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The nature of resilience: A person-centered approach using latent profile analysis

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The Nature of Resilience:

A Person-centered Approach Using Latent Profile Analysis

by

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DEDICATION

I would like to dedicate this dissertation to my parents, my friends, my mentors, and every brilliant and brave soul relentlessly persevering through adversity.

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"*Out of suffering have emerged the strongest souls;*

the most massive characters are seared with scars."

(*Kahlil Gibran*)

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ABSTRACT

Resilience research has become increasingly popular in organizational sciences in recent years. Different factor structures of resilience have been proposed and yet no consensus has been reached regarding its underlying dimensions. Such a variable-centered perspective of studying resilience may be well complemented by a typological approach, which may shed fresh light on the nature of resilience. The current study took a person-centered approach with the advantage of using latent profile analysis to explore a set of latent profiles of resilience. Two studies were conducted. In Study 1 ($N = 479$), archival undergraduate data were used to explore resilience profiles and their relationships with personality variables (i.e., the Big Five and trait affect) and related outcomes (i.e., interpersonal counterproductive work behavior, job satisfaction, and life satisfaction). In Study 2 ($N = 483$), an employee sample collected on Amazon's Mechanical Turk (MTurk) were used to confirm the set of identified latent profiles and extend Study 1 by including two additional outcome variables (job burnout and stress). Finally, this study compared the person- and variable-centered approaches to examine whether latent profiles of resilience provided incremental validity over dimensions of resilience in predicting outcomes in both studies. Four latent profiles of resilience emerged in the undergraduate sample and showed differential relationships with personality variables and outcomes; three out of four profiles were replicated in the MTurk sample. Profile membership provided incremental validity beyond dimensions of resilience, the Big Five, and trait affect in the MTurk sample but not the undergraduate sample. These mixed findings, strengths and limitations of the study, and implications for theory and practice were discussed.

INTRODUCTION

Individual resilience is commonly understood as a construct describing the extent to which individuals bounce back from adversity and has enjoyed increasing popularity in organizational research. Yet, the precise definition, operationalization, underlying factor structure, and theoretical framework of resilience have not been fully agreed upon among resilience researchers (Britt et al., 2016; Fletcher & Sarkar, 2013; Richardson, 2002; Windle, 2011). To date, more than 100 different definitions have been proposed to describe resilience as a(n) 1) ability, 2) adaptation and "bouncing back" to the baseline, 3) growth after recovering from adversity, 4) personality trait, 5) psychological state, 6) process, and 7) positive outcome and recovery from adverse events (Meredith et al., 2011; Pangallo, 2014).

Another issue concerning the examination of resilience is the lack of a unifying theoretical framework (Conley et al., 2016; King, 2016). Research has mainly focused on identifying resilient qualities, risk and protective factors, and processes of developing resilience (Richardson, 2002). Resilience theory has drastically evolved in family psychology and positive psychology, but it is unclear whether or how these theories apply to organizational research (Conley et al., 2016; King, 2016). New theories of resilience in the context of organizational science are much needed (King, 2016): a thorough review of the literature indicates a lack of theoretical developments since 2016.

In addition to—and perhaps as a result of—the lack of consensus on the definition and theoretical framework of resilience, the factor structure of resilience remains the center of heated debate. Although it is agreed upon that resilience is a multidimensional construct consisting of protective factors that individuals use to cope with difficult situations (DeSimone et al., 2016; Martin et al., 2015; Pangallo, 2014; Pangallo et al., 2015), the nature and number of such protective factors remains to be decided. For example, some researchers argue that resilience consists of eight factors—self-efficacy, access to a social support network, optimism, perceived economic and social resources, spirituality and religiosity, relational accord, emotional expression and communication, and emotional regulation (Martin et al., 2015), whereas others contend that resilience has a five-factor structure (Connor & Davidson, 2003; DeSimone et al., 2016). Connor and Davidson (2003) created the widely used Connor-Davidson Resilience Scale (CD-RISC) that conceptualizes resilience as five factors: 1) acceptance of change and secure relationships, 2) personal competence, high standards, and tenacity, 3) trust in one's instincts, tolerance of negative affect, and strengthening effects of stress, 4) spiritual influences, and 5) control. DeSimone et al. (2016) agreed that resilience has five underlying factors but presented a bi-factor factor structure with a different set of factors—adaptability, emotion regulation, optimism, self-efficacy, and social support.

To reconcile the conflicting literature, researchers quantitatively or qualitatively summarized existing literature in hopes of presenting a unifying factor structure of resilience, to no avail. Some adopted an empirical approach and factor-analyzed existing resilience scales to clarify the underlying factor structure of resilience. Pangallo (2014) factor-analyzed five well validated resilience measures and identified eight factors, six of which represent intrapersonal resources (self-efficacy, psychological capital, bounce back ability, hardiness, planned future, and ego-resiliency) while the remaining two represent interpersonal resources (family cohesion and social resources). Maltby et al. (2015) studied a different set of resilience scales and presented three correlated factors (i.e., engineering, ecological, and adaptive). Also studying five resilience measures, Grossman (2017) presented a correlated 8-factor model: 1) Distress Tolerance and Recovery Speed, 2) Support From Others, 3) Faith, Purpose, and Future, 4) Challenge and Curiosity, 5) Work Ethic and Organization, 6) Social Skills, 7) Family Coherence, and 8) Positivity and Self-Reliance, although the final factor was dropped after content validation.

Other research utilized qualitative methods to summarize common themes measured in existing scales or studied in existing literature. Pangallo et al. (2015) qualitatively summarized factors measured in 13 existing resilience scales and presented eight general themes along with 16 subthemes measured by these scales. Some themes (e.g., adaptability, self-efficacy, active coping, and positive emotions) are considered internal resources, while others (e.g., supportive relationships) are deemed external resources. Taking a different qualitative approach, Schetter and Dolbier (2011) surveyed existing literature and presented a taxonomy of resilience resources in the context of chronic stress, which consists of six broad categories: 1) Personality & Dispositional Resources, 2) Self and Ego-Related Resources, 3) Interpersonal and Social Resources, 4) World Views & Culturally-Based Beliefs and Values, 5) Behavioral & Cognitive Skills, and 6) Other Resources. Each category contains several factors, constituting a total of 35 resilience resources. To list a few, Personality & Dispositional Resources includes dispositional optimism, the Big Five, positive affectivity/emotional resources, etc.; Self and Ego-Related Resources includes self-efficacy, secure adult attachment style, autonomy, etc.; Behavioral & Cognitive Skills includes active or proactive coping skills or style, emotion regulation, behavioral and cognitive flexibility, etc. While the aforementioned research efforts are laudable, more and more factors have been proposed, making it impractical, if not impossible, to capture all resilience factors in any given study.

Although it is crucial to form a uniform framework of the factors of resilience (and the corresponding factor structure) for theory development and practical applications, it is worth noting that such a variable-centered approach is not without limitations. A variable-centered approach (i.e., an examination of relationships among variables) assumes that the population from which a sample is drawn is homogenous and estimates made from variable-focused analyses are for a prototypical person and applicable to the entire population (Morin, Gagne, et al., 2016, p. 8). This approach fails to consider that a population may be composed of heterogenous subpopulations that may have different relationships with the predictors and outcomes of the construct in question. As such, when assumptions of population homogeneity are not met, interpretations of estimates may not be as meaningful and conducive to theory development (Meyer et al., 2013). Although including interaction terms among the factors of a particular construct may account for subpopulations having different patterns and relationships with theoretically relevant covariables, such practice does not make it possible to pinpoint the subgroups or include group memberships directly in other analyses (Meyer et al., 2013; Vandenberg & Stanley, 2009). Additionally, if a construct has numerous dimensions, including all possible combinations of these dimensions as interactions in variable-focused analyses may make it too complicated to interpret all the significant interactions (Meyer & Morin, 2016). Severe collinearity problems may also occur if all dimensions and interactions are used in regression models to predict relevant outcomes (Fox, 1997; Pedhazur, 1997).

Person-Centered Approach

The person-centered approach has risen in popularity in the past few years and may help to shed fresh light on resilience research. A person-centered approach puts a focus on examining relationships between individuals, as opposed to variables, and takes into account samples that may be drawn from heterogenous populations, which consist of subpopulations with unique dynamics and behavioral outcomes (Howard & Hoffman, 2018; Meyer et al., 2013; Wang & Hanges, 2011; Woo et al., 2018). Each subpopulation has its own unique set of parameters and relationships with covariates, permitting studying different groups of individuals' response patterns. Compared with the variable-centered approach, the person-centered approach provides an opportunity to simultaneously take into account multiple dimensions of resilience and the interactions among them without forgoing interpretability or producing collinearity. One of the well-known person-centered analytical techniques is latent class analysis (LCA), which uses individuals' responses on a set of observed categorical indicators to describe the probabilities of their belonging to different latent group memberships; these latent group memberships are called latent classes (Muthén & Muthén, 2000). The main aim of LCA is to find the optimal number of latent classes that best describe the response patterns on a given set of observed categorical indicators. The resulting parameter estimates are probabilities of individuals belonging to each identified latent class. Covariates (i.e., predictors and outcomes) may also be added in LCA models to describe the relationships of latent classes with predictors and outcomes in terms of probabilities. While LCA focuses on responses on observed categorical variables, latent profile analysis (LPA), an extension of LCA, permits analyzing observed continuous variables (Masyn, 2013; Nylund-Gibson & Choi, 2018).

Of note, many topics of research have benefited from a person-centered perspective for the purposes of theory development and predictive modeling (Bouckenooghe et al., 2019; Gabriel et al., 2015; Meeusen et al., 2018; Meyer et al., 2013; Morin, Boudrias, et al., 2016; Morin et al., 2017; Sahdra et al., 2017). For example, to examine the structure of prejudice, Meeusen et al. (2018) took advantage of LCA to complement confirmatory factor analysis

(CFA), a variable-centered approach, and interpreted results yielded by LCA vs. CFA. They found that CFA revealed a hierarchical structure containing a general factor (i.e., generalized prejudice) and two specific factors (i.e., ethnic and symbolic prejudice), indicating that individuals who show more bias against one group are likely to be hostile toward other groups. In comparison, LCA revealed the specificity of people's prejudice beyond the generality presented by CFA by considering specific patterns of prejudice. In particular, Meeusen et al. found five unique prejudice patterns: generally negative, moderate nondifferentiators, generally positive, ethnically prejudiced, and ethnic differentiators; while the first three reflect people's consistent tendency of bias against minority groups (consistent with interpretations of the results revealed by CFA), the latter two patterns indicate some people's specific tendency of bias against ethnic minorities (ethnically prejudiced) or Eastern Europeans and Roma (ethnic differentiators). They further found that people in these two groups feel more threatened by immigrants, despite being more socially progressive and educated, compared to those in the general negative group. Such nuanced patterns of prejudice would not be readily revealed solely using a variable-centered approach.

In addition to theory development, a person-centered approach may provide added utility when predicting relevant outcomes, compared with studies solely based on a variable-centered approach. For instance, Sahdra et al. (2017) used latent profiles of mindfulness, derived from factor scores of the bifactor exploratory structural equal modeling model (ESEM), as categorical variables to predict theoretically relevant outcomes. Profile membership explained unique variances in life satisfaction and life effectiveness after controlling for scale scores of dimensions of mindfulness (i.e., a variable-centered approach). Research in psychological capital, a construct-related to resilience, has also benefited from adopting a person-centered approach to complement a variable-centered approach (Bouckenooghe et al., 2019). In particular, when latent profiles of psychological capital were used as dummy-coded grouping variables to predict work-related outcomes, profile membership explained 6% and 12% additional variance in work engagement and job performance, respectively, beyond psychological capital composite scores, age, and gender. In comparison, all possible combinations of the four dimensions of psychological capital did not produce significant incremental variance beyond the psychological capital composite scores, age, and gender.

Organizational researchers and practitioners may benefit from using a person-centered approach to examine resilience. Particularly, rather than defining resilience in terms of factors or dimensions, researchers may categorize individuals into different groups, each of which has unique patterns of resilient behaviors and theoretically relevant correlates and outcomes. Such an approach may provide an opportunity to examine multiple resilience factors in tandem, offering additional insights on how different resilience styles influence work and life outcomes. Consider the following scenario for the moment: assume that resilience has four components—adaptability, emotion regulation, optimism, and self-efficacy—and that individuals may have low, moderate, or high levels on any of these four dimensions; further assume that these four dimensions are equally predictive of individuals' levels of daily stress. Some individuals have high levels of adaptability and self-efficacy but low levels of emotion regulation and optimism (Group A), whereas others have high levels of emotion regulation and optimism but low levels of adaptability and self-efficacy (Group B). Suppose that individuals in Group A experience lower levels of daily stress than those in Group B even though they are lower on emotion regulation and optimism—their high levels of self-efficacy and adaptability fully compensate for their low functioning in emotion regulation and optimism. In comparison, Group B's higher levels of emotion regulation and optimism cannot compensate for their low level of self-efficacy and adaptability, making them more prone to the negative effects of daily stress.

Such nuanced compensatory effects are not easily captured or interpreted by a variable-centered approach. For instance, in a typical linear regression model, one of the basic variable-centered analyses, individuals in Group A would be predicted to have the same level of daily stress as those in Group B because all four dimensions of resilience would have the same regression weights in the model. Including group membership (Group A or Group B) as a categorical variable in the model (i.e., using a person-centered holistic approach) would provide additional information and more accurately predict individuals' levels of daily stress in both groups. Additionally, the aforementioned patterns of responses may not be well reflected or interpreted by including interaction terms in the regression model. In particular, even though regression coefficients of all interactions seemingly represent the relationships of daily stress with all possible combinations of the four dimensions, the coefficients would be very small due to collinearity. The resulting prediction would be that the level of daily stress is the same for both groups. In contrast, a person-centered analysis categorizes these unique patterns of resilience factors into subgroups, making it possible to examine and easily interpret the relations between groups and relevant covariates. Group memberships may be added as a categorical variable to accurately predict daily stress. Thus, the present study adopted a person-centered approach to study resilience.

Latent Profiles of Resilience

Multiple techniques exist for person-centered analyses, one of which is LPA, an extension of LCA to continuous variables. LPA has notable advantages over other well-known analytical techniques, such as cluster analysis and midpoint-splits (Meyer & Morin, 2016; Meyer et al., 2013; Morin et al., 2011; Vermunt & Magidson, 2002; Woo et al., 2018). Specifically, LPA is a model-based latent-variable technique that takes into account measurement error and allows inclusion of covariates (antecedents and outcomes), relies on a set of model fit indices to select the optimal number of classes/profiles, and is robust to including variables with different scales of measurement (Meyer et al., 2013). Thus, the present study took advantage of LPA to explore a set of latent profiles of resilience.

As there is no commonly agree-upon framework of resilience with which to identify the latent profiles of resilience, no specific profile configurations or numbers were hypothesized. An inductive approach was taken to explore the number and nature of the latent profiles and frame the current study as a research question to be examined. The latent profiles of resilience were identified based on statistical indices generated from LPA and the interpretability of LPA models.

> Research Question 1: Can we identify a meaningful set of latent profiles of resilience? What are the profiles?

For the purpose of the current study, the 5-by-5 Resilience Scale (5×5 RS; DeSimone et al., 2016) was used to measure resilience. The 5×5 RS has a bi-factor structure with a general resilience factor and five dimensions theoretically related to individual resilience: adaptability, emotion regulation, optimism, self-efficacy, and social support. The five dimensions were originally selected by the authors to capture a number of internal and external protective factors that are theoretically or empirically related to resilience, with social support being the external factor and the other four being the internal factors. Even though these five dimensions are not a comprehensive representation of all factors of resilience, they adequately cover some overlapping themes that emerged from the existing literature (see a discussion on pp.3-4).

Although there is no commonly agreed-upon factor structure of resilience, the five dimensions of the 5×5 RS provide a reasonably good representation of some theoretically and empirically identified factors contributing to resilience. Additionally, the 5×5 RS has shown acceptable reliability, construct- and criterion-related validity, and stable bi-factor structure in both community and MTurk (i.e., Amazon's Mechanical Turk) samples. Thus, the 5×5 RS were used in the present study on the basis of theoretical and psychometric considerations.

It is worth mentioning that the current study is a first step, a "proof of concept" to explore whether examination of latent profiles of resilience is meaningful for theory development and whether a person-centered approach to studying resilience provides added value over a variable-centered dimensional approach in predicting related outcomes. The results of LPA rely on the variables entered in the LPA models. Even though the 5×5 RS provides good coverage of the factors contributing to resilience, no consensus has been reached regarding the nature or number of factors of resilience and thus no definitive conclusions can be made on latent profiles of resilience based on the five factors measured by the 5×5 RS. The profiles to be identified and validated in the current study were by no means "the" latent profiles of resilience, but rather a set of latent profiles. More research is needed to clarify an agreed-upon factor structure of resilience; until then, the interpretation of the latent profiles of resilience based on any measure of resilience remains tentative.

One additional concern pertains to separating the *shape* from *level* of the profiles when exploring the number of latent profiles of resilience using LPA (Morin, Boudrias, et al., 2016; Morin et al., 2017; Morin & Marsh, 2015). The level of the latent profiles of resilience refers to the quantitative difference in global resilience; one can be high, medium, or low across all of the dimensions of resilience. The shape of the profiles refers to the relative positions of one's responses on different dimensions of resilience; one can have a unique pattern of high, medium, or low levels of dimensions of resilience. When the effects of the shape and level are not distinguished, the resulting latent profiles of resilience may not be as meaningful or offer practical values. That is, the resulting profiles could simply indicate that some people are relatively high on all five dimensions and high on global resilience, and that others are comparatively lower on all dimensions and lower on global resilience (see Figures 1 and 2 in Bouckenooghe et al., 2019 for an example). Such results would conceal the meaningful and different configurations of responses on different dimensions of resilience.

Morin and colleagues (2016; 2017) recommended an estimation procedure to separate the shape from level of the latent profiles. Specifically, they argue that using factor scores derived from a bi-factor model, estimated using CFA or exploratory structural equation modeling (ESEM; Morin, Arens, et al., 2016), as inputs in LPA may be particularly advantageous when separating the level from shape of latent profiles. Using bifactor factor scores permits for the inclusion of factor scores of the general factor in LPA models as input thus allowing estimation of both the level and shape of profiles. Using factor scores also makes it possible to partially control for measurement error. Additionally, they recommend that the first step is to estimate and compare fit indices of the CFA and ESEM models to investigate whether there is a multidimensional factor structure in which there is a global general factor and multiple correlated dimensions. If model fit indicates a bi-factor structure, the bifactor model should be adopted; if model fit favors the ESEM model over the CFA model, factor scores derived from the bifactor ESEM model should be used in the LPA estimation process, and vice versa. Morin and colleagues’ (2016; 2017) recommendations were followed in the current study.

Exploratory vs. Confirmatory

LPA is known for its exploratory nature because no hypothesis is made a priori regarding the appropriate number of latent profiles (Bauer & Curran, 2003, 2004; Finch & Bronk, 2011; Meyer et al., 2013; Schmiege et al., 2018). The number and nature of latent profiles are determined by a set of criteria based on model fit indices and theoretical meaningfulness. Such an exploratory approach may be adequate when no theory or few studies exist to guide hypothesis formation or when one intends to explore novel patterns of responses for theory development or reconciliation of conflicting literature. However, confirmatory studies need to be conducted later to replicate the initial results of LPA (Muthén, 2003). Thus, a second sample was used in the present study to replicate a set of latent profiles of resilience identified in the first sample.

Unfortunately, no methodological advancement has been made to develop a confirmatory technique to conduct LPA (Schmiege et al., 2018). Granted, one confirmatory approach to LCA (i.e., confirmatory LCA) has been developed and has shown efficacy in confirming previously identified latent classes by including parameter constraints in a confirmatory LCA model (Finch & Bronk, 2011; Schmiege et al., 2018); researchers might be tempted to apply the same parameter constraints methods to LPA models, however, LPA has a more complex mean and variance/covariance structure and its own unique set of assumptions. Using model constraints in LPA models requires a consideration of all these complexities (see Schmiege et al., 2018 for a detailed discussion) and is beyond the scope of the present study. Thus, a qualitative approach was used to evaluate whether latent profiles of resilience were replicated in the second sample in terms of the number of profiles and similarities of response patterns on indicators. The identified latent profiles of resilience in Study 1 were considered to be replicated when 1) the number of latent profiles was the same in both studies based on interpretability of profiles and quality of fit indices in each study, 2) the profiles in Study 2 were similar to those in Study 1 in terms of relative positions of the means on the five indicators, and 3) the profile proportions were similar in both studies.

> Research Question 2: Would a set of latent profiles of resilience be replicated using a second sample?

Personality Correlates and Associated Outcomes of Latent Profiles of Resilience

After establishing a set of latent profiles of resilience, a natural next step was to assess construct validity of latent profiles by examining their relationships with theoretically related correlates and associated outcomes (Asparouhov & Muthén, 2014a; Lanza et al., 2013; Woo et al., 2018, p. 834). The current study thus investigated how the identified latent profiles of resilience differentially related to personality correlates and work and life outcomes, and then interpreted such differences. It is worth mentioning that the purpose of the current study was not to establish the definitive nomologic net of latent profiles of resilience, but rather to begin to explore latent profiles and assess their construct- and criterion-related validity. To this end, only empirically supported variables including a number of personality correlates and outcomes related to one's functioning in life and at work were included in the study. In terms of personality correlates, previous research studies have offered evidence that resilience correlates moderately to strongly with the Big Five personality traits (Fredrickson et al., 2003; Grossman, 2014; Luthans et al., 2007) and positive affect (PA; Grossman, 2014; Hu et al., 2015; Lee et al., 2013), and correlates moderately with negative affect (NA; Burns & Anstey, 2010; Grossman, 2014; Lee et al., 2013). The construct validity of the profiles identified in the current study was examined by assessing how the profiles differentially related to commonly researched personality correlates, namely the Big Five, PA, and NA.

Research Question 3: How are a set of latent profiles of resilience related to the Big Five, PA, and NA?

To examine the criterion-related validity of the identified profiles of resilience, both life- and work-related outcomes were examined. Previous studies have shown that resilience has moderate correlations with the interpersonal dimension of counterproductive work behavior (CWB-I; Daljeet, 2015; Sharma & Sharma, 2015; Shoss et al., 2018), moderate to strong correlations with job burnout (Grossman, 2014; Hao et al., 2015; Kim et al., 2019; Shoss et al., 2018), and small to moderate correlations with job satisfaction (Hudgins, 2016; Kašpárková et al., 2018; Kim et al., 2019; Luthans et al., 2007; Meneghel et al., 2016; Öksüz et al., 2019; Teng & Brannick, 2019; Youssef & Luthans, 2007; Zheng et al., 2017). Additionally, Shoss et al. (2018) took advantage of a 2-wave longitudinal design and demonstrated that resilience predicted and buffered the negative effects of job insecurity on full-time employees' CWB-I and burnout assessed one month later. Thus, CWB-I, job burnout, and job satisfaction were examined. In addition to work-related outcomes, resilience has shown moderate to strong correlations with stress (Crane & Searle, 2016; Lee et al., 2013; Panchal et al., 2016; Teng & Brannick, 2019; Teng et al., 2018) and life satisfaction (Fredrickson et al., 2003; Grossman, 2014; Hu et al., 2015; Lee et al., 2013; Liu et al., 2014; Martínez-Martí & Ruch, 2017; Yang, 2014). Thus, stress and life satisfaction were examined.

Research Question 4: How well do a set of latent profiles of resilience differentially predict mean levels of CWB-I, job satisfaction, burnout, stress, and life satisfaction?

Variable- vs. Person-centered Approach

As discussed previously, a person-centered approach is advantageous in theoretical development and may provide additional predictive power beyond a variable-centered approach. The benefits of person-centered approaches do not negate the strengths of the variable-centered approach; nor does it indicate that it should substitute for variable-centered analyses (Woo et al., 2018). In fact, person- and variable-centered approaches are often considered complementary (Meeusen et al., 2018; Meyer et al., 2013; Morin et al., 2017; Woo et al., 2018), and selecting which approach to take should be dictated by the research questions being investigated and the purpose of the study (Howard & Hoffman, 2018; Woo et al., 2018). If one intends to understand the relationships among variables, then variable-centered analyses are ideal; if one is to examine whether subpopulations with similar characteristics exist in a population and how they differ, then person-centered perspectives are appropriate (Howard & Hoffman, 2018).

A reoccurring criticism against (or concern of) the person-centered approach pertains to the question of whether it adds predictive benefits above and beyond the variable-centered approach, such as linear regressions (Morin et al., 2011; Schmitt et al., 2007; Woo et al., 2018). Even if there is evidence supporting the incremental validity of person-centered analyses beyond variable-centered analyses, the increment is often negligible (Morin et al., 2011). However, it is worth noting that even if the incremental variance offered by person-centered methods is small, such an incremental variance (e.g., 1%- 3%) may still be useful in organizational settings; the topological approach may contribute to theoretical development and provide heuristic values for organizations to categorize employees for various human resources purposes (Meyer & Morin, 2016; Morin et al., 2017; Woo et al., 2018). Additionally, research on the added predictive power of person-centered analyses is still in its infancy and there is limited evidence available to make a conclusive statement that the person-centered approach does not add incremental validity beyond the variable-centered approach (Woo et al., 2018). As previously mentioned, person-centered analyses have begun to show promise of providing incremental variance in recent studies (Donnellan & Robins, 2010; Graves et al., 2015; Roth & von Collani, 2007; Sahdra et al., 2017), helping to capture nuances in behavior that might otherwise be missed. Clearly, more research needs to be done to improve our understanding of the predictive power of person-centered analyses. The present study was designed to help to shed more light on this issue, and investigated whether a set of latent profiles of resilience (i.e., the person-centered approach) provided incremental validity above and beyond the five dimensions of resilience (i.e., the variable-centered approach) when predicting outcomes.

Research Question 5: Do the profiles capture meaningful variance beyond what is captured by ordinary regression using the dimension scales as independent variables?

In sum, the following research questions were addressed in this study:

1. Can we identify a meaningful set of latent profiles of resilience? How many profiles are there and what are their interpretations?
2. Will a set of latent profiles of resilience be qualitatively replicated using a second sample?
3. How are the resilience profiles related to personality correlates?
4. How are the resilience profiles related to work and life outcomes?
5. Do resilience profiles explain variance in work and life outcomes beyond resilience dimensions?

To this end, the current project included two studies. In Study 1, archival undergraduate data were used to identify the latent profiles of resilience using LPA, examine their relationships with personality correlates as well as outcomes, and explore incremental validity over the dimensions of resilience. Variables included in the archival data were resilience, the Big Five personality traits, affect (i.e., PA and NA), CWB-I, job satisfaction, and life satisfaction. Study 1 was conducted to address Research Questions 1 and 3-5.

In Study 2, an MTurk employee sample was used to qualitatively replicate the resilience profiles identified in Study 1 in order to address Research Question 2. Additionally, a secondary aim of Study 2 was to expand the nomologic net of latent profiles of resilience and provide evidence of construct validity by including two additional outcome variables (job burnout and stress) plus variables used in Study 1. Study 2 was designed to also assess whether resilience profiles provided incremental validity over resilience factors when predicting job burnout and stress (in addition to outcomes included in Study 1). Studies were conducted to achieve the following aims:

1. Define a set of latent profiles of resilience using an undergraduate sample
2. Replicate the identified latent profiles of resilience using an MTurk sample
3. Assess construct validity of the established resilience latent profiles by examining their relationships with personality correlates (Big Five, PA, and NA) and outcomes (CWB-I, job and life satisfaction, burnout, and stress) using both undergraduate and MTurk samples
4. Explore incremental validity of the latent profiles of resilience over dimensions of resilience using both undergraduate and MTurk samples

Overview

The current study consisted of three steps, the first two of which involved using archival student data to explore latent profiles of resilience and examining construct- and criterion-related validity of the profiles. The first step in Study 1 was conducted to establish the latent profiles of resilience. In this step, LPA was conducted on data from the 5×5 RS and different classes of profiles were assessed against multiple fit indices (Nylund et al., 2007; Tofighi & Enders, 2007). The second step related to examination of construct- and criterion-related validity of the established profiles using the same set of student data. In this step, the relationships between resilience profiles and antecedents as well as outcomes were assessed. Antecedents included the Big Five personality traits (i.e., extraversion, conscientiousness, agreeableness, openness, and neuroticism) and trait affect (i.e., PA and NA); outcome variables included CWB-I, job satisfaction, and life satisfaction.

The last step entailed using data from an employee sample collected on MTurk to confirm the established latent profiles and further validate the construct- and criterion-related validity of the profiles. In this step, LPA was conducted in the same way as in Study 1 and the number of profiles was determined using the same set of criteria. Then, the profiles revealed in Study 2 were compared with those in Study 1 by examining the number of profiles, the shape of the profiles, and the profile proportions. Last, the relationships between resilience profiles and antecedents and associated outcomes were investigated; incremental variance explained by the profiles over dimensions of resilience in predicting outcomes were assessed using hierarchical regression models. Antecedents were the same as those in Study 1 (i.e., Big Five and trait affect). Outcome variables included job burnout and stress, in addition to outcomes assessed in Study 1.

