

Modeling Multisystem Physiological Dysregulation

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ABSTRACT

Objectives: The purposes of this study were to compare the relative fit of two alternative factor models of allostatic load (AL) and physiological systems, and to test factor invariance across age and sex.

Methods: Data were from the Midlife in the United States II Biomarker Project, a large ($n = 1255$) multisite study of adults aged 34 to 84 years (56.8% women). Specifically, 23 biomarkers were included, representing seven physiological systems: metabolic lipids, metabolic glucose, blood pressure, parasympathetic nervous system, sympathetic nervous system, hypothalamic-pituitary-adrenal axis, and inflammation. For factor invariance tests, age was categorized into three groups (≤ 45 , 45–60, and > 60 years).

Results: A bifactor model where biomarkers simultaneously load onto a common AL factor and seven unique system-specific factors provided the best fit to the biomarker data (comparative fit index = 0.967, root mean square error of approximation = 0.043, standardized root mean square residual = 0.028). Results from the bifactor model were consistent with invariance across age groups and sex.

Conclusions: These results support the theory that represents and operationalizes AL as multisystem physiological dysregulation and operationalizing AL as the shared variance across biomarkers. Results also demonstrate that in addition to the variance in biomarkers accounted for by AL, individual physiological systems account for unique variance in system-specific biomarkers. A bifactor model allows researchers greater precision to examine both AL and the unique effects of specific systems.

Key words: physiological dysregulation, allostatic load, biomarkers, Midlife in the United States.

INTRODUCTION

Psychosomatic research has characterized the relations of psychological variables and indicators of major physiological regulatory systems in humans such as the parasympathetic nervous system (PNS) and the hypothalamic-pituitary-adrenal (HPA) axis (for examples of reviews, see Refs. (1–3)). Measures of physiological systems are frequently operationalized via the use of biomarkers. As the field of psychosomatic medicine has advanced, it is increasingly common for multiple biomarkers to be assessed. Although many biomarkers exist for each physiological system, there is little consensus on how to integrate these biomarkers to assess the state and functioning of physiological systems and multisystem physiological dysregulation. Despite the lack of consensus on how to integrate multiple biomarkers, it does seem that using combinations

of biomarkers is valuable. For example, in one study, a composite risk score of biomarkers predicted all-cause mortality over and above age and sex (4), and in another study, the number of high-risk biomarkers combined demonstrated a gradient relationship with mortality (5).

AL = allostatic load, CFI = comparative fit index, CRP = C-reactive protein, DBP = diastolic blood pressure, DHEA-S = dihydroepiandrosterone sulfate, E = epinephrine, HFHRV = high-frequency spectral power, HOMA-IR = homeostatic model assessment of insulin resistance, HPA = hypothalamic-pituitary-adrenal axis, IL-6 = interleukin-6, LDL = low-density lipoprotein, PNS = parasympathetic nervous system, MIDUS = Midlife in the United States, NE = norepinephrine, RMSEA = root mean square error of approximation, RMSSD = root mean square of successive differences (RMSSD) of beat-to-beat intervals, SBP = systolic blood pressure, sE-Selectin = soluble E-selectin, SNS = sympathetic nervous system, SRMR = standardized root mean square residual

SDC Supplemental Content

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One conceptual approach to integrating biomarkers of multiple systems is allostatic load (AL), which posits that the body's adaptation to challenge and demands of the environment (allostasis; (6)) over time takes a physiological toll and results in cumulative wear-and-tear or dysregulation across multiple physiological systems (7). Thus, the dysregulation is hypothesized to be a multisystems phenomenon that occurs across multiple regulatory systems rather than in particular systems only (for a review, see Ref. (8)). Figure 1 shows a diagram of three potential levels of analysis for biomarkers, from using specific biomarkers as outcomes (bottom), to combining multiple biomarkers to assess specific physiological systems (middle), and the highest aggregate combining multiple physiological systems (AL; top). The primary goal of this study is to test two plausible measurement models of biomarkers hypothesized to represent both overall AL and individual physiological systems.

