CFA). Considering this finding, the following proposal was put forward: for each of the three factors, each of the four newly written items demonstrating the highest loadings on each factor in the EFA could be suggested as an alternative for measuring that resilience dimension. For clarity, we now refer to these 12 new items as the Resilient Systems Scales. However, to explore the structural validity and stability of this interpretation, we administered the Resilient Systems Scales items, alongside the 12

"borrowed" items, to the second sample (noting that we reversed the scoring of the two negatively worded original items).

It is necessary to demonstrate the incremental value of proposed CFA models (Barrett, 2007). Therefore, we compared two models: (i) a unidimensional model, proposing that all 24 items could load on one factor, reflecting an underlying latent factor of resilience; and (ii) a three-factor model, suggesting that the 24 items would form engineering, ecological, and adaptive capacity trait resilience factors. In comparing these two models, we predicted that the three-factor would present the better fit to the data due to the theoretical assertion of three different resilience systems and the findings from the EFA, which suggested that the factors shared no more than 27% of the variance.

To assess each of the proposed models, we used standard goodness-of-fit indices recommended by Hu and Bentler (1999) and Kline (2005): the relative chi-square (CMIN/DF), alongside the chi-square and degrees of freedom, comparative fit index (CFI), non-normed fit index (NNFI), root mean square error of approximation (RMSEA), and standardised root mean square residual (SRMR). Statistics that represent an "acceptable" fit are indicated by a CMIN/DF of less than 3, CFI and NNFI greater than .90, RMSEA of less than .08, and SRMR of less than .08 (Browne & Cudeck, 1993; Hu & Bentler, 1999; Tabachnick et al., 2007), with an improved model indicated by a change in CFI (ΔCFI) greater than .01 (Cheung & Rensvold, 2002). The goodness-of-fit statistics for the four models are presented in Table 2. The three-factor model demonstrates acceptable fit, with improved goodness-of-fit statistics over the unidimensional model (ΔCFI > .01). Therefore, these findings suggest that the three separate factors of engineering, ecological, and adaptive capacity resilience best explain the variance in these data.

- Insert Table 2 here -

Equivalence Analysis

Samples 1 and 2 were used for an equivalence analysis between the new and previous versions of the resilience scales. Sample 1 was also used to complete an equivalence analysis between the new and previous versions of the resilience scale and the five-factor model of personality. Sample 2 was also used to complete an equivalence analysis between the new and previous versions of the resilience scale, and depressive and anxiety symptoms.

To assess the equivalence between using the Resilient Systems Scales and the "borrowed" items from other resilience scales, we looked at (i) the concurrent validity between the three subscales from the Resilient Systems Scales and the scales formed from the "borrowed" items; and (ii) equivalence in terms of the associations between the Resilient Systems Scales and the "borrowed" subscales, on the one hand, and the five-factor model of personality (Sample 1) and depressive and anxiety symptoms (Sample 2), on the other. Table 3 presents all the Cronbach's (1951) alpha coefficients, means, and correlations between the scales, for Samples 1 and 2. In terms of reliability, all the scales exceed the .6 criterion, above which internal reliability may be considered "adequate" (Kline, 1999; Nunnally, 1978). To assess the equivalence between the Resilient Systems Scales and the "borrowed" scales, we used Campbell and Fiske's (1959) formula for assessing discriminant validity, accounting for the reliability of the scales, to calculate the correlation between each pair of resilience scales (all $r > .943$) across both samples.

All of these values were above the.85 criterion, providing evidence of the concurrent validity of the Resilient Systems Scales. In terms of the equivalence, no significant difference was found in Sample 1 between the correlation statistics from the two versions of the resilience scales, for the relationship between engineering resilience and emotionality stability ($z = .90$, $p = .368$), that between ecological resilience and conscientiousness ($z = -.91$, $p = .363$), or that between adaptive capacity and openness to experience ($z = .53$, $p = .596$). Similarly, in Sample 2, no significant differences were found between the correlation statistics

for the relationships between the two versions of engineering resilience and either depression (z = .10, p = .920) or anxiety (z = .12, p = .905), for the two versions of ecological resilience and either depression (z = -.10, p = .920) or anxiety (z = .36, p = .719), or for the two versions of adaptive capacity and either depression (z = -.65, p = .516) or anxiety (z = .49, p = .624).