METHOD

Study 1

Design

Cross-sectional archival data were used to identify the latent profiles of resilience and to investigate their relationships with personality variables and outcomes. Archival data were collected from college students who worked at least 20 hours each week at the time of data collection. Resilience was measured using the 5×5 RS, which measures five dimensions (adaptability, emotion regulation, optimism, self-efficacy, and social support). To explore the latent profiles of resilience, scores on these five dimensions were used to conduct preliminary analyses using LPA.

To examine the relationships of resilience profiles with personality variables, the Big Five personality traits (i.e., extraversion, agreeableness, conscientiousness, neuroticism, and openness) and trait affect (i.e., PA and NA) were included in further analysis. To examine criterion-related validity of the profiles, CWB-I, job satisfaction, and life satisfaction were included.

Lastly, to examine whether resilience latent profiles provided an increment in criterion-related validity over resilience dimensions, hierarchical regressions were conducted. Specifically, personality variables, age, and gender were entered in Step 1; the dimension composites were added to the regressions in Step 2; the dummy-coded profiles were entered in Step 3. Changes in R^2 were calculated to assess incremental validity (see the Analytical Strategy section for details pertaining to analysis).

Participants

Undergraduate students (*N* = 1305) with an age of at least 18 years and proficiency in English were invited to complete a personality questionnaire online. Participants who spent less than 10 minutes completing the survey (*N* = 84), filled out less than 70% of the survey (*N* = 91), or failed an attention check (*N* = 126) were excluded from analysis. Additionally, those who worked less than 20 hours per week at the time of data collection (*N* = 386) or who did not provide such information (*N* = 136) were excluded; so were duplicate responses (*N* = 3). Four hundred and seventy-nine participants (M_{age} = 21.96, SD_{age} = 5.45; 80.20% female, 18.60% male, 1% transgender, 0.20% other; 48.20% White, 12.10% Black, 9.20f% Asian or Pacific Islander, 22.10% Hispanic/Latino, 7.30% multiracial) who worked on average 28.09 hours per week (*SD* = 9.98) remained and were included for data analysis.

Measures

Resilience. The 25-item 5-by-5 Resilience Scale (5×5 RS; DeSimone et al., 2016) was used to measure resilience. The scale is composed of five dimensions—adaptability, emotion regulation, optimism, self-efficacy, and social support each of which has 5 items. Participants indicated the extent to which each statement accurately described them as who they generally were at the time on a 5-point Likert scale (1 = *Very inaccurate*, 5 = *Very accurate*). Raw item scores were used for CFA and ESEM in Study 1 and Study 2 (detailed in the Analytical Strategy section). Arithmetic mean scale scores for each subscale were used for hierarchical regressions examining incremental validity of profile memberships.

Big Five Personality. Big Five personality traits were measured using the 44-item Big Five Inventory (BFI; John & Srivastava, 1999). The BFI consists of five dimensions: extraversion (8 items), conscientiousness (9 items), agreeableness (9 items), neuroticism (8 items), and openness (10 items). Participants indicated the extent to which they agreed with each statement on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). Arithmetic mean scores for each subscale were used for analysis.

Trait Affect. The Positive and Negative Affect Schedule (Watson et al., 1988) was used, with the Positive Affect subscale (10 items) measuring positive affect (PA) and the Negative Affect subscale (10 items) measuring negative affect (NA). Participants indicated how they felt in the previous few weeks in response to each item on a 5-point Likert scale (1 = *Very slightly or not at all*, 5 = *Extremely*). Arithmetic mean scores for each subscale were used.

Counterproductive Work Behavior. The interpersonal dimension of counterproductive work behavior (CWB-I) was measured using the CWB-Interpersonal (CWBI; 7 items) subscale of Bennett and Robinson's (2000) measure of workplace deviance. Participants indicated to what extent they agreed with statements related to their own performance at work on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). A sample item was "Acted rudely toward someone at work". Arithmetic mean scores were used.

Job Satisfaction. Three items adopted from Cammann, Fichman, Jenkins, and Klesh (1983) were used to measure overall job satisfaction. Participants indicated their level of agreement with statements (e.g., "In general, I like working here") on a 5-point Likert scale (1 = *Strongly disagree*, 5 = *Strongly agree*). Arithmetic mean scores were used.

Life Satisfaction. Five items from the Satisfaction with Life Scale (Diener et al., 1985) were used to measure life satisfaction. Participants indicated the extent to which they agreed with statements (e.g., "In most ways my life is close to my ideal") on a 7-point Likert scale (1 = *Strongly disagree*, 7 = *Strongly agree*). Arithmetic mean scores were used for analysis.

Study 2

Design

A follow-up study was conducted using working adults recruited on MTurk to confirm the latent profiles of resilience established in Study 1 and further validate the construct- and criterion-related validity of the profiles. Similar to Study 1, scores on the five dimensions of the 5×5 RS were used to replicate the latent profiles of resilience identified in Study 1. The relationships of the confirmed resilience profiles with personality variables (i.e., the Big Five, PA, and NA) were examined next. Criterion-related validity of the profiles were evaluated by examining the degree to which the profiles predicted outcomes including CWB-I, job satisfaction, and life satisfaction. Job burnout and stress were two additional outcomes to be examined in Study 2. To investigate whether a person-centered approach provided added value over a variable-centered approach, incremental validity of the latent profiles of resilience over resilience dimensions were also examined.

Participants

Part- or full-time employees were recruited on Amazon's Mechanical Turk (MTurk) to fill out an online questionnaire and a total of 1623 responses were collected. Inclusion criteria included: 1) an age of at least 18 years, 2) proficiency in English, 3) residing in the U.S., and 4) part-time or full-time employment (working at least 20 hours/week) at the time of data collection. Many MTurk workers did not meet the criterion related to part-time or full-time employment but still managed to participate; their responses ($N = 416$) were excluded. Participants who failed at least one of the three attention check items ($N = 364$) or spent less than 10 minutes on the survey ($N = 306$) were excluded from data analysis. Fifty-four aberrant responses were then excluded using item response theory modeling (see Appendix C for the method used for aberrant responding detection**).** A total of 483 participants (M_{age} = 40.30, SD_{age} = 12.23; 54.20% female, 45.30% male, 0.40% other; 76.40% White, 10.60% Black, 7.70% Asian or Pacific Islander, 0.40% American Indian or Alaska Native, 4.60% Hispanic/Latino, 0.20% multiracial) who worked at least 20 hours per week (M = 36.39 hours per week, SD = 8.99 hours per week) were included in the analysis. Previous research suggests that a sample size of at least 500 would be sufficient to accurately estimate the number of latent profiles with adequate statistical power; thus this sample size is reasonably adequate for subsequent analysis (Tein et al., 2013).

Measures

All measures used in Study 1 remained in Study 2. Two additional measures were included to assess job burnout and stress. Attention check items were inserted randomly throughout the questionnaire.

Job Burnout. The work-related burnout subscale (7 items) of the Copenhagen Burnout Inventory (CBI; Kristensen et al., 2005) was used to measure the psychological and physical aspects of job burnout. Three items asked participants to indicate to what extent the statements applied to them on a 5-point scale (0 = *To a very high degree*, 4 = *To a very low degree*); the remaining four items asked them to indicate how frequently the statements occurred on a 5-point scales (0 = *Always*, 4 = *Never/almost never*). Mean scores of all items were used for analysis.

Stress. The stress subscale (7 items) of the Depression Anxiety and Stress Scale (DASS-21; Lovibond & Lovibond, 1995) was used to capture overall levels of stress. Participants indicated the extent to which statements (e.g., “I found it difficult to relax) described them over the past week on a 4-point Likert scale (0 = *Did not apply to me at all*, 3 = *Applied to me very much, or most of the time*). Mean scores on the stress subscale were used for analysis.

Analytical Strategy

Study 1

Latent Profile Analysis. In the first step, LPA with a robust maximum likelihood (MLR) estimator was conducted on scores from the 5×5 RS to explore profiles of resilience. It has been shown that the 5×5 RS demonstrates a bi-factor structure in which all 25 items load a general factor and five items load on each of the five specific dimensions (adaptability, emotion regulation, optimism, self-efficacy, and social support; DeSimone et al., 2016). The bi-factor structure of the 5×5 RS has shown good model fit in both MTurk and community samples. Following Morin and colleagues' (2016; 2017) recommendations, the reported bi-factor structure of the 5×5 RS needed to be confirmed before conducting LPA. Thus, CFA was first conducted on the 5×5 RS and the bi-factor model was specified and evaluated against model fit indices. Model fit indices included the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample-size adjusted BIC (sBIC). If model fit appeared satisfactory, factor scores derived from the bi-factor CFA model were then used for subsequent analysis including LPA and LPA containing auxiliary variables to better separate the level and shape effects. Specifically, factor scores of the general factor and the five specific factors (adaptability, emotion regulation, optimism, self-efficacy, and social support) of the 5×5 RS were entered in LPA models (detailed below).

One limitation of CFA models is that CFA model specification does not allow item cross-loadings; that is, one item loads on one factor, which may not be realistic in applied research (Marsh et al., 2014). On the other hand, ESEM (Asparouhov & Muthén, 2009) has advantages over the conventional CFA approach in that ESEM allows items to cross-load on different factors, therefore more realistically representing the multidimensional nature of an instrument such as the 5×5 RS (Morin, Arens, et al., 2016). Additionally, LPA based factor scores derived from the bi-factor ESEM model has demonstrated better model fit and better separation of level and shape of the profiles (Morin, Boudrias, et al., 2016; Morin et al., 2017). Thus, a bi-factor ESEM model was also considered to investigate model fit of the 5×5 RS, in the event of poor model fit for the bi-factor CFA model (Morin, Arens, et al., 2016). If model fit for the bi-factor ESEM model showed improvement over that of the CFA model, factor scores derived from the bi-factor ESEM model would be entered in subsequent LPA models (Morin, Boudrias, et al., 2016; Morin et al., 2017).

Next, latent profiles of resilience were examined using LPA in an exploratory manner. At this class enumeration stage, the number of latent profiles started from one and increased one by one. Model fit of each LPA model was evaluated against multiple model fit indices and the optimal number of latent profiles was determined by model fit indices and parsimony of the model. Following guidelines laid out by Nylund et al. (2007) and Tofighi and Enders (2007), a set of model fit indices were evaluated, including log likelihood (LL), AIC, BIC, sBIC, Lo-Mendell-Rubin likelihood ratio test (LMRT; Lo et al., 2001), bootstrapped likelihood ratio test (BLRT; McLachlan, 1987; McLachlan & Peel, 2000), and entropy. As there are no specific cutoffs offered by previous literature to select the best fitting model, a few guidelines were followed: a better fitting model should have lower AIC, BIC, and sBIC, as well as higher entropy value compared to other models, and have significant LMRT and BLRT values ($p < .05$). Additionally, the percentage of individuals assigned to each of the identified profiles should be at least 5% across profiles (Marsh et al., 2009). Another consideration was balancing statistical adequacy with parsimony of the chosen model: if a more complex LPA model produces only slight improvement in model fit indices than a simpler model, the simpler model is more parsimonious and thus a better LPA solution. Last, the interpretability of the LPA models was assessed, and a more interpretable solution was favored over a less meaningful one.

As discussed previously, it is important to separate the *shape* from *level* of the latent profiles when exploring the number of latent profiles of resilience using LPA (Morin, Boudrias, et al., 2016; Morin et al., 2017; Morin & Marsh, 2015). Following Morin and colleagues' (2016; 2017) recommendations, factor scores of both the general factor and five specific dimensions (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) derived from a bi-factor CFA or ESEM model mentioned earlier were entered as indicators in the main LPA models (see pp. 13–14 for a detailed discussion on the shape and level of latent profiles).

Relationships with Personality Variables. The next step was to examine the relationships of latent profiles of resilience with personality variables (i.e., Big Five, PA, and NA). After the best fitting model was selected, multinomial logistic regressions were conducted using the R3STEP approach in Mplus (Asparouhov & Muthén, 2013, 2014a) to examine the probability of belonging to one profile over another with an increment in one of the personality variables.

Relationships with Outcomes. In the third step, the relationships of latent profiles of resilience with outcomes were examined with the automatic BCH approach in Mplus (Asparouhov & Muthén, 2014b; Bakk & Vermunt, 2016; Bolck et al., 2004; Vermunt, 2000). In essence, the BCH approach uses a weighted analysis of variance (ANOVA) on observed variables, with weights inversely related to classification error probabilities; each observation in each class/profile is assigned with a weight and the LPA model with distal variables is estimated as a weighted ANOVA using these weights. The automatic BCH method in Mplus estimates the

LPA model and independently estimates the means of distal outcomes across profiles; estimation of the LPA model is not influenced by including the distal outcome variables (Asparouhov & Muthén, 2014b). With this BCH procedure, membership probability weights generated in the identified best-fitting unconditional model (the 4-profile model) were automatically included in the auxiliary model containing outcome variables to examine whether profiles differentially relate to the outcomes (i.e., CWB-I, job satisfaction, and life satisfaction). This approach was chosen over other methods such as multivariate analysis of variance because it accounts for the measurement error of the latent profiles using these BCH weights. It also shows advantages over other method because it accounts for classification error and different variance of the distal outcome variable across profiles (Asparouhov & Muthén, 2014b; Bakk & Vermunt, 2016). The R3STEP and BCH analyses were conducted separately as they could not be run together in Mplus.

Comparison of the Person- vs. Variable-centered approach. Last, to compare the criterion-related validity of the latent profiles of resilience with that of the resilience dimensions, multiple regressions were conducted with the dummy-coded resilience profiles as predictors and distal outcomes (i.e., CWB-I, job satisfaction, and life satisfaction) as criteria; similarly, regressions were conducted with the composite dimensional scores as predictors and the same distal outcomes as criteria. R-squares were calculated to indicate the variance explained by the latent profiles vs. dimensions of resilience.

Additionally, hierarchical regressions were conducted to examine whether the latent profiles of resilience demonstrate incremental validity over the dimension composites in predicting outcomes (i.e., CWB-I, job satisfaction, and life satisfaction). Specifically, personality variables (i.e., Big Five, PA, and NA), age, and gender were entered in Step 1; the dimension composites were added to the regression models in Step 2; the dummy-coded profiles were entered in Step 3. Changes in R-squares were calculated to assess incremental validity. Because the objective of these analyses (multiple regressions mentioned previously and hierarchical regressions) was to determine how profile classification works in practice when predicting important organizational and life outcomes, scale scores (as opposed to factor scores) of the five dimensions were used.

Study 2

All analyses included in Study 2 were the same as those in Study 1 except for two additional analyses. First, the similarities of the extracted profile configurations in Study 1 and Study 2 were compared to assess how well the set of latent profiles found in Study 1 was replicated in Study 2. After the best fitting LPA model was selected following the guidelines detailed in the previous section, the number of the profiles and the proportions of people assigned to the profiles in both studies were compared. The number of the profiles was expected to be the same in both studies and the profile proportions were expected to be similar. The set of means on the five dimensional indicators for the profiles was presented graphically and the patterns (shapes) of the profiles in both studies were expected to be similar. The set of profiles revealed in Study 1 would be considered replicated in Study 2 if these three conditions were met.

Second, two additional outcome variables (i.e., job burnout and stress) were included in hierarchical regressions to assess criterion-related and incremental validity of the confirmed latent profiles.

RESULTS

Study 1

Latent Profile Analysis

I first analyzed undergraduate students' responses to the 5×5 RS to explore latent profiles. First, CFA and ESEM were conducted to confirm the bi-factor structure of the 5×5 RS, followed by LPA to explore latent profiles of resilience. CFA was conducted using *lavaan* package (Rosseel, 2012) in R Version 3.4.4. ESEM and LPA were conducted using Mplus Version 7.3 (Muthén & Muthén, 1998-2014).

First, CFA was conducted using ML estimation to evaluate model fit of the bi-factor model of the 5×5 RS; each of the five specific factors (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) had five of 25 items and the general factor loaded on all 25 items[1]. The bifactor structure did not demonstrate good model fit, χ^2 (250) = 1151.823, $p <$ .001, CFI = 0.850, TLI = 0.820, RMSEA = 0.087 [0.082, 0.092], SRMR = 0.075, AIC = 31210.877, BIC = 31628.047, sBIC = 31310.658.

Next, the bi-factor structure of the 5×5 RS was examined using ESEM with ML estimation and orthogonal rotation; item cross-loadings on multiple factors were allowed, but restricted to be near zero in model specification[2]. The bi-factor ESEM model proved excellent model fit, χ^2 (165) = 434.523, $p <$ .001, CFI = 0.955, TLI = 0.919, RMSEA = 0.058 [0.052,

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[1] To be thorough, the correlated five-factor CFA model and the higher-order CFA model of the 5×5 RS were also examined and revealed worse model fit (see Appendix Table A.1 for fit statistics).
[2] For the sake of being thorough, ESEM was conducted on the correlated-factor model and higher-order factor model, both of which demonstrated worse model fit than the bi-factor ESEM model (see Appendix A Table A.2 for fit statistics).

0.065], SRMR = 0.023, AIC = 30663.576, BIC = 31435.341, sBIC = 30848.172, and a better model fit than the bi-factor CFA model, $\Delta\chi^2(85) = 717.300$, $p < .001$ (see Table 2). Factor scores derived from the best fitting model (i.e., the bi-factor ESEM model) were saved and used as indicators for LPA models in subsequent steps.

To separate the *level* and *shape* of the profiles, the recommendations of Morin et al. (2016) were adopted. Specifically, factor scores for both the general factor and five specific dimensions (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) of the 5×5 RS were specified in the LPA models. The general factor of resilience in the bi-factor ESEM represents the overall *level* (quantitative difference) of resilience, whereas the specific factors indicate the differences between each of the factors and the overall mean of resilience, thus representing the *shape* (qualitative pattern) of resilience profiles. All LPA models were run using 10,000 random sets of starting values, 1,000 iterations, and 500 final stage optimizations. Due to the complexity of the LPA models containing factor scores of the bi-factor ESEM model, different seed values were explored to facilitate model convergence.

LPA class enumeration was conducted, starting with a model with one profile and increasing the number of profiles by one in each iteration until six profiles were reached; 6 LPA models were examined in total (see Table 4 for fit statistics). With all model fit criteria (detailed in the Analytical Plan section) taken into consideration, the 4-profile LPA model was selected as the best solution. The rationale for such model selection is as follows. As the number of profiles being examined increased, all fit statistics generally improved except for BIC and LMRT values. Specifically, the 6-profile model provided a worse LMRT value (not statistically significant) than that of the 5-profile model; the improvement in BIC and entropy of the 6-profile model over the 5-profile model (smaller BIC and larger entropy) was negligible at the cost of losing parsimony. Thus, the 6-profile model was not selected, leaving the decision between the 5-profile and 4-profile models. Even though the 5-profile model provided seemingly better fit statistics than the 4-profile model, the more parsimonious 4-profile model produced a better (i.e., smaller) BIC value than the 5-profile model and the increment in entropy the 5-profile model produced was negligible. Close examination of the percentages of individuals assigned to each profile provided additional evidence favoring the 4-profile solution. As shown in Table 5, only 3.13% of the individuals were assigned to the 5th profile in the 5-profile solution; in comparison, close to 5% of the individuals were assigned to the 4th profile in the 4-profile solution.

Next, the meaningfulness/interpretation of the two LPA solutions were examined to further compare the two models (see Figures 1 and 2 for graphic depictions of the 4-and 5-profile models respectively). As shown in Figure 2, Profile 3 and Profile 4 in the 5-profile model were less differentiated in terms of the patterns of the five specific factors; both profiles had similar levels on all factors except for self-efficacy. Profile 5 had the highest levels on all five factors, but the lowest level of global resilience, meaning that individuals are the least resilient despite having the highest levels of adaptability, emotion regulation, optimism, self-efficacy, and social support. Such a result is difficult to interpret. In comparison, the 4-profile model shown in Figure 1 demonstrated distinct patterns for all five factors, and meaningful congruence between all four profiles and global resilience. As a result of these considerations, the 4-profile LPA model appeared to be the optimal solution. See Table 6 for the estimated means of the indicators (bi-factor ESEM factor scores of general resilience and five dimensions of resilience) for the four profiles in the 4-profile LPA model.

As indicated in Figure 1, the first profile (N = 243; 50.73%) had the lowest level of global resilience out of any of the profiles, and was relatively low on all five dimensions of resilience as compared to other profiles ; thus, I labeled people belonging to this profile "*the overall fragile*." The second profile (N = 30; 6.26%) is the second highest on global resilience, the highest on self-efficacy and optimism, and the second highest on adaptability, while being the lowest on social support and relatively low on emotion-regulation; because the second profile is self-efficacious and less reliant on others to be resilient, I labeled those in this profile group "*lone wolves*." The third profile (N = 183; 38.21%) is the second lowest on global resilience and adaptability, and the lowest on self-efficacy, while being the highest on emotion-regulation and the second highest on optimism and social support; because this profile group is low on resilience and relies on indirect coping strategies such as emotion regulation and social support rather than tacking problems head on (such as being adaptable), I labeled this group "*white knuckles*." The fourth profile (N = 23; 4.80%) is the highest on global resilience, adaptability, and social support, and the second highest on self-efficacy, despite being the lowest on emotion regulation and optimism; consequently, I labeled those belonging to this group "*the bending-not-breaking*."

Personality Correlates of the Profiles

Next, the relationships of latent profiles of resilience and personality variables (i.e., Big Five, PA, and NA) were examined using multinomial logistic regressions based on the R3STEP approach (see Table 9 and Figure 4 for descriptive statistics of personality variables for each latent profile). As seen in Table 7 (top), all personality variables except for agreeableness significantly differentiated between some of the profiles, however no single variable significantly differentiated between all of the profiles. Specifically, NA and neuroticism significantly differentiated Profile 1 from the rest of the profiles, such that people with higher levels of NA and neuroticism were more likely to fit into Profile 1. Conscientiousness and openness significantly separated Profile 2 from Profiles 1 and 3, and Profile 4 from Profile 3. People with higher levels of conscientiousness and openness were more likely to belong to Profile 2 than Profiles 1 and 3, and more likely to belong to Profile 4 than Profile 3. PA significantly separated Profile 2 from Profiles 1 and 3, such that those with higher PA were more likely to belong to Profile 2 than Profiles 1 and 3. Last, extraversion effectively differentiated Profile 3 from Profiles 1 and 2, such that individuals with higher levels of extraversion were more likely to fit into Profile 3 than Profile 1 but less likely to belong to Profile 2. Agreeableness was not related to profile membership.

In sum, individuals with higher levels of PA, conscientiousness, and openness were more likely to be members of Profile 2 (second highest on global resilience and adaptability, highest on self-efficacy and optimism, lowest on social support and low on emotion regulation) relative to Profiles 1 and 3. Those with higher levels of NA and neuroticism were more likely to belong to Profile 1 (lowest on global resilience and relatively low on all dimensions) than all other profiles. Individuals with higher levels of conscientiousness and openness were more likely to be in Profile 4 (highest on global resilience and adaptability and social support, second highest on self-efficacy, lowest on emotion regulation and optimism) than to Profile 3 (second lowest on global resilience and adaptability, second lowest on self-efficacy, highest on emotion regulation, second highest on optimism and social support). It is worth noting that none of the personality variables measured effectively differentiated Profile 2 from Profile 4, even though the two profiles displayed distinct patterns; it may be that other variables not included in this study might explain the differences observed between these two profiles.

Outcomes of the Profiles

The four latent profiles showed significant relationships with the outcomes and demonstrated differential relationships with the three outcomes measured in the undergraduate sample (see Table 8 top). For life satisfaction, the means of Profiles 2 and 4 were significantly higher than those of Profiles 1 and 3, but were not significantly different from each other; Profile 3 had higher life satisfaction than Profile 1. The means of job satisfaction in Profiles 2 and 4 was significantly higher than in Profile 1; Profiles 2 and 4 were not significantly different from each other. Profile 4 (but not Profile 2) had significantly higher job satisfaction than Profile 3, which had significantly higher job satisfaction than Profile 1. Finally, Profiles 2 and 4 both had significantly lower CWB-I than Profile 1, but did not differ from Profile 3. Profile 3 had significantly lower CWB-I than Profile 1, and there were no significant differences between Profiles 2 and 4 (see Figure 5 and Table 10 for the means of the outcomes involving the four profiles).

Comparison of the Person- vs. Variable-centered Approach

Three sets of regressions were conducted and revealed the following findings. Controlling for age and gender, including dummy coded profile variables significantly increased the variance accounted for in life satisfaction, job satisfaction, and CWB-I (see Table 11). However, controlling for age and gender, including the profiles did not significantly increase the variance explained in the three outcomes beyond the five subscale scores of the 5×5 RS (see Table 12). After personality variables were included in the models predicting the three outcomes (Step 1), including the five subscale scores of the 5×5 RS in Step 2 only provided significant incremental variance in Life Satisfaction (2%); including profile variables in Step 3 did not explain additional variance in any of the three outcomes (see Table 13).

Summary

In conclusion, four latent profiles of resilience have been successfully identified and showed differential relations with personality variables and outcomes. However, adding profile membership in regression predicting the outcomes did not show incremental validity beyond the five subscale scores of the 5×5 RS and personality variables. In Study 2, the same four latent profiles were expected and the patterns of profiles were expected to be similar to those depicted in Figure 1 and the profile proportions were expected to be similar to those of the same profiles detailed in the Study 1 results. Additionally, Study 2 examined the relationships between profiles, personality correlates, and outcomes as well as the incremental validity of the LPA profiles over the variable-centered approach for predicting outcome variables.

Study 2

Latent Profile Analysis

Analyses were conducted to examine whether the profiles found in Study 1 would be replicated using a sample of individuals who were employed either part- or full-time recruited via Mturk. ESEM with ML estimation and orthogonal rotation was first conducted on the responses to the 5×5 RS to confirm the bi-factor structure of the 5×5 RS and the results indicated that the bi-factor ESEM model[3] had excellent model fit, χ^2 (165) = 375.475, $p < .001$, CFI = 0.960, TLI = 0.928, RMSEA = 0.051 [0.045, 0.058], SRMR = 0.023, AIC = 30049.390, BIC = 30822.693, sBIC = 30235.517. Following Morin et al. (2016), factor scores for both the general and five specific factors derived from the bi-factor ESEM model were saved and used as indicators in LPA models, which were run using 3,000 random sets of starting values, 1,000

[3] For thoroughness, ESEM was conducted on the correlated-factor model and higher-order factor model, both of which demonstrated worse model fit than the bi-factor ESEM model; CFAs on the correlated-factor model, higher-order factor model, and the bi-factor model were also examined and displayed worse fit than the ESEM bi-factor model (see Appendix B for fit statistics).

iterations, and 500 final stage optimizations. Different seed values were explored for each model to help model convergence.

Class enumeration was conducted, starting with one profile and incrementing by one until six profiles (see Table 4 bottom for fit statistics). All model fit criteria except for BLRT values[4] listed in the Analytical Strategy section were evaluated, and the 4-profile model was selected as the best fitting solution as follows. As the number of profiles included in the models increased, the LL, AIC, and sBIC decreased (improved), while the BIC increased (worsened) in the 4-, 5-, and 6-profile solutions. Entropy increased (improved) as the number of profiles increased up to the 4-profile model, which showed the highest entropy value. LMRT values were significant for all models, except for the 6-profile model; thus, the 6-profile solution was not selected. Compared to the 5-profile solution, the 4-profile model demonstrated better model fit statistics.

The graphs for the 3-, 4-, and 5-profile solutions (see Figures 1-3 bottom) indicate irregular patterns of these LPA solutions. Specifically, Profile 2 in the 4-profile and 5-profile models demonstrated inverse relationships between the general factor and five specific indicators. Contrary to expectation, people with the highest levels of emotion regulation, optimism, and social support and second highest levels of adaptability showed the lowest levels of global resilience in both models. Profile 3 in the 3-profile model also showed a similar pattern in which people with highest levels of all five specific factors showed the lowest levels of global resilience. The interpretation of these findings is not obvious, making it difficult to identify the best-fitting LPA model.

[4] BLRT values and significant levels for the 3-, 4-, 5-, and 6-profile LPA models were not obtained due to local maxima of the bootstrapped likelihood ratio tests with 5,000 bootstrapped resamples. Different BLRT random starts were explored but did not solve the local maxima problem. Other model fit statistics were reliably obtained (i.e., no local maxima or convergence issues occurred).