An individual with allostatic overload and systemwide dysregulation will demonstrate some degree of dysregulation in multiple physiological regulatory systems involved in allostasis, and this physiological dysregulation may be assessed using a composite index from multiple systems. To date, such indices of AL have typically been created by assuming equal influence of individual biomarkers, dichotomizing them into high and low health risk based on quartiles or clinical risk points, averaging within a particular physiological system (e.g., cardiovascular), and then summing (e.g., Refs. (4,9)). Similar indices have been created by first standardizing individual biomarkers and then summing (e.g., Ref. (10)). Although less commonly applied to biological data, scale development and testing methods such as factor analysis have been used for years to develop

and validate measures of latent constructs (e.g., depressive symptoms) from multiple observed indicators (e.g., feeling sad or blue, loss of interest). For an introduction to factor analysis in psychosomatic research, see Ref. (11).

The few studies that have examined the psychometric properties and tested the factor structure of biomarkers in relation to AL found that a second-order AL factor (i.e., biomarkers load onto individual system factors which in turn load onto AL) provided adequate fit to the data (12–14). Related work in metabolic syndrome has shown a similar hierarchical factor structure (e.g., Refs. (15,16)). In addition, a second-order AL factor model of biomarkers was found to be invariant across sex and ethnicity (13), and provided good fit when controlling for sex and age (12); it did, however, differ between participants on and off of medications in an elderly sample (14).

Limitations are apparent in the existing literature on AL. First, previous research has had relatively few biomarkers per system, leaving open the question whether the same factor structure will emerge when systems are more comprehensively assessed. Second, although AL is hypothesized to be prominent in the aging process (17), to our knowledge, no previous study has tested whether the measurement of AL is invariant across adulthood or whether the relations among biomarkers differ as a function of age. Finally, although a second-order factor model provided adequate fit in previous studies, there was room for improvement of model fit. Given the complex relations among biomarkers, examining alternative models may be valuable.

In the present study, we used data from the Midlife in the United States (MIDUS) II Biomarker Project, to address the following aims.

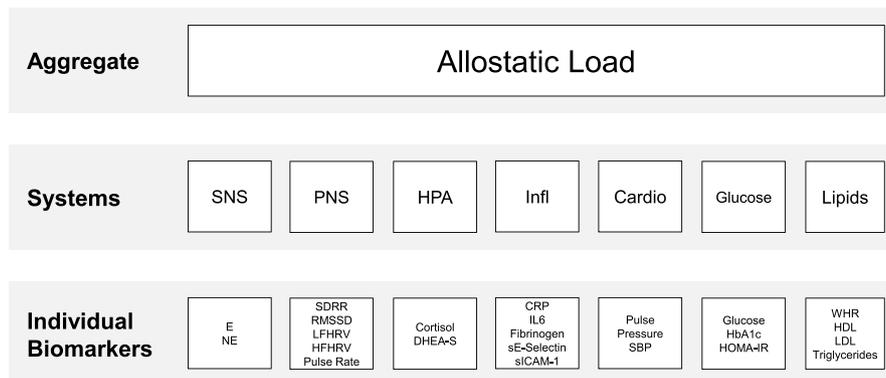


FIGURE 1. Continuum of specificity of biomarker outcomes, from the level of individual biomarkers, to individual physiological systems, to composites across multiple systems. SNS = sympathetic nervous system; PNS = parasympathetic nervous system; HPA = hypothalamic-pituitary-adrenal axis; Infl = inflammation; Cardio = cardiovascular; E = epinephrine; NE = norepinephrine; SDRR = standard deviation of beat-to-beat intervals; RMSSD = root mean square of successive differences (RMSSD) of beat-to-beat intervals; LFHRV = low-frequency spectral power; HFHRV = high-frequency spectral power; DHEA-S = dihydroepiandrosterone sulfate; CRP = C-reactive protein; IL-6 = interleukin-6; sE-Selectin = soluble E-selectin; sICAM-1 = soluble intracellular adhesion molecule 1; SBP = systolic blood pressure; HbA1c = glycosylated hemoglobin; HOMA-IR = homeostatic model assessment of insulin resistance; WHR = waist-to-hip ratio; HDL = high-density lipoprotein; LDL = low-density lipoprotein.

Aim 1

To test and compare two theoretically derived factor models that reflect the following hypotheses: a) biomarkers within a physiological system are associated, and b) based on AL theory that there is systemwide dysregulation, biomarkers or systems should load onto a common factor. The structure of the two models is diagrammed in Figure 2.