- Insert Table 3 here –

Test re-test and comparison analyses

Sample 3 was used for the test re-test analysis, comparing Resilient Systems Scales scores with other measures of resilience in terms of predicting of well-being outcomes, and with measures of cognitive, social, and emotional psychological traits. For the 164 respondents who completed the Resilient Systems Scales twice, the interclass correlation coefficients (engineering ICC = .79; ecological ICC = .74; adaptive capacity ICC = .75) were all above the .6 minimum threshold suggested by Chinn (1991), with two of the scales above the threshold of .75, representing "excellent" reliability (Fleiss, 1986).

To examine the utility of the new scale we investigated the comparative value of the Resilient Systems Scales against four extant resilience measures (PRS; CD-RISC; ER-89; HS) in determining the two well-being outcomes (psychological well-being and physical health) that were assessed at Time 1. We tested this through two multiple regressions in which all the resilience variables were entered as predictor variables, and psychological well-being and physical health were used as outcome variables.

The variance inflation factors (VIFs) and tolerance factors for the predictor variables were no larger than 4.56 and no smaller than .217 respectively. Therefore, they did not contravene the threshold values for VIFs of at least 5 and for tolerance statistics of less than .2 that are used to suggest collinearity between independent variables (Kutner, Nachtsheim, Neter, & Li, 2004). The results of the regression analysis are presented in Table 4. The measures of resilience demonstrate statistical significance in predicting psychological well-

being (F [14, 295] = 46.16, r = .83; r^2 = .69, adj r^2 = .67, p < .001) and health (F [14, 295] = 5.18, r = .44; r^2 = .20, adj r^2 = .16, p < .001).

Five of the fourteen resilience subscales predicted statistically significant unique variance in psychological well-being. These were (with parental scale in parentheses), in order of descending size of standardised beta, control (CD-RISC), ecological (RSS), control (HS), ego-resilience (ER-89), and commitment (HS). Four of the fourteen resilience subscales predicted statistically significant unique variance in physical health. These were (with parental scale in parentheses), in order of descending size of standardised beta, personal competence (CD-RISC), acceptance of change (CD-RISC), engineering (RSS), and control (CD-RISC). It is worth noting that the unique variance accounted for by the personal competence (CD-RISC) subscale predicted poorer physical health.

A check of the initial correlation between the personal competence subscales of the CD-RISC and physical health scales indicated a statistically significant negative correlation of r = .17, p = .003, indicating a small effect size, but in the opposite direction to the association suggested by the multiple regression. Reversals in the direction of association (magnitude or direction) are frequently caused by collinearity, too many variables in the model, or suppression effects (Mosteller & Tukey, 1977). As the main reason for including CD-RISC was to compare the Resilient Systems Scales against the variance accounted for by extant resilience variables, this finding does not undermine the finding that the Resilient Systems Scales predict unique variance in psychological well-being and physical health when compared against extant resilience measures.

- Insert Table 4 here -

Table 5 presents all the Cronbach's (1951) alpha coefficients and means for, and correlations between, the scales administered at Time 2, namely, the Resilient Systems Scales, DEX, TEIQue-Short Form, Rosenberg Self-Esteem Scale, New General Self-Efficacy Scale,

and Lie subscale. The Cronbach's alpha coefficients for the scales used exceed the aforementioned internal reliability criterion of $\alpha > .60$ as "acceptable".