That said, a comparison of the patterns of the 4-profile model in the undergraduate sample (Figure 4 top) with those of the MTurk sample (Figure 4 bottom) showed that the shapes of the profiles (except for Profile 2) in the MTurk sample were similar to the shapes of the profiles in the undergraduate sample. Specifically, Profile 1 in both samples had the lowest levels of global resilience, low (or lowest) levels of adaptability, self-efficacy, optimism, social support, and emotion regulation. Profile 3 in both samples had low (or lowest) levels of self-efficacy, adaptability and high (or highest) levels of emotion regulation. Profile 4 in both samples had the highest levels of adaptability and global resilience, high levels of self-efficacy and social support, and lowest levels of emotion regulation. Additionally, the percentages of individuals assigned to each profile for the 4-profile model were similar in both samples. Despite some small differences in the findings, taken together, the results of Studies 1 and 2 indicate that resilience likely functions similarly in both undergraduate and Mturk samples, and partially confirms a set of four latent profiles of resilience.

Personality Correlates of the Profiles

Table 7 (bottom) shows the results of multinomial logistic regressions using the R3STEP approach to examine the relationships between the four latent profiles of resilience and personality variables. Table 9 (bottom) and Figure 4 (bottom) show the descriptive statistics of the personality variables for each latent profile. Overall, each of the personality variables significantly differentiated between some of the profiles. Specifically, PA and NA significantly differentiated Profile 2 from Profiles 1, 3, and 4; individuals with higher levels of PA and NA were more likely to have Profile 2 membership relative to the other three profiles. Additionally, extraversion predicted higher likelihood to have Profiles 3 and 4 membership than to have Profiles 1 and 2 membership; openness separated Profiles 3 and 4 from Profile 1 but did not differentiate Profiles 3 and 4 from Profile 2. Conscientiousness was what differentiated Profile 2 from Profiles 1 and 3, such that those with lower levels of conscientiousness are more likely to have Profile 2 relative to Profiles 1 and 3. Contrary to the findings of study 1, agreeableness significantly separated Profile 3 from Profiles 1 and 2, which means that higher levels of agreeableness predict higher likelihood to Profile 3 membership relative to Profiles 1 and 2. Neuroticism was what differentiated Profile 1 from the other profiles, such that those with higher levels of neuroticism tend to belong to Profile 1 over other profiles. Last, and also contrary to the findings of study 1, PA, NA, neuroticism, and extraversion separated Profile 2 from Profile 4. Specifically, individuals with higher levels of PA or extraversion, or lower levels of NA or neuroticism are more likely to belong to Profile 4 over Profile 2. Of note, these four personality traits did not significantly differentiate Profile 2 from Profile 4 in the undergraduate sample, even though Profile 2 in the undergraduate sample showed similar patterns in terms of the mean differences in these personality traits between Profiles 2 and 4, which might explain the different findings.

Outcomes of the Profiles

Table 8 (bottom) presents the different levels of outcomes among the four profiles in the MTurk sample and shows that all four profiles significantly related to all outcomes, as indicated by the overall tests. For life satisfaction, the mean of Profile 1 was significantly lower than the means of Profiles 2, 3, and 4; there were no significant differences among Profiles 2, 3, and 4. The mean of job satisfaction in Profile 3 was significantly higher than the means of Profiles 1 and 2; the means of other profiles did not differ significantly from each other.

As for CWB-I, the means of all profiles were significantly different from each other except that the mean of Profile 3 was not significantly higher than that of Profile 4. Notably, Profile 4 had significantly lower CWB-I than Profile 1, and had the lowest CWB-I out of all the profiles. Even though Profile 2 had the highest CWB-I compared to other profiles, this profile showed an unexpected pattern, in which high levels of adaptability, emotion regulation, optimism, and social support corresponded to the lowest level of global resilience, and thus should be interpreted with caution.

In terms of stress, there were statistically significant differentiations among all the profiles except between Profiles 3 and 4; Profile 4 showed the lowest level of stress. The highest level of stress was found in in Profile 2, however, this finding should be taken with a grain of salt as the pattern of Profile 2 found in the undergraduate sample was not replicated in the MTurk sample. Lastly, Profile 1 had significantly higher job burnout than Profile 3; even though the mean of Profile 2 was also significantly higher than that of Profile 3, this result may not offer much meaningful insight due to the uninterpretable shape of Profile 2. No other significant differences among the profiles were detected (see Figure 5 and Table 10 for the means of the outcomes among the four profiles).

Comparison of the Person- vs. Variable-centered Approach

Similar to Study 1, including dummy coded profile variables significantly predicted life satisfaction, job satisfaction, and CWB-I after controlling for age and gender. The models predicting stress and job burnout were also significant (see Table 14). Controlling for age and gender, including profile variables accounted for significant incremental variance in life satisfaction (6%), job satisfaction (2%), CWB-I (7%), and stress (3%) beyond the five-dimension scale scores of the 5×5 RS, indicating that the latent profiles (i.e., the person-center approach) provided added benefits beyond the dimensional scores (i.e., the variable-centered approach) when predicting work and life outcomes (see Table 15). Last, the incremental validity of the profiles beyond personality variables and the 5×5 RS scores was examined. As shown in Table 16, the profiles provided incremental validity predicting life satisfaction (3%) and job satisfaction (6%) beyond the personality variables and 5×5 RS dimensional scores, offering additional evidence that including the resilience profiles provided additional predictive power beyond dimensional scores and personality. The inclusion of the profiles did not significantly increase the variance explained by CWB-I (1%) and job burnout (1%).

Summary

The four latent profiles identified in Study 1 were partially replicated in Study 2 and demonstrated differential relationships with personality variables and outcomes. Further, including profile membership in regression models predicting life satisfaction and job satisfaction explained additional variance beyond the 5×5 RS dimensional scores and personality variables, suggesting that a person-centered approach may provide added benefits beyond a variable-centered approach when predicting work and life outcomes.

Table 1. Correlation matrix in the undergraduate (top) and MTurk samples (bottom).

Study 1	*M*	*SD*	1	2	3	4	5	6	7
1.AD	3.62	0.80	(.81)						
2.ER	2.86	0.91	.38***	(.81)					
3.OP	3.64	0.98	.46***	.41***	(.87)				
4.SE	3.99	0.72	.46***	.20***	.53***	(.82)			
5.SS	3.69	0.87	.44***	.29***	.63***	.53***	(.79)		
6.Positive affect	3.57	0.87	.40***	.26***	.52***	.54***	.52***	(.94)	
7.Negative affect	2.29	0.87	-.33***	-.46***	-.58***	-.31***	-.46***	-.20***	(.90)
8.Extraversion	3.31	0.81	.26***	.08	.31***	.35***	.53***	.45***	-.19***
9.Agreeableness	3.88	0.64	.26***	.09	.40***	.31***	.41***	.33***	-.33***
10.Conscientiousness	3.71	0.61	.26***	.26***	.44***	.52***	.43***	.45***	-.32***
11.Neuroticism	3.04	0.82	-.45***	-.72***	-.57***	-.33***	-.46***	-.40***	.58***
12.Openness	3.61	0.59	.35***	.10*	.17***	.39***	.22***	.25***	-.03
13.Stress	1.08	0.78	-.36***	-.43***	-.57***	-.36***	-.45***	-.31***	.56***
14.Life Satisfaction	4.73	1.48	.30***	.26***	.50***	.35***	.51***	.54***	-.42***
15.Job Satisfaction	4.52	1.49	.27***	.10*	.34***	.26***	.31***	.35***	-.25***
16.CWB-I	2.02	1.18	-.14***	-.04	-.26***	-.21***	-.22***	-.11*	.21***

Table 1. (Continued)

8	9	10	11	12	13	14	15	16
(.90)								
.18***	(.92)							
.25***	.38***	(.90)						
-.29***	-.31***	-.34***	(.85)					
.17***	.23***	.13***	-.15***	(.80)				
-.19***	-.33***	-.25***	.59***	-.13***	(.84)			
.38***	.29***	.30***	-.39***	.09*	-.40***	(.91)		
.23***	.29***	.24***	-.24***	.07	-.24***	.46***	(.88)	
.04	-.40***	-.23***	.08	-.10*	.28***	-.17***	-.17***	(.86)

Table 1. (Continued)

Study 2	*M*	*SD*	1	2	3	4	5	6	7
1.AD	3.55	0.73	(.77)						
2.ER	3.17	0.88	.28***	(.83)					
3.OP	3.68	0.88	.40***	.50***	(.85)				
4.SE	4.05	0.62	.30***	.30***	.48***	(.81)			
5.SS	3.66	0.88	.32***	.30***	.58***	.40***	(.81)		
6.Positive affect	3.20	0.90	.33***	.17***	.41***	.31***	.44***	(.92)	
7.Negative affect	1.88	0.78	-.14***	-.42***	-.52***	-.25***	-.37***	-.20***	(.91)
8.Extraversion	3.11	0.83	.26***	.08	.37***	.28***	.62***	.44***	-.16***
9.Agreeableness	3.87	0.70	.26***	.18***	.54***	.37***	.52***	.39***	-.36***
10.Conscientiousness	4.04	0.68	.14***	.33***	.52***	.53***	.43***	.27***	-.42***
11.Neuroticism	2.47	0.87	-.41***	-.64***	-.72***	-.43***	-.59***	-.47***	.60***
12.Openness	3.58	0.65	.30***	.03	.23***	.41***	.20***	.24***	-.08
13.Stress	0.75	0.66	-.20***	-.48***	-.55***	-.28***	-.44***	-.18***	.72***
14.Life Satisfaction	4.70	1.38	.23***	.29***	.40***	.31***	.45***	.48***	-.21***
15.Job Satisfaction	3.87	0.80	.10*	.11*	.37***	.37***	.40***	.39***	-.26***
16.CWB-I	1.73	0.83	-.08	-.19***	-.38***	-.30***	-.28***	.06	.39***
17.Job burnout	2.49	0.78	-.17***	-.25***	-.45***	-.22***	-.39***	-.34***	.37***

Note. *N* = 479 (Study 1) and 483 (Study 2). AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$

Table 1. (Continued)

8	9	10	11	12	13	14	15	16	17
(.83)									
.32***	(.82)								
.19***	.53***	(.85)							
-.39***	-.50***	-.54***	(.87)						
.24***	.30***	.25***	-.20***	(.80)					
-.22***	-.50***	-.49***	.67***	-.09*	(.89)				
.36***	.26***	.30***	-.44***	.06	-.24***	(.91)			
.33***	.41***	.31***	-.32***	.11*	-.28***	.40***	(.85)		
-.08	-.49***	-.44***	.28***	-.19***	.44***	-.01	-.25***	(.91)	
-.35***	-.42***	-.33***	.48***	-.14***	.49***	-.26***	-.51***	.24***	(.88)

Table 2. Standardized loadings of the bi-factor ESEM model of the 5×5 RS in the undergraduate (left) and MTurk samples (right).

	G	AD	ER	OP	SE	SS	G	AD	ER	OP	SE	SS
	Study 1 (undergraduate)						Study 2 (MTurk)					
Item 1	.39	.49	.12	.07^{+}	.26	.08	.28	.43	.02+	.03+	.22	.08+
Item 2	.43	.74	.01^{+}	.03^{+}	.07	.04^{+}	.31	.78	- .00+	- .01+	.05+	- .01+
Item 3	.57	.45	- .03^{+}	- .14	- .14	- .05^{+}	.36	.66	- .02+	- .05+	- .13	- .05+
Item 4	.48	.55	.05^{+}	.08	.30	.12	.39	.53	.09	.08	.26	.15
Item 5	.43	.43	.16	- .18	- .14	- .11	.27	.46	.07+	.09+	- .14	.04+
Item 6	.22	- .06^{+}	.67	.00^{+}	- .18	- .11	.27	- .05+	.64	- .00+	- .13	- .14
Item 7	.03^{+}	.13	.77	.12	.06^{+}	.09	.20	.12	.68	.14	.06+	.04+
Item 8	.36	.15	.51	.03^{+}	.17	.10	.42	.13	.46	.16	.20	.05+
Item 9	.54	.00^{+}	.50	- .12	- .12	- .07^{+}	.58	- .02+	.55	- .07	- .03+	.00+
Item 10	.55	.03^{+}	.59	- .04^{+}	- .13	- .12	.58	- .04+	.59	- .14	- .05+	- .13
Item 11	.73	-.06	.11	.26	- .08	- .07	.70	.07	.07	.16	- .05+	- .01+
Item 12	.75	-.12	.01^{+}	.35	- .01^{+}	- .04^{+}	.76	- .03+	- .05+	.28	- .02+	- .01+
Item 13	.54	.13	.05^{+}	.42	.23	.20	.53	.13	- .00+	.57	.09	.21
Item 14	.68	- .01^{+}	.13	.21	- .10	- .14	.62	.00+	.19	.26	- .10	- .11
Item 15	.71	- .09	- .15	.41	- .05^{+}	.03^{+}	.71	- .07	- .01+	.30	- .01+	- .05+
Item 16	.39	.06^{+}	- .08	- .13	.68	- .03^{+}	.30	- .02+	.02+	.01+	.72	- .07
Item 17	.49	.08	- .04^{+}	- .14	.69	.00^{+}	.37	.17	.08	- .05+	.69	.00+
Item 18	.53	- .08	- .10	.12	.19	- .07^{+}	.65	- .15	- .13	- .14	.29	- .09
Item 19	.51	.07	- .05^{+}	.15	.53	.13	.46	.02+	- .07+	.07+	.44	.07+
Item 20	.50	.22	.00^{+}	.25	.47	.17	.43	.08	.02+	.10	.51	.14
Item 21	.38	.13	- .08	.05^{+}	.14	.56	.31	.16	- .10	.10	.10	.68
Item 22	.63	- .14	- .07	.08	.00^{+}	.15	.63	- .15	- .01+	.09	.02+	.27
Item 23	.63	- .03^{+}	- .02^{+}	- .09	- .06^{+}	.19	.62	- .07	- .03+	- .18	- .08	.37
Item 24	.47	.14	.01^{+}	.03^{+}	.13	.60	.40	.13	- .00+	.05+	.03+	.61
Item 25	.67	- .16	- .02^{+}	- .03^{+}	- .07	.40	.60	- .08	- .07	.03+	- .09	.39

Table 2. (Continued)

Note. N = 479 (Study 1) and 483 (Study 2). $^{+}$ indicates non-statistically significant loadings; unmarked loadings are statistically significant. AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support; G = global resilience.

Table 3. Model comparison between the bi-factor CFA vs. ESEM models in the undergraduate sample.

		LRT							
	$\chi^2(df)$	$\Delta\chi^2$ (df)	RMSEA	ΔRMSEA	CFI	ΔCFI	TLI	ΔTLI	SRMR
CFA	1151.823(250)***		0.087		0.850		0.820		0.075
ESEM	434.523(165)***	717.300(85)***	0.058	0.029	0.955	0.105	0.919	0.099	0.023

Note. N = 479; df = degrees of freedom; LRT = likelihood ratio test; 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; sBIC = sample-size adjusted BIC; CFA = confirmatory factor analysis; ESEM = exploratory structural equation modelling. *** $p < .001$

Table 3. (Continued)

AIC	BIC	sBIC
31210.877	31628.047	31310.658
30663.576	31435.341	30848.172

Table 4. Fit statistics for LPA models using factor scores derived from a bi-factor ESEM of the 5×5 RS as indicators in the undergraduate sample (top) and MTurk sample (bottom).

Model	LL	#fp	AIC	BIC	sBIC	LMRT	LMRT (p)	BLRT	BLRT (p)	Entropy
					Study 1 (undergraduate)					
1-profile	-3703.345	12	7430.691	7480.751	7442.665	–	–	–	–	–
2-profile	-3592.245	25	7234.490	7338.783	7259.435	219.465	0.0000	222.201	0.0000	0.751
3-profile	-3546.320	38	7168.640	7327.165	7206.557	165.501	0.0010	167.563	0.0000	0.701
4-profile	-3512.491	51	**7126.982**	**7339.739**	7177.870	**166.791**	0.0048	**168.870**	0.0000	**0.767**
5-profile	-3494.988	60	**7109.975**	**7360.277**	7169.844	**85.711**	0.0015	**86.868**	0.0000	**0.785**
6-profile	-3442.398	77	7038.797	**7360.017**	7115.628	92.623	**0.1541**	93.778	0.0000	**0.798**
					Study 2 (MTurk)					
1-profile	-3726.675	12	7477.350	7527.511	7489.424	–	–	–	–	–
2-profile	-3610.202	25	7270.404	7374.905	7295.556	230.082	0.0000	232.946	0.0000	0.658
3-profile	-3566.704	38	7209.407	7368.248	7247.639	85.927	0.0005	NaN	NaN	0.746
4-profile	-3531.345	51	7164.690	**7377.871**	7216.001	89.361	0.0001	NaN	NaN	**0.794**
5-profile	-3501.025	64	7130.051	**7397.572**	7194.441	60.470	0.0183	NaN	NaN	**0.755**
6-profile	-3479.678	77	7113.357	7435.218	7190.826	43.022	0.1649	NaN	NaN	0.779

Note. N = 479 (Study 1) and 483 (Study 2); LL = loglikelihood; #fp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; sBIC = sample-size adjusted BIC; LMRT = Lo-Mendel-Rubin likelihood ratio test; BLRT =bootstrapped likelihood ratio test; ESEM = exploratory structural equation modelling; LPA = latent profiles analysis. Values in bold were discussed in the results section; models highlighted in grey were selected for further comparison. BLRT values and significance levels (shown in NaNs) cannot be estimated in the MTurk sample due to local maxima for the BLR tests.

Table 5. Distribution of data points assigned to profiles for each LPA model in the undergraduate sample (left) and MTurk sample (right).

	Class	Count	Percentage	Count	Percentage
		Study 1 (undergraduate)		Study 2 (MTurk)	
1-profile	1	479	100.00%	483	100.00%
2-profile	1	313	65.34%	301	62.32%
	2	166	34.66%	182	37.68%
3-profile	1	236	49.27%	196	40.58%
	2	212	44.26%	245	50.73%
	3	31	6.47%	42	8.70%
4-profile	1	243	50.73%	237	49.07%
	2	30	6.26%	43	8.90%
	3	183	38.21%	190	39.34%
	4	23	4.80%	13	2.69%
5-profile	1	55	11.48%	169	34.99%
	2	110	22.97%	44	9.11%
	3	115	24.01%	79	16.36%
	4	184	38.41%	178	36.85%
	5	15	3.13%	13	2.69%
6-profile	1	111	23.17%	40	8.28%
	2	57	11.90%	64	13.25%
	3	173	36.12%	143	29.61%
	4	109	22.76%	44	9.11%
	5	15	3.13%	179	37.06%
	6	14	2.92%	13	2.69%

Note. N = 479 (Study 1) and 483 (Study 2). Values in grey were discussed in the results section.

Table 6. Estimated means of the indicators (bi-factor ESEM factor scores of global resilience and five dimensions of resilience) in the 4-profile LPA model in the undergraduate sample (top) and MTurk sample (bottom).

	AD	ER	OP	SE	SS	G
			Study 1 (undergraduate)			
Profile 1	-0.08	-0.12	-0.08	0.19	-0.02	-0.49
Profile 2	0.50	0.02	0.27	0.66	-0.24	1.07
Profile 3	-0.05	0.19	0.10	-0.39	0.04	0.32
Profile 4	0.67	-0.17	-0.27	0.20	0.21	1.57
			Study 2 (MTurk)			
Profile 1	-0.25	-0.11	-0.14	0.03	-0.25	-0.34
Profile 2	0.47	0.44	0.52	0.10	0.58	-1.27
Profile 3	0.19	0.07	0.08	-0.10	0.19	0.64
Profile 4	0.87	-0.24	0.10	0.57	0.40	1.55

Note. N = 479 (Study 1) and 483 (Study 2). AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support; G = global resilience.

Table 7. Results of personality variables in relation to the four profiles in the undergraduate (top) and MTurk sample (bottom).

Study 1 (undergraduate)		PA	NA	E	A	C	N	O
Profile 1 vs. Profile 2 (Profile 1 as ref)	*Est.*	2.14***	-1.96***	-0.57	0.15	1.64**	-1.28*	1.23*
	SE	0.70	0.46	0.46	0.51	0.58	0.50	0.50
	OR	**8.45**	**0.14**	0.57	1.17	**5.14**	**0.28**	**3.41**
Profile 1 vs. Profile 3 (Profile 1 as ref)	*Est.*	0.01	-1.33***	0.51*	-0.15	-0.24	-1.59***	-0.12
	SE	0.25	0.33	0.26	0.36	0.39	0.36	0.37
	OR	1.01	**0.27**	**1.67**	0.86	0.79	**0.20**	0.89
Profile 1 vs. Profile 4 (Profile 1 as ref)	*Est.*	1.22	-1.34*	0.53	0.31	1.35+	-2.03***	1.25+
	SE	1.32	0.68	0.68	0.99	0.79	0.60	0.66
	OR	3.39	**0.26**	1.70	1.37	3.84	**0.13**	3.50
Profile 2 vs. Profile 3 (Profile 2 as ref)	*Est.*	-2.12**	0.64	1.08*	-0.3	-1.88***	-0.31	-1.35**
	SE	0.71	0.43	0.47	0.48	0.55	0.48	0.47
	OR	**0.12**	1.89	**2.94**	0.74	**0.15**	0.73	**0.26**
Profile 2 vs. Profile 4 (Profile 2 as ref)	*Est.*	-0.91	0.62	1.10	0.16	-0.29	-0.75	0.03
	SE	1.34	0.7	0.79	1.00	0.83	0.65	0.72
	OR	0.40	1.86	2.99	1.17	0.75	0.47	1.03
Profile 3 vs. Profile 4 (Profile 3 as ref)	*Est.*	1.21	-0.01	0.02	0.46	1.59*	-0.44	1.38*
	SE	1.34	0.65	0.70	0.99	0.77	0.57	0.62
	OR	3.35	0.99	1.02	1.58	**4.89**	0.64	**3.96**
Summary		Profile 2 > 1, 3	Profile 1 > 2, 3, 4	Profile 3 > 1, 2		Profile 2 > 1, 3, 4 > 3	Profile 1 > 2, 3, 4	Profile 2 > 1, 3, 4 > 3

Table 7. (Continued)

Study 2 (MTurk)		PA	NA	E	A	C	N	O
Profile 1 vs. Profile 2 (Profile 1 as ref)	*Est.*	1.73***	1.33***	0.03	-1.05+	-2.37**	-1.44***	0.46
	SE	0.50	0.31	0.36	0.60	0.75	0.45	0.46
	OR	**5.63**	**3.80**	1.03	0.35	**0.09**	**0.24**	1.58
Profile 1 vs. Profile 3 (Profile 1 as ref)	*Est.*	-0.28	-0.4	1.40***	1.15**	-0.74	-2.19***	0.66*
	SE	0.3	0.38	0.37	0.41	0.52	0.50	0.32
	OR	0.75	0.67	**4.07**	**3.17**	0.48	**0.11**	**1.94**
Profile 1 vs. Profile 4 (Profile 1 as ref)	*Est.*	-0.10	-0.41	3.07***	0.47	-1.41	-4.65***	2.23*
	SE	0.53	0.61	0.96	1.01	0.87	1.39	1.09
	OR	0.90	0.67	**21.59**	1.60	0.24	**0.01**	**9.26**
Profile 2 vs. Profile 3 (Profile 2 as ref)	*Est.*	-2.01***	-1.73***	1.38***	2.20***	1.63*	-0.75	0.21
	SE	0.53	0.38	0.42	0.63	0.82	0.49	0.50
	OR	**0.13**	**0.18**	**3.97**	**9.05**	**5.12**	0.47	1.23
Profile 2 vs. Profile 4 (Profile 2 as ref)	*Est.*	-1.83**	-1.74**	3.05**	1.52	0.96	-3.21*	1.77
	SE	0.68	0.61	0.97	1.1	1.06	1.38	1.15
	OR	**0.16**	**0.18**	**21.06**	4.58	2.61	**0.04**	5.85
Profile 3 vs. Profile 4 (Profile 3 as ref)	*Est.*	0.18	-0.01	1.67^{+}	-0.68	-0.67	-2.46^{+}	1.56
	SE	0.44	0.52	0.89	0.94	0.72	1.30	1.05
	OR	1.20	0.99	5.31	0.51	0.51	0.09	4.76
Summary		Profile 2 > 1, 3, 4	Profile 2 > 1, 3, 4	Profile 3, 4 >1, 2	Profile 3 > 1, 2	Profile 1, 3 > 2	Profile 1 > 2,3,4, Profile 2 > 4	Profile 3, 4 > 1

Table 7. (Continued)

Note. $N = 479$ (Study 1) and 483 (Study 2). PA = positive affect, NA = negative affect, E = extraversion, A = agreeableness, C = Conscientiousness, N = Neuroticism, O = Openness. *SE* = standard error of the estimated coefficient; OR = odds ratio. The estimate and OR present the influence of the predictor on the likelihood of profile membership into the second profile relative to the first profile (the reference group). ORs in bold are statistically significant. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. $^{+}p < .1$

Table 8. Results of the outcome variables in relation to the four profiles in the undergraduate sample (top) and MTurk sample (bottom).

Study 1	Life Satisfaction			Job Satisfaction			CWB-I		
Profiles	χ^2	*df*	*p*	χ^2	*df*	*p*	χ^2	*df*	*p*
Profile 1 vs. Profile 2	**80.37**	1	**0.00**	**30.43**	1	**0.00**	**5.53**	1	**0.02**
Profile 1 vs. Profile 3	**60.10**	1	**0.00**	**35.31**	1	**0.00**	**4.59**	1	**0.03**
Profile 1 vs. Profile 4	**73.95**	1	**0.00**	**37.68**	1	**0.00**	**7.88**	1	**0.01**
Profile 2 vs. Profile 3	**7.10**	1	**0.01**	2.75	1	0.10	1.24	1	0.27
Profile 2 vs. Profile 4	0.04	1	0.84	0.01	1	0.94	0.11	1	0.74
Profile 3 vs. Profile 4	**5.83**	1	**0.02**	**3.21**	1	**0.07**	2.45	1	0.12
Overall Test	136.35	3	0.00	64.92	3	0.00	13.47	3	0.00

Study 2	Life Satisfaction			Job Satisfaction			CWB-I			Stress			Job Burnout		
Profiles	χ^2	*df*	*p*	χ^2	*df*	*p*	χ^2	*df*	*p*	χ^2	*df*	*p*	χ^2	*df*	*p*
Profile 1 vs. Profile 2	**48.81**	1	**0.00**	0.44	1	0.51	**68.42**	1	**0.00**	**27.03**	1	**0.00**	0.16	1	0.69
Profile 1 vs. Profile 3	**58.49**	1	**0.00**	**14.59**	1	**0.00**	**22.21**	1	**0.00**	**49.84**	1	**0.00**	**34.63**	1	**0.00**
Profile 1 vs. Profile 4	**29.18**	1	**0.00**	2.48	1	0.12	**37.00**	1	**0.00**	**35.62**	1	**0.00**	2.69	1	0.10
Profile 2 vs. Profile 3	0.46	1	0.50	**16.18**	1	**0.00**	**117.07**	1	**0.00**	**106.74**	1	**0.00**	**28.12**	1	**0.00**
Profile 2 vs. Profile 4	0.94	1	0.33	3.18	1	0.07	**127.02**	1	**0.00**	**80.06**	1	**0.00**	2.17	1	0.14
Profile 3 vs. Profile 4	1.98	1	0.16	0.13	1	0.72	6.15	1	0.01	2.14	1	0.14	0.08	1	0.78
Overall Test	81.10	3	0.00	24.29	3	0.00	156.71	3	0.00	152.15	3	0.00	45.72	3	0.00

Note. N = 479 (Study 1) and 483 (Study 2). Bolded are statistically significant χ^2s. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 9. Descriptive statistics of personality correlates by the four latent profiles the undergraduate sample (top) and MTurk sample (bottom).

	PA		NA		E		A		C		N		O	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Study 1 (undergraduate)														
Profile 1	3.35	0.92	2.69	0.87	3.12	0.88	3.75	0.64	3.55	0.64	3.44	0.76	3.56	0.63
Profile 2	4.34	0.64	1.66	0.49	3.50	0.85	4.27	0.65	4.26	0.40	2.48	0.65	3.92	0.45
Profile 3	3.65	0.73	1.94	0.65	3.45	0.65	3.94	0.59	3.75	0.51	2.70	0.65	3.58	0.53
Profile 4	4.36	0.63	1.66	0.66	3.93	0.68	4.40	0.53	4.27	0.48	2.17	0.61	4.02	0.52
Study 2 (MTurk)														
Profile 1	2.87	0.88	2.02	0.78	2.78	0.86	3.67	0.72	3.94	0.67	2.87	0.86	3.45	0.69
Profile 2	3.63	0.67	2.67	0.81	3.08	0.43	3.37	0.48	3.33	0.51	2.82	0.54	3.40	0.33
Profile 3	3.46	0.82	1.57	0.59	3.44	0.70	4.18	0.54	4.29	0.56	1.97	0.61	3.73	0.59
Profile 4	3.91	0.85	1.34	0.47	4.16	0.45	4.52	0.54	4.60	0.54	1.38	0.60	4.18	0.59

Note. N = 479 (Study 1) and 483 (Study 2). PA = positive affect, NA = negative affect, E = extraversion, A = agreeableness, C = Conscientiousness, N = Neuroticism, O = Openness.