Model 1

Biomarkers load onto their respective physiological system, and the seven systems, in turn, load onto a second-order factor. This model tests whether relations among biomarkers are explained by each physiological subsystem, and the relations among the physiological subsystems are explained by a single, common second-order factor (AL).

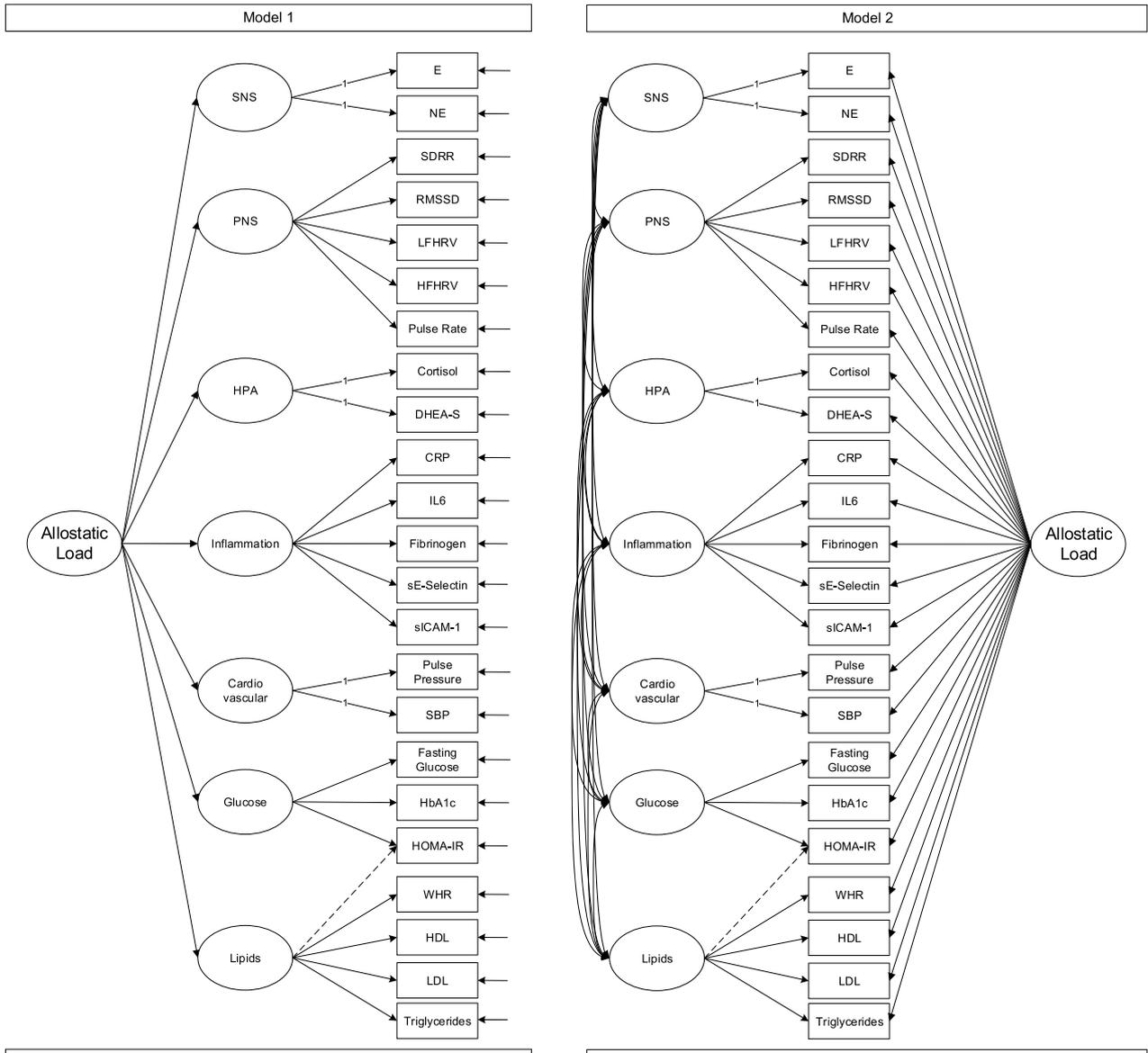


FIGURE 2. Sample diagrams of the two plausible factor models tested and compared. Adapted from <http://score-project.org> and reprinted with permission. SNS = sympathetic nervous system; PNS = parasympathetic nervous system; HPA = hypothalamic-pituitary-adrenal axis; E = epinephrine; NE = norepinephrine; SDRR = standard deviation of beat-to-beat intervals; RMSSD = root mean square of successive differences (RMSSD) of beat-to-beat intervals; LFHRV = low-frequency spectral power; HFHRV = high-frequency spectral power; DHEA-S = dihydroepiandrosterone sulfate; CRP = C-reactive protein; IL-6 = interleukin-6; sE-Selectin = soluble E-selectin; sICAM-1 = soluble intracellular adhesion molecule 1; SBP = systolic blood pressure; HbA1c = glycosylated hemoglobin; HOMA-IR = homeostatic model assessment of insulin resistance; WHR = waist-to-hip ratio; HDL = high-density lipoprotein; LDL = low-density lipoprotein.

Model 2

Biomarkers load onto their respective physiological system, and the seven systems are allowed to freely covary; in addition, each biomarker loads directly onto a common factor (AL). This bifactor model tests whether the relations among biomarkers are explained by two processes: a) a common factor, capturing the notion that there is an underlying process influencing multiple physiological systems, and 2) system-specific factors, capturing the notion that beyond the common portion shared across biomarkers, there are unique effects of particular physiological systems that are independent of other systems. Model 1 is nested within Model 2 allowing for a direct test of fit.

Specifically, we hypothesize that Model 1 will demonstrate acceptable fit and represent a parsimonious version of a correlated-systems model. Finally, if systemwide effects drive the individual systems, then Model 2 will demonstrate no better fit than Model 1 and be less parsimonious. However, if the systemwide and system-specific effects have unique and nonoverlapping elements, Model 2 should demonstrate better fit. Because we expect important, unique systemwide and system-specific effects, we hypothesize that Model 2 will demonstrate the best fit.

Aim 2