- Insert Table 5 here -

In terms of assessing the magnitude of the zero-order correlations between the measures, we report statistical significance using a frame of reference, with $r \geq .37$ representing a large effect size, $.24 \leq r < .37$ representing a moderate effect size, and $.1 \leq r < .24$ representing a small effect size (Cohen, Cohen, West, & Aiken, 2003; McGrath & Meyer, 2006), and a moderate effect size deemed to be the minimum at which the findings can be considered of practical significance (Cohen, 1992). This criterion differs from the well-cited effect size of .1 = small to .5 = large, as Cohen based the comparisons with the *d* effect size criteria using a biserial correlation, while comparison with the *d* effect size for Pearson product moment correlation coefficients should be based on point biserial correlation (McGrath & Meyer, 2006). The engineering resilience scores were positively associated with lower dysexecutive symptoms, and higher emotional intelligence, self-esteem and self-efficacy, all to a magnitude of a large effect size. The ecological resilience scores were positively associated with higher emotional intelligence, self-esteem and self-efficacy, to a magnitude of a large effect size, and associated with lower dysexecutive symptoms to a medium effect size. The adaptive capacity resilience scores were positively associated with higher emotional intelligence, to a magnitude of a medium effect size, and associated with higher self-esteem and self-efficacy to a small effect size, even though they share a statistically significant association. The adaptive capacity resilience scores were not significantly associated with dysexecutive symptoms. Furthermore, none of the subscales of the Resilient Systems Scales were significantly associated with socially desirable responding.

Discussion

The aim of the current study was to develop a set of items designed to directly measure trait levels of Holling's ecological systems model of resilience (Holling, 1973, 2006) and that did not borrow items from existing measures of resilience. The findings suggest a three-factor structure, acceptable internal and test re-test reliability, and concurrent validity against a previously reported measure of these resilience systems, albeit comprising items borrowed from other scales (Maltby et al., 2015). This view is further supported by the equivalence of scores obtained on the three Resilient Systems Scales and scores on the three resilience scales formed from the "borrowed" items, in terms of the associations with scores obtained for the personality and well-being measures. Furthermore, these findings replicate previous findings in the UK and the USA that have explored the relationship between resilience, personality, and mental health measures (Maltby et al., 2016, 2015). That is, engineering resilience shows the highest association with emotional stability, and ecological resilience shows the highest association with conscientiousness. The findings also suggest that all aspects of resilience are significantly related to better mental health, noting that, on this occasion, a small effect size was found for the association between adaptive capacity and lower anxiety and depression. Together, this suggests the Resilient Systems Scales items provide an equivalent measure of the three dimensions of resilience (engineering, ecological and adaptive capacity) to that of the previous formulation.

The findings also provide new information on how the Resilient Systems Scales compare with (i) extant measures of resilience in predicting well-being outcomes, and (ii) adaptive expressions of other cognitive, social, and emotional psychological traits. Specifically, when the Resilient Systems Scales are compared with the four most cited resilience scales in the literature, ecological resilience predicts unique variance in psychological well-being, and engineering resilience predicts unique variance in physical health. The findings also show that Resilient System Scales, and particularly engineering and

ecological resilience (i.e., in terms of the associations found, which were of at least a moderate effect size), share statistically significant associations with lower levels of dysexecutive symptoms and higher emotional intelligence, self-esteem, and self-efficacy. The only exception to this is that the adaptive capacity scale is not related to dysexecutive symptoms. Together, these current findings suggest two things regarding the Resilient Systems Scales. First, the Resilient Systems Scales are competitive in terms of researcher choice of which measures of resilience to use. Second, the Resilient Systems Scales are related to a series of positive cognitive, social, and emotional psychological traits via intention, social regulation, abstract problem solving, and lower inhibition (i.e., lower dysexecutive functioning), promotion of well-being, self-control, emotionality, sociability (i.e., higher emotional intelligence), and higher emotional evaluation of one's own worth or competence in achievement (i.e., higher self-esteem and self-efficacy).

Though these findings do not immediately seem to present much progress over using the "borrowed" items, their introduction is important because they are more theoretically consistent with Holling's (1973, 2006) descriptions of resilient systems, avoid colloquialisms, are free to use, and do not contain the same items as the five most cited measures of resilience, thereby facilitating the simultaneous use of different resilience scales. Within this context, the Resilient Systems Scales provide a relatively short assessment (12 items) of three well-recognised systems, and this item-to-construct ratio seems favourable when compared to other extant measures of resilience. This is important for the measurement and examination of trait resilience, not least because the conceptual and measurement understanding of trait resilience has previously been somewhat ambiguous (Pangallo et al., 2015; Windle et al., 2011). Therefore, the current findings also suggest the Resilient Systems Scales can be employed to assess independent three-trait resilience systems to inform the planning and goals of interventions, both individually and with systems.