Table 10. Descriptive statistics of outcomes by the four latent profiles the undergraduate sample (top) and MTurk sample (bottom).

Study 1	Life Satisfaction		Job Satisfaction		CWB-I	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Profile 1	4.15	0.12	4.27	0.12	2.15	0.10
Profile 2	5.72	0.26	5.09	0.33	1.42	0.19
Profile 3	5.25	0.11	4.69	0.13	1.98	0.11
Profile 4	5.70	0.22	5.24	0.33	1.58	0.31

Study 2	Life Satisfaction		Job Satisfaction		CWB-I		Stress		Job Burnout	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Profile 1	4.08	0.11	3.73	0.06	1.76	0.06	0.91	0.05	2.72	0.06
Profile 2	5.45	0.15	3.65	0.10	3.33	0.18	1.51	0.10	2.67	0.08
Profile 3	5.33	0.10	4.10	0.06	1.37	0.04	0.39	0.05	2.15	0.06
Profile 4	5.77	0.29	4.21	0.30	1.13	0.09	0.22	0.11	2.23	0.29

Note. N = 479 (Study 1) and 483 (Study 2).

Table 11. Regressions of the dummy-coded resilience profiles on outcomes (i.e., life satisfaction, job satisfaction, and CWB-I) in the undergraduate sample.

	Criterion variables		
Predictors (β)	Life Satisfaction	Job Satisfaction	CWB-I
Age	.01	.00	.05
Gender (female)	.07	.11*	-.15**
Other (gender)	.04	.06	.00
Profile 2	.22***	.09*	-.15**
Profile 3	.26***	.10	-.02
Profile 4	.20***	.11*	-.14**
R^2(adj.)	.12(.11)***	.03(.02)*	.06(.05)***

Note. $N = 479$. Profile 1 and male were used as reference variable. Values in parentheses are adjusted R^2s; scores on job satisfaction and CWB-I were log-transformed. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 12. Incremental validity of the resilience profiles over the five-dimensional scale scores of the 5×5 RS in the undergraduate sample.

Predictors (β)	Criterion variables: Life Satisfaction		Job Satisfaction		CWB-I	
	Step 1	*Step 2*	*Step 1*	*Step 2*	*Step 1*	*Step 2*
Age	.04	.04	.02	.03	.04	.03
Gender (female)	.04	.04	.08	.08	-.14**	-.14**
Other (gender)	.03	.03	.05	.05	.00	.00
AD	.01	.03	.12*	.16**	-.07	-.06
ER	.06	.06	-.06	-.05	-.01	-.03
OP	.26***	.27***	.20**	.25***	-.16*	-.20**
SE	.04	.04	.01	.00	-.11	-.06
SS	.30***	.31***	.10	.12	-.02	-.04
Profile 2		.00		-.09		.00
Profile 3		-.01		-.08		.12*
Profile 4		-.06		-.10		.01
R^2(adj.)	.32(.31)***	.32(.31)***	.12(.11)***	.13(.11)***	.11(.09)***	.12(.10)***
ΔR^2(adj.)		.00(.00)		.01(.00)		.01(.00)

Note. N = 479. AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support. Profile 1 and male were used as reference variable. Age, gender, and the dimension composites were entered in Step 1; the dummy-coded profiles were entered in Step 2. Changes in R^2s were calculated to assess incremental validity. Values in parentheses are adjusted R^2s; scores on job satisfaction and CWB-I were log-transformed.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 13. Incremental validity of the resilience profiles over personality variables and the five-dimensional scale scores of the 5×5 RS in the undergraduate sample.

Predictors (β)	Life Satisfaction			Job Satisfaction		
	Step 1	*Step 2*	*Step 3*	*Step 1*	*Step 2*	*Step 3*
PA	.42***	.37***	.37***	.23***	.20**	.19**
NA	-.29***	-.22***	-.22***	-.11*	-.09	-.09
E	.14***	.09*	.09*	.08	.08	.08
A	.05	.02	.02	.15**	.12*	.12*
C	-.04	-.05	-.05	-.01	.01	.02
N	-.09	-.04	-.05	-.06	-.09	-.10
O	-.06	-.05	-.05	-.05	-.07	-.07
Age	.03	.04	.04	.02	.03	.03
Gender (female)	.08*	.06	.06	.10*	.09	.09
Other (gender)	.03	.03	.03	.06	.06	.05
AD		-.02	-.01		.10	.15**
ER		.01	.00		-.10	-.11
OP		.12*	.13*		.08	.14
SE		-.04	-.04		-.04	-.06
SS		.15**	.16**		-.03	-.02
Profile 2			-.01			-.10*
Profile 3			-.02			-.09
Profile 4			-.05			-.10
R^2(adj.)	.39(.38)***	.42(.40)***	.42(.39)***	.17(.15)***	.18(.15)***	.19(.16)***
ΔR^2(adj.)		.02(.01)*	.00(.00)		.01(.00)	.01(.01)

Table 13. (Continued)

Note. $N = 479$. AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support; PA = positive affect; NA = negative affect; E = extraversion; A = agreeableness; C = Conscientiousness; N = Neuroticism; O = Openness. Profile 1 and male were used as reference variable. Personality variables (i.e., Big Five, PA, and NA), age, and gender were entered in Step 1; the dimension composites were added to the regression models in Step 2; the dummy-coded profiles were entered in Step 3. Changes in R^2s were calculated to assess incremental validity. Values in parentheses are adjusted R^2s; scores on job satisfaction and CWB-I were log-transformed.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 13. (Continued)

CWB-I		
Step 1	*Step 2*	*Step 3*
-.06	-.01	-.01
.11*	.07	.08
.12*	.12*	.10
-.35***	-.36***	-.35***
-.09	-.07	-.07
-.01	-.06	-.04
-.05	-.01	-.01
.03	.02	.02
-.11*	-.10*	-.11*
.00	.00	.01
	-.06	-.06
	-.03	-.04
	-.07	-.11
	-.06	-.02
	.03	.01
		.02
		.11
		.02
.24(.22)***	.24(.22)***	.25(.22)***
	.01(.00)	.01(.00)

Table 14. Regressions of the dummy-coded resilience profiles on outcomes (i.e., CWB-I, job satisfaction, life satisfaction, stress, and job burnout) in the MTurk sample.

	Criterion variables				
Predictor variables (β)	Life Satisfaction	Job Satisfaction	CWB-I	Stress	Job Burnout
Age	-.08	.02	-.19***	-.11**	-.10*
Gender (female)	-.02	.05	-.16***	.06	.08
Other (gender)	-.01	.01	-.10*	.02	-.01
Profile 2	.21***	.01	.31***	.20***	-.01
Profile 3	.35***	.17***	-.13**	-.29***	-.25***
Profile 4	.18***	.06	-.14***	-.18***	-.09*
R^2(adj.)	.14(.13)***	.03(.02)*	.24(.23)***	.21(.20)***	.09(.08)***

Note. $N = 483$. Profile 1 and male were used as reference variable. Values in parentheses are adjusted R^2s; scores on job satisfaction, stress, and CWB-I were log-transformed. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 15. Incremental validity of the resilience profiles over the five-dimensional scale scores of the 5×5 RS in the MTurk sample.

Predictors (β)	Life Satisfaction		Job Satisfaction		CWB-I	
	Step 1	*Step 2*	*Step 1*	*Step 2*	*Step 1*	*Step 2*
Age	-.11**	-.10*	.01	.02	-.19***	-.18***
Gender (female)	.02	.01	.03	.03	-.17***	-.18***
Other (gender)	-.02	-.01	.00	-.01	-.10*	-.10*
AD	.02	-.01	-.14**	-.11*	.07	.06
ER	.12*	.10*	-.09	-.10*	-.03	-.05
OP	.13*	.19***	.20***	.25***	-.23***	-.16**
SE	.09*	.14**	.22***	.25***	-.14**	-.08
SS	.30***	.29***	.25***	.28***	-.06	-.05
Profile 2		.26***		.10*		.27***
Profile 3		.03		-.08		-.02
Profile 4		-.01		-.12*		-.07
R^2(adj.)	.26(.25)***	.32(.31)***	.23(.21)***	.25(.23)***	.20(.19)***	.27(.26)***
ΔR^2(adj.)		.06(.06)***		.02(.02)***		.07(.07)***

Note. $N = 483$. Profile 1 and male were used as reference variable. AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support. Age, gender, and the dimension composites were entered in Step 1; the dummy-coded profiles were entered in Step 2. Changes in R^2s were calculated to assess incremental validity. Values in parentheses are adjusted R^2s; scores on job satisfaction, stress, and CWB-I were log-transformed. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 15. (Continued)

Stress		Job Burnout	
Step 1	*Step 2*	*Step 1*	*Step 2*
-.07	-.06	-.07	-.08
-.01	-.02	.07	.07
.00	.01	.00	.00
.06	.04	.03	.02
-.27***	-.29***	-.01	.00
-.33***	-.29***	-.34***	-.37***
.02	.06	.03	.01
-.19***	-.19***	-.21***	-.23***
	.18***		-.05
	.02		.05
	-.02		.08
.38(.37)***	.41(.40)***	.24(.23)***	.25(.23)
	.03(.03)***		.01(.00)

Table 16. Incremental validity of the resilience profiles over personality variables and the five-dimensional scale scores of the 5×5 RS in the MTurk sample.

Predictors (β)	Life Satisfaction			Job Satisfaction		
	Step 1	*Step 2*	*Step 3*	*Step 1*	*Step 2*	*Step 3*
PA	.15***	.32***	.26***	.24***	.23***	.19***
NA	.40	.06	.02	-.12*	-.10	-.12*
Extraversion	-.04**	.06	.06	.17***	.11*	.12*
Agreeableness	-.20	-.09	-.07	.16**	.14*	.15**
Conscientiousness	-.06**	.08	.13*	.07	-.07	-.06
Neuroticism	.35***	-.10	-.05	.04	.03	.04
Openness	.06**	-.12**	-.13**	-.06	-.09	-.08
Age	-.03*	-.10*	-.10**	.01	.02	.03
Gender (female)	.04	.06	.04	.06	.06	.05
Other (gender)	.01	.01	.02	.01	.00	-.01
AD		-.02	-.02		-.16***	-.12*
ER		.11*	.09		-.05	-.06
OP		.08	.10		.09	.13*
SE		.08	.11*		.24***	.26***
SS		.18**	.17**		.08	.12
Profile 2			.19***			.06
Profile 3			.06			-.09
Profile 4			.01			-.11*
R^2(adj.)	.33(.32)***	.36(.34)***	.39(.37)***	.24(.22)***	.30(.27)***	.31(.28)***
ΔR^2(adj.)		.03(.03)***	.03(.03)***		.06(.05)***	.01(.01)*

Table 16. (Continued)

Note. $N = 483$. Profile 1 and male were used as reference variable. AD = adaptability; ER = emotion regulation; OP = optimism; SE = self-efficacy; SS = social support. Personality variables (i.e., Big Five, PA, and NA), age, and gender were entered in Step 1; the dimension composites were added to the regression models in Step 2; the dummy-coded profiles were entered in Step 3. Changes in R^2s were calculated to assess incremental validity. Values in parentheses are adjusted R^2s; scores on job satisfaction, stress, and CWB-I were log-transformed. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. $^{+}p < .1$

Table 16. (Continued)

CWB-I			Stress			Job Burnout		
Step 1	*Step 2*	*Step 3*	*Step 1*	*Step 2*	*Step 3*	*Step 1*	*Step 2*	*Step 3*
.26***	.26***	.20***	.15***	.14***	.12**	-.06	-.06	-.03
.14**	.12*	.07	.40***	.39***	.38***	.13**	.10*	.12*
-.04	-.02	-.02	-.04	-.05	-.05	-.17***	-.18***	-.19***
-.38***	-.37***	-.35***	-.20***	-.21***	-.21***	-.19***	-.17***	-.18***
-.14**	-.09	-.05	-.06	-.08	-.06	-.02	-.03	-.04
-.01	-.11	-.07	.35***	.31***	.33***	.19**	.20**	.19*
-.07	-.06	-.06	.06*	.05	.04	.03	.00	.00
-.14***	-.14***	-.14***	-.03	-.02	-.02	-.07	-.06	-.06
-.07	-.08*	-.10*	.04	.03	.02	.06	.08	.08
-.07	-.07	-.07	.01	.00	.01	.00	.00	.00
	.02	.04		.01	.00		.06	.03
	-.05	-.07		-.07	-.09*		.04	.04
	-.12	-.08		.01	.01		-.14*	-.17**
	-.07	-.04		.05	.06		.07	.06
	-.01	.00		.00	-.01		.03	.00
		.17***			.07*			-.05
		.01			.05			.07
		-.06			.00			.09*
.34(.32)***	.35(.33)***	.37(.35)***	.62(.61)***	.63(.61)***	.63(.62)***	.32(.30)***	.33(.31)***	.34(.31)
	.01(.01)$^{+}$	.02(.02)***		.00(.00)	.00(.00)		.01(.01)	.01(.01)$^{+}$

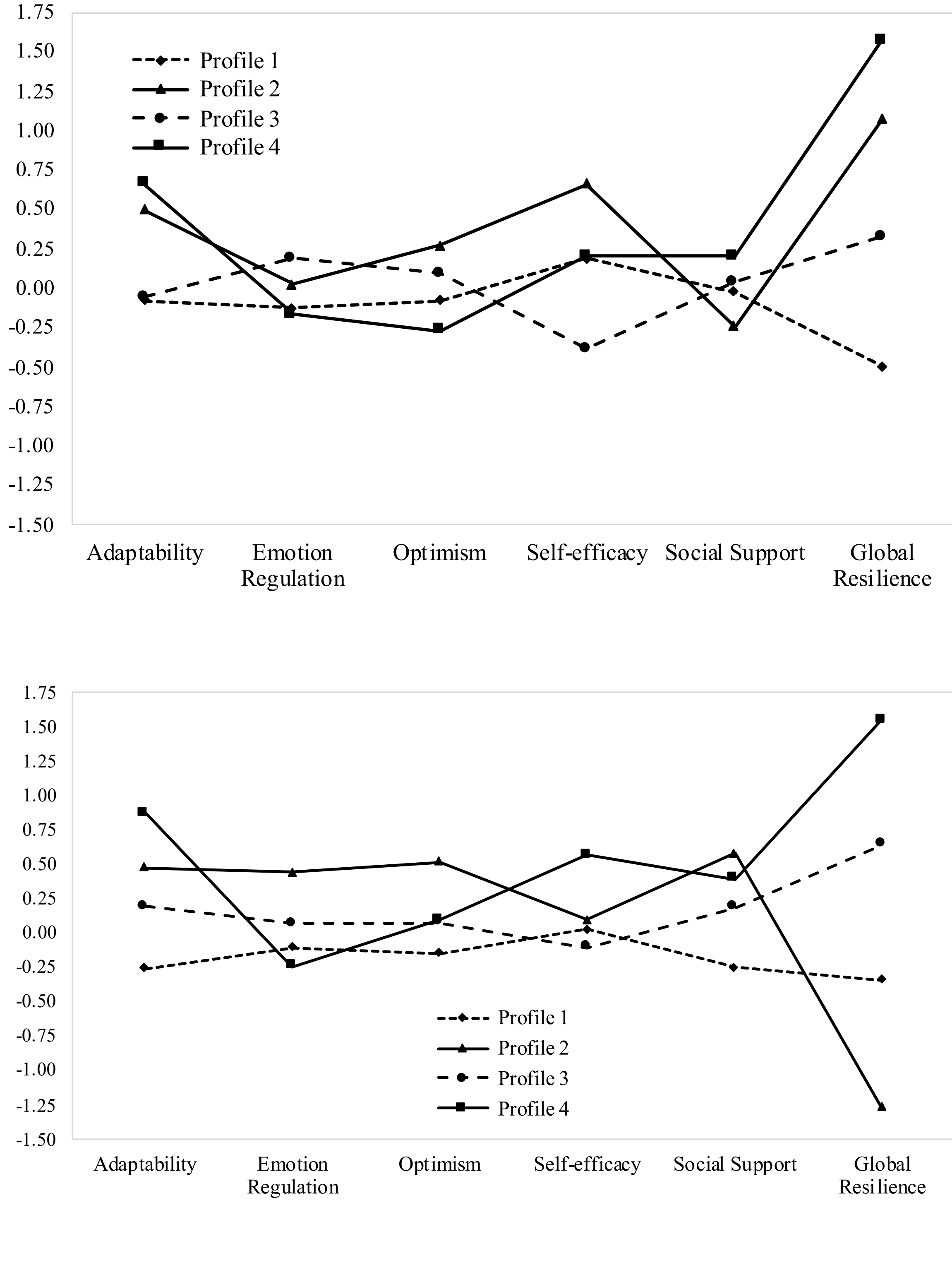
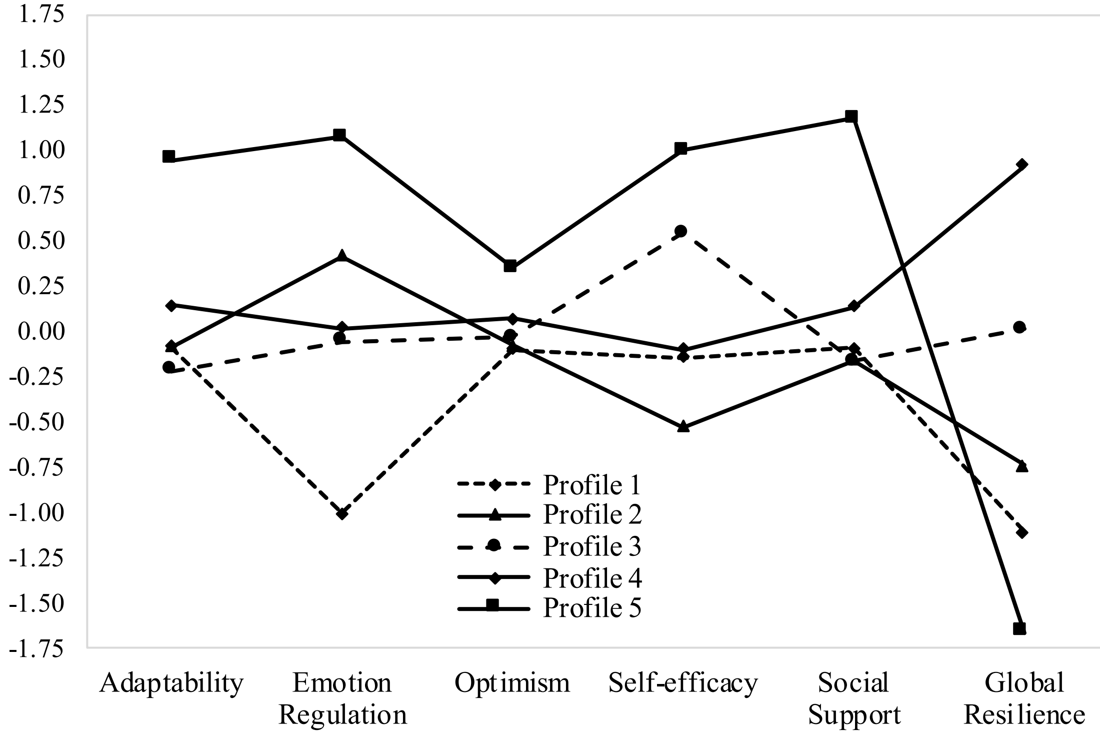


Figure 1. The 4-profile LPA model showing four latent profiles of five specific factors (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) and global factor of resilience in the undergraduate sample (top) and MTurk sample (bottom).



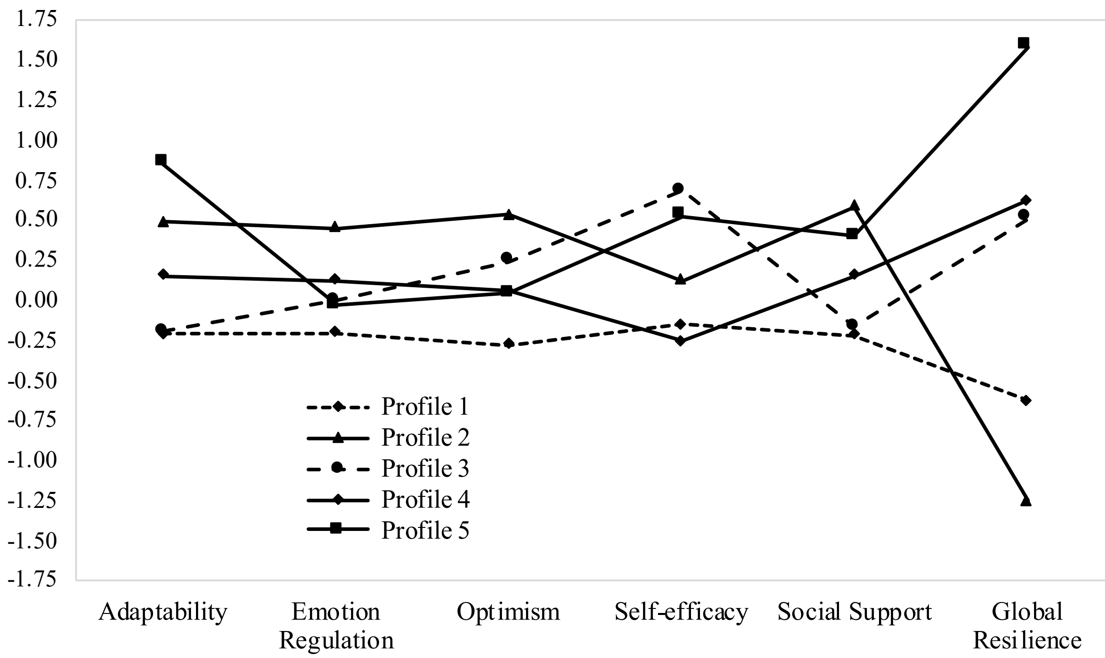


Figure 2. The 5-profile LPA model showing five latent profiles of five specific factors (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) and global factor of resilience in the undergraduate sample (top) and MTurk sample (bottom).

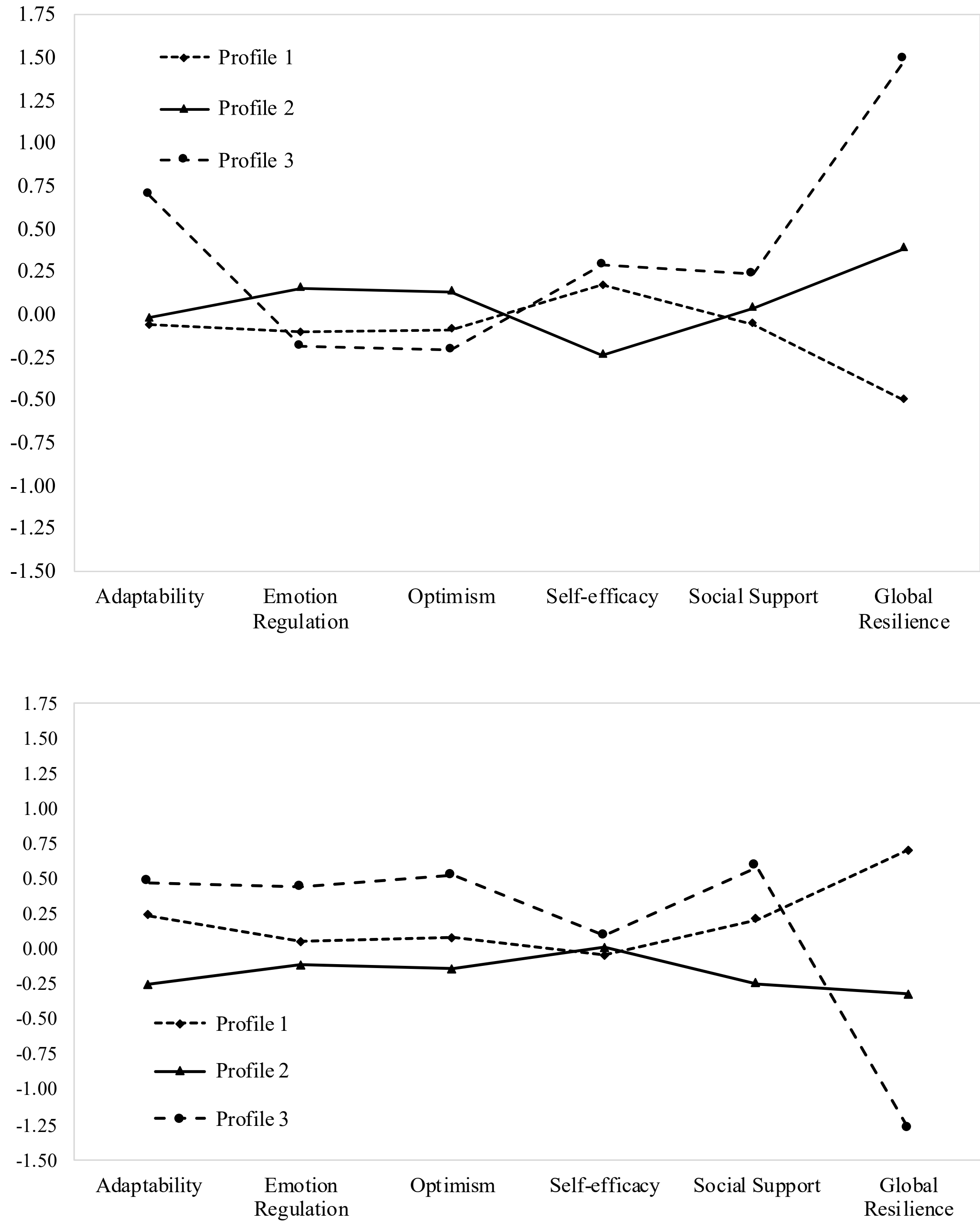


Figure 3. The 3-profile LPA model showing three latent profiles of five specific factors (i.e., adaptability, emotion regulation, optimism, self-efficacy, and social support) and global factor of resilience in the undergraduate sample (top) and MTurk sample (bottom).