To test whether the optimal factor structure underlying biomarkers of AL (Aim 1) is invariant across adulthood from 34 to 84 years of age and sex.

METHODS

Sample

The sample came from the larger MIDUS study. The first wave of data, MIDUS I, included phone interviews and mailed questionnaires to a national sample of adults aged 25 to 74 years and was designed to assess factors related to physical and psychological health and well-being in early adulthood, middle adulthood, and older age. Data for MIDUS I were collected in 1994 to 1995 in four parts: a large, national probability sample (the core sample; $n = 3487$); siblings of the core sample ($n = 950$); twins ($n = 957$ pairs); and an oversampling in metropolitan areas ($n = 757$). Participants from MIDUS I, as well as an additional sample of urban African Americans living in Milwaukee, WI ($n = 592$, to increase diversity), were assessed in 2005 for MIDUS II (18). MIDUS II included follow-up questionnaires, and a subset of participants who were eligible and consented ($n = 1054$ from the original sample and $n = 201$ from the Milwaukee sample) participated in the MIDUS II Biomarker Project, where extensive biological data were collected (19). Thus, a total of 1255 participants were included coming from 1098 families (944 families contributing one participant, 152 families contributing two participants, 1 family contributing three participants, and 1 family contributing four participants).

Procedure

As part of the MIDUS II Biomarker Project, participants went to one of three (University of California, Los Angeles; University of Wisconsin; and Georgetown University) General Clinical Research Centers for a medical examination and comprehensive biomarker assessment (e.g., fasting blood draw, 12-hour urine, and electrocardiography), and reported on medication history. Details on MIDUS are available online at <http://www.midus.wisc.edu>, and for the biomarker project, see Ref. (19). The MIDUS II Biomarker Project was approved by the institutional review boards of the University of Wisconsin, Madison; the University of California, Los Angeles; and Georgetown University.

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Demographics and Health Outcomes

Demographic data including age, sex, and ethnicity were collected via self-report. Self-reported medication use, including antihypertensive medications, heart rate reducing (e.g., β -blockers), diabetes medications, cholesterol-lowering medications, and fibrates, was collected and used to identify medication-free participants.