There are two further aspects to consider in terms of the current findings. The first is that the items were written through a focus group of students. This approach meant that the item writing extended beyond what might have been achieved by the authors alone, and was done within an informed context of working with strong theoretical definitions and example items. However, it may have introduced idiosyncratic wording into the items. Further research might consider whether, within other contexts (e.g. with children or in other languages), the items developed are optimal, not least because these resilience factors may have different meanings across cultures (Maltby et al., 2016). The second is that the current study only considers resilience at one time point, in terms of contributions to well-being outcomes. This presents a weakness in terms of attributing the contributing effects of resilience to mental health outcomes over time, based on this study, though previous studies have confirmed this in terms of resilience predicting better mental health (Maltby et al., 2015).

In summary, the current findings suggest the identification of a free-to-use resilience scale that comprises original items (i) to assess an ecological systems model of resilience, comprising engineering resilience, ecological resilience, and adaptive capacity, (ii) that map onto several positive expressions of personality, cognitive, social, emotional, and health traits and states, and (iii) that can be used alongside existing trait resilience scales.

References

Barrett, P. (2007). Structural equation modelling: Adjudging model fit. *Personality and Individual Differences*, *42*(5), 815–824. https://doi.org/10.1016/j.paid.2006.09.018

Bartone, P. T., Ursano, R. J., Wright, K. M., & Ingraham, L. H. (1989). The impact of a military air disaster on the health of assistance workers. A prospective study. *The Journal of Nervous and Mental Disease*, *177*(6), 317–328. https://doi.org/10.1097/00005053-198906000-00001

Block, J., & Kremen, A. M. (1996). IQ and ego-resiliency: conceptual and empirical connections and separateness. *Journal of Personality and Social Psychology*, *70*(2), 349–61. https://doi.org/10.1037/0022-3514.70.2.349

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models.* (p. 136–162.). Newbury Park, CA: Sage.

Campbell, D. T., & Fiske, D. W. (1959). Convergent and Discriminant validation by the Multitrait-Multimethod Matrix. *Psychological Bulletin*, *56*(2), 80–105.

Cattell, R. B. (1966). The Scree Test For The Number Of Factors. *Multivariate Behavioral Research*, *1*(2), 245–276. https://doi.org/10.1207/s15327906mbr0102_10

Cattell, R. B. (1978). *The scientific use of factor analysis in behavior and life sciences.* New York: Plenum.

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a New General Self-Efficacy Scale. *Organizational Research Methods*, *4*(1), 62–83. https://doi.org/10.1177/109442810141004

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Chinn, S. (1991). Statistics in respiratory medicine. 2. Repeatability and method comparison. *Thorax*, *46*(6), 454–456. https://doi.org/10.1136/thx.46.6.454

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Cohen, J., Cohen, P., West, S., & Aiken, L. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences.* (3rd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Comrey, A. L., & Lee, H. B. (1992). *A first course in factor analysis*. Hillsdale, NJ: Erlbaum.

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: the Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety*, *18*(2), 76–82. https://doi.org/10.1002/da.10113

Cooper, A., & Petrides, K. V. (2010). A Psychometric Analysis of the Trait Emotional Intelligence Questionnaire–Short Form (TEIQue–SF) Using Item Response Theory. *Journal of Personality Assessment*, *92*(5), 449–457. https://doi.org/10.1080/00223891.2010.497426

Cronbach, L. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*, 297–334.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1*(1), 16–29. https://doi.org/10.1037/1082-989X.1.1.16

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272–299. https://doi.org/10.1037/1082-989X.4.3.272

Fleiss, J. L. (1986). *The design and analysis of clinical experiments*. New York: John Wiley and Sons.