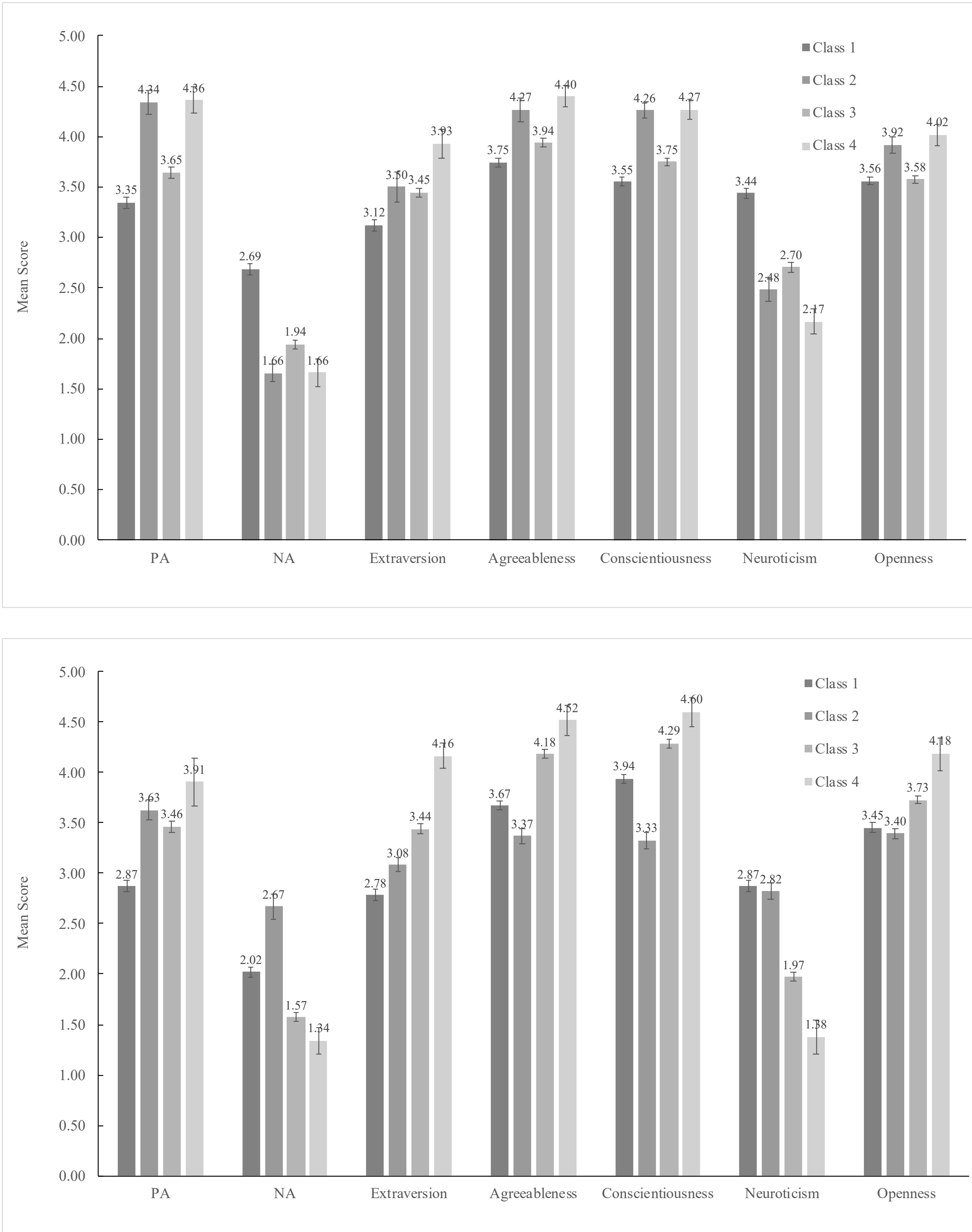
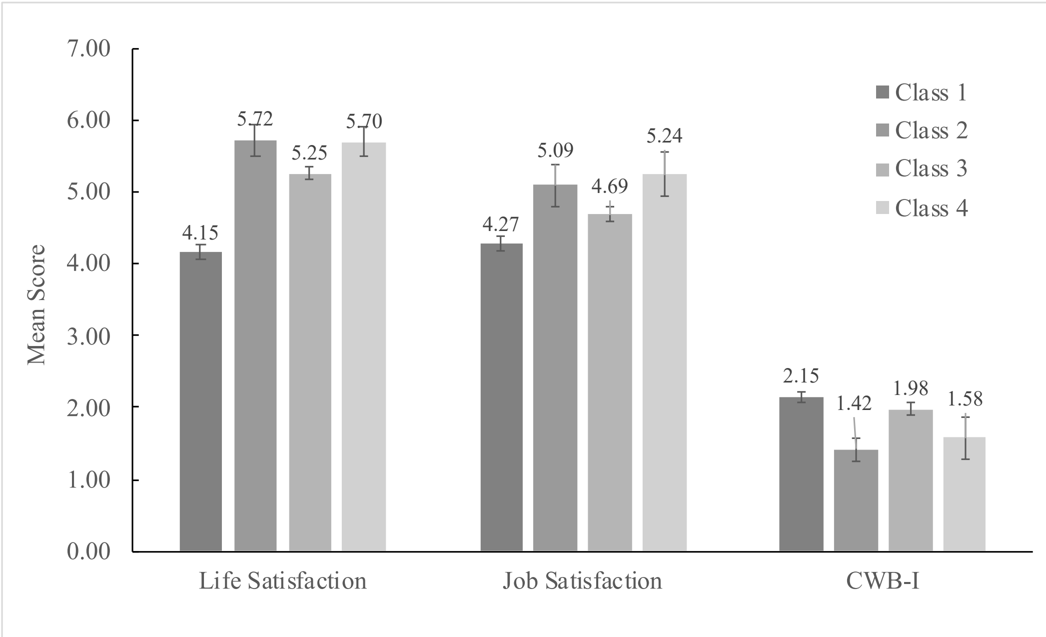


Figure 4. Mean scores of personality correlates by the four latent profiles in the undergraduate sample (top) and MTurk sample (bottom). Error bars show standard errors.



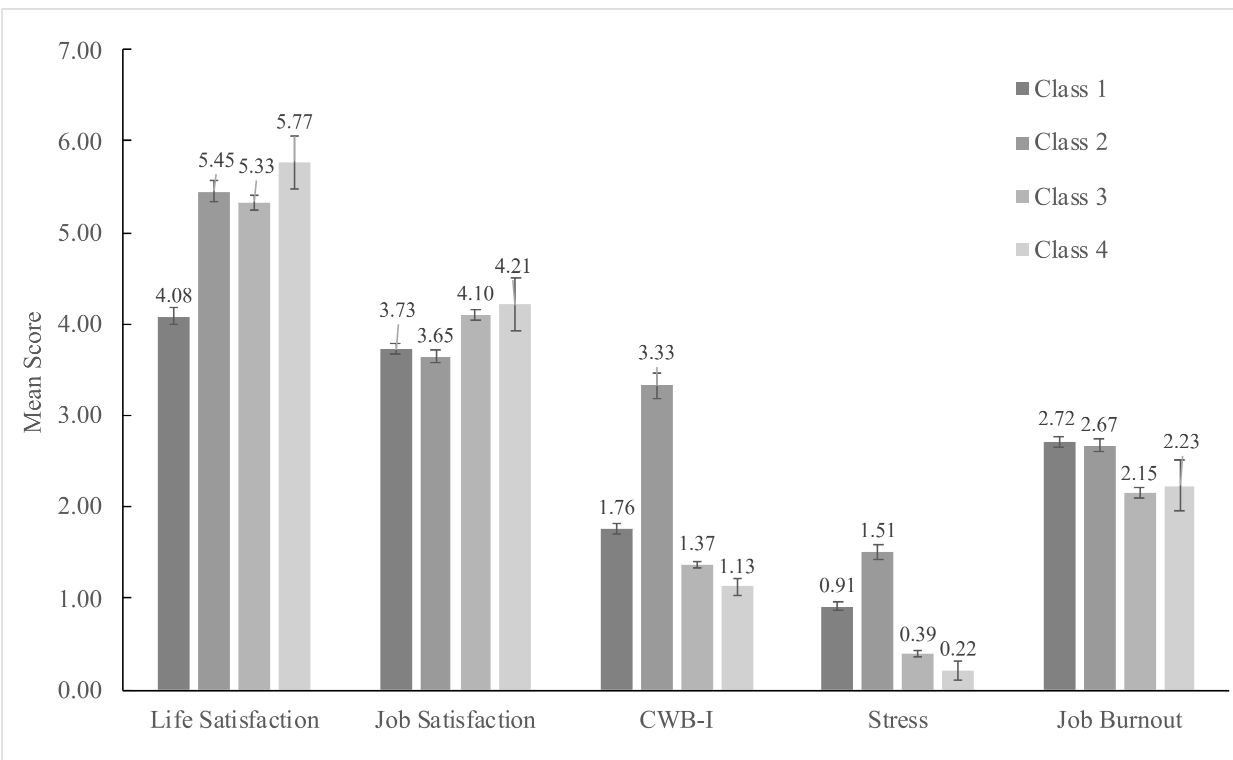


Figure 5. Mean scores of outcomes by the four latent profiles in the undergraduate sample (top) and MTurk sample (bottom). Error bars show standard errors.

DISCUSSION

The current project explored the nature and construct validity of latent profiles of resilience, using both undergraduate and MTurk samples and compared the results of a person-centered approach with the results of a variable-centered approach predicting work and life outcomes. In Study 1, a set of four latent profiles of resilience was successfully identified in the undergraduate sample, and the profiles demonstrated differential relationships with personality variables and outcomes. In Study 2, the 4-profile solution was partially replicated in the MTurk sample; three out of four profiles showed similar patterns as demonstrated in the undergraduate sample. Additionally, the profiles revealed in the MTurk sample showed meaningful differentiations predicted by personality variables and differential relationships with outcomes. Last, profile membership provided incremental validity beyond resilience dimension scores and personality variables, suggesting that a person-centered approach may be a promising complement to the more traditional variable-centered approach to predicting outcomes. A few findings are worth highlighting and are discussed below.

Study 1

LPA in Study 1 indicated a set of four latent profiles of resilience, with unique patterns and differential relationships with personality variables and work and life outcomes. In particular, there were four profiles of undergraduate students with varying levels of global resilience and differently shaped patterns depicting the relative positions of the five indicators. Specifically, both Profiles 1 and 3 had the lowest and second lowest levels of global resilience. Profile 1 was relatively low on all five resilience indicators, whereas Profile 3 had the highest (or second highest) levels of emotion regulation, optimism, and social support even though it was low(est) on adaptability and self-efficacy. It may be that high levels of emotion regulation, optimism, and social support in Profile 3 serve as a "buffer" against low levels of adaptability and self-efficacy, resulting in relatively higher global resilience compared to Profile 1. Profile 3 also had higher levels of extraversion and lower levels of NA and neuroticism than Profile 1, which had the highest levels of NA and neuroticism. Individuals in Profile 1 reported worse work and life outcomes than other profiles—with the lowest levels of life and job satisfaction and highest levels of CWB-I.

Additionally, both Profiles 2 and 4 in Study 1 had (between-profile) high levels of global resilience; however, the within-profile relative positions of the five indicators are different: Profile 4 had low levels of optimism and emotion regulation but high levels of adaptability, social support, and self-efficacy; in comparison, Profile 2 had high levels of self-efficacy, adaptability, and optimism, but low levels of social support and emotion regulation. It seems that the high levels of adaptability, social support, and self-efficacy found in Profile 4 may have a "compensatory" effect on low levels of emotion regulation and optimism. Further, the high levels of self-efficacy, optimism, and adaptability in Profile 2 may offset the negative effects of low social support and emotion regulation. It may be that the high levels of global resilience found in these profiles is facilitated by this compensatory effect.

It is noteworthy that even though Profiles 2 and 4 had different patterns relating to the five dimensions, they were not differentiated based on Big Five personality traits or affect. It is possible that other individual differences such as coping styles (e.g., approach vs. avoidance; seeking emotional/instrumental social support, positive reinterpretation and growth, or venting of emotions; see Carver, 1997) or emotion regulation strategies (e.g., cognitive reappraisal, acceptance or expressive suppression; Gross & John, 2003; Segal et al., 2002) might explain the differences found between Profiles 2 and 4. For instance, individuals in Profile 4 may seek instrumental/emotional support to cope with stress, whereas individuals in Profile 2 may resort to positive reinterpretation or cognitive reappraisal to reframe challenging situations.

Even though Profiles 2 and 4 are distinct (Profile 4 had low optimism and emotion regulation, and high adaptability and social support, whereas Profile 2 had high optimism, low social support and emotion regulation), comparisons of their work and life outcomes suggest that both profiles have similar outcomes. Both profiles have higher levels of both life and job satisfaction, along with lower levels of CWB-I. As discussed previously, it is conceivable that the higher levels of other dimensions in members of these two profiles may offset the negative effects of the weaker dimensions (i.e., optimism and emotion regulation in Profile 4 and social support and emotion regulation in Profile 2), the result of which is that people with either profile have positive work and life outcomes.

Study 2

Profile membership in the MTurk sample provided significant incremental variance in life satisfaction and job satisfaction beyond the five dimensions of resilience, Big Five personality traits, and trait affect. This finding provides empirical support for the potential benefits of considering a person-centered approach when attempting to predict outcomes such as these. Specifically, profiles offered 2-7% additional variance explained in life satisfaction, job satisfaction, CWB-I, and stress beyond the five dimensions of the 5×5 RS. After personality variables (the Big Five, PA, and NA) were taken into consideration, profile membership explained an additional 3% and 6% of the variance, respectively, beyond resilience dimensions and personality variables in life and job satisfaction. Although it is relatively small, accounting for this variance has the potential to greatly benefit theoretical development and organizational practices. Adopting a person-centered approach in addition to a variable-centered approach may be advantageous in explaining and predicting both work and life outcomes. The advantage of the person-centered approach shown in the present study is consistent with Roth and von Collani (2007), who found that the Big Five topology provided additional predictive power beyond personality dimensions, but is contrary to Pilarska et al. (2018) who found no evidence for the increment in predictive power provided by personality types. Although the findings of Study 2 are encouraging, these efforts should be considered preliminary, as no significant incremental variance was detected in Study 1. Importantly, the incremental variance found in the Study 2 MTurk sample appears to be largely due to Profile 2 significantly predicting life satisfaction and CWB-I (see Table 15). The results of the present study indicate that a person-centered approach is complementary to a variable-centered approach, and may be beneficial when exploring different patterns of resilience and attempting to answer different types of research questions (see pp. 15-17 for a discussion on using person- vs. variable-centered approaches in research). The study should be replicated in both student and full-time working populations to examine incremental validity of the profiles before definitive conclusions can be made.

Comparing Studies 1 and 2

Although the profiles found in Study 1 were partially replicated in Study 2, some important differences were observed. Specifically, while Profiles 1, 3, and 4 demonstrated similar shapes in both samples, Profile 2 exhibited opposite patterns in Studies 1 and 2. In Study 1, Profile 2 had the second highest levels of global resilience, high(est) levels of self-efficacy, optimism, adaptability, and lowest levels of social support; whereas in Study 2 it had low self-efficacy, high(est) levels of emotion regulation, optimism, social support, and adaptability, and yet lowest levels of global resilience. Additionally, profiles in both studies showed somewhat similar patterns of associations with personality variables and outcomes (see Figures 4-5 and Tables 7-8) and the mean levels of these personality and outcome variables for the profiles were comparable (see Tables 9 and 10 for descriptive statistics). For instance, neuroticism significantly differentiated Profile 1 from other profiles in both studies, such that individuals with higher levels of neuroticism were more likely to be in Profile 1 (lowest levels of global resilience and low levels of all five indicators) compared to other profiles. Profile 4 (highest levels of global resilience and adaptability, high levels of self-efficacy and social support, and lowest levels of emotion regulation) had significantly lower levels of CWB-I than Profile 1 in both samples. Last, profile membership showed incremental validity beyond the five dimensions of resilience and personality variable when predicting life and job satisfaction in Study 2, whereas no significant incremental validity was found in Study 1.

One potential explanation for these differences is demographic differences observed between the undergraduate and MTurk samples. As shown in Table F.1., the undergraduate sample was younger, predominantly female, more diverse, had less years of education, and a lighter workload per week, as compared with the MTurk sample, which was older, more gender balanced, predominantly white, had more years of education, and heavier workload per week. Another explanation for the differences in profiles observed is a potential cohort effect resulting data collection that occurred during the ongoing COVID-19 pandemic. In an attempt to at least partially account for this, the MTurk sample in Study 2 was administered four single-item questions to assess the impact of the pandemic on their emotional well-being, employment, and their life in general (see Appendix G for the questions). As shown in Table F.2. the pandemic had considerable impact on emotional well-being, employment, and life in general. The findings in Study 2 may be idiosyncratic to this sample due to them completing the study during the pandemic. In particular, the distinct (and seemingly counterintuitive) pattern seen in Profile 2 might be due to this cohort effect. However, Profile 2 did not differ significantly from other profiles regarding their ratings of how COVID-19 had impacted them. Further, the demographic characteristics of Profile 2, and the correlations between the five resilience indicators and COVID-related questions, were not noticeably different compared to other profiles (see Figures F.2.–F.9.).

Also included in the survey were questions measuring psychological distress, reflected by symptoms associated with depression, anxiety, and stress (see Appendix G for DASS-21, which consists of depression, anxiety, stress three subscales). A total (sum) score for psychological distress was calculated, along with scores for each of the three subscales. Profile 2 had much higher levels of psychological distress compared to other profiles (see in Table F.2. for descriptive statistics). It may be that individuals in Profile 2 experienced severe psychological distress or physical and/or mental health problems, possibly due in large part to the pandemic, which resulted in Profile 2 having the lowest level of global resilience, despite scoring relatively higher on the five indicators than the other profiles. Nevertheless, additional employee data needs to be collected to examine whether the nature of the resilience profiles found in Study 2 is unique to this particular MTurk sample.

Strengths

Based on a thorough review of the literature, the current project appears to be the first study of its kind to explore the nature of latent profiles of resilience and compare a person-centered approach with a variable-centered approach. As initially hypothesized, a set of latent profiles of resilience was found in both undergraduate and MTurk samples. The four profiles represented different combinations of the resilience indicators and global resilience, and had unique relationships with personality variables and outcomes. Notably, Profiles 2 and 4 in Study 1 demonstrated that some aspects of resilience may have trade-off effects which allow individuals to maintain high levels of global resilience and positive work and life outcomes, despite having deficits in other dimensions. Such nuanced trade-off patterns would not be easily captured based solely on a variable-centered approach. Additionally, the present study demonstrated some of the potential advantages of utilizing a person-centered approach (based on latent profiles of resilience) to predict work and life outcomes in addition to a variable-centered approach. Specifically, the MTurk sample in Study 2 demonstrated that profile membership provided added predictive value beyond resilience dimensions and personality when predicting life and job satisfaction. The promising results of the current exploratory research help set the stage for future studies to further examine resilience typology and explore the utility of using a person-centered approach in conjunction with a variable-centered approach.

Additionally, the present project utilized novel methodologies when conducing LPA to separate the *shape* of the profiles from their *levels*. Specifically, based on recommendations from Morin and colleagues (2016; 2017), factor scores were derived from a bi-factor ESEM model and used for LPA model estimation, allowing the separation of mean differences in the overall levels of resilience (global resilience) from the relative positions of responses on dimensions of resilience. Using factor scores also partially controlled for measurement error in the responses. This approach provides a more interpretable representation of the profiles, helping to clarify which profile has ipsatively higher or lower levels of resilience indicators and associated overall normative differences in global resilience.

Finally, another strength of the current study was the use of two samples with different demographic characteristics to explore latent profiles of resilience and investigate whether the identified profiles were generalizable across different populations. Three of four profiles were similar across the undergraduate and MTurk samples. The wide range of personality and outcome variables included helped to examine construct validity, establish a preliminary nomological net, and provide additional meaning to the profiles. Although the profiles identified in the undergraduate sample were only partially replicated in the MTurk sample, the relatively consistent findings between samples (such as the shapes of Profiles 1, 3, and 4, and their relationships with personality and outcomes) hold promise for future research to investigate whether latent profiles of resilience are stable across various populations.

Limitations

While the findings of this research are notable, and advance the current state of resilience literature, it is not without limitations. First, BLRT values for the Profiles 3 through 6 could not be obtained in the MTurk sample due to local maxima in the bootstrapped likelihood ratio tests, despite multiple attempts using different random start values for the BLRT to aid in model convergence. Even though the BLRT has notable advantages over other model fit indices, it relies on assumptions that may be violated and thus may not be suitable for complex survey data compared to the LMRT (Nylund et al., 2007). Additionally, simulation studies on the use of fit indices and tests of significance may have "limited generalizability for applied researchers who seek to test models with real data" (Marsh et al., 2009, p. 214), particularly in the case of complex data and LPA models in which latent profiles "represent a combination of differences in level and shape" (p.215). Responses collected from the MTurk sample, and the use of factor scores derived from a bi-factor ESEM model, may have resulted in complexities in the data, which rendered the BLRT an unfeasible statistical test for the current project. Rather than relying solely on the BLRT to select the best LPA solution, other model fit indices were considered, as well as the distribution of responses in each profile, the shapes of the profiles, and “a priori predictions” based on the results of Study 1 (see Marsh, .2004; Marsh et al., 2009 for arguments against solely using fitness indices and significance testing when determining model selection). Nevertheless, future examination of this topic would be wise to collect additional data to further examine BLRT statistics and significance levels and determine whether the problems encountered here are widespread.

Another potential limitation of this study is due to the quality of the MTurk data and potential systematic differences in data collected from participants via MTurk during the pandemic. While extensive efforts were made to exclude careless responders and aberrant responses, data collected during a once-in-a-century pandemic may also limit the generalizability of the findings, and should be interpreted with caution. Additionally, even though aberrant responding detection was conducted to exclude inconsistent responses, the distribution of the l_z values was negatively skewed, violating the assumption that the l_z distribution follows a standard normal curve; the use of l_z person-fit statistic is also predicated on good model-data fit and item-data fit, which may not be robust in this MTurk sample (Meijer & Tendeiro, 2012). Instead of relying on the conventionally adopted cutoff of $l_z < -1.645$ at $\alpha = .05$, the bottom 10% of the l_z values was used as the cutoff point, excluding 10.06% of the responses. These caveats need to be kept in mind when interpreting the results found in the MTurk sample.

Last, Profile 2 in the MTurk sample had a different shape than in the undergraduate sample, and elevated levels of psychological distress (conceivably due to the pandemic). Profile 2 might have also contributed to the significant incremental validity that profile membership added beyond resilience dimensions and personality variables in the MTurk sample; in comparison, profiles did not provide significant incremental variance in the undergraduate sample. Further examination of employee samples is needed to evaluate whether the results found in Study 2 are unique to this particular MTurk sample or are replicable in other employee samples.

Implications and Future Research

Implications for Theory

The latent profiles of resilience found in this study support the argument that “there is no single resilient type” (Bonanno, 2005, p. 135) (Bonanno, 2005, p.135); rather, patterns of resilience in individuals exist heterogeneously (Bonanno, 2005; Coifman et al., 2007). Indeed, both undergraduate and MTurk samples in this study demonstrated distinct patterns of resilience that were differentially associated with the Big Five, trait affect, and work and life outcomes. Additionally, latent profiles of resilience may suggest a new avenue of research within the broaden-and-build theoretical framework (Fredrickson, 1998, 2001). According to the broaden-and-build theory of positive emotions, individuals with high levels of psychological resilience experience more positive emotions, which help to more effectively regulate their emotions and bounce back from stressful situations and flourish. A prospective study found that resilient individuals experienced more positive emotions, which in turn predicted lower levels of depressive symptoms and higher levels of personal growth (in the form of life satisfaction, optimism, and tranquility) after the 9/11 attacks (Fredrickson et al., 2003). Tugade and Fredrickson (2004) also found that resilient individuals showed faster physiological recovery from negative emotional experiences and were better able to find meaning and purpose in negative encounters. The latent profiles found in the current study suggest that individuals with varying levels and patterns of resilience might have different coping and emotion regulation strategies to boost positive emotions during challenging circumstances. It may be that profile membership moderates the pathway through which resilient individuals utilize different strategies to increase positive emotions that in turn buffer the adverse impact of stress and/or trauma and help to find positive meaning and thrive.

Furthermore, it is important to consider examining both *intra*- and *inter*-individual differences. Recent research argues that there may be different adjustment trajectories of resilience (minimal-impact vs. emergent resilience) as a function of the impact and length of the adverse event (single-incident traumas vs. chronic adversity). In a similar vein, there might be varying coping trajectories associated with different latent profiles of resilience. In fact, there is preliminary evidence that different types of recovery trajectories of resilience are present among police officers, although the overall level of resilience remained relatively stable over a 9-month time period (Meulen et al., 2019). An important next step is to collect longitudinal data and model the results using longitudinal latent class analysis (LLCA) to address the question of whether the set of latent profiles of resilience shown in the current study are associated with different coping and adjustment trajectories over time.

Implications for Practice

Training. The present study bears practical implications regarding employee training and development in organizations; latent profiles of resilience may present a relatively holistic opportunity for organizations and managers to categorize and understand employees. Managers and organizations may identify employees based on the level and shape of their profiles and provide targeted feedback and training to improve their overall resilience and/or target relatively weaker (within-person) dimensions of resilience. Training programs may also potentially be developed for people with different profiles to improve their overall resilience and coping strategies in a comprehensive manner, rather than targeting specific dimensions of resilience. It is conceivable that employees with high levels of global resilience and (within-person) low levels of specific resilience indicators undergo training programs that are targeted toward their weaker areas (social support in Profile 2 for example), while those with low levels of global resilience and low levels of specific resilience dimensions enroll in a more comprehensive resilience-building program. Such a targeted approach may be more cost-efficient to organizations and more effective at improving resilience.

Additionally, using a person-centered approach and latent profiles of resilience may be relevant to the field of occupational health psychology (OHP) and organizational efforts to improve employee psychological well-being, job satisfaction, emotional exhaustion, engagement, interpersonal relationships (e.g., bullying, OCB-I, CWB-I), and turnover (Bouckenooghe et al., 2019; Cooke et al., 2019; Liu et al., 2014). The present study suggests that different profiles of resilience are associated with different levels of job satisfaction, burnout, and CWB-I to varying degrees; one profile has relatively higher/lower levels of these outcomes than another profile. It is conceivable that pinpointing employees who are more likely to have negative outcomes based on their profiles, and encouraging them to participate in training programs tailored to their profiles, organizations may be able to improve employee well-being, job and life satisfaction, and productivity.

Selection. Organizational scientists and practitioners might be tempted to consider using latent profiles of resilience for personnel selection, and rightly so. A person-centered configural approach linking individual differences and performance has in fact been explored in selection research (Shen, 2011). It is thus reasonable to contemplate including latent profiles of resilience in the selection process, especially in settings where resilience is crucial to work outcomes (e.g., law enforcement, healthcare, competitive sports, military), after profile membership has been empirically validated. That said, latent profiles of resilience may be better suited for training than for selection in high stakes settings. Specifically, a clear consensus is lacking when it comes to defining and operationalizing resilience (Pangallo et al., 2015; Teng et al., 2019), and there is a criterion problem particularly when applied to the workplace (Britt et al., 2016). It is unclear which outcome(s) should be emphasized and included in evaluating the criterion-related validity of resilience, or whether the assessment is tapping into the demonstration of resilience or resilience itself. It is also unclear whether resilience predicts job performance even though similar constructs, such as PsyCap and hardiness, have demonstrated positive correlations with performance in recent meta-analyses (Avey et al., 2011; Eschleman et al., 2010; Newman et al., 2014). For example, one study reported that resilience positively correlated with perceived (but not objective) job performance (Youssef & Luthans, 2007); one meta-analysis found that the effectiveness of resilience-training programs on objective performance (supervisor ratings and task completion) diminished over time after more than 1 month following training (Vanhove et al., 2015). Additionally, although assessments of resilience have been incorporated into selection systems in military contexts (Drasgow et al., 2012; Naemi et al., 2014), "evidence for whether they *should* select for resilience and *how* to best select for resilience seems to be less clear, especially in jobs or situations where the likelihood of experiencing significant trauma or adversity is low" (Britt et al., 2016, p.389). It remains to be established whether measures of resilience will consistently and directly predict (objective) job performance outside military contexts (Kašpárková et al., 2018; Youssef & Luthans, 2007), especially over time (Britt, et al., 2016). Potential adverse impacts of using assessments of resilience in selection needs also to be investigated.

Moreover, considering that definitions and conceptualizations of the construct are under debate, resilience assessments may suffer from construct deficiency or contamination, potentially having varying degrees of overlap with some aspects of the Big Five and other personality traits; whether these resilience measures provide incremental validity beyond these personality inventories commonly used for selection needs to be carefully examined (see Britt, et al., 2016 pp. 388-389 for a discussion on using assessments of resilience for selection). Similarly, it is unclear whether latent profiles of resilience may add incremental variance beyond overall resilience and known predictors such as general mental ability, the Big Five, and integrity; the incremental validity provided by profile membership demonstrated in the current study was limited to CWB-I. Critically, resilience is commonly assessed with self-report measures, which are susceptible to social desirability and faking (Eschleman & Wright, 2016). Although assessments may be developed and used for selection that are more faking-resistant (e.g., assessment centers), it is unclear whether similar (or the same) latent profiles of resilience would emerge and be valid for selection purposes. Thus, it is reasonable to suggest that resilience as a construct, and more specifically latent profiles of resilience, may be more relevant for training. Hiring practices relying on assessments of resilience and latent profiles should proceed with caution.

Finally, given consistently demonstrated associations between resilience and psychological distress and disorders (Grossman, 2014; Hu et al., 2015), it may be that latent profiles of resilience are associated with mental health problems, although assessing differential mental health outcomes between resilience profiles is not within the scope of the current study.

Mental health concerns may have legal implications for organizational hiring practices and bring challenges to companies' existing employee assistance programs (EAPs), both of which are costly to organizations (Follmer & Jones, 2018). Thus, it is advisable that the set of four latent profiles of resilience presented in this study be explored further before being considered for selection practices.

Conclusion

In closing, the current investigation utilized two samples to generate and explore a set of latent profiles of resilience and associated variables, such as personality and work and life outcomes. A person-centered approach was examined in comparison with a variable-centered approach for predicting these outcomes. Four latent profiles in the undergraduate sample and were partially replicated in the MTurk sample. The four profiles show preliminary evidence of construct validity, evidenced by their differential relationships with personality variables and work and life outcomes. Lastly, in Study 2 profile membership showed incremental validity predicting outcomes beyond personality and resilience dimensions. The current findings have implications for theoretical development within the framework of broaden-and-build theory of positive emotions, and may help to improve practices related to training and employee experiences in organizations in regard to training and employee experience. Considering that using a person-centered approach for studying resilience and applying to organizational practices is still in infancy, the current project points to a promising avenue to advance our understanding of different styles of resilience and move the field forward.