Biological Measures

Seven physiological systems were measured using 23 biomarkers. Details on collection and assay of biomarkers are reported in Supplementary Data File 1, <http://links.lww.com/PSYMED/A264>, in Ref. (20).

Sympathetic Nervous System

The sympathetic nervous system (SNS) was measured using 12-hour, overnight urinary epinephrine (E) in mg/g creatinine and norepinephrine (NE) in mg/g creatinine.

Parasympathetic Nervous System

The PNS was measured using heart rate variability and resting pulse rate (in beats per minute). Heart rate variability was assessed via electrocardiography and was operationalized as the standard deviation of beat-to-beat intervals (R-R interval), root mean square of successive differences (RMSSD), low-frequency spectral power, and high-frequency spectral power (HFHRV).

Hypothalamic-Pituitary-Adrenal Axis

The HPA axis was measured using 12-hour, overnight urinary cortisol $\mu\text{g/g}$ creatinine and blood serum dihydroepiandrosterone sulfate (DHEA-S) in $\mu\text{g/dL}$.

Inflammation

Inflammation was measured using plasma levels of C-reactive protein (CRP) in mg/L, interleukin-6 (IL-6) in ng/L, fibrinogen in mg/dL, soluble E-selectin (sE-Selectin) in ng/mL, and soluble intracellular adhesion molecule 1 in mg/L.

Cardiovascular

The cardiovascular system was measured with resting systolic blood pressure (SBP) in mm Hg and diastolic blood pressure (DBP) in mm Hg. For the model, these were converted into pulse pressure (SBP – DBP) and SBP.

Glucose

The metabolic glucose system was measured using the homeostatic model assessment of insulin resistance (HOMA-IR), fasting glucose in mg/dL, and glycosylated hemoglobin in percent.

Lipids

The metabolic lipid system was measured using waist-to-hip ratio, high-density lipoprotein cholesterol in mg/dL, low-density lipoprotein (LDL) cholesterol in mg/dL, and triglycerides in mg/dL.

Data Analysis

Structural equation modeling was used to compare the two alternative models of the relations among biomarkers, with age and sex included as covariates for each biomarker.

Model fit indices were used to find the best fitting of the two hypothesized factor structures. In addition, Model 1 is nested within Model 2. A χ^2 difference test adjusted for the scaling factor (21) was conducted between Models 1 and 2. Multiple-group structural equation modeling was used to

test whether the best-fitting model (1,2) was the same (invariant) or varied across different groups. Specifically, model invariance was tested for age group (≤ 45 , 45–60, >60 years) to establish whether the structure is consistent or differs for younger and older participants and sex (female versus male). To compare factor means across groups (a common objective in research on AL), it is generally considered necessary (22) that the models at least demonstrate the following: configural invariance (i.e., the same number of factors and indicators loading on the same factors), metric

invariance (i.e., the factor loadings are identical across groups), and scalar invariance (i.e., the intercepts of the indicators are identical across groups). Sequentially, more constrained models (i.e., configural only, configural + metric, and configural + metric + scalar) across groups were tested. χ^2 tests are reported, but results are considered consistent with model invariance only if the most restrictive configural + metric + scalar invariance was met as demonstrated both by adequate model fit and by minimal change in model fit (comparative fit index [CFI], root mean square