Francis, L. J., Brown, L. B., & Philipchalk, R. (1992). The development of an abbreviated form of the revised Eysenck personality questionnaire (EPQR-A): Its use among students in England, Canada, the U.S.A. and Australia. *Personality and Individual Differences*, *13*(4), 443–449. https://doi.org/10.1016/0191-8869(92)90073-X

George, D., & Mallery, M. (2010). *SPSS for Windows Step by Step: A Simple Guide and Reference, 17.0 update*. Boston, MA: Pearson.

Gerstorf, D., Siedlecki, K. L., Tucker-Drob, E. M., & Salthouse, T. A. (2008). Executive dysfunctions across adulthood: measurement properties and correlates of the DEX self-report questionnaire. *Neuropsychology, Development, and Cognition. Section B, Aging, Neuropsychology and Cognition*, *15*(4), 424–45. https://doi.org/10.1080/13825580701640374

Glorfeld, L. W. (1995). An Improvement on Horn's Parallel Analysis Methodology for Selecting the Correct Number of Factors to Retain. *Educational and Psychological Measurement*, *55*(3), 377–393. https://doi.org/10.1177/0013164495055003002

Gorsuch, R. L., & Hillsdale, N. J. (1983). *Factor Analysis* (2nd ed.). New Jersey: Lawrence Erlbaum Associates.

Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, *37*(6), 504–528. https://doi.org/10.1016/S0092-6566(03)00046-1

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecological Systems*, *4*, 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245

Holling, C. S. (1978). *Adaptive environmental assessment and management. Wiley International Series on Applied Systems Analysis* (Vol. 3). Chichester: Wiley.

Holling, C. S. (2006). Engineering Resilience versus Ecological Resilience. In P. Schulze (Ed.), *Engineering within Ecological Constraints* (pp. 31–44). Washington, D.C.: The

National Academies Press.

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185. https://doi.org/10.1007/BF02289447

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

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, *20*(1), 141–151. https://doi.org/10.1177/001316446002000116

Kline, P. (1999). *The handbook of psychological testing*. London: Routledge.

Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2nd ed.). New York: Guilford Press.

Kutner, M. H., Nachtsheim, C., Neter, J., & Li, W. (2004). *Applied linear statistical models*. New York: McGraw-Hill/Irwin.

Ledesma, R. D., & Valero-Mora, P. (2007). Determining the Number of Factors to Retain in EFA: an easy-to-use computer program for carrying out Parallel Analysis. *Practical Assessment, Research & Evaluation*, *12*(2), 2–11. https://doi.org/http://pareonline.net/getvn.asp?v=12&n=2

Maltby, J., Day, L., & Hall, S. (2015). Refining Trait Resilience: Identifying Engineering, Ecological, and Adaptive Facets from Extant Measures of Resilience. *PloS One*, *10*(7), e0131826. https://doi.org/10.1371/journal.pone.0131826

Maltby, J., Day, L., & Macaskill, A. (2013). An Introduction to Psychometric Testing. In J. Maltby, L. Day, & L. Macaskill (Eds.), *Personality, Individual Differences, and Intelligence* (3rd ed., pp. 631–670). Harlow: Pearson Education.

Maltby, J., Day, L., Zemojtel-Piotrowska, M., Piotrowski, J., Hitokoto, H., Baran, T., …

Flowe, H. D. (2016). An ecological systems model of trait resilience: Cross-cultural and clinical relevance. *Personality and Individual Differences*, *98*, 96–101. https://doi.org/10.1016/j.paid.2016.03.100

McGrath, R. E., & Meyer, G. J. (2006). When effect sizes disagree: The case of r and d. *Psychological Methods*, *11*(4), 386–401. https://doi.org/10.1037/1082-989X.11.4.386

MIMAS. (2017). *Web of Science Service for UK Education*. Manchester: The University of Manchester.

Mosteller, F., & Tukey, J. W. (John W. (1977). *Data analysis and regression : a second course in statistics*. Addison-Wesley Pub. Co.

Nunnally, J. C. (1978). *Psychometric Theory (2nd ed.)*. New York: McGraw-Hill.