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APPENDIX A:

SUPPLEMENTAL FACTOR ANALYSIS IN STUDY 1

Table A.1. CFA on scores on the 5×5 RS

Model	$\chi^2(df)$	CFI	TLI	RMSEA	SRMR	AIC	BIC	sBIC
Correlated factor	1370.948(265)***	0.816	0.792	0.093 [0.088, 0.098]	0.084	31400.002	31754.596	31484.816
Higher-order factor	1432.920(270)***	0.807	0.786	0.095 [0.090, 0.100]	0.089	31451.974	31785.710	31531.799
Bifactor	1151.823(250)***	0.850	0.820	0.087 [0.082, 0.092]	0.075	31210.877	31628.047	31310.658

Note. $N = 479$; df = degrees of freedom; 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; sBIC = sample-size adjusted BIC; CFA = confirmatory factor analysis. *** $p < .001$

Table A.2. ESEM analysis on scores on the 5×5 RS

Model	$\chi^2(df)$	CFI	TLI	RMSEA	SRMR	AIC	BIC	sBIC
Correlated factor	648.971(185)***	0.923	0.875	0.072 [0.066, 0.078]	0.031	30838.025	31526.355	31002.664
Higher-order factor	665.104(190)***	0.921	0.875	0.072 [0.066, 0.078]	0.034	30844.158	31511.630	31003.808
Bifactor	434.523(165)***	0.955	0.919	0.058 [0.052, 0.065]	0.023	30663.576	31435.341	30848.172

Note. $N = 479$; df = degrees of freedom; 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; sBIC = sample-size adjusted BIC; ESEM = exploratory structural equation modelling. *** $p < .001$

APPENDIX B:

SUPPLEMENTAL FACTOR ANALYSIS IN STUDY 2

Table B.1. CFA on scores on the 5×5 RS in the MTurk sample

Model	$\chi^2(df)$	CFI	TLI	RMSEA	SRMR	AIC	BIC	sBIC
Correlated factor	1166.664(265)***	0.830	0.808	0.084 [0.079, 0.089]	0.077	30640.579	30995.880	30726.097
Higher-order factor	1177.581(270)***	0.829	0.810	0.083 [0.079, 0.088]	0.079	30641.496	30975.897	30721.983
Bifactor	933.896(250)***	0.871	0.846	0.075 [0.070, 0.080]	0.063	30437.811	30855.813	30538.421

Note. N = 483; df = degrees of freedom; 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; sBIC = sample-size adjusted BIC; CFA = confirmatory factor analysis. *** $p < .001$

Table B.2. ESEM analysis on scores on the 5×5 RS in the MTurk sample

Model	$\chi^2(df)$	CFI	TLI	RMSEA	SRMR	AIC	BIC	sBIC
Correlated factor	549.281(185)***	0.931	0.889	0.064 [0.058, 0.070]	0.030	30183.196	30872.898	30349.201
Higher-order factor	552.887(190)***	0.932	0.892	0.063 [0.057, 0.069]	0.030	30176.802	30845.604	30337.777
Bifactor	375.475(165)***	0.960	0.928	0.051 [0.045, 0.058]	0.023	30049.39	30822.693	30235.517

Note. N = 483; df = degrees of freedom; 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; sBIC = sample-size adjusted BIC; ESEM = exploratory structural equation modelling. *** p < .001

Table B.3. Model comparison between the bi-factor CFA vs. ESEM models in the MTurk sample

		LRT							
	$\chi^2(df)$	$\Delta\chi^2$ (df)	RMSEA	ΔRMSEA	CFI	ΔCFI	TLI	ΔTLI	SRMR
CFA	933.896(250)***		0.075		0.871		0.846		0.063
ESEM	375.475(165)***	558.421(85)***	0.051	0.024	0.960	0.089	0.928	0.082	0.023

Note. $N = 483$; df = degrees of freedom; LRT = likelihood ratio test; 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; sBIC = sample-size adjusted BIC; CFA = confirmatory factor analysis; ESEM = exploratory structural equation modelling. *** $p < .001$

Table B.3. (Continued)

AIC	BIC	sBIC
30437.811	30855.813	30538.421
30049.390	30822.693	30235.517

APPENDIX C:

DETECTING ABERRANT RESPONSES IN STUDY 2

Aberrant responding analysis was conducted to exclude inconsistent responses. Because the 5×5 RS consists of five dimensions and responses are on a Likert-type scale, multidimensional item response theory (MIRT; Reckase, 2009) analysis was conducted using the graded response model (GRM; Samejima, 1969) to address the unidimensionality assumption. The *mirt* package (Chalmers, 2012) was used for the MIRT analysis and person-fit analysis. Goodness-of-fit statistics indicated good fit: AIC = 31417.17, BIC = 32338.66, sample-adjusted BIC = 31656.18, CFI = 0.97, TLI = 0.95, RMSEA [90% CI] = 0.049 [0.041, 0.057], RMSR =0.046. Next, person-fit analysis on the multidimensional GRM of the 5×5 RS was conducted to detect aberrant responses. l_z person-fit statistic for the multidimensional mode (Drasgow et al., 1991; Drasgow et al., 1985) was calculated. As seen Figure C.1., the distribution of the l_z values was negatively skewed. The bottom 10% of the l_z values was used as the cut-off point (Drasgow et al., 1991; Ferrando, 2012; Levine & Drasgow, 1983; Meijer et al., 2016); responses of which l_z values fell below the 10% cut-off were marked as aberrant responses. As a result, 54 aberrant responses were identified and excluded.

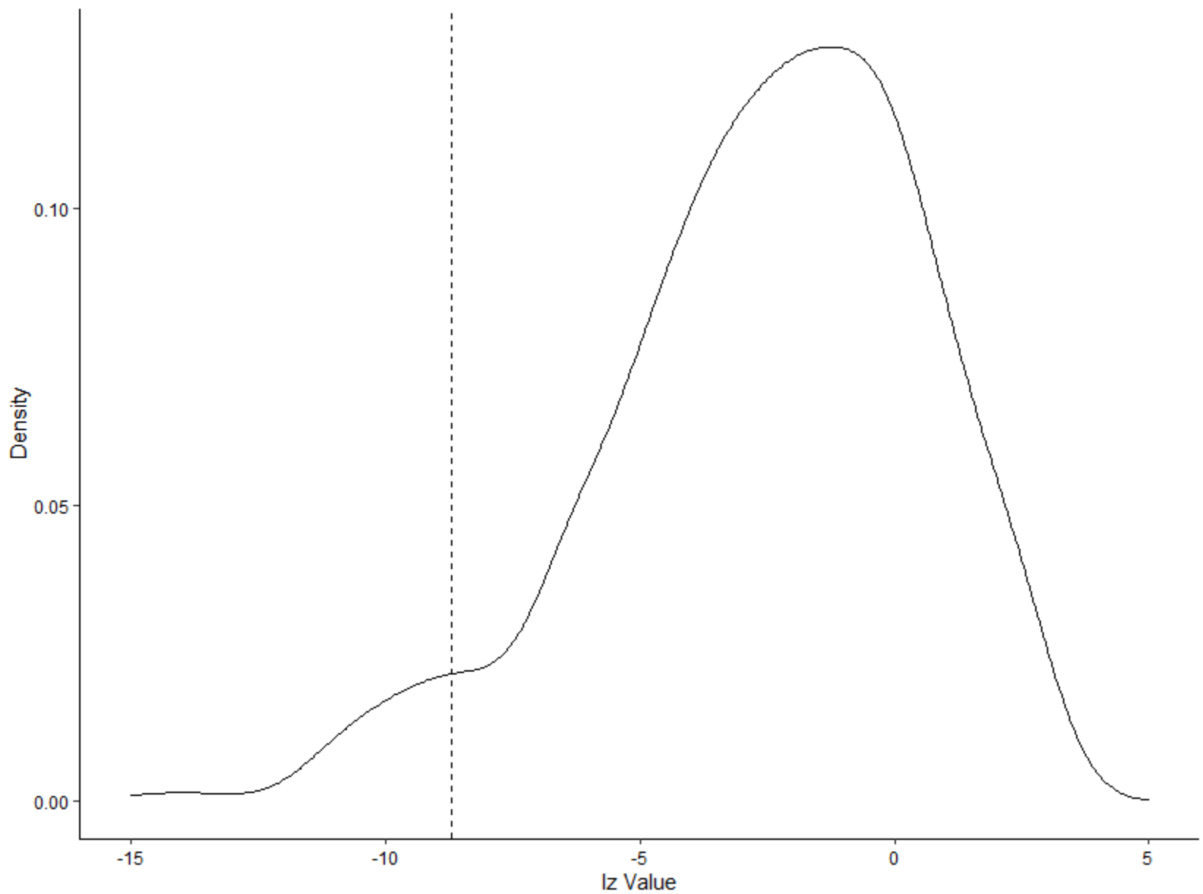

Figure C.1. Density distribution of the l_z values and cut-off point

APPENDIX D:

RELATIONSHIPS BETWEEN THE SUBSCALE SCORES OF THE 5×5 RS AND OUTCOMES BY PROFILE MEMBERSHIP IN STUDY 1

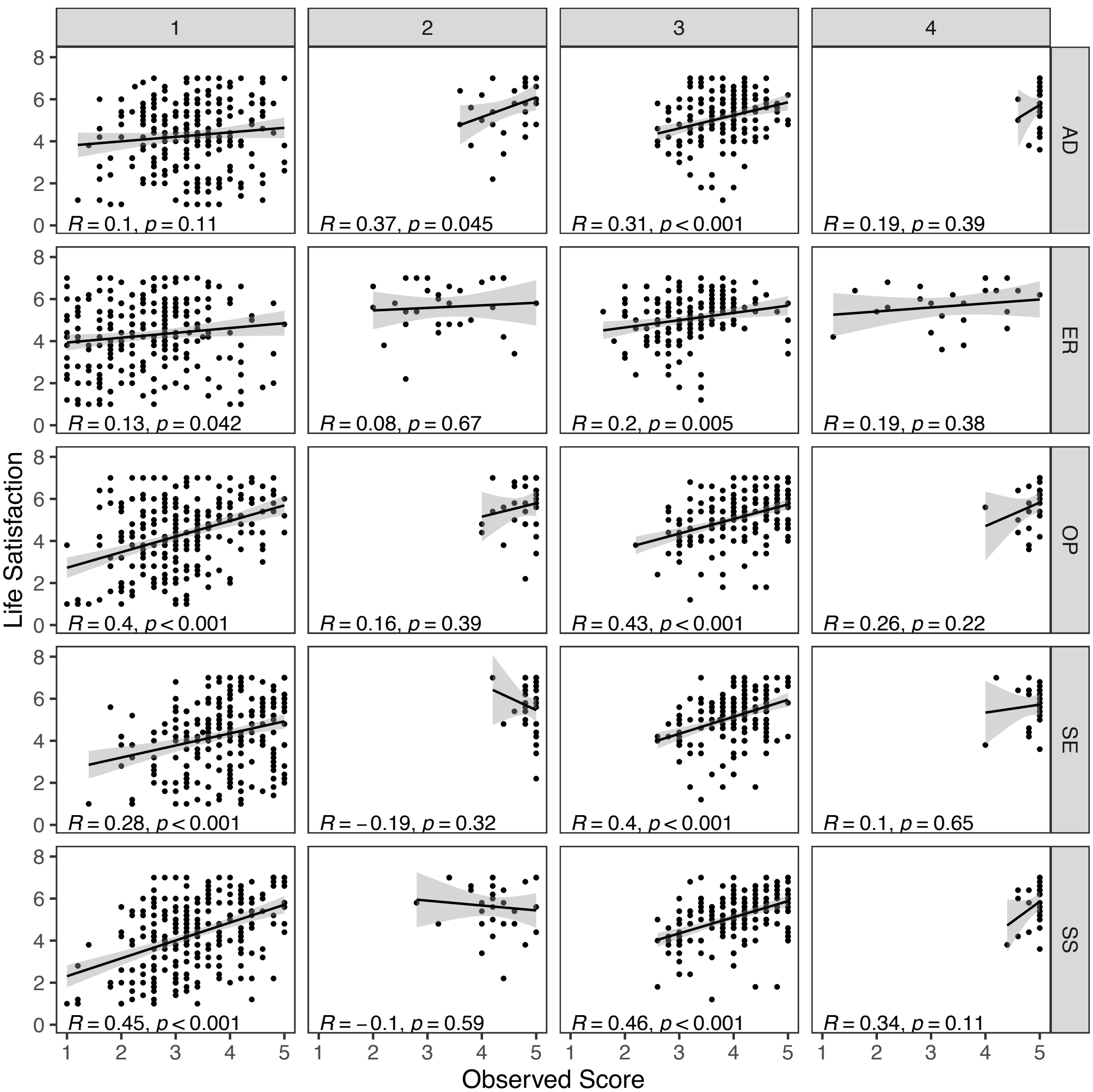

Figure D.1. Relationships between the subscale scores of the 5×5 RS and life satisfaction by profile membership in Study 1

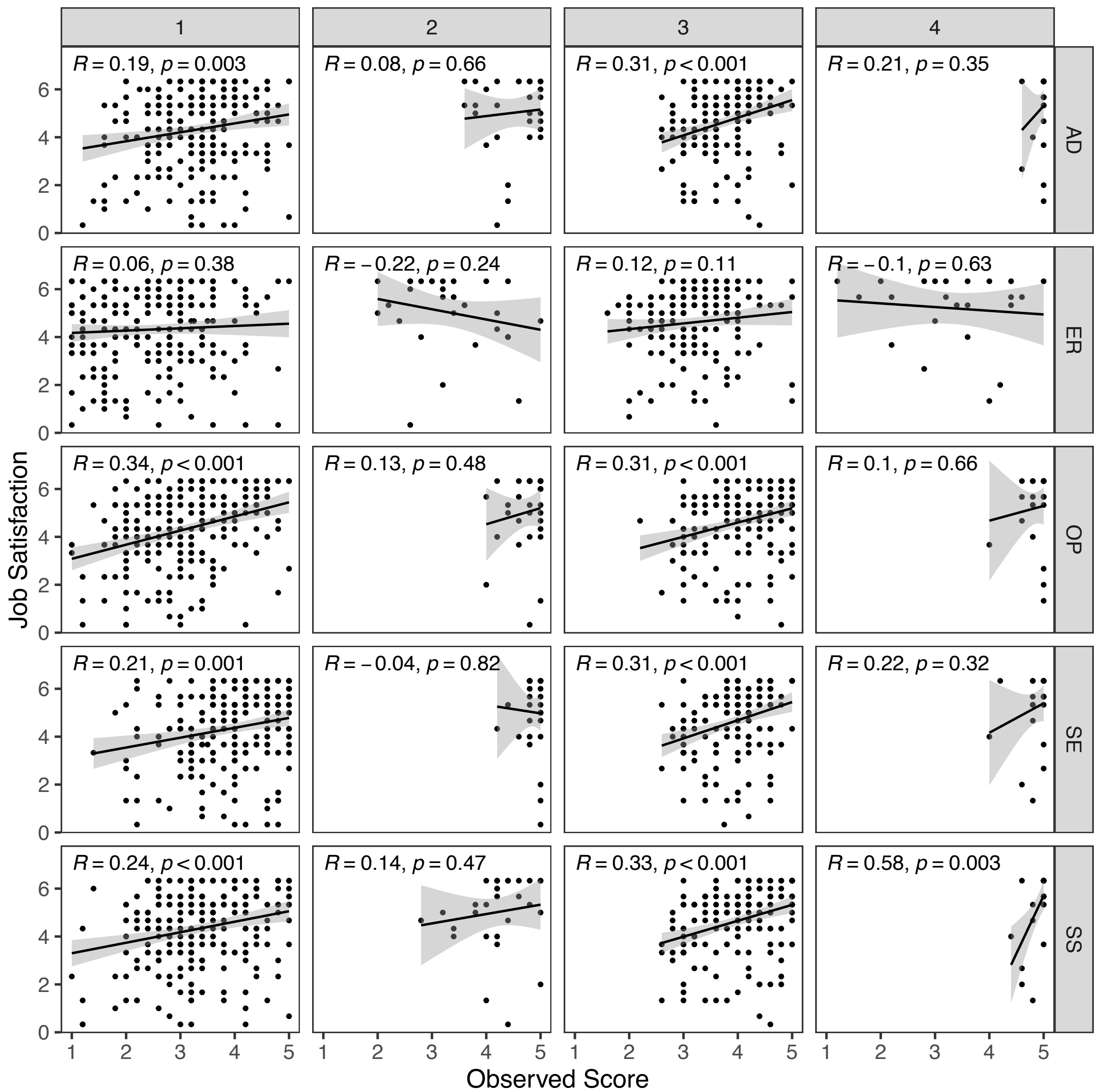

Figure D.2. Relationships between the subscale scores of the 5×5 RS and job satisfaction by profile membership in Study 1

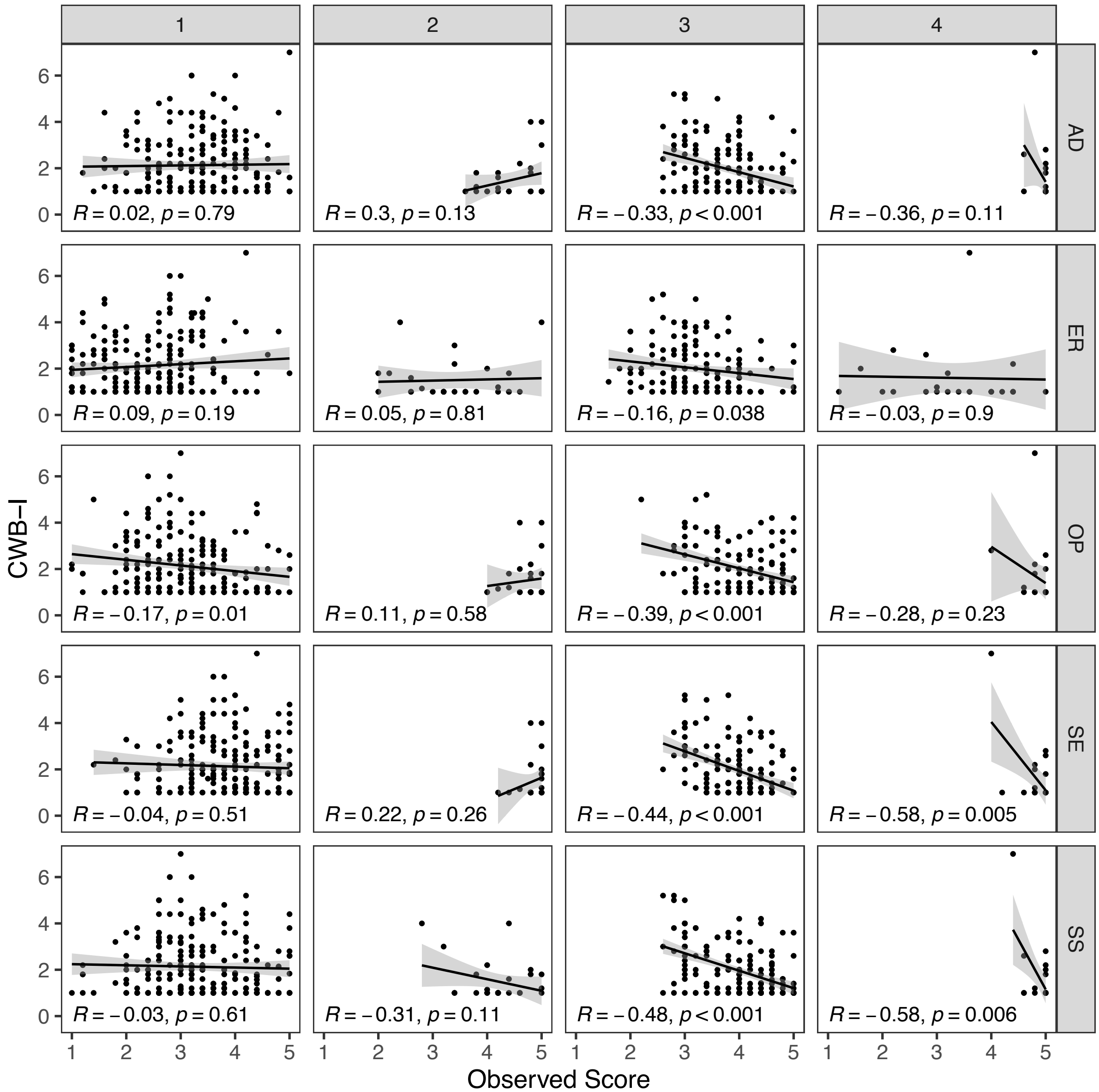

Figure D.3. Relationships between the subscale scores of the 5×5 RS and CWB-I by profile membership in Study 1

APPENDIX E:

RELATIONSHIPS BETWEEN THE SUBSCALE SCORES OF THE 5×5 RS AND OUTCOMES BY PROFILE MEMBERSHIP IN STUDY 2

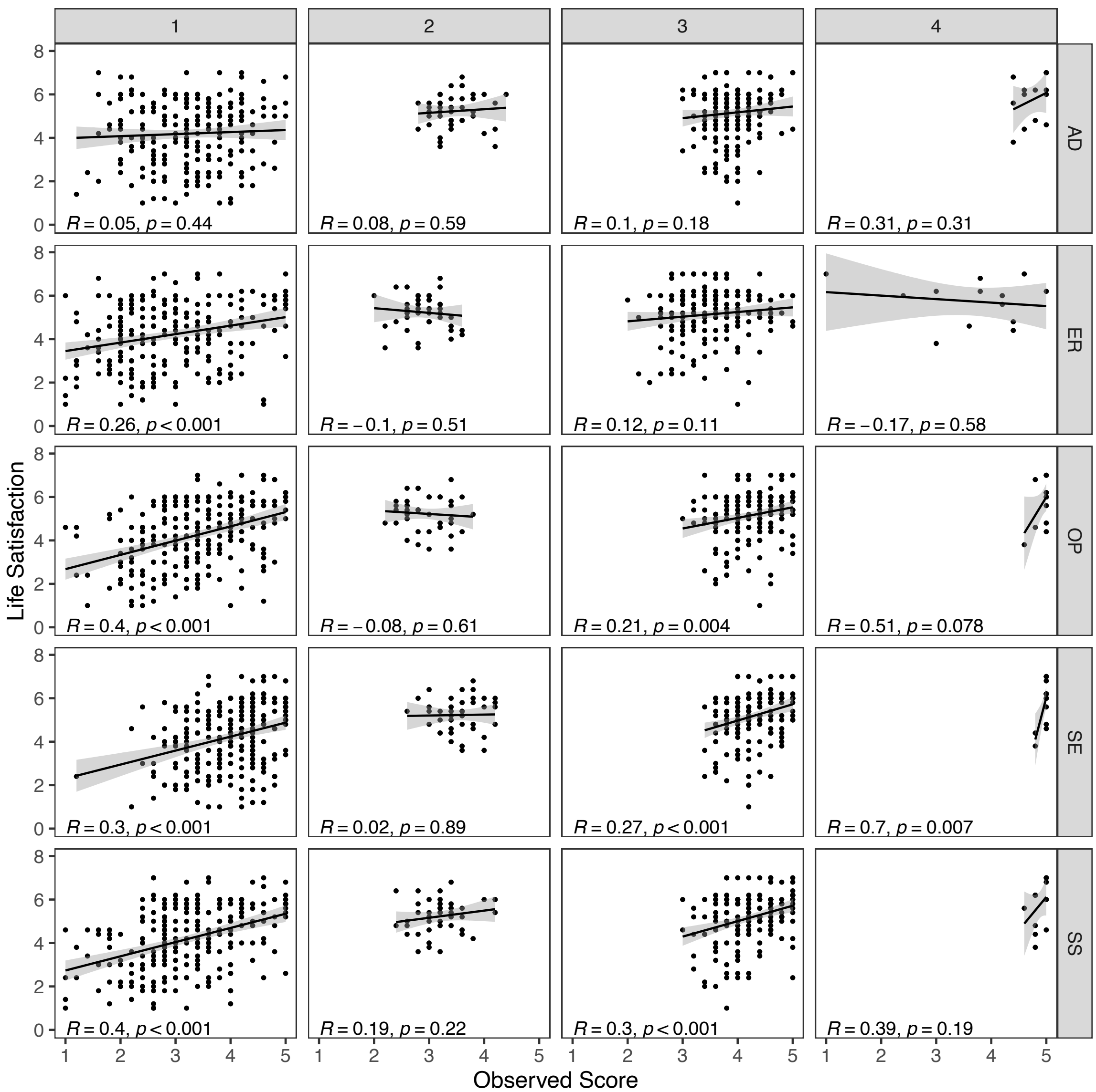

Figure E.1. Relationships between the subscale scores of the 5×5 RS and life satisfaction by profile membership in Study 2

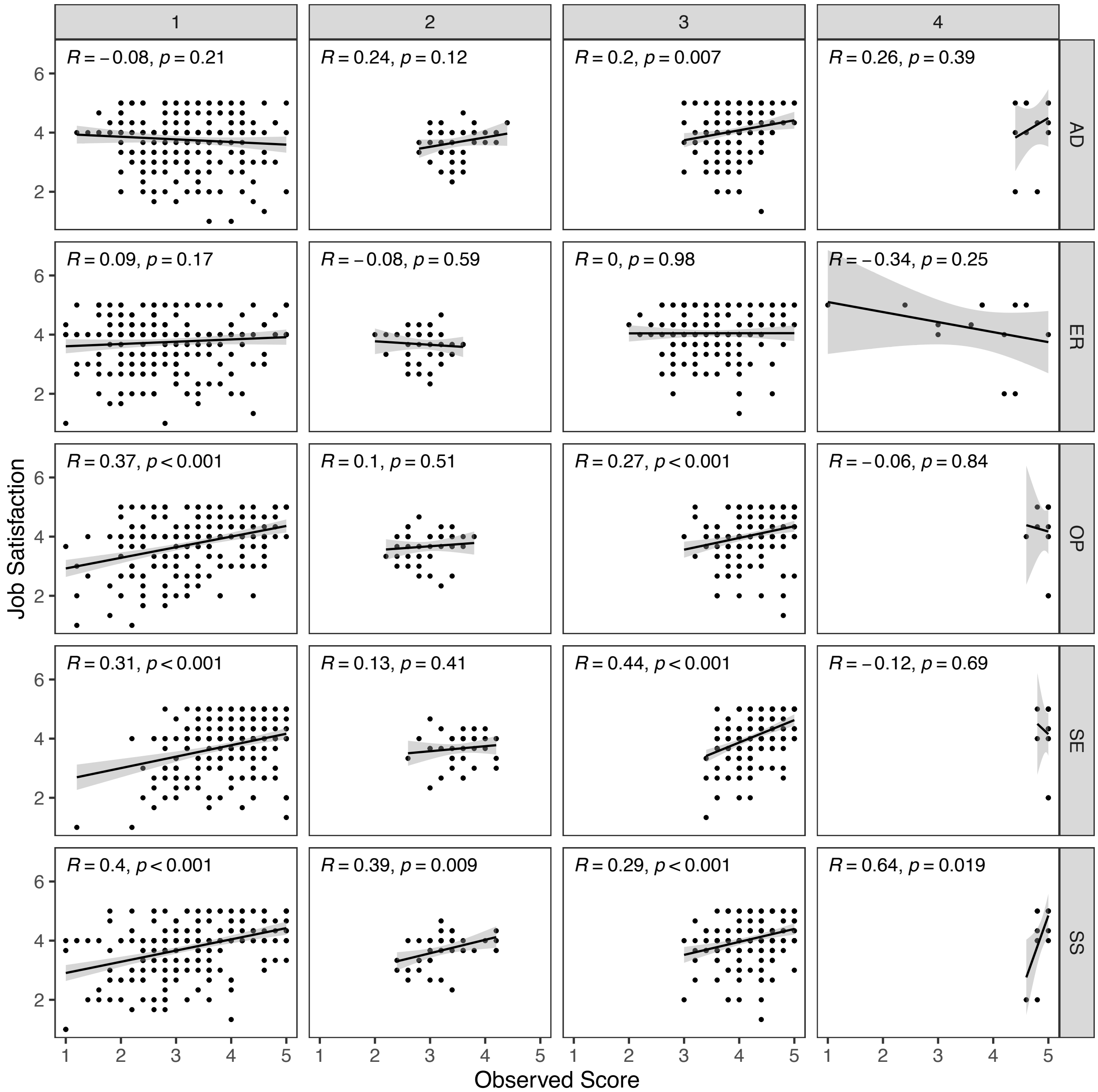

Figure E.2. Relationships between the subscale scores of the 5×5 RS and job satisfaction by profile membership in Study 2

