Article

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Assessing Differential Effects of Somatic Amplification to Positive Affect in Midlife and Late Adulthood—A Regression Mixture Approach

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Abstract

This study aims to provide an empirical demonstration of a novel method, regression mixture model, by examining differential effects of somatic amplification to positive affect and identifying the predictors that contribute to the differential effects. Data derived from the second wave of Midlife in the United States. The analytic sample consisted of 1,766 adults aged from 33 to 84 years. Regression mixture models were fitted using Mplus 7.4, and a two-step model-building approach was adopted. Three latent groups were identified consisting of a maladaptive (32.1%), a vulnerable (62.5%), and a resilient (5.4%) group. Six covariates (i.e., age, education level, positive relations with others, purpose in life, depressive symptoms, and physical health) significantly predicted the latent class membership in the regression mixture model. The study demonstrated the regression mixture model to be a flexible and efficient statistical tool in assessing individual differences in response to adversity and identifying resilience factors, which contributes to aging research.

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Adverse circumstances are usually associated with impaired psychological well-being (e.g., Surachman et al., 2019). Given that advancing age is accompanied by adversities such as declines in physical health, cognitive functioning, and psychological well-being (Keyes et al., 2002; World Health Organization [WHO], 2015), there is growing research interest in the factors that help buffer the negative health outcomes in midlife (National Institute on Aging, 2017). For example, conducting a systematic review of resilience factors in the aging research, Ryff et al. (2012) found individual differences in reactions to stress and adversity depending on a number of factors, such as purpose in life (PIL; Morozink et al., 2010) and social relations (Cotter & Lachman, 2010), which can buffer aging-associated declines in mental and physical health.

Among many resilience factors, the favorable effects of positive affect (PA) on various aspects of health have gained considerable support in terms of enhanced health behaviors of medication adherence, sleep, and physical activity (e.g., Sin et al., 2015). PA represents a positive psychological construct moderately associated with, but still independent of, negative affect; hence, a reduction in emotional disorders does not necessarily equal an increase in positive aspects of mental health (Keyes, 2005). PA has been found to be a significant predictor of reduced risk of coronary heart disease (Davidson et al., 2010), lower mortality rates in both healthy and patient samples (Chida & Steptoe, 2008), lower morbidity rates of physical symptoms, and improved immune and cardiovascular functioning (for a thorough review, see Pressman and Cohen, 2005). In a recent study by Hittner et al. (2020), less decline in memory was found associated with PA across middle-aged and older adults.

The value of PA is not limited to health outcomes, but is well recognized in multiple areas of life, such as employment, marriage, and interpersonal relationships (Lyubomirsky et al., 2005). According to Fredricksons (1998) broaden-and-build theory, PA broadens one's attention, thinking, and action scope, which, in turn, builds up one's personal resources such as physical health, learning and mastery, and social relationships, and thus would help cancel out the adverse effects of negative emotions and promote health. Sirgy (2021) also showed that not only have well-being factors been linked to various aspects of better health, but there are also links between PA and work success, better ethics, and positive social relationships.

In addition, there are several recent studies investigating the PA as the source of resilience in adulthood (Pillay, 2020; Ong et al., 2020), where resilience refers to the ability to adapt the acute stress or chronic adversity and sustain psychological well-being (Luthar et al., 2000). For example, Pillay (2020) showed in her recent study that PA is strongly related to resilience, which was also indirectly related through mindfulness. Ong et al. (2020) advocated that the nature of PA and health in later adulthood are nuanced and should be investigated more deeply using the more advanced methodology. These findings suggest that it is not only important to focus on physical and emotional health problems, but that there is a need to acknowledge the importance of understanding the mechanism underlying the positive psychological constructs. Therefore, this study uses PA as the outcome variable to identify the factors that help maintain positive aspects of mental health in midlife and older adults.

Somatic Amplification and Mental Health

Somatic amplification (SA) is defined as the disposition to perceive bodily sensations as noxious and disturbing (Barsky et al., 1988). It entails heightened attention to somatic sensations and a tendency to appraise mild sensations as being unusual and alarming (Barsky et al., 1988). SA has been widely used in health care settings as a measure of individual differences in perceived symptoms (Köteles & Witthöft, 2017). Thus, higher SA has been found to be associated with greater depression and anxiety (Barsky et al., 1988) as well as a number of psychiatric diagnoses (Barsky et al., 1990). Moreover, people with higher SA tend to demonstrate higher levels of hypochondriasis and health anxiety (Barsky et al., 1990; Köteles & Simor, 2014), greater self-reported physical symptoms (Köteles & Simor, 2014; Nakao & Takeuchi, 2018), and elevated risks of various pathological conditions, such as chronic pain, asthma, and functional dyspepsia (for details, see Köteles and Witthoft, 2017).

As midlife is a period characterized by multiple responsibilities involving work, family, and other social roles, as well as the start of aging-related physical and cognitive declines (Lachman, 2015), individuals at this stage of their lives are exposed to multiple stressors, which may manifest in impaired mental health (Hill et al., 2018) or heightened physical symptoms (Ahmad & Zakaria, 2015). Thus, assessment of SA captures the influence of multiple stressors has on midlife and older adults. Yet, despite the significant role that SA plays in various characteristics of mental and physical health, to date there is limited evidence of how SA is related to positive mental outcomes, which constitute an indispensable component of overall mental health.

Protective Factors to Mental and Physical Dysfunction

While adverse circumstances bring about impairments in health outcomes, everybody does not react to stress and trauma following the same pattern. Previous studies have explored individual differences in reactions to challenges through examining moderation effects of demographic variables, including age and gender. Specifically, Wong and Shobo (2017) examined the differential effects of a number of daily stressors on the cortisol level—a biomarker of stress—by age and gender. Findings showed that older retirees were more vulnerable to daily stressors as evidenced by greater risk for subsequent hypothalamic-pituitary-adrenal dysregulation than their younger counterparts. Grzywacz et al. (2004) assessed the differential effects of socioeconomic status on physical symptoms and psychological distress and found that individuals with more education were more resilient to stress. With regard to physical dysfunction, Morozink et al. (2010) found a significantly negative relationship between educational level and the biomarker of health risk, measured by interleukin-6 (IL-6), indicating that the more educated demonstrated less risk. On the other hand, Shook et al. (2017), who also utilized the Midlife in the United States (MIDUS) dataset, used demographic information such as educational level as covariates in an assessment of both positive and negative affect and found no significant relationship between educational levels and affect measures.