Pangallo, A., Zibarras, L., & Lewis, R. (2015). Resilience Through the Lens of Interactionism: A Systematic Review, *27*(1), 1–20. https://doi.org/10.1037/pas0000024

Petrides, K. V., & Furnham, A. (2006). The Role of Trait Emotional Intelligence in a Gender-Specific Model of Organizational Variables1. *Journal of Applied Social Psychology*, *36*(2), 552–569. https://doi.org/10.1111/j.0021-9029.2006.00019.x

Rosenberg, M. (1965). *Society and the Adolescent Self-Image.* Princeton, NJ: Princeton University Press.

Rutter, M. (2013). Annual Research Review: Resilience--clinical implications. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *54*(4), 474–87. https://doi.org/10.1111/j.1469-7610.2012.02615.x

Ryff, C. D., & Keyes, C. L. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, *69*(4), 719–727. https://doi.org/10.1037/0022-3514.69.4.719

Schat, A. C. H., Kelloway, E. K., & Desmarais, S. (2005). The Physical Health Questionnaire (PHQ): construct validation of a self-report scale of somatic symptoms. *Journal of*

Occupational Health Psychology, *10*(4), 363–381. https://doi.org/10.1037/1076-8998.10.4.363

Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: assessing the ability to bounce back. *International Journal of Behavioral Medicine*, *15*(3), 194–200. https://doi.org/10.1080/10705500802222972

Tabachnick, B. G., Fidell, L. S., & Boston, M. A. (2007). *Using multivariate statistics (5th ed.*

Wagnild, G. M., & Young, H. M. (1993). Development and psychometric evaluation of the Resilience Scale. *Journal of Nursing Measurement*, *1*(2), 165–178. https://doi.org/10.1016/j.apnu.2010.05.001

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social-ecological systems. *Ecology and Society*, *9*(2), 5.

Wilson, B. A., Evans, J. J., Emslie, H., Alderman, N., & Burgess, P. (1998). The development of an ecologically valid test for assessing patients with a dysexecutive syndrome. *Neuropsychological Rehabilitation*, *8*(3), 213–228.

Windle, G., Bennett, K. M., & Noyes, J. (2011). A methodological review of resilience measurement scales. *Health and Quality of Life Outcomes*, *9*, 8. https://doi.org/10.1186/1477-7525-9-8

Zigmond, A. S., & Snaith, R. P. (1983). The Hospital Anxiety and Depression Scale. *Acta Psychiatrica Scandinavica*, *67*(6), 361–370. https://doi.org/10.1111/j.1600-0447.1983.tb09716.x

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, *99*(3), 432–442. https://doi.org/10.1037/0033-2909.99.3.432

Tables

Table 1

Maximum Likelihood Factor Analysis with Promax Rotation of Resilience Items

	1	2	3
Engineering			
I recover from difficult situations with ease*	.91	-.06	.01
I recover from a stressful time quickly*	.91	-.02	.01
I quickly get back to my normal self following problems in my life*	.90	-.01	.04
I easily get back to my normal self after tough experiences*	.89	-.02	.03
I quickly recover when there is a disturbance in my life	.89	-.04	.02
I don't find it hard to recover from difficult situations	.89	.03	.01
I don't find it difficult to recover from a stressful event	.86	-.01	-.07
long time to get over set-backs	-.86	-.05	.04
It doesn't take me a long time to recover from tough experiences in my life	.83	.06	-.01
hard to snap back	-.83	-.06	-.02
come through difficult times	.78	.09	.01
does not take me a long time to recover	.76	-.05	.01
Ecological			
I always give all I can, regardless of what may happen*	-.08	.82	-.03
Determined	-.07	.81	-.02
I remain strong-willed, no matter what problems occur*	.01	.81	.02
Even when there are problems, I am able to function to achieve my goals*	-.06	.80	.08
Work to attain goals no matter what roadblocks	-.01	.80	-.01