TABLE 1. Descriptive Statistics for Sample Demographics and Raw Biomarker Values

	Median (IQR)/n (%)
Demographics	
Age, y	54 (45–62)
Sex (female)	713 (56.8%)
Ethnicity	
White	967 (77.2%)
African American	222 (17.7%)
Other	64 (5.1%)
Medications (none)	486 (38.7%)
Sympathetic nervous system	
Urine epinephrine, mg/g of creatinine	1.67 (1.13–2.46)
Urine norepinephrine, mg/g of creatinine	24.80 (18.14–32.94)
Parasympathetic nervous system	
R-R interval standard deviation, ms	32.53 (23.72–44.62)
Root mean square of successive differences, ms	18.38 (12.13–27.57)
Low-frequency power, ms ²	245.95 (114.95–514.50)
High-frequency power, ms ²	140.45 (58.80–304.75)
Resting heart rate, beats/min	70.00 (64.00–79.00)
Hypothalamic-pituitary-adrenal axis	
Urine cortisol, mg/g of creatinine	12.00 (6.75–19.00)
Serum dehydroepiandrosterone sulfate, μ g/dL	87.00 (52.00–145.00)
Inflammation	
Serum C-reactive protein, mg/L	1.44 (0.69–3.64)
Serum interleukin-6, ng/L	2.17 (1.37–3.52)
Fibrinogen, mg/dL	344.00 (291.00–403.00)
Soluble E-selectin, ng/mL	39.16 (28.17–52.41)
Soluble intracellular adhesion molecule 1, mg/L	273.85 (220.03–338.08)
Cardiovascular	
Pulse pressure, mm Hg	54.00 (45.00–64.00)
Systolic blood pressure, mm Hg	130.00 (119.00–143.00)
Glucose	
Fasting blood glucose, mg/dL	96.00 (90.00–105.00)
Blood glycosylated hemoglobin, %	5.86 (5.60–6.24)
Homeostasis model–assessed insulin resistance	2.40 (1.43–4.35)
Lipids	
Waist-to-hip circumference ratio	0.89 (0.82–0.97)
High-density lipoprotein cholesterol, mg/dL	52.79 (42.50–66.25)
Low-density lipoprotein cholesterol, mg/dL	102.00 (80.23–128.32)
Serum triglycerides, mg/dL	106.00 (77.00–155.00)

IQR = interquartile range.

error of approximation [RMSEA], standardized root mean square residual [SRMR]) from less constrained models, with $\Delta\text{CFI} < 0.01$ being suggested as one indicator of an invariant model (23). Residual variances were not constrained to be equal across groups, as it is expected that variability may differ between groups (e.g., participants in the youngest age group may not have the same range on biomarkers as older adults may have).

Finally, if the bifactor model is correct, it should exhibit item parameter invariance (24); that is, the same general and system-specific factor loadings should result regardless of the specific subset of biomarkers or systems assessed. This follows from the logic that if the items are indicators of the latent factors specified, we should be measuring the same latent factor regardless of which specific indicators are used, and so when some items are dropped, the factor loadings of the remaining items should not change (i.e., be invariant). To examine item parameter invariance, seven additional models were fit. Each of the seven models started with the overall bifactor model on all participants and systematically dropped one of the seven systems by removing all the biomarkers of a particular system as well as the system-specific factor. For example, one model was the bifactor model without the inflammation system and dropped CRP, IL-6, fibrinogen, sE-Selectin, and soluble intracellular adhesion molecule 1, leaving 18 biomarkers, one common AL factor, and six system-specific factors.

Statistical Methods

Biomarkers were assessed for univariate normality, and log transformations were applied to E, NE, standard deviation of beat-to-beat interval, RMSSD, low-frequency spectral power, HFHRV, cortisol, DHEA-S, CRP, IL-6, sE-Selectin, glycosylated hemoglobin, fasting glucose, HOMA-IR, and triglycerides. Outliers were addressed by Winsorizing the lower and upper 0.5%. Because multivariate nonnormality remained despite these transformations, a robust estimator and standard errors were used. To address the small amount (<3%) of missing data, full information maximum likelihood estimation was used (25). Standard errors and model tests were adjusted for nonindependence within families using clustered standard errors based on the Huber-White “sandwich” estimator implemented in Mplus; thus, independence is assumed among cluster units, not individual units.

Good model fit was chosen as the combination of the CFI > 0.95, SRMR < 0.08, and RMSEA < 0.06 (26). Example Mplus input scripts are available from the Standardizing Physiological Composite Risk Endpoints Project Web site: <http://score-project.org>. Data management, descriptive statistics, and transformations were conducted using R v. 3.1.1 (27) and Mplus v. 7.3 (Muthén & Muthén, Los Angeles, CA) via Mplus-Automation v. 0.6–3 (28) for the structural equation models.

RESULTS

Participant age ranged from 34 to 84 years, with approximately equal numbers of women and men. Sample characteristics and descriptive statistics for the biomarkers (untransformed) are presented in Table 1. Based on preliminary analyses, three modifications were made to all hypothesized models. First, HOMA-IR was allowed to cross load on both the lipid metabolism and glucose metabolism factors. Second, heart rate was used as an indicator of the PNS rather than the cardiovascular factor. Third, a residual correlation between HFHRV and RMSSD was allowed. No other modifications to the hypothesized models were made.