Beyond demographic variables, psychosocial factors have also been widely examined as moderators of the relationship between adversity and health outcomes. Under Ryff's (1989) eudaimonic well-being model, psychosocial factors consist of autonomy, PIL, environmental mastery, personal growth, positive relations with others, and self-acceptance. According to Ryff (2014), these six constructs serve as human resilience factors to help buffer against the negative effects of health risks, social inequalities, and life challenges.

In an examination of the ways in which the six constructs of Ryff's eudaimonic well-being moderated the association between educational attainment and level of health risk (IL-6), Morozink et al. (2010) found that the negative relationship between educational level and IL-6 was strengthened by including eudaimonic well-being factors in the model. Further, Hill et al. (2018) found that PIL significantly buffered the influence of daily stress on physical symptoms and negative affect. Similarly, Friedman and Ryff (2012) reported that PIL and positive relations with others significantly buffered against the negative effects of aging (e.g., higher levels of inflammation). For demonstration purposes, we focus on PIL and positive relations with others as the psychosocial factors, given that they are the eudaimonic well-being variables frequently demonstrated to buffer against aging-related adversities (Cotter & Lachman, 2010; Friedman & Ryff, 2012; Ryff et al., 2012).

In the following, we describe and demonstrate the utility of the regression mixture model to shed light on how individuals respond to the various sources of adversity using the MIDUS (Ryff and Almeida, 2017) survey data. Next, we apply the exploratory approach of regression mixture models to identify individuals based on the differential effect of SA on PA. Finally, we investigate which characteristic variables are significantly related to the subgroups of individuals identified based on the latent class variable in regression mixtures.

Analytical Methods for Moderation Effects in Psychological Well-Being Studies

As Ong et al. (2020) pointed out; the existing methodology used to examine different reactions to stressful events among midlife and older adults is concentrated on the regression–interaction method, which incorporates multiplicative interaction terms to the model. For example, Morozink et al. (2010) tested the moderation effect of each psychosocial factor by including two-way interaction terms in the hierarchical regression analyses. Similarly, Friedman and Ryff (2012) used the multiplicative interaction terms between the number of chronic conditions and the psychological functioning measures to examine how the effect of chronic conditions on IL-6 can be buffered by different factors, including positive relationships with others and PIL. In another study, Wong and Shobo (2017) used the regression interaction approach under the multilevel modeling to test whether the effect of daily stressor on the level of stress, measured by cortisol level, was differed by age and gender.

While this method is valuable in acknowledging the contribution of prespecified moderators to buffering the negative effects of adversity, it is subject to limitations that specific hypothesis about the moderators needs to be made in advance and the differential effects are tested given the constraints of the limited set of moderators (Van Horn et al., 2015). Given the mounting evidence of the differential effects of adverse circumstances, methodology limitations warrant attention.

Recently, regression mixture models have gained increasing attention and wider application to social science data as a means of detecting latent heterogeneity underlying a population. Based on their utility for identifying unobserved classes based on the effect of predictors on the outcome, regression mixture models have been found to be an innovative method to explore the potential heterogeneity in the effect of interest. Based on a nationally representative sample of midlife and older adults, the current study furthers aging research by introducing the use of regression mixture models to examine the differential effects of resilience and vulnerability factors on quality of life. More specifically, we utilized a regression mixture model to explore the potential heterogeneity in the relationship between SA and PA, which is a hallmark of overall well-being (Lyubomirsky et al., 2005).

Compared to the regression interaction approach, where researchers specify the grouping or moderating variables a priori, the regression mixture model allows researchers to detect the unobserved (latent) heterogeneity in the effect of predictors on the outcome without requiring the grouping variable. The potential differential effects are detected based on the number of latent classes, which represents the different patterns of the relationship between the predictor and the outcome variables. Based on the identified latent classes, researchers can investigate which factors increase the probability of belonging to a certain latent class by including the latent class predictors in the model.

In the current study, we considered a broad range of demographic variables as well as psychosocial factors and as potential latent class predictors to understand the characteristics of latent classes derived from the regression mixture models. In addition, we included well-being and health conditions, specifically subjective physical health and depression. The inclusion of these variables is based on Almeidas's (2005) framework of resilience and vulnerability factors, which suggests that sociodemographic, psychosocial, and health factors may explain individual differences in stressor exposure and mental and physical reactivity to stressors, which in turn affect well-being. In the following section, we describe the regression mixture modeling.

Regression Mixture Models

The regression mixture model, which is a type of finite mixture model (McLachlan & Peel, 2000), represents a novel statistical tool to detect latent subpopulations underlying the overall population. It features identifying heterogeneous effects from predictors to outcomes in regression and has gained increasing attention in the social sciences recently (Coles et al., 2018; Van Horn et al., 2015). Originally proposed by Quandt (1972) as a switching regression model, regression mixture has attracted attention in a wide range of areas such as marketing (e.g., Desarbo et al., 2001; Sarstedt, 2008), education (e.g., Silinskas et al., 2013), substance use (Daeppen et al., 2013; Fagan et al., 2013), and health (e.g., Coles et al., 2018; Schmiege et al., 2012).

Regression Mixture Models Compared to the Regression Interaction Approach

Regression mixture models follow several statistical assumptions comparable to those of regression interactions, including linearity, precise measurement of the predictors, independent observations, and normally distributed residuals (Van Horn et al., 2015). Beyond these similarities, regression mixture modeling has several advantages over the conventional regression interaction models (Van Horn et al., 2015). For example, it enables the detection of latent subpopulations only based on the differential regression effects without having to provide a priori hypotheses given the limited set of variables. Since the heterogeneous effects are based on the relationships between the predictor(s) and outcome, the model does not require the third variable (moderator) to be in place and, therefore, enables researchers to gain new insights into potential predictors as a means of understanding the differences in the effects.

On the other hand, the traditional interaction approach is a more direct way to test the differential effects when the predictor (moderator) of the differential effects is known. It allows estimating the unbiased parameter of the differential effects when the predictors are measured without errors. However, when the moderator variable contains measurement error, which often is the case with psychosocial factors (e.g., PIL and relationship with others), the regression mixture approach might perform better in estimating the parameter of the differential effects based on a previous simulation study (Van Horn et al., 2015). Specifically, the study showed that the coefficients of the regression interaction were substantially underestimated whereas those from the regression mixture approach were less biased when the moderator was unreliably measured.