Best effort no matter what	-.10	.75	.01
No matter what happens, I find ways to get things done*	-.02	.73	-.05
You can achieve goals, even if obstacles	.08	.70	.04
Even if I have problems, I always give my best effort	.12	.67	.05
When I experience difficulties, I never lose interest in my goals	.17	.66	-.01
When I am prevented from getting what I want, I never give up	.13	.65	-.04
I am a determined person	.19	.63	-.07
Adaptive capacity			
I like it when life changes*	.02	-.03	.82
I like coping with unpredictable situations*	.05	-.14	.82
I enjoy dealing with new and unusual situations	-.01	.04	.81
Uncertain situations interest me*	-.06	.11	.79
I like it when things are uncertain or unpredictable	.05	-.16	.77
Changes in routine are interesting to me	-.04	.01	.76
I like to do new and different things	-.10	.21	.74
I enjoy it when there are changes to my routine*	.05	-.11	.73
I like life to be uncertain	.09	-.16	.71
I like having new and different experiences	-.03	.15	.70
I enjoy dealing with novel and unusual things	.01	.04	.69
I like experiencing novel and different events	-.04	.09	.49

Items in italics are the original items from existing scales described in Maltby et al. (2015), abbreviated due to copyright.

Key: * Items suggested for the Resilient Systems Scales. We suggest ordering items by using one item from each factor in sequence, until all 12 items have been employed

Table 2

Confirmatory Factor Analysis Fit Statistics for the Different Models Proposed for Resilience Systems Scales.

	*x*2	df	*P* =<	CMIN/DF	CFI	NNFI	RMSEA	SRMR
Unidimensional	3433.103	252	.000	13.623	.518	.472	.183	.189
Three-factor	777.306	249	.000	3.122	.920	.911	.076	.045

Table 3

Alpha Coefficients and Means for, and Correlations between, the Resilience Measures ("Borrowed" Items and Resilient Systems Scales), Personality (Sample 1) and Well-being (Sample 2) measures

							Sample 1 (n = 444)										
	Mean	SD	Min	Max	Skewness	Kurtosis	α	2	3	4	5	6	7	8	9	10	11
1. Engineering (borrowed)	13.18	4.29	4.00	20.00	-.43	-.86	.90	.90**	.46**	.45**	.29**	.31**	.34**	.22**	.34**	.66**	.27**
2. Engineering (RSS)	12.96	4.41	4.00	20.00	-.40	-.95	.95	1	.43**	.40**	.31**	.32**	.35**	.20**	.33**	.62**	.26**
3. Ecological (borrowed)	15.86	3.17	4.00	20.00	-1.10	1.6	.85		1	.85**	.27**	.21**	.29**	.25**	.47**	.38**	.29**
4. Ecological (RSS)	15.81	3.16	4.00	20.00	-.95	.84	.85			1	.25**	.21**	.32**	.30**	.52**	.41**	.26**
5. Adaptive capacity (borrowed)	12.40	3.76	4.00	20.00	-.22	-.60	.85				1	.88**	.39**	.09	.06	.28**	.53**
6. Adaptive capacity (RSS)	11.98	3.68	4.00	20.00	-.10	-.64	.86					1	.36**	.09	.05	.31**	.50**
7. Extraversion	3.48	1.85	1.00	7.00	.37	-1.02	N/A						1	.14**	.19**	.27**	.34**
8. Agreeableness	5.25	1.39	1.00	7.00	-.61	-.53	N/A							1	.33**	.30**	.23**
9. Conscientiousness	5.42	1.37	1.00	7.00	-.80	-.01	N/A								1	.42**	.20**
10. Neuroticism	4.83	1.74	1.00	7.00	-.51	-.76	N/A									1	.25**
11. Openness	4.50	1.47	1.00	7.00	-.60	-.36	N/A										1

							Sample 2 (n = 378)							
							a	2	3	4	5	6	7	8
1. Engineering (borrowed)	13.32	4.26	4.00	20.00	-.38	-.91	.90	.86**	.41**	.44**	.31**	.32**	-.54**	-.56**
2. Engineering (RSS)	13.06	4.30	4.00	20.00	-.40	-.97	.93	1	41**	.42**	.29**	.31**	-.53**	-.56**
3. Ecological (original)	16.25	3.05	4.00	20.00	-1.01	1.23	.83		1	.83**	.24**	.22**	-.42**	-.33**
4. Ecological (RSS)	15.78	3.12	4.00	20.00	-.99	1.03	.84		*	1	.24**	.24**	-.43**	-.36**
5. Adaptive capacity (borrowed)	12.80	3.89	4.00	20.00	-.08	-.84	.85				1	.85**	-.10*	-.14**
6. Adaptive capacity (RSS)	12.38	3.65	4.00	20.00	.03	-.82	.84					1	-.15**	-.18**
7. Depression	4.44	4.20	.00	21.00	.94	.22	.87						1	.68**
8. Anxiety	6.22	4.59	.00	20.00	.54	-.33	.86							1