Aim 1: Model Comparisons

Model fit indices comparing the two alternative models (Fig. 2) are shown in Table 2. The second-order model

TABLE 2. Model Fit Statistics

Second-Order	Bifactor	Bifactor Invariance Testing		
		Age	Sex	
Parameters	120	156	364	214
χ^2	1174.1	623.6	1215.4	1004.6
<i>df</i>	225	189	671	430
<i>p</i>	<.001	<.001	<.001	<.001
CFI	0.928	0.967	0.957	0.953
TLI	0.904	0.948	0.942	0.940
RMSEA	0.058	0.043	0.044	0.046
LL	0.055	0.039	0.040	0.042
UL	0.061	0.047	0.048	0.050
SRMR	0.056	0.028	0.051	0.042
AIC	66,297.9	65,750.2	65,704.4	65,726.6
BIC	66,914.0	66,551.1	67,573.2	66,825.3

CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation; LL = 90% CI lower limit for RMSEA; UL = 90% CI upper limit for RMSEA; SRMR = standardized root mean square residual; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

Age groups were ≤ 45 ($n = 324$), 45 to 60 ($n = 557$), and > 60 years ($n = 373$), and sex groups were female ($n = 712$) and male ($n = 542$). Invariance was tested for the best-fitting, bifactor model. Continuous age and sex were included as covariates in all models, except that sex was omitted as a covariate in the sex invariance model. n ranged from 1252 to 1254 due to missing data.

(Model 1) demonstrated acceptable fit, with two of three indices meeting the criteria for good fit, although the CFI did not (CFI = 0.928, RMSEA = 0.058, SRMR = 0.056). As expected, the bifactor model (Model 2) demonstrated the best fit to the data and met all criteria for good model fit (CFI = 0.967, RMSEA = 0.043, SRMR = 0.028). The bifactor model also fit significantly better than the second-order factor model ($\Delta\chi^2_{(df=36)} = 508.68, p < .001$). These results suggest that a common factor does underlie the individual biomarkers, but that there are also unique, system-specific effects.

Aim 2: Model Invariance

The fit of the bifactor model was tested across age (≤ 45 , 45–60, > 60 years) and sex (female, male) groups using a multiple group model. Results from the configural, configural + metric, and configural + metric + scalar invariance tests are shown in Table S1, Supplemental Digital Content 1, <http://links.lww.com/PSYMED/A264>, and sex-specific loadings are shown in Figure S1, in Supplemental Digital Content 1, <http://links.lww.com/PSYMED/A264>. The configural + metric + scalar invariant models were tested against the configural only model for sex. The configural only model for age did not converge, so for

age, the configural + metric invariant model was used as the comparison. For this reason, age group-specific loadings also could not be shown as only the constrained models converged, which by definition have identical loadings. Although the configural + metric + scalar invariant model fit statistically significantly worse for both age and sex (all p values $< .05$), the change in fit indices was small for age ($\Delta\text{CFI} = 0.003$, $\Delta\text{RMSEA} = 0.001$, $\Delta\text{SRMR} = 0.002$) and sex ($\Delta\text{CFI} = 0.007$, $\Delta\text{RMSEA} = 0.001$, $\Delta\text{SRMR} = 0.008$). In addition, the configural + metric + scalar invariant models demonstrated good fit (all CFIs > 0.95 , all RMSEAs < 0.06 , all SRMRs < 0.08). Thus, overall the results were consistent with model invariance by age and sex. The final configural + metric + scalar invariant model fit indices are shown in Table 2.

Final Model Estimates

The standardized loadings of each biomarker on the system-specific and common AL factor for the final overall bifactor model are shown in Table 3. With the exception of LDL, E, and DHEA-S, all biomarkers loaded significantly and in the direction such that higher AL scores indicate more physiological dysregulation. LDL and DHEA-S were not statistically significant, and E loaded negatively on AL, indicating that the higher the AL score, the lower E. Although biomarkers from the PNS and cardiovascular (blood pressure) systems loaded in the expected directions and were statistically significant, loadings were small or modest. In the bifactor model, most correlations among biomarkers across systems will be captured by the common AL factor, so as expected the estimated correlations among the latent system-specific factors were generally small, with the largest two between the HPA and SNS ($r = 0.34$) and cardiovascular system ($r = 0.23$), with all other factor correlations ≤ 0.20 (see Table 4 for details).