Another benefit of using the regression mixture approach is that interpreting the latent classes associated with multiple covariates might be more understandable than interpreting the higher-order interaction models (e.g., three- or four-way interaction). Despite the great potential and explanatory powers of regression mixture models, they are still fairly new in the field of research in aging and their use to date, therefore, has been limited.

Regression Mixture Model Formulation

According to Kim et al. (2016), a typical regression mixture model consists of four components, as shown in Figure 2. It starts with a basic regression model with X (the predictors) exerting influence on Y (the outcomes). In addition, it specifies a latent class factor denoted as C, which affects both the intercept and slope of the regression model, and thus is aimed at capturing the underlying heterogeneity in the relationship between X and Y. Further, it specifies Z, set of covariates potentially contributing to the latent class enumeration, which helps identify factors predicting the differential effects. The dashed line pointing from Z to Y suggests that nonsignificant effects of covariates to the outcome may be removed.

A basic regression mixture model with a single predictor X and the covariate Z may be expressed as follows:

$$Y_{i|X,k} = \beta_{0k} + \beta_{1k}x_i + \beta_2 z_i + \varepsilon_{ik}$$

$$\varepsilon_{ik} \sim N(0, \sigma_k^2)$$

where k denotes the given class, β_{0k} is the intercept for class k, β_{1k} is the class-specific regression coefficient that captures the differential effect of predictor X on the outcome Y across latent classes, β_2 is the effect of the class predictor on the outcome. The class-specific residual is denoted as ε_{ik}, and it is presumed to follow a normal distribution with the class-specific variance being σ_k^2.

Also of interest is the multinomial regression structure in the relationship between Z and C, as expressed below:

$$\Pr(c_i = k|z_i) = \frac{\exp\left(a_k + \sum_{q=1}^{Q} \gamma_{qk} z_{iq}\right)}{\sum_{s=1}^{K} \exp\left(a_s + \sum_{q=1}^{Q} \gamma_{qs} z_{iq}\right)}$$

where $\Pr(c_i = k|z_i)$ refers to the probability of person I to fall into latent class K given the covariate Z among the set of covariates in the model. a_k refers to the latent class intercept, indicating the log odds of being in class K versus the reference class when all covariates Z are constrained to be zero. γ_k refers to the regression coefficient of

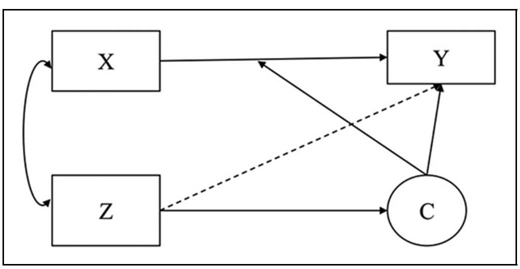

Figure 1. Graphical representation of regression mixture model (based on Kim et al., 2016).

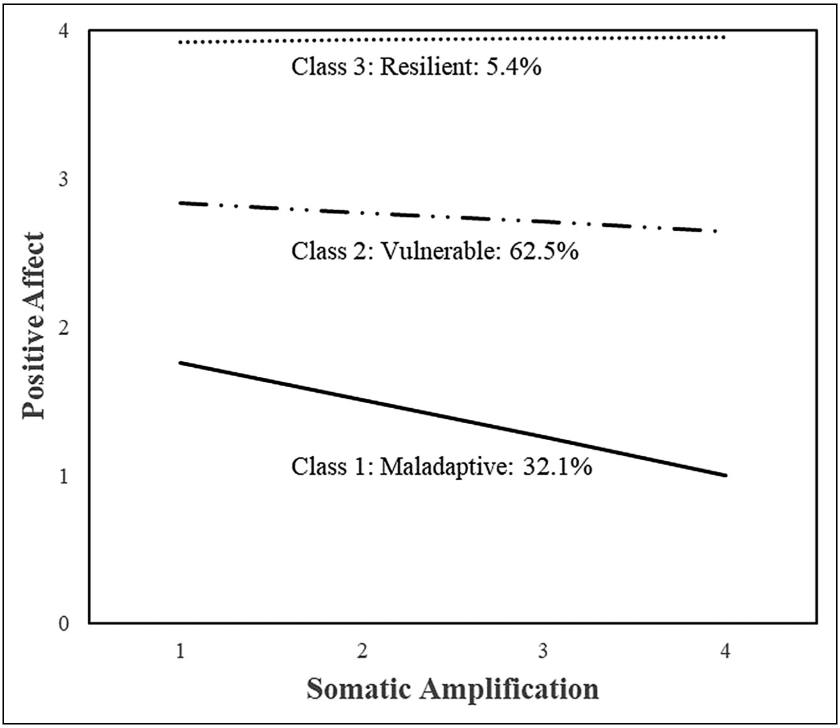

Figure 2. Regression patterns in the unconditional three-class regression mixture solution.

the latent class predictor Z on the probability of being classified into class K versus the reference class.

Purpose of the Study

This study demonstrated the utility of a regression mixture model in identifying latent classes characterized by heterogeneous regression patterns, illustrated through an empirical example of the effect of SA on PA using the second wave of the MIDUS (MIDUS-II) survey. In this demonstration, we aimed to (a) detect the appropriate number of latent classes for the regression mixture model to best fit the data and (b) identify the covariates contributing to the latent class membership under the guidance of theory.

Method

Participants

Data were drawn from the main survey and diary portion of the second wave of the MIDUS (MIDUS-II, 2004–2006; Ryff et al., 2007). MIDUS-II is a follow-up study of the first wave of the MIDUS (MIDUS-I), which includes a national probability sample of English-speaking, noninstitutionalized adults selected through random digit dialing procedures in 1995–1996. The MIDUS study was designed to determine the relationship among physical health, psychological well-being, and social responsibility of American adults. From the initial MIDUS-I, a subset of people ($n = 1{,}483$) participated in the National Study of Daily Events, a daily diary study where people were telephoned and asked about the events of their day across eight consecutive days (see Almeida et al., 2009 and Almeida et al., 2002 for a full description of participant data).