* p < .05; ** p < .01

Key: RSS = Resilient Systems Scales.

Table 4

Regression Analysis with Psychological Well-being and Physical Health as Dependent Variables, and Resilience Subscales used as Predictor Variables (Sample 3).

	B	β	t	p	B	β	t	p
	Psychological well-being				Physical health			
Step 1								
Engineering (RSS)	.08	.02	.51	.614	-.73	-.21	-2.94	.004
Ecological (RSS)	1.02	.22	4.20	.001	.06	.01	.14	.886
Adaptive capacity (RSS)	-.18	-.05	-1.26	.208	-.09	-.03	-.37	.708
Personal competence (PRS)	.02	.03	.35	.725	-.03	-.03	-.30	.768
Acceptance of self and life (PRS)	.12	.06	1.05	.293	-.08	-.04	-.44	.662
Personal competence (CD-RISC)	-.03	-.01	-.17	.864	.71	.28	2.54	.012
Trust in instincts (CD-RISC)	-.23	-.07	-1.37	.171	.28	.09	1.01	.313
Positive acceptance of change (CD-RISC)	.28	.07	1.28	.202	-.96	-.24	-2.61	.010
Control (CD-RISC)	1.52	.28	5.49	.001	-1.15	-.20	-2.47	.014
Spiritual influences (CD-RISC)	.05	.01	.23	.820	-.02	-.01	-.06	.951
Commitment (HS)	.24	.12	2.27	.024	-.22	-.11	-1.28	.201
Control (HS)	.58	.21	4.42	.000	-.21	-.07	-.95	.341
Challenge (HS)	.23	.07	1.79	.074	-.11	-.03	-.51	.612
Ego-resilience (ER-89)	.31	.15	3.11	.002	.21	.10	1.28	.203

Key: PRS = Psychological Resilience Scale; CD-RISC = Connor-Davidson Resilience Scale; HS = Hardiness Scales; ER-89 = Ego Resilience Scale; RSS = Resilient Systems Scales.

Table 5

Alpha Coefficients and Means for, and Correlations between, the Resilient Systems Scales, Dysexecutive Symptoms, Emotional Intelligence, Self-Esteem, Self-Efficacy, and Social Desirability (Sample 3).

	n = 164													
	Mean	SD	Min	Max	Skewness	Kurtosis	α	2	3	4	5	6	7	8
1. Engineering (RSS)	13.40	3.72	4.00	20.00	-.47	-.40	.93	.39**	.31**	-.38**	.54**	.54**	.42**	-.07
2. Ecological (RSS)	14.99	2.73	8.00	20.00	-.15	-.42	.78	1	.13	-.36**	.49**	.44**	.55**	-.06
3. Adaptive capacity (RSS)	10.84	3.78	4.00	20.00	.26	-.37	.89		1	-.02	.34**	.23**	.21**	-.05
4. Dysexecutive symptoms	26.84	13.03	1.00	57.00	.28	-.71	.89			1	-.67**	-.48**	-.35**	.20**
5. Emotional intelligence	140.63	24.10	81.00	199.00	.18	-.59	.91				1	.72**	.60**	-.20*
6. Self-esteem	28.25	5.82	11.00	40.00	-.06	-.24	.90					1	.58**	-.07
7. Self-efficacy	29.23	4.75	16.00	40.00	-.33	-.09	.88						1	.08
8. Social desirability	3.46	1.76	0.00	6.00	-.08	-1.15	.67							1

* $p < .05$; ** $p < .01$

Key: RSS = Resilient Systems Scales.