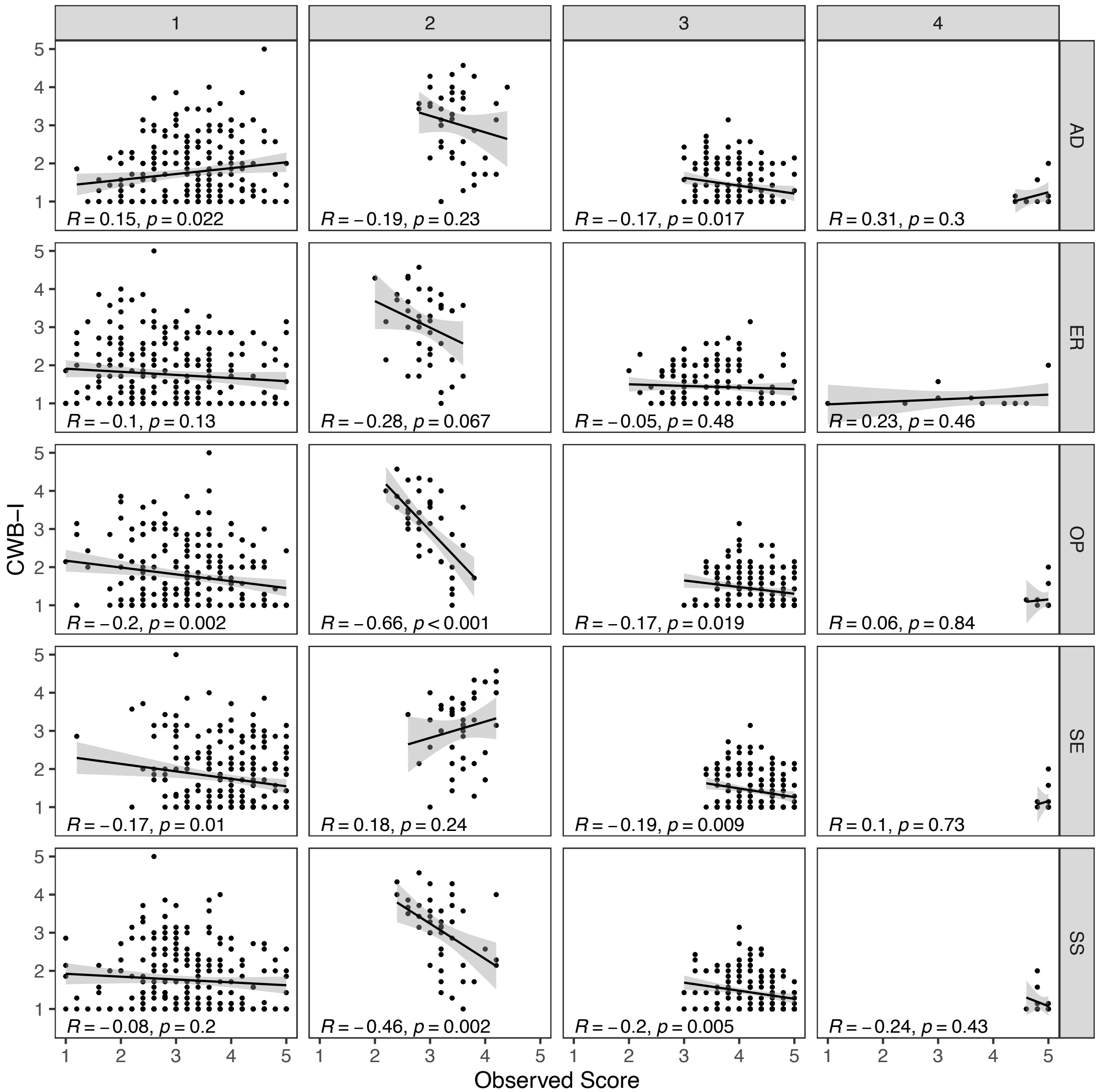

Figure E.3. Relationships between the subscale scores of the 5×5 RS and CWB-I by profile membership in Study 2

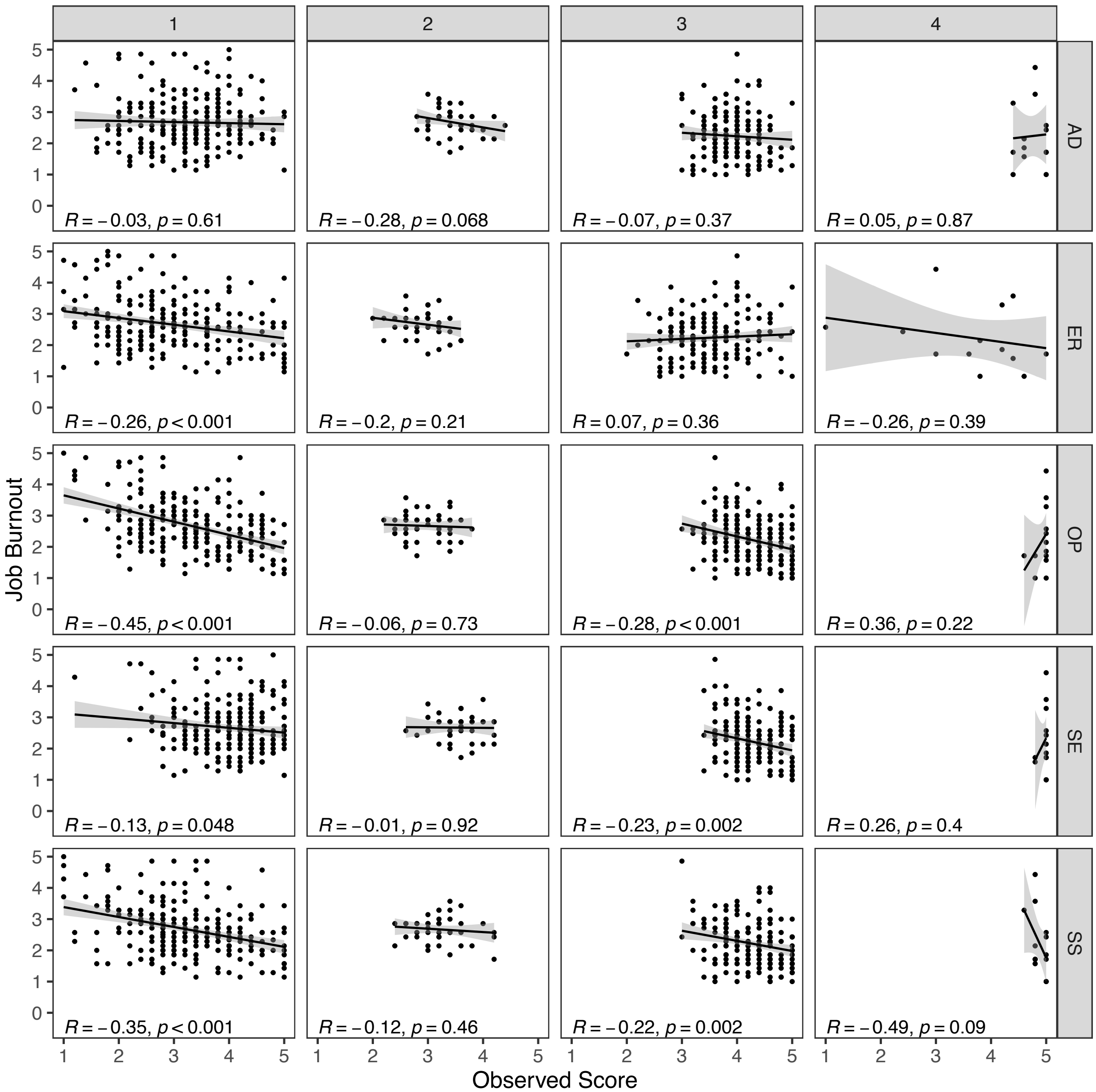

Figure E.4. Relationships between the subscale scores of the 5×5 RS and burnout by profile membership in Study 2

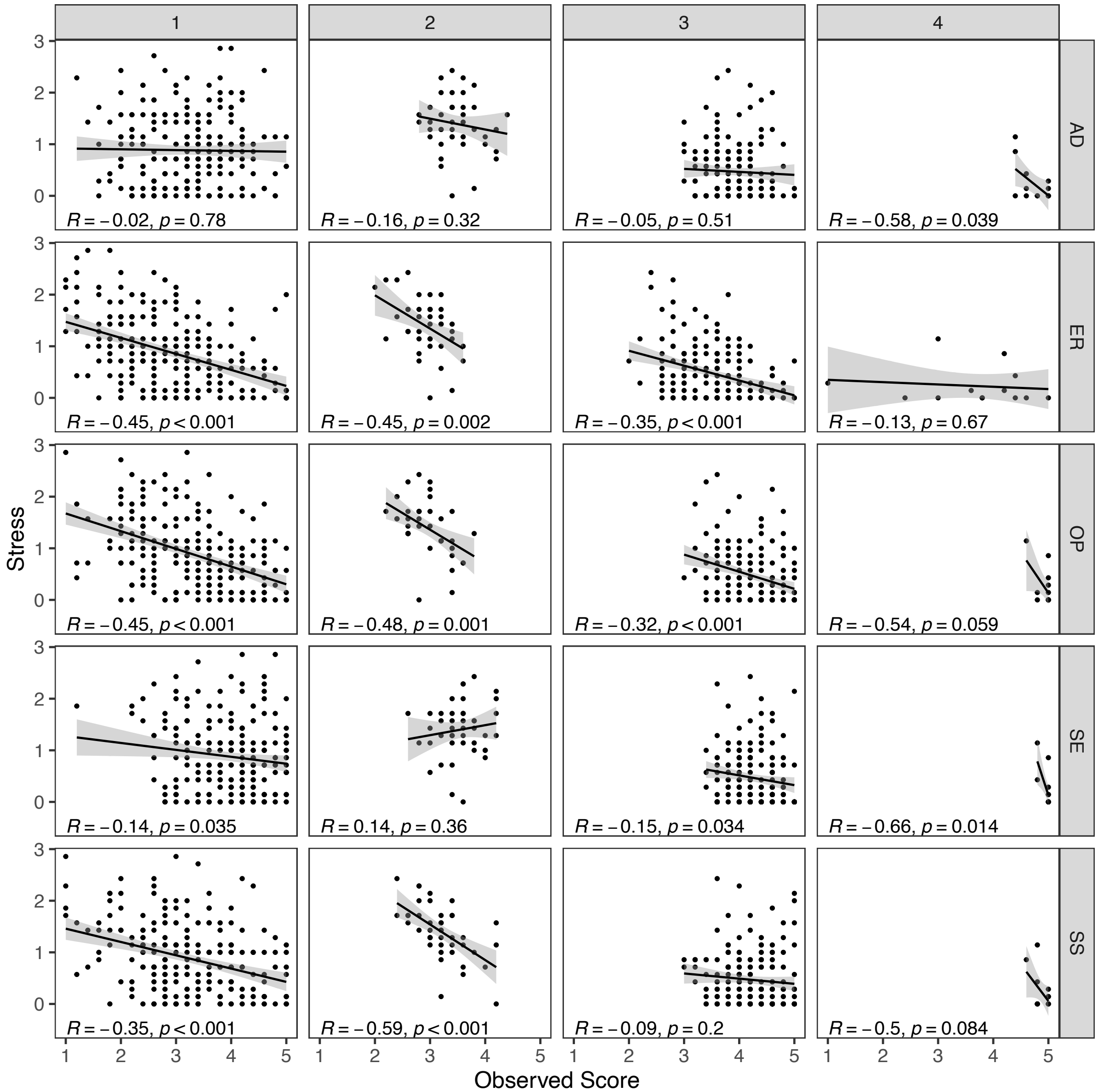

Figure E.5. Relationships between the subscale scores of the 5×5 RS and stress by profile membership in Study 2

APPENDIX F:

SUPPLEMENTAL ANALYSIS

Table F.1. Demographic characteristics in the undergraduate (Study 1) and MTurk (Study 2) samples.

	Study 1 (*N* = 479)	Study 2 (*N* = 483)
Age		
Mean (*SD*)	21.96 (5.45)	40.30 (12.23)
Gender		
Male	18.60%	45.30%
Female	80.20%	54.20%
Race		
White	48.20%	76.40%
Black/African American	12.10%	10.60%
Asian/Pacific Islander	9.20%	7.70%
Hispanic/Latino	22.10%	4.60%
American Indian or Alaska Native	–	0.40%
Multiracial	7.30%	0.20%
Work hour/week		
Mean (*SD*)	28.09 (9.98)	36.39 (8.99)
Education		
Grade school	0.20%	0.40%
High school graduate, or GED	10.40%	8.70%
Trade/technical/vocational training	–	2.50%
Some college, no degree	42.40%	15.30%
Associate degree	41.50%	8.90%
Bachelor's graduate	4.80%	43.30%
Post-graduate training	0.60%	20.90%

Table F.2. Descriptive statistics of questions assessing the impact of the COVID-19 pandemic in Study 2.

	Impact on employment (Q1)		Impact on life (Q2)		Emotional impact (Q3)		Psychological distress	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Sum*	*SD*
Profile 1	3.20	0.08	3.50	0.07	3.30	0.07	15.10	12.50
Profile 2	3.60	0.13	3.70	0.11	3.60	0.12	28.90	12.00
Profile 3	3.20	0.09	3.60	0.06	3.10	0.08	7.00	8.30
Profile 4	3.50	0.39	3.90	0.33	2.80	0.30	2.30	3.90

*Note***.** Q1 asked "to what extent is your employment impacted by the covid-19 outbreak?"; Q2 asked "to what extent is your life impacted by the covid-19 outbreak?"; Q3 asked "to what extent are you affected emotionally by the covid-19 outbreak?" All questions were rated on a 5-point Likert scale: 1 = to a very low degree, 2 = to a low degree, 3 = Somewhat, 4 = to a high degree, and 5 = to a very high degree. Psychological distress was measured by DASS-21 and sum scores were calculated.

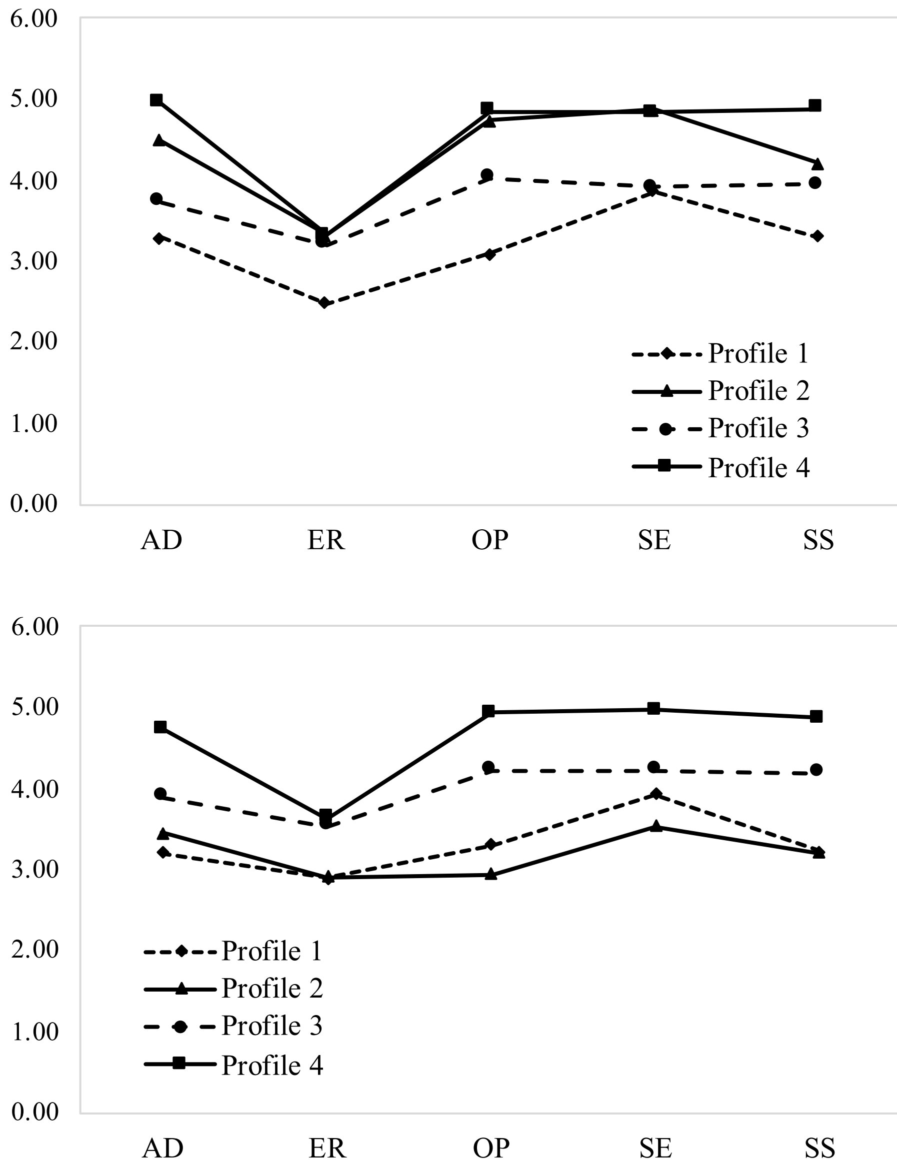

Figure F.1. Mean observed subscale scores of the 5×5 RS the for each profile for the undergraduate (top) and MTurk (bottom) samples

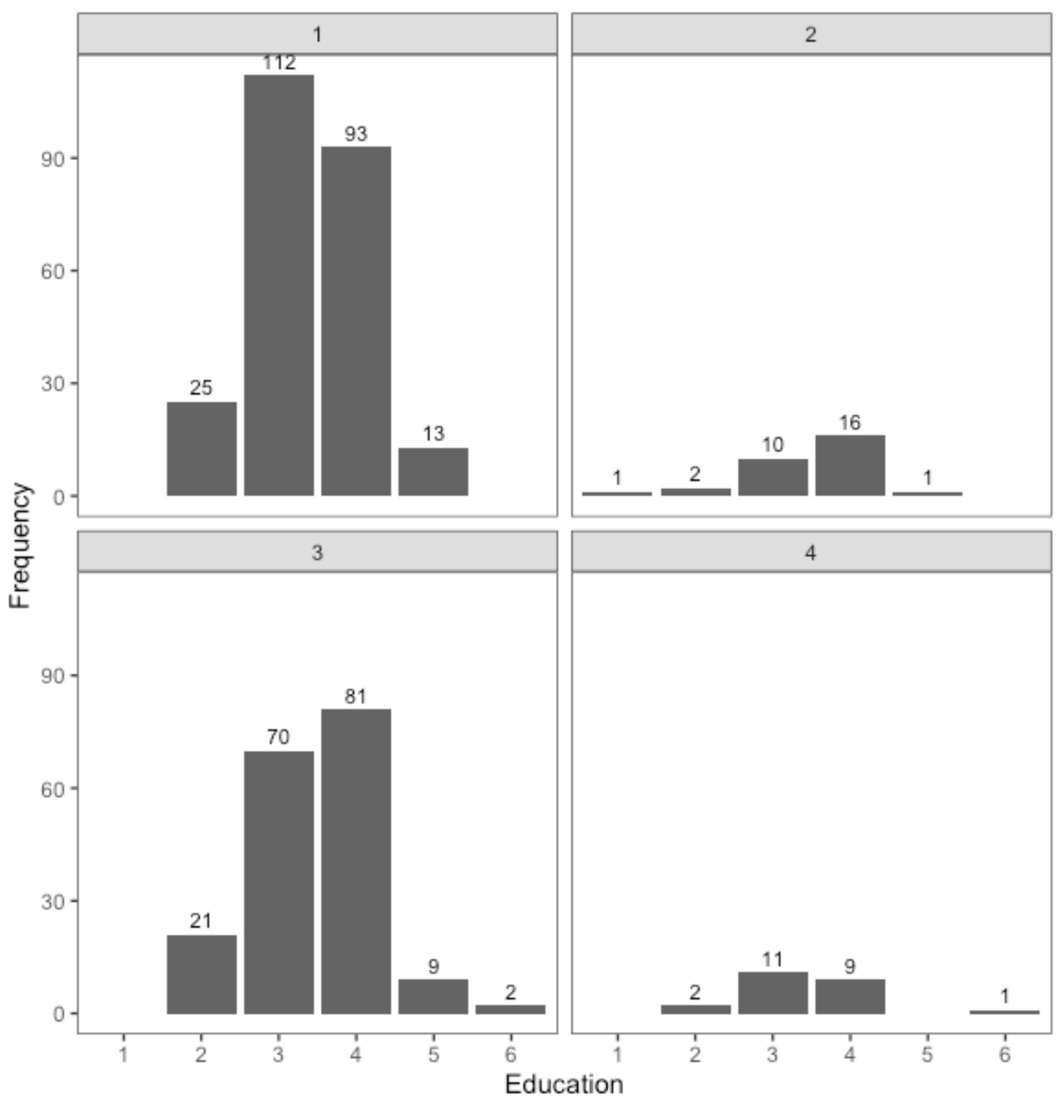

Figure F.2. Education level of people in each profile in the undergraduate sample. 1 = Grade school; 2 = High school graduate, diploma or the equivalent (e.g., GED); 3 = some college, no degree; 4 = Associate degree; 5 = Bachelor's degree; 6 = Post-graduate training.

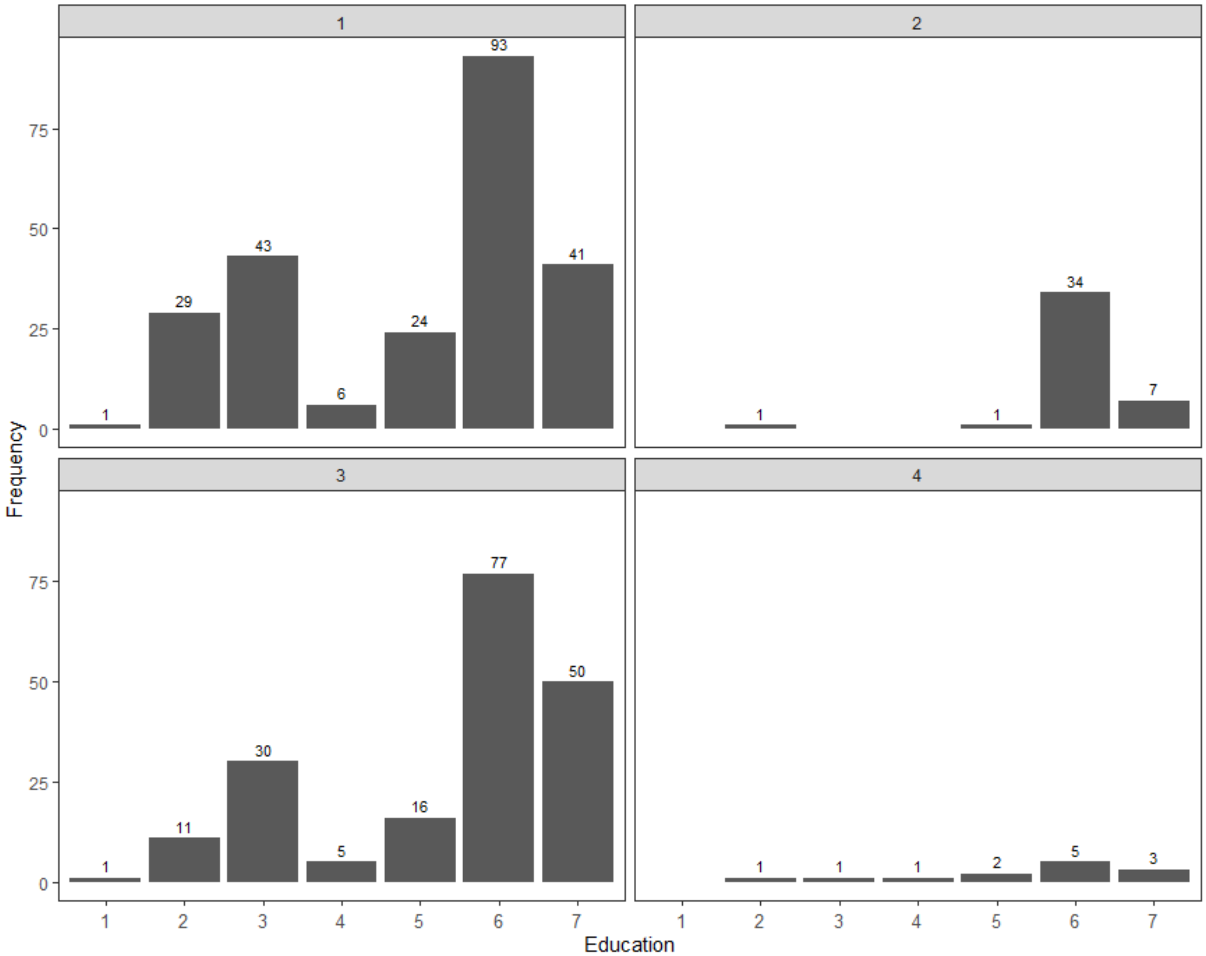

Figure F.3. Education level of people in each profile in the MTurk sample. 1 = Some high school, no diploma; 2 = High school graduate, diploma or the equivalent (e.g., GED); 3 = some college, no degree; 4 = Trade/technical/vocational training; 5 = Associate degree; 6 = Bachelor's degree; 7 = Post-graduate training.

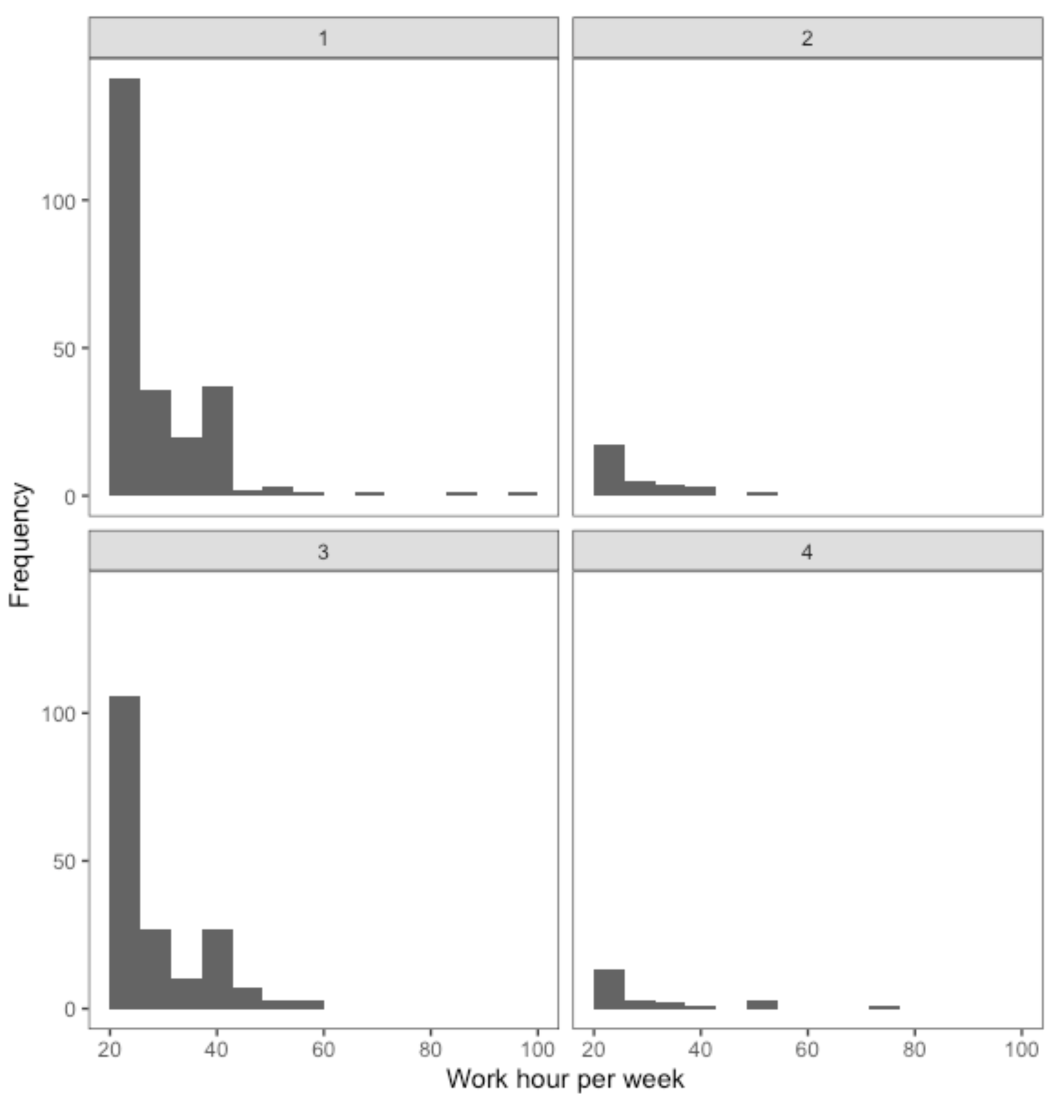

Figure F.4. Work hour per week of people in each profile in the undergraduate sample.