The MIDUS-II follow-up was conducted in 2004–2006, including both participants from the original MIDUS-I and new participants, and the main survey was designed to investigate demographic and psychosocial factors that affect physical and mental health across adulthood. The daily diary project of the National Study of Daily Experiences II (NSDE-II) included 793 participants from the original MIDUS-I and added new participants ($n = 1{,}229$) as well. As a part of the NSDE, participants completed a 15- to 20-min phone interview across eight consecutive evenings on daily stressors, time use, and mood experienced in the previous 24 h.

Among the total sample of 2,022, the current study used included 1,766 individuals (87.3%), who provided valid responses for both the SA measure from the main survey and the measure of PA at Day 1. We particularly utilized the response data from Day 1 because the first day sustains the largest sample size, which is a critical requirement for using the regression mixture models (Jaki et al., 2019).[1] The participants also completed psychosocial assessment and demographic information in an initial project. The analytic sample had a mean age of 56.68 years ($SD = 12.17$, range = 33–84), and a mean household income of \$40,606 ($SD = 38{,}366$, range = 0–200,000). Fifty-seven percent were female, 93% were White, 72% married, and 40% had at least a four-year college degree (see Table 1).

Measures

Somatic Amplification

The SA Scale (Barsky et al., 1988) consists of five items ranging from 1 (*not at all true*) to 4 (*extremely true*) assessing perceptions of bodily sensations. Sample items include "I hate to be too hot or too cold" and "I have a low tolerance for pain." An examination of inter-item correlations showed that the first item, "I am often aware of various things happening within my body," had either weak or nonsignificant associations with other items, and thus was deleted. A confirmatory factor analysis (CFA) treating items as ordinal data suggested a good fit. Factor scores were then saved from the unidimensional CFA model to represent the SA construct, with higher scores indicating greater amplification. Cronbach's alpha for the SA scale was 0.60 in the current study.

Positive Affect

PA was assessed via telephone interviews containing 13 items. Respondents rated their affect experiences in the past 24 h on a 5-point Likert scale ranging from 0 (*none of the*

Table 1. Descriptive Statistics of the Variables.

	M	*SD*	Skewness	Kurtosis	Min	Max
Somatic amplification	0.00	0.99	0.00	−0.25	−2.46	2.69
Positive affect	2.66	0.75	−0.60	0.39	0.00	4.00
Purpose in life	38.89	6.84	−0.54	−0.27	10.00	49.00
Positive relations with others	40.96	6.85	−0.81	−0.04	14.00	49.00
Depression	0.53	1.65	2.98	7.31	0.00	7.00
Self-rated physical health	2.38	0.99	0.53	−0.03	1.00	5.00
Age	56.68	12.17	0.17	−0.83	33.00	84.00
Female	56.50%					
White	92.50%					
Married (yes)	72.30%					
Education						
No school/some grade school (1)	0.30%					
Eight grade/junior high school (2)	1.10%					
Some high school (3)	3.70%					
GED (4)	0.90%					
Graduated from high school (5)	23.60%					
1 to 2 years of college, no degree (6)	18.60%					
3 or more years of college, no degree yet (7)	4.10%					
Graduated from a 2-year college (8)	7.30%					
Graduated from a 4- or 5-year college (9)	20.70%					
Some graduate school (10)	3.70%					
Master's degree (11)	11.50%					
Ph.D. or other professional degrees (12)	4.60%					

Note. *M* = mean; *SD* = standard deviation; Min = minimum; Max = maximum; GED = general equivalency diploma.

time) to 4 (*all of the time*). Sample items included "cheerful?," "in good spirits?," and "full of life?" Scores were averaged to create a composite score with higher scores referring to higher PA. The mean PA level was 2.66 ($SD = 0.75$). Cronbach's alpha for the current sample was 0.904.

Psychosocial Factors

The measures of PIL and positive relations with others were derived from Ryff's (1989) six-dimensional psychological well-being scale. Both measures consisted of seven items rated on a 1 (*strong disagree*) to 7 (*strongly agree*) Likert-type scale. Example items of PIL included "I have a sense of direction and PIL." and "I enjoy making plans for the future and working to make them a reality." Positive relations with others consisted of examples such as “Most people see me as loving and affectionate.” and “ I enjoy personal and mutual conversations with family members and friends.” For each well-being domain, scores were summed across items to yield a composite score with a possible range from 7 to 49, with higher scores indicating a greater level of the construct. In the current sample, Cronbach’s alpha was 0.70 for PIL and 0.78 for positive relations with others.

Physical Health and Depression

Subjective physical health was measured by one item: “In general, would you say your physical health is excellent, very good, good, fair, or poor?” Responses were coded on a 1–5 rating scale, with higher scores indicating worse health. Depression consisted of seven items (1: *yes*; 0: *no*) about depressed affect experienced in the past year (e.g., “lose interest” and “lose appetite”). A sum score was calculated to represent depressive symptoms. Physical health and depression data were collected in the main survey of the MIDUS-II project.

Other Covariates

Demographic variables included sex (1: female; 0: male), race (1: White; 0: others), marital status (1: married; 0: unmarried), and age (in years). The continuous scale of educational attainment ranged between 1 and 12 (coding schemes are in Table 1), is also included as a covariate in the current model.

Statistical Analysis

Descriptive statistics for all variables in the main analysis were examined, including the skewness and kurtosis of the outcome variable PA to check the normality assumptions. For the main analysis, we used the 2-step model building strategy to adopt the regression mixture model, which first decides the number of latent classes without any covariates and then brings the latent class predictors into the model in the next step (Kim et al., 2016). First, an unconditional regression mixture model was analyzed to detect the number of latent classes featuring differential effects of SA on PA using Mplus 7.30 (Muthén & Muthén, 1998–2012). The intercept, regression slope, and residuals were allowed to vary across classes.

The indices of Bayesian information criterion (BIC), sample size adjusted BIC (ABIC), described in Appendix A, and the bootstrapped likelihood ratio test (BLRT) were used for the class enumeration process. The BLRT is a popular fit index employed to select the number of latent classes in finite mixture models in general. However, previous simulation studies have shown that the BIC and ABIC appear to be more effective at detecting the latent classes of differential effects in regression mixture models (George et al., 2013; Kim et al., 2016; Van Horn et al., 2012, 2015). In this study, we used all three fit indices because it is a more conservative approach to examine them all instead of using a sole criterion (Kim et al., 2016). Lower values of BIC and ABIC indicate a better model. The BLRT provides the likelihood ratio test for comparing the specified model with the $k-1$ class model for its significance in the model fit improvement. The significant p-value indicates the supporting evidence of choosing the k number of latent classes instead of $k-1$ classes. The TECH14 command in Mplus was used for testing the BLRT.

It is worth noting that entropy, an indicator of classification accuracy, is not necessarily used for evaluating class enumeration in situations where the classes are mainly defined by differential regression coefficients (Van Horn et al., 2015). On the other hand, a higher value of entropy than the unconditional model is expected when a set of predictors for the latent class are added for better individual classification. We have conducted a series of models by gradually increasing the number of latent classes from 1-class to 5-class and comparing the models based on fit indices. Class proportion also was considered to be a factor in deciding the number of latent classes; if a class proportion is too small (i.e., <5%), it is regarded as a sampling error rather than increasing the number of latent classes.

Next, after determining the most adequate number of latent classes from the unconditional model, predictors were added to the latent class and PA, with a unified regression coefficient across classes. A final set of predictors are determined by their statistical significance guided with the information criteria (i.e., BIC and ABIC) as well as the increased value of entropy compared to the unconditional model, combined with a stable model interpretation within each class (Van Horn et al., 2015). The paths from covariates to the latent class follow multinomial regression. One class would serve as the reference class and odds ratio (OR) was calculated to facilitate the result interpretation. Mplus syntax for the 2-step model building procedure is provided in the Appendix.

Results

Table 1 presents the descriptive information about the main variables and covariates. As illustrated, the distribution of the dependent variable, PA, was approximately normal, which conforms to the normality assumption with the regression mixture model. (The correlations among all the variables included in the analysis are presented in a table in the Appendix.) Following the 2-step model building approach (Kim et al., 2016), we first analyzed the series of unconditional models without covariates for class enumeration.

Step 1: Class Enumeration Using the Unconditional Regression Mixture Model

Table 2 exhibits the model comparison results for 1-class through 5-class regression mixture solution. To determine the number of latent classes, BIC, ABIC, and BLRT were considered. Models with smaller BIC and ABIC values are generally selected as the better-fitting, and the significance of BLRT indicates the support for the k number of classes. Based on both BIC and ABIC, the 3-class model solution yielded the best fit (BIC = 3,798, ABIC = 3,763). The information indices of the 2-class (BIC = 3,854, ABIC = 3,832) and 4-class models (BIC = 3,812, ABIC = 3,764) were worse than those of the 3-class model. Likewise, the BLRT was significant for choosing the 3-class model over the 2-class model, but not significant for the 4-class model over the 3-class model. The 5-class model was not converged, which can be an indication of the existence of too many latent classes to be estimated in regression mixtures (Van Horn et al., 2015). Even though the proportion of the third class in the 3-class model solution is relatively small, given the estimates of the third class that can be distinctively distinguished by other classes and the best fit of ABIC in the 3-class model, we considered the 3-class model, shown in Figure 3, as our unconditional model for subsequent analyses.

Table 3 presents the parameter estimates from the 3-class unconditional model for the class-specific intercepts (β_{0k}), regression weights (β_{1k}; differential effect of SA on PA), residual variance ($\sigma^2{}_k$), and the class mean (α_k). As shown in Figure 3, Class 1 (solid line) contained about 32.1% of the sample. Since it had the lowest intercept ($\beta_{00} = 2.016$, $SE =$ 0.084) and negative effect of SA on PA ($\beta_{10} = -0.254$, $SE = 0.039$) among three latent classes, Class 1 was named a *maladaptive group,* indicating that people in this latent class were significantly and negatively affected by their level of SA on PA. Next, Class 2 (dashed line in the middle) contained about 62.5% of the sample, which was characterized by a slightly higher intercept of PA ($\beta_{01} = 2.893$, $SE = 0.031$) but a relatively modest negative slope ($\beta_{11} = -0.062$, $SE = 0.024$) compared to Class 1. Class 2 was named a *vulnerable group* since people in this latent class were significantly and negatively affected by their level of SA on PA, but the effect of PA was relatively weaker than that of Class 1. Lastly, Class 3, which represented as a dashed line topmost, contained about 5.4% of the sample that had the highest intercept ($\beta_{02} =$ 3.908, $SE = 0.031$) among three latent classes and for whom the effect of SA on PA was not statistically significant ($\beta_{12} = 0.012$, $SE = 0.015$). Class 3 was named a *resilient group* since people classified in this class showed that their PA was not noticeably affected by their level of SA. Based on the 3-class model solution, we proceeded to

Table 2. Fit Indices for Regression Mixture Models From Step 1 for Class Enumeration..

	1-class	2-class	3-class	4-class	5-class
Log-likelihood	−1,960	−1,901	−1,858	−1,850	Nonconvergence
Parameters	3	7	11	15	
BIC	3,942	3,854	3,798	3,812	
ABIC	3,932	3,832	3,763	3,764	
p-BLRT	—	<0.001	<0.001	0.088	
Entropy	NA	0.383	0.606	0.535	
% class 1	100.0%	30.5%	32.1%	14.8%	
% class 2		69.5%	62.5%	43.5%	
% class 3			5.4%	5.8%	
% class 4				36.0%	

Note. BIC = Bayesian information criterion; ABIC = adjusted BIC; *p*-BLRT = *p*-bootstrapped likelihood ratio test.

an analysis of the conditional model to understand the characteristics of the two qualitatively different groups.

Step 2: Conditional Regression Mixture Model With Latent Class Predictors

In the second step, we added a number of latent class predictors to characterize the qualitatively different classes, which included demographic (i.e., age, gender, White, marital status, and educational attainment), psychosocial (i.e., positive relations with others and PIL), and physical and mental health condition variables (i.e., depression and self-rated physical health). Next, we removed the variables that were not statistically significant at $p < 0.05$, yielded lower class separation (indicated by lower entropy), or produced results with class proportions deviating much from the unconditional model. This led to the removal of gender, White, and marital status variables. Although the direct effects of latent class predictors on outcome variable PA (dotted line in Figure 2) were included in the next step followed by the 2-step model building procedure (Kim et al., 2016), the model was not properly converged, possibly due to its excessive complexity. Thus, all direct effects were ruled out for the sake of model parsimony. Thus, the final model included six latent class predictors (i.e., age, educational attainment, positive relations with others, PIL, depression, and self-rated physical health), which characterized the three latent classes that emerged.