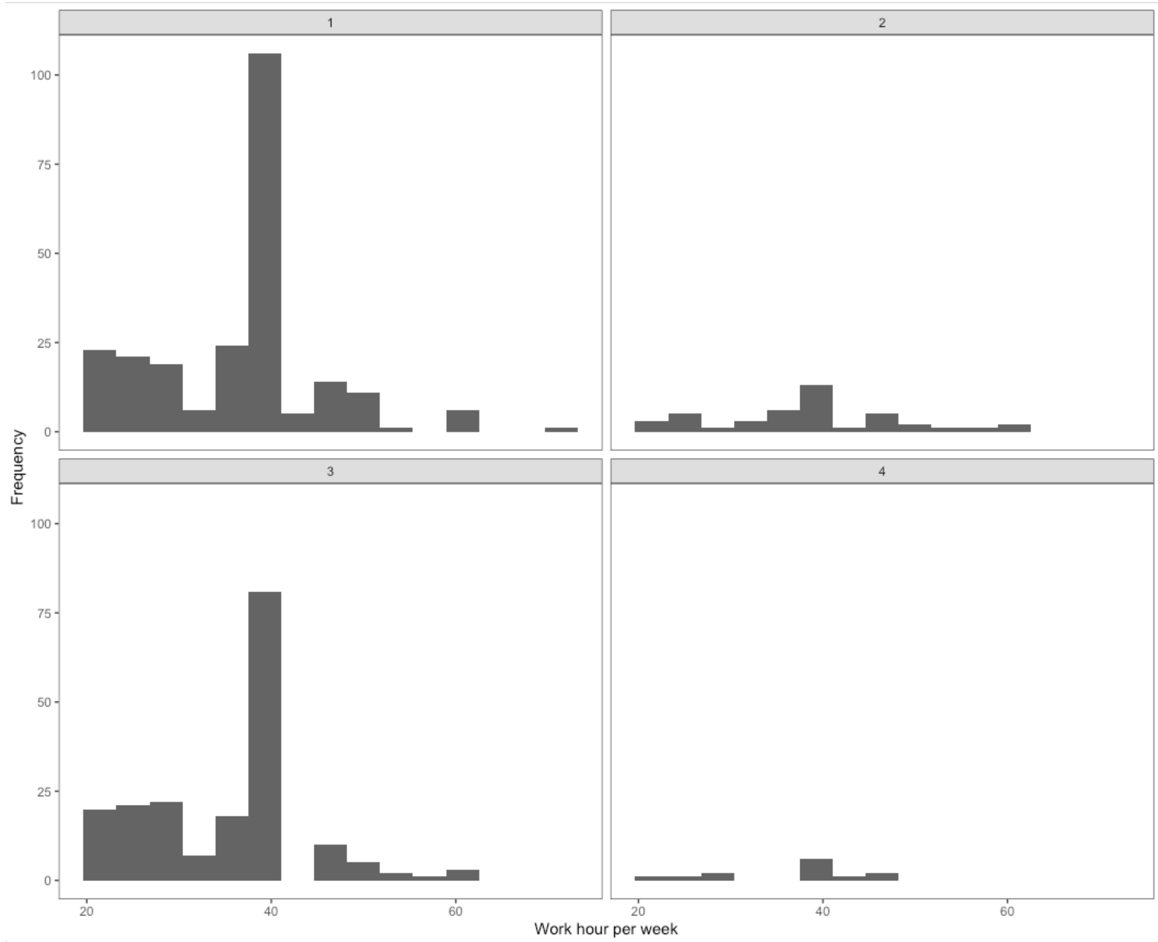

Figure F.5. Work hour per week of people in each profile in the MTurk sample.

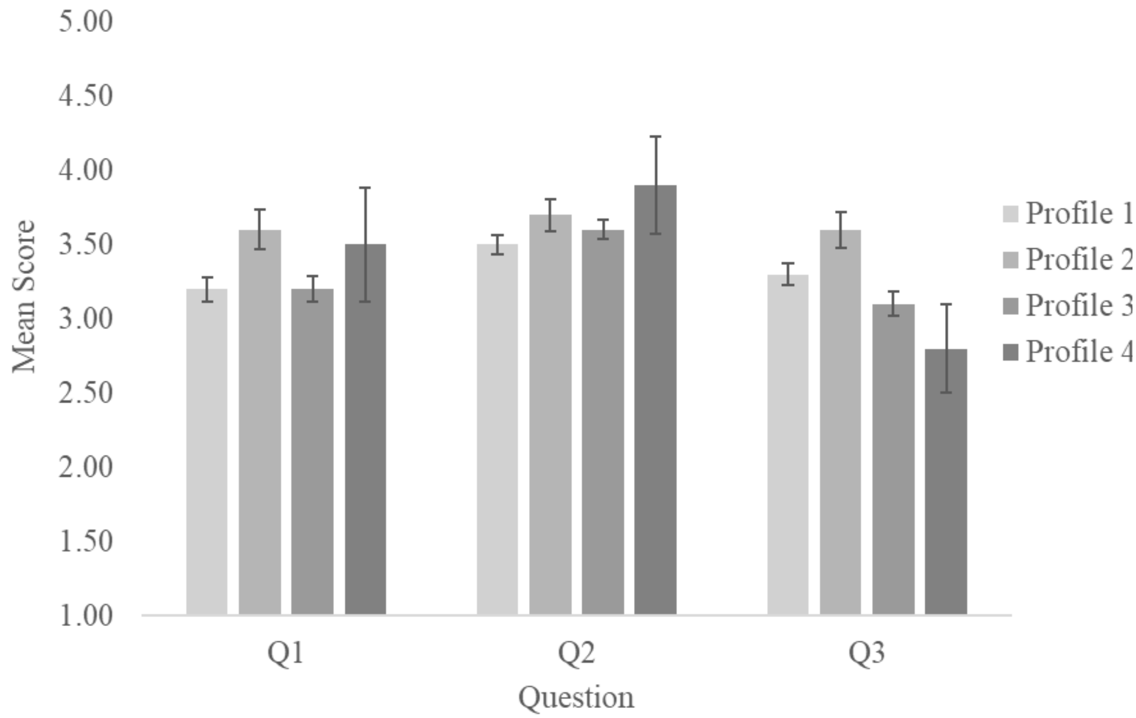

Figure F.6. Mean scores of responses to COVID-19 related questions by profile membership. Error bars show standard errors. Q1 asked “to what extent is your employment impacted by the covid-19 outbreak?”; Q2 asked “to what extent is your life impacted by the covid-19 outbreak?”; Q3 asked “to what extent are you affected emotionally by the covid-19 outbreak?” All questions were rated on a 5-point Likert scale: 1 = to a very low degree, 2 = to a low degree, 3 = Somewhat, 4 = to a high degree, and 5 = to a very high degree.

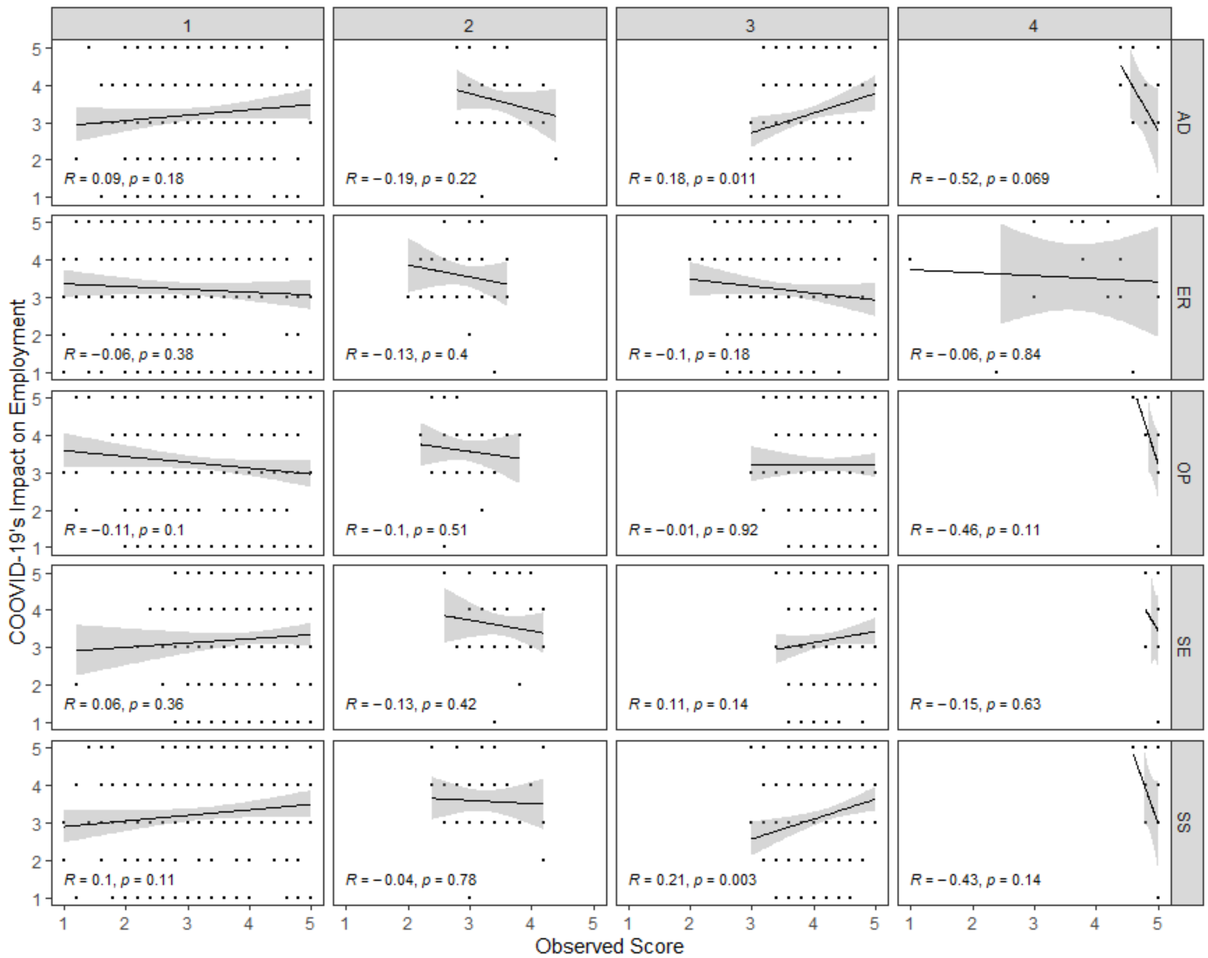

Figure F.7. Relationships between the Subscale Scores of the 5×5 RS and COVID-related question Q1 by Profile Membership. Q1 asked “to what extent is your employment impacted by the covid-19 outbreak?” and was rated on a 5-point Likert scale: 1 = to a very low degree, 2 = to a low degree, 3 = Somewhat, 4 = to a high degree, and 5 = to a very high degree.

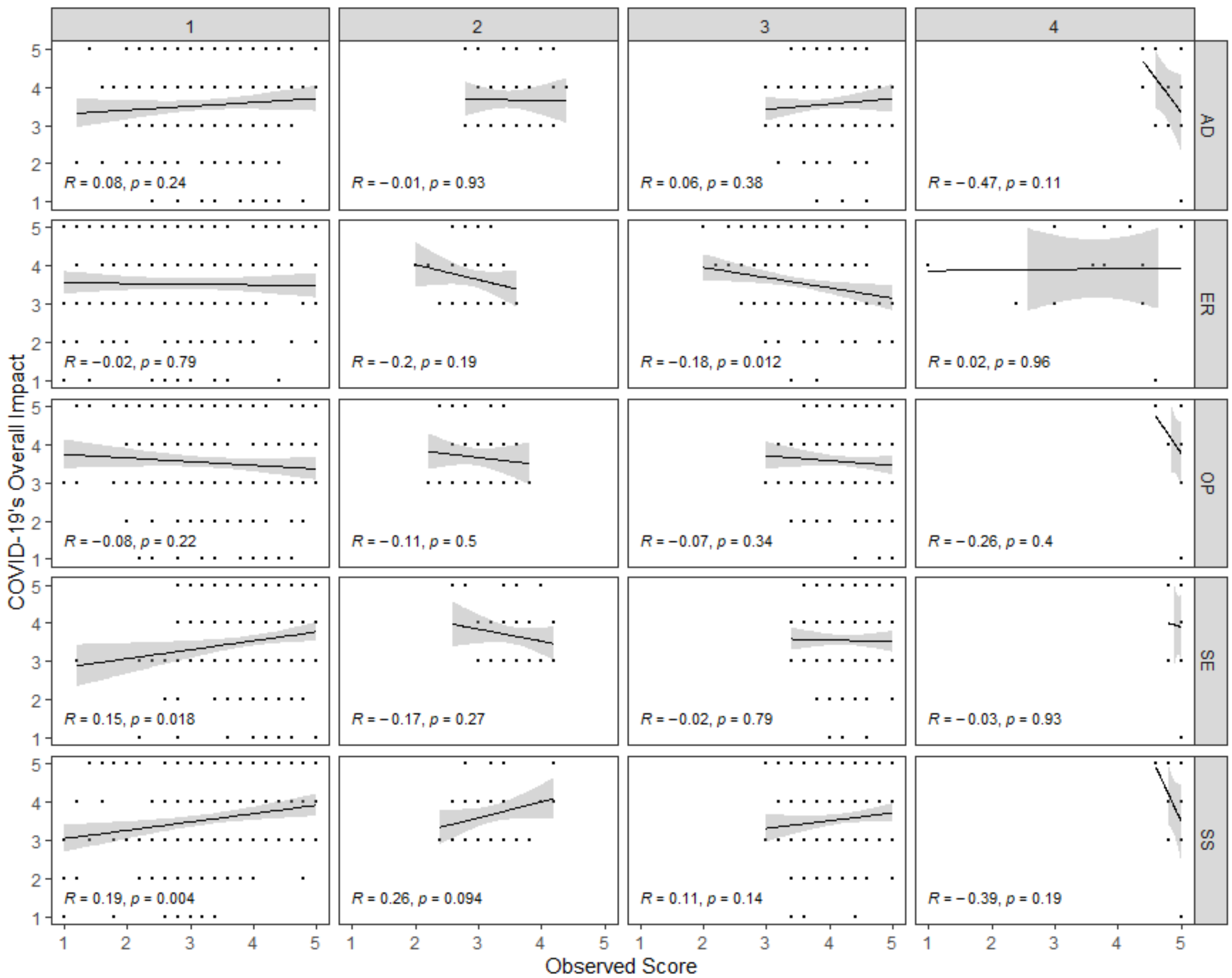

Figure F.8. Relationships between the Subscale Scores of the 5×5 RS and COVID-related question Q2 by Profile Membership. Q2 asked "to what extent is your life impacted by the covid-19 outbreak?" and was rated on a 5-point Likert scale: 1 = to a very low degree, 2 = to a low degree, 3 = Somewhat, 4 = to a high degree, and 5 = to a very high degree.

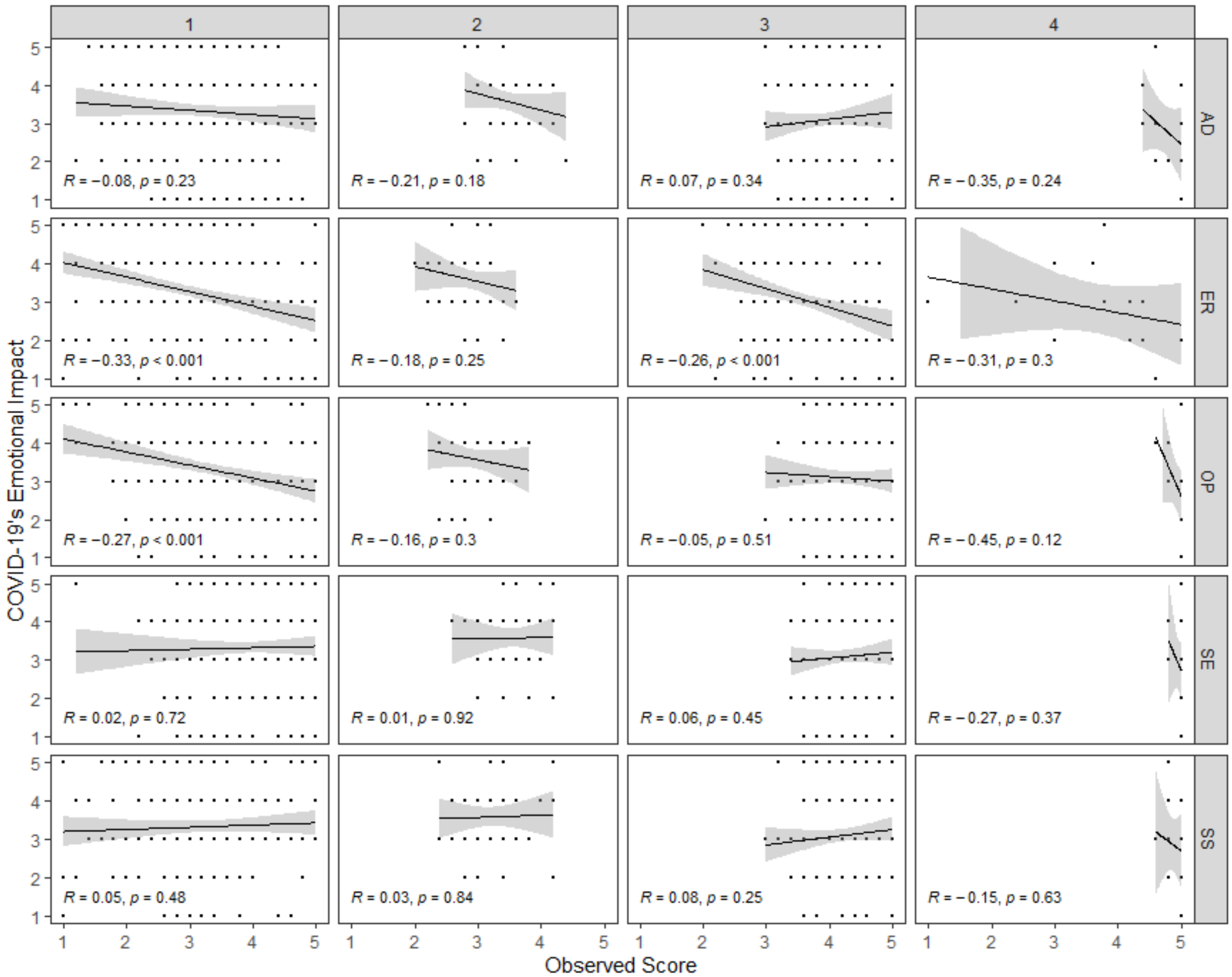

Figure F.9. Relationships between the Subscale Scores of the 5×5 RS and COVID-related question Q2 by Profile Membership. Q Q3 asked "to what extent are you affected emotionally by the covid-19 outbreak?" and was rated on a 5-point Likert scale: 1 = to a very low degree, 2 = to a low degree, 3 = Somewhat, 4 = to a high degree, and 5 = to a very high degree.

Appendix G:

ALL MEASURES USED IN THE PROJECT

Demographic

The following questions will give researchers a more complete look at this study. You will be asked some questions about yourself. Your answers are highly appreciated.

1. *What is your age? (years)
2. What is your gender?
    - Male
    - Female
    - Transgender
    - Other
    - Prefer not to respond
3. What is your race/ethnicity?
    - White
    - African American or Black
    - Asian
    - Native Hawaiian or Other Pacific Islander
    - American Indian or Alaska Native
    - Multiracial
    - Hispanic/Latino
    - Prefer not to respond
4. What is your highest level of attained education?
    - Grade school
    - High school graduate, or GED
    - Some college, no degree
    - Associate degree
    - College graduate
    - Post-graduate training
5. *How many hours do you work in a typical week?

Note. * indicates that the question is open-ended.

COVID-19 related questions

1. To what extent is your employment impacted by the covid-19 outbreak?
    - To a very high degree
    - To a high degree
    - Somewhat
    - To a low degree
    - To a very low degree

2. To what extent is your life impacted by the covid-19 outbreak?
    - To a very high degree
    - To a high degree
    - Somewhat
    - To a low degree
    - To a very low degree
3. To what extent are you affected emotionally by the covid-19 outbreak?
    - To a very high degree
    - To a high degree
    - Somewhat
    - To a low degree
    - To a very low degree

Attention Check

1. If you live in the U.S. select Strongly Agree.[a]
2. The sun rotates around the earth.[a]
3. If you are paying attention to the survey right now, click Very Accurate.[b]
4. If you are paying attention right now, select slightly disagree.[a]
5. The sky is blue.[a]
6. I am using a computer currently.[a] (R)
7. I am enrolled in a Psychology course currently.[a] (R)
8. I do not understand a word of English.[a] (R)

Note. [a] Each item is rated on a 5-point scale where 1 = Strongly disagree, 2 = Disagree a little, 3 = Neither agree nor disagree, 4 = Agree a little, and 5 = Strongly agree. R = item reversed coded (strongly disagree or disagree not selected).
[b] Item 3 is rated on a on a 5-point scale where 1 = Very inaccurate, 2 = Moderately inaccurate, 3 = Neither inaccurate nor accurate, 4 = Moderately accurate, and 5 = Very Accurate.

The 5-by-5 Resilience Scale

Please use the rating scale below to describe how accurately each statement describes you. Describe yourself as you generally are now, not as you wish to be in the future. Indicate your answer in the response column.

1. Can switch gears easily.
2. Am open to change.
3. Don't like the idea of change.
4. Adapt easily to new situations.
5. Dislike the unknown.
6. Experience my emotions intensely.
7. Am not easily affected by my emotions.
8. Keep my emotions under control.
9. Am very sensitive and easily hurt.
10. Get overwhelmed by emotions.
11. See difficulties everywhere.
12. Expect things to fail.
13. Look at the bright side of life.
14. Fear for the worst.

15. Have a dark outlook on the future.
16. Am good at analyzing problems.
17. Can handle complex problems.
18. Am less capable than most people.
19. Excel in what I do.
20. Can tackle anything.
21. Make friends easily.
22. Feel empty in my relationships.
23. Tend to find social situations confusing.
24. Feel comfortable around people.
25. Feel isolated from other people.

Note. Each item is rated on a 5-point scale where 1 = Very inaccurate, 2 = Moderately inaccurate, 3 = Neither inaccurate nor accurate, 4 = Moderately accurate, and 5 = Very Accurate.

Personality Variables

The Big Five Inventory

Here are a number of characteristics that may or may not describe you. For example, do you agree that you are someone who is talkative? Please bubble in the number which best indicates the extent to which you agree or disagree with each statement listed below.

I see myself as someone who...

1. Is talkative.
2. Tends to find fault with others.
3. Does a thorough job.
4. Is depressed, blue.
5. Is original, comes up with new ideas.
6. Is reserved.
7. Is helpful and unselfish with others.
8. Can be somewhat careless.
9. Is relaxed, handles stress well.
10. Is curious about many different things.
11. Is full of energy.
12. Starts quarrels with others.
13. Is a reliable worker.
14. Can be tense.
15. Is ingenious, a deep thinker.
16. Generates a lot of enthusiasm.
17. Has a forgiving nature.
18. Tends to be disorganized.
19. Worries a lot.
20. Has an active imagination.
21. Tends to be quiet.
22. Is generally trusting.
23. Tends to be lazy.
24. Is emotionally stable, not easily upset.
25. Is inventive.
26. Has an assertive personality.

27. Can be cold and aloof.
28. Perseveres until the task is finished.
29. Can be moody.
30. Values artistic, aesthetic experiences.
31. Is sometimes shy, inhibited.
32. Is considerate and kind to almost everyone.
33. Does things efficiently.
34. Remains calm in tense situations.
35. Prefers work that is routine.
36. Is outgoing, sociable.
37. Is sometimes rude to others.
38. Makes plans and follows through with them.
39. Gets nervous easily.
40. Likes to reflect, play with ideas.
41. Has few artistic interests.
42. Likes to cooperate with others.
43. Is easily distracted.
44. Is sophisticated in art, music, or literature.

Note. Each item is rated on a 5-point scale where 1 = Strongly disagree, 2 = Disagree a little, 3 = Neither agree nor disagree, 4 = Agree a little, and 5 = Strongly agree.

The Positive and Negative Affect Schedule

This scale consists of a number of words that describe different feelings and emotions. Read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you have felt this way during the past few weeks.

1. Interested.
2. Distressed.
3. Excited.
4. Upset.
5. Strong.
6. Guilty.
7. Scared.
8. Hostile.
9. Enthusiastic.
10. Proud.
11. Irritable.
12. Alert.
13. Ashamed.
14. Inspired.
15. Nervous.
16. Determined.
17. Attentive.
18. Jittery.
19. Active.
20. Afraid.

Note. Each item is rated on a 5-point scale where 1 = Very slightly or not at all, 2 = A little, 3 = Moderately, 4 = Quite a bit, and 5 = Extremely.

Outcomes

Copenhagen Burnout Inventory

Below are some statements that you may agree or disagree with. Using the scale below indicate your agreement with each item by clicking the appropriate number. Please be open and honest in your responding.

1. Do you feel worn out at the end of the working day? [a]
2. Are you exhausted in the morning at the thought of another day at work? [a]
3. Do you feel that every working hour is tiring for you? [a]
4. Do you have enough energy for family and friends during leisure time? [a]
5. Is your work emotionally exhausting? [b]
6. Does your work frustrate you? [b]
7. Do you feel burnt out because of your work? [b]

Note. [a] Items are rated on a 5-point scale where 1 = Never/Almost never, 2 = Seldom, 3 = Sometimes, 4 = Often, and 5 = Always. [b] Items are rated on a on a 5-point scale where 1 = To a very high degree, 2 = To a high degree, 3 = Somewhat, 4 = To a low degree, and 5 = To a very low degree.

Counterproductive work behavior

The questions on this page ask you to rate your own job performance. Please click the option that accurately reflects your response to each question, and please be as honest as possible. Please note that these ratings are completely confidential.

If you are currently working remotely or out of work, please think of your most recent experience at work and answer the following questions.

1. Made fun of someone at work
2. Said something hurtful to someone at work
3. Made an ethnic, religious, or racial remark at work
4. Cursed at someone at work
5. Played a mean prank on someone at work
6. Acted rudely toward someone at work
7. Publicly embarrassed someone at work

Note. Each item is rated on a 5-point scale where 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly agree.

Overall Job Satisfaction

Please respond to the following items with respect to your general findings about the company that employs you. If you hold multiple jobs, please describe your primary job.

1. All in all, I am satisfied with my job.
2. In general, I like working here.
3. Generally speaking, I am very satisfied with this job.

Note. Each item is rated on a 5-point scale where 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly agree.

Satisfaction with Life Scale

Below are five statements that you may agree or disagree with. Using the 1-7 scale below indicate your agreement with each item by clicking the appropriate number. Please be open and honest in your responding.

1. In most ways my life is close to my ideal.
2. The conditions of my life are excellent.
3. I am satisfied with my life.
4. So far I have gotten the important things I want in life.
5. If I could live my life over, I would change almost nothing.

Note. Each item is rated on a 7-point scale where 7 = Strongly agree, 6 = Agree, 5 = Slightly Agree, 4 = Neither agree nor disagree, 3 = Slightly disagree, 2 = Disagree, and 1 = Strongly disagree.

Depression Anxiety Stress Scales –21 (DASS – 21)

Please read each statement and circle a number 0, 1, 2 or 3 that indicates how much the statement applied to you over the past week. There are no right or wrong answers. Do not spend too much time on any statement. The rating scale is as follows:

1. I found it hard to wind down
2. I was aware of dryness of my mouth
3. I couldn't seem to experience any positive feeling at all
4. I experienced breathing difficulty (e,g., excessively rapid breathing, breathlessness in the absence of physical exertion)
5. I found it difficult to work up the initiative to do things
6. I tended to over-react to situations
7. I experienced trembling (e,g., in the hands)
8. I felt that I was using a lot of nervous energy
9. I was worried about situations in which I might panic and make a fool of myself
10. I felt that I had nothing to look forward to
11. I found myself getting agitated
12. I found it difficult to relax
13. I felt down-hearted and blue
14. I was intolerant of anything that kept me from getting on with what I was doing
15. I felt I was close to panic
16. I was unable to become enthusiastic about anything
17. I felt I wasn't worth much as a person
18. I felt that I was rather touchy
19. I was aware of the action of my heart in the absence of physical exertion (eg, sense of heart rate increase, heart missing a beat)
20. I felt scared without any good reason
21. I felt that life was meaningless

Note. 0 = Did not apply to me at all, 1 = Applied to me to some degree, or some of the time, 2 = Applied to me to a considerable degree, or a good part of time, 3 = Applied to me very much, or most of the time.

APPENDIX H:

IRB APPROVAL LETTER FOR STUDY 2

UNIVERSITY OF SOUTH FLORIDA

EXEMPT DETERMINATION

February 19, 2020

Yuejia Teng
30515 USF Holly Dr
Tampa, FL 33620

Dear Yuejia Teng:

On 2/14/2020, the IRB reviewed and approved the following protocol:

Application Type:	Initial Study
IRB ID:	STUDY000383
Review Type:	Exempt 2
Title:	Latent profile analysis of resilience
Funding:	None
Protocol:	• STUDY000383 Protocol Resilience LPA.docx

The IRB determined that this protocol meets the criteria for exemption from IRB review.

In conducting this protocol, you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Please note, as per USF policy, once the exempt determination is made, the application is closed in BullsIRB. This does not limit your ability to conduct the research. Any proposed or anticipated change to the study design that was previously declared exempt from IRB oversight must be submitted to the IRB as a new study prior to initiation of the change. However, administrative changes, including changes in research personnel, do not warrant a modification or new application.

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit a new request to the IRB for a determination.

Sincerely,

Tabassum Tasnim
IRB Research Compliance Administrator

A PREEMINENT RESEARCH UNIVERSITY

Institutional Review Boards / Research Integrity & Compliance
FWA No. 00001669
University of South Florida / 3702 Spectrum Blvd., Suite 165 / Tampa, FL 33612 / 813-974-5638