The estimated parameters for the three latent classes from the conditional model are presented in Table 3. Compared to the unconditional model, entropy for the conditional model increased from 0.606 to 0.677, revealing higher class separation and suggesting the appropriateness of the covariate inclusion (Fagan et al., 2013). In addition, the conditional model showed similar class proportions as before (32.1%, 62.5%, and 5.4% vs. 38.5%, 55.7%, and 5.8% for the maladaptive, vulnerable, and resilient group, respectively). Further, the pattern of relationship between SA and PA was comparable to that of the unconditional model. For example, similar to the unconditional model, the intercept of the maladaptive group ($\beta_{00} = 2.083$, $SE = 0.068$) was the lowest, and the resilient group ($\beta_{02} = 3.899$, $SE = 0.024$) had the highest intercept. Also, the regression slope revealed a significantly negative pattern in the maladaptive group ($\beta_{10} = -0.150$, $SE = 0.036$), a moderately negative pattern in the vulnerable group ($\beta_{11} = -0.032$, $SE = 0.020$), and was still almost flat and not significant in the resilient group ($\beta_{12} = -0.020$, $SE = 0.013$). These results provide strong evidence for model stability before and after adding covariates to the latent class, reflecting that the class enumeration was based on the differential effect of SA on PA rather than being driven by the latent class predictors.

The logistic regression results of the covariates on the latent class membership are displayed in Table 3 with the maladaptive group (Class 1) serving as the reference group. The results showed that older people were more likely to belong to the resilient group ($\gamma_{12} = 0.071$, $SE = 0.013$, OR = 1.074) and vulnerable group ($\gamma_{11} = 0.034$, $SE = 0.008$, OR = 1.035) than the maladaptive group, respectively. In the case of educational attainment, more educated people were less likely to fall into the resilient group

Table 3. Parameter Estimates and Standard Errors for the 3-Class Model.

	Step 1: unconditional model						Step 2: conditional model					
	Maladaptive		Vulnerable		Resilient		Maladaptive		Vulnerable		Resilient	
Class proportion	32.1%		62.5%		5.4%		38.5%		55.7%		5.8%	
	B	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*	*B*	*SE*
Entropy	0.606						0.677					
Intercept (β_{0k})	2.016***	0.084	2.893***	0.031	3.908***	0.031	2.083***	0.068	2.948***	0.036	3.899***	0.024
Somatic amplification (β_{1k})	−0.254***	0.039	−0.062**	0.024	0.012	0.015	−0.150***	0.036	−0.032	0.020	0.020	0.013
Residual variance (σ^2_k)	0.482**	0.027	0.198***	0.019	0.009**	0.003	0.465***	0.030	0.168***	0.018	0.010***	0.003
Latent class mean (α_k)	2.446***	0.224	1.779***	0.243	–	–	–	–	−6.504***	1.068	−5.477**	2.066
Latent class predictor												
Age (γ_1)	–	–	–	–	–	–	–	–	0.034***	0.008	0.071***	0.013
Educational attainment (γ_2)	–	–	–	–	–	–	–	–	−0.127*	0.049	−0.278***	0.067
Positive relations with others (γ_3)	–	–	–	–	–	–	–	–	0.098***	0.018	0.135**	0.042
Purpose in life (γ_4)	–	–	–	–	–	–	–	–	0.080***	0.019	0.107***	0.030
Depression (γ_5)	–	–	–	–	–	–	–	–	−0.300**	0.089	−0.081	0.119
Self-rated physical health (γ_6)	–	–	–	–	–	–	–	–	−0.405***	0.111	−0.776**	0.229

Note. $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

($\gamma_{22} = -0.278$, $SE = 0.067$, OR = 0.757) and vulnerable group ($\gamma_{21} = -0.127$, $SE = 0.079$, OR = 0.880) than the maladaptive group, respectively. In other words, the more educated people tend to belong to the class with the more negative effect of the SA on PA.

Both coefficients of positive relations with others were significant and positive, meaning that people with a higher level of positive relations with others were more likely to fall into the resilient ($\gamma_{32} = 0.135$, $SE = 0.042$, OR = 1.145) or the vulnerable group ($\gamma_{31} = 0.098$, $SE = 0.018$, OR = 1.103) than the maladaptive group. Similarly, people who had a higher level of PIL were more likely to fall into the resilient group ($\gamma_{42} = 0.107$, $SE = 0.030$, OR = 1.113) or the vulnerable group ($\gamma_{41} = 0.080$, $SE = 0.019$, OR = 1.083) than the maladaptive group. Depression was significant only when compared with the vulnerable group ($\gamma_{51} = -0.300$, $SE = 0.089$, OR = 0.741), meaning that the odds of being in the vulnerable group was 25.9% lower than being in the maladaptive group for those who scored one unit higher in depression. That is, if people demonstrate higher levels of depression, they are more likely to be classified in the most negative group (maladaptive group). Lastly, both coefficients of self-rated physical health were significant and negative, meaning that if people thought of themselves as unhealthy, they were more likely to fall into the maladaptive group than the vulnerable ($\gamma_{61} = -0.405$, $SE = 0.111$, OR = 0.667) or the resilient group ($\gamma_{62} = -0.776$, $SE = 0.229$, OR = 0.460).

Discussion

This study describes and demonstrates the utility of a regression mixture model to explore individual differences in reaction to adversity based on a population sample of midlife and older adults. Rather than making a priori hypotheses of a fixed set of moderators using the conventional regression interaction approach, the novel method tests the differential regression patterns by specifying a latent class variable C, which represents the unobserved subpopulation underlying the effect of interest.

Based on the 2-step model building approach, three latent classes were detected representing the differential effects of SA on PA from the first step. The first class (32.1%), named the maladaptive group, showed a negative relationship between the SA and PA. This group will possibly be the focus of future investigations in clinical research to determine who the group members are and why they are prone to sensitivity to the effect of SA on their daily PA. The second class (62.5%), labeled the vulnerable group, also showed negative effects of SA on PA, but the effect was relatively smaller than for the first group. The last class (5.4%) was the resilient group, displaying no significant relationship between the two variables. This finding is consistent with previous studies showing that not all adults respond to difficult circumstances in the same manner (Ryff et al., 2012) and highlights the important need to capture differential responses in the study of well-being and health in adulthood.

In the second step of regression mixture analysis, several latent class predictors are added to the 3-class model to understand the characteristics of the three latent classes. The results supported the previous findings that PIL and positive relations with others served as protective factors buffering the negative effects of adverse situations on mental well-being (Friedman & Ryff, 2012), whereas depressive symptoms constituted a risk factor accentuating the effects of stressful circumstances (Hill et al., 2018; Morozink et al., 2010). The significant effect of PIL in terms of predicting the latent classes may be understood to mean that adults with central life goals tend to allocate more resources to activities consistent with their goals, which enables them to appraise and respond to adversities within a broader framework (McKnight & Kashdan, 2009), thus being resistant to the stressful circumstances. The significant buffering effect of positive relationships with others supports previous findings that PA is significantly related to positive relationships in older adults, including romantic relationships (Levenson et al., 1994; Steptoe et al., 2011), friendships (Huxhold et al., 2014), and parent–child relationships (Mancini & Blieszner, 1989). A review of studies involving PA and close relationships also supports the finding that the aforementioned three types of positive relationships are bidirectionally related to PA across the lifespan (Ramsey & Gentzler, 2015).

Our findings regarding age support previous research of the “well-being paradox” within successful aging, showing that all aspects of well-being do not decline with age, but that some, such as subjective well-being, are stable or may even increase (Baltes & Carstensen, 2003; Hansen & Slagsvold, 2012). For example, one study found a significant increase in reported mindfulness and PA in older adults (Shook et al., 2017). In another study using a longitudinal design, PA was stable and negative affect decreased, contradicting the prevalent belief that life satisfaction decreases with age (Hansen & Slagsvold, 2012). Mroczek and Kolarz (1998) also found a relationship between PA and age, although the nature of the relationship changes with sex (linear among men and an accelerating curve among women).

Concerning physical status, previous studies have shown that individuals with high PA levels report fewer disease symptoms and more positive self-rated physical health (Elkins et al., 1999; Gatten et al., 1993; Grootscholten et al., 2003; Pressman & Cohen, 2005). The results of the current study also showed that the level of the self-rated physical is a factor causing the difference in the effect of SA on PA. Specifically, the negative effect of SA on PA was stronger if people reported many symptoms of their own underlying diseases. This suggests that those two factors are associated; however, there are small differences with previous studies that have studied the direct relationship between PA and self-reported health (Pressman & Cohen, 2005). This relationship between health and PA may be due to happiness relating to lower stress responses, such as cortisol level and ambulatory heart rate (Steptoe & Wardle, 2005).

In terms of the relationship between education and PA, findings from the present study showed that respondents with higher education levels were less likely to belong to the resilient group than the maladaptive group. Previous studies have shown mixed findings with regard to the relationship between educational level and the affect measures. For example, one study involving age and affect (both positive and negative) found that education had a negative relationship with PA, but only in men (Mroczek & Kolarz, 1998). This same study found that even though education was not related to PA for women, it was a significant predictor of negative affect, with higher education relating to lower negative affect. Charles et al. (2001) found that an increase in the years of education related to an increase in average PA. Another study that utilized MIDUS-II demonstrated that although education level was positively and linearly related to optimism, it was not associated with PA (Boehm et al., 2015). Finally, a study in Spain found an indirect effect of education on happiness (through labor status and income); however, the direct effect was determined not to be reliant on the actual level of education (Cuñado & de Garcia, 2012).

The current study has significant implications for adopting a methodology for future research in the field of aging. As Pressman et al. (2019) advocated in their study, novel statistical approaches are in need to understand the possible patterning of PA related to health outcomes and when and how these associations occur. The finding of three distinct and theoretically meaningful latent classes shows the capacity of a regression mixture model to uncover heterogeneous groups based on the effect of the primary predictor on the outcomes without associating the third variable. As such, it demonstrates that individual differences in the regression pattern can be tested and extracted empirically. Given that the promotion of well-being has public health significance, regression mixture methodology can serve as a valuable tool in investigating middle-aged and older adults' capacity to maintain high levels of well-being across diverse contexts with research questions such as, "Are there any individual variations in the effect of a key variable to the outcome?" Furthermore, this methodological approach can deepen the existing resilience literature by better capturing the risk factors that increase vulnerability in midlife and late adulthood that, in turn, may lead to disparities in physical health functioning.

Limitations and suggestions for future directions are as follows. First, for demonstration purposes, only a limited number of variables were used to represent adversity, mental health, and resiliency. It is recommended that future research extend the current findings to a broader range of adverse circumstances, well-being outcomes, and moderators to provide more evidence about the utility of the novel statistical tool in aging research. For example, the method is applicable to other large-scale aging datasets, including The English Longitudinal Study of aging (Banks et al., 2010), Health and Retirement Study (Health and Retirement Study, 2008), The Wisconsin Longitudinal Study (Sewell et al., 2004), and Survey of Midlife in Japan (Ryff et al., 2018), to help address broader research questions of resilience in aging in different cultures.

Second, the internal reliability for the SA and PIL scales was somewhat low. Especially, the reliability of the SA was.60, which can be considered as the lowest cutoff value to be adopted for further analysis. According to Ishii (2019), the low reliability of the SA scale has been shown across different cultures and it might be due to that SA is associated not only with interoception but also with exteroception (Köteles & Witthöft, 2017). Although the SA with low reliability has been used in previous studies (Ishii, 2019; Ryff et al., 2007), we note that the conceptual ambiguity of SA might affect the substantive interpretation of the analytical results.

Third, in the daily diary portion of the MIDUS-II sample, PA was measured repeatedly for eight consecutive days. Although we opted to use the measure from Day 1 for the sake of retaining the largest sample size as well as to reduce the complexity of our demonstration, repeated measures can be incorporated into the regression mixture models by extending it to the multilevel regression mixture models (Vermunt, 2010), repeated-measures regression mixture models (Kim et al., 2020), or factor mixture models (Lubke & Muthen, 2005). Future research is warranted to take into account all available information from the repeated measures to validate the current findings based on a single response to PA.

Related to that, we only included the manifest variables in the current regression mixture models, but latent constructs could be formed to represent the psychosocial or physical health factors. For example, the current approach can be extended to a more general model under the factor mixture models (Lubke & Muthén, 2005) by including the latent constructs comprised of the observed indicators. It should be noted that researchers are responsible for checking the model assumptions (e.g., local independence) when employing the latent constructs in the finite mixture models, including the regression mixture models (Raykov et al., 2016).

Additionally, while we have highlighted the advantages of the regression mixture models over the traditional regression interaction approach, we have no intention to discourage the use of the traditional methods given that they have their own benefits, such as efficiently testing a priori identified interaction terms. Thus, the main goal of this study was to demonstrate the application of the regression mixture approach using the publicly available secondary data MIDUS-II, but not to compare the regression mixture approach to the conventional regression interaction method. Readers who are interested in learning more about comparisons of the two methods are directed to the simulation study conducted by Van Horn et al. (2015).

Conclusion

The study demonstrated that the use of a regression mixture approach brings unique strengths to identifying heterogeneity in the population as well as investigating predictors that help explain the heterogeneous patterns of associations between variables. Its application to MIDUS-II, a study on well-being and health in adulthood, showcases its utility in identifying latent subgroups and exploring resilience factors. It is highly recommended that future aging research consider adopting the regression mixture method to better capture the complexity underlying reactions to adversity.

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Supplemental Material

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Note

1. Additionally, we have analyzed the regression mixture for the Day 2 and 3 data, and found consistent results across different days of data.

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Appendix A.

The BIC (Schwarz, 1978) can be written as follows:

$$\text{BIC} = -2\log L + p\log(N)$$

where $\log L$ is the maximized log-likelihood value, p is the number of parameters, and N is the number of cases. BIC also penalizes complex models and a smaller BIC value indicates a more favorable model when comparing models.

The sample-size ABIC (Sclove, 1987) can be written as follows:

$$\text{ABIC} = -2\log L + p\log[(N+2)/24]$$

which in general gives less penalty for the large sample size compared to BIC (Dziak et al., 2020).

Appendix B. Pearson Correlations Among the Study Variables.

	SA	PA	Relations	PIL	Physical	Depression	Gender	White	Education	Marital	Age
SA	1										
PA	−0.184**	1									
Relations	−0.156**	0.369**	1								
PIL	−0.203**	0.324**	0.592**	1							
Physical	0.204**	−0.219**	−0.232**	−0.290**	1						
Depression	0.206**	−0.242**	−0.215**	−0.222**	0.210**	1					
Gender	0.212**	0.015	0.143**	−0.013	0.006	0.116**	1				
White	−0.072**	0.013	0.062**	0.03	−0.111**	0.023	0.009	1			
Education	−0.105**	−0.028	0.052*	0.142**	−0.214**	−0.045	−0.123**	0.052*	1		
Marital	−0.073**	0.056*	0.124**	0.169**	−0.069**	−0.103**	−0.148**	0.073**	0.067**	1	
Age	−0.004	0.166**	0.135**	−0.033	0.122**	−0.129**	−0.025	0.03	−0.097**	−0.069**	1

Note. SA = somatic amplification; PA = positive affect; Relations = positive relations with others; PIL = purpose in life; Physical = self-rated physical health; Marital = marital status. $*p < 0.05$; $**p < 0.01$.

Appendix C.

Mplus syntax for the two-step model building procedure

```
!In step-1, the number of latent class C is explored through fitting a series of unconditional
!regression mixture models. For demonstration purpose, 1-, 2-, 3-class model were fit, higher
!number of latent classes can be fit in the same manner.

!Unconditional regression mixture model when the number of C is 1;
title: Unconditional regression mixture model when the number of C is 1;
data: file is c:\data\midus2.dat;
variable:
names are PA SA age edu relations pil depression physical;
!positive affect, somatic amplification, age, education, positive relation with others,
!purpose in life, depression, self-rated physical health
usevariables are PA SA;
missing are all (999);
classes = c(1); !the number of latent C is 1.
analysis: type = mixture;
model:
%overall%
PA on SA;
output:
sampstat standardized;

!Unconditional regression mixture model when the number of C is 2;
title: Unconditional regression mixture model when the number of C is 2;
data: file is c:\data\midus2.dat;
variable:
names are PA SA age edu relations pil depression physical;
!positive affect, somatic amplification, age, education, positive relation with others,
!purpose in life, depression, self-rated physical health
usevariables are PA SA;
missing are all (999);
classes = c(2); !the number of C is 2.
analysis: type = mixture;
model:
%overall%
PA on SA;
%C#2% !Separate model for latent class 2.
PA on SA; !Allows regression coefficient to be freely estimated.
PA; !Allows the residual variance of the outcome to be freely estimated across classes.
```

```
output:
sampstat standardized;

!Unconditional regression mixture model when the number of C is 3;
title: Unconditional regression mixture model when the number of C is 3;
data: file is c:\data\midus2.dat;
variable:
names are PA SA age edu relations pil depression physical;
!positive affect, somatic amplification, age, education, positive relation with others,
!purpose in life, depression, self-rated physical health
usevariables are PA SA;
missing are all (999);
classes = c(3); !the number of C is 3.
analysis: type = mixture;
model:
%overall%
PA on SA;
%C#2% !Separate model for latent class 2.
PA on SA; !Allows regression coefficient to be freely estimated.
PA; !Allows the residual variance of the outcome to be freely estimated across classes.
%C#3% !Separate model for latent class 3.
PA on SA; !Allows regression coefficient to be freely estimated.
PA; !Allows the residual variance of the outcome to be freely estimated across classes.
output:
sampstat standardized;

!Step-2: after the number of latent class C (=3) is determined through the previous procedure,
!conditional regression mixture models are fitted by adding covariates
!while fixing the number of C to be 3.
!Below is the Mplus syntax for the final model used in this study.
title: Conditional regression mixture model;
data: file is c:\data\midus2.dat;
variable:
names are PA SA age edu relations pil depression physical;
!positive affect, somatic amplification, age, education, positive relation with others,
!purpose in life, depression, self-rated physical health
usevariables are PA SA age edu relations pil depression physical;
missing are all (999);
classes = c(3); !the number of latent C is fixed to 3.
analysis: type = mixture;
model:
%overall%
```

```
PA on SA;
c ON age edu relations pil depression physical;
!Logistic regression (the effect of the age, education, positive relation with others,
!purpose in life, depression, and self-rated physical health on positive affect.
B2DPOSAV ON B1PDEPAF B1SPWBU2 edu;
%C#2% !Separate model for latent class 2.
PA on SA; !Allows regression coefficient to be freely estimated.
PA; !Allows the residual variance of the outcome to be freely estimated across classes.
%C#3% !Separate model for latent class 3.
PA on SA; !Allows regression coefficient to be freely estimated.
PA; !Allows the residual variance of the outcome to be freely estimated across classes.
output:
sampstat standardized;
```