As a sensitivity analysis, the factor loadings from the final bifactor model on only those 486 participants who were medication-free are also presented in Table 3. In general, the results are quite similar, with some additional nonsignificant parameters due to the reduced sample size.

Finally, item parameter invariance was examined by comparing the standardized loadings from the seven reduced models (each now with only six systems assessed) to the full bifactor model. None of the loadings from the reduced models fell outside the confidence interval for the overall bifactor model, and most exhibited minimal differences (Fig. 3). These results are consistent with what would be expected if the model had item parameter invariance.

DISCUSSION

Across 23 biomarkers in a large sample of adults, a bifactor model of AL provided both good fit and was the best-fitting model. This result has two important implications.

First, it confirms what previous studies have demonstrated that consistent with AL theory, a common factor underlies biomarkers of multisystem physiological functioning (12–14). Second, it is the first study, to our knowledge, that demonstrates that in addition to the common underlying AL factor, individual physiological systems account for unique variance in biomarkers not accounted for by the common factor. Composites of biomarkers within a system or factor scores from the second-order factor (Model 1) model will conflate system-specific effects and effects of the common factor. Using a bifactor model (Model 2) provides an alternative and novel method that allows the examination of either the common AL factor, the system-specific factors unconfounded from AL, or both.

Most loadings were in the expected directions, but there were exceptions. Contrary to AL theory, E loaded negatively on the common AL factor, although it correlated positively with NE ($r = 0.50$), which did load positively on the AL factor. To our knowledge of the three other studies that examined the factor structure of AL, only one assessed E and found that it was not significantly associated with AL (9). Cortisol also loaded negatively onto the common AL factor, but it is less clear whether high or low values of basal cortisol are desirable (e.g., Seeman and colleagues (13) found that higher AL was associated with a lower cortisol awakening response and flatter change over the day). Alternatively, this may be unique to the MIDUS study as participants had to travel to one of three clinical research centers for the overnight stay when their biomarkers were assessed, which may have affected their overnight urinary cortisol.

Overall, the largest factor loadings for the common AL factor were from biomarkers from the inflammation, glucose, and lipid systems. Biomarkers in the SNS, PNS, and cardiovascular (blood pressure) systems did not load strongly on the common AL factor, but did load onto their system-specific factors. These systems also had the strongest correlations among the system-specific factors. Although AL theory does not hypothesize stronger associations among these systems than other systems, these results make sense in that the biomarkers from these systems only load modestly on the common AL factor, with more of their variance accounted for by the system-specific factors, leading to higher correlations among the system factors (although none of these correlations are large). These results suggest that for the SNS, PNS, and cardiovascular (blood pressure) systems, it may be particularly important to examine their unique effects beyond overall AL. By examining shared and system-specific effects, we believe that this bifactor model can facilitate greater precision in the next generation of research. For example, different types of stressors (e.g., low-grade chronic stress versus traumatic stress) may be associated with higher allostatic, but show differential effects on specific systems, such as SNS or PNS.

TABLE 3. Standardized Factor Loadings From the Final Bifactor Model

	Overall Bifactor Model		Medication-Free Bifactor Model	
	System Loadings, Loading [95% CI]	AL Loadings, Loading (95% CI)	System Loadings, Loading (95% CI)	AL Loadings, Loading (95% CI)
SNS				
E	0.70*** (0.67 to 0.74)	-0.27*** (-0.35 to -0.18)	0.70*** (0.64 to 0.77)	-0.33*** (-0.47 to -0.18)
NE	0.70*** (0.66 to 0.73)	0.14** (0.05 to 0.22)	0.71*** (0.65 to 0.76)	0.10 (-0.04 to 0.25)
PNS				
SDRR	-0.93*** (-0.96 to -0.91)	-0.20*** (-0.28 to -0.12)	-0.94*** (-0.98 to -0.91)	-0.12 (-0.27 to 0.03)
RMSDD	-0.81*** (-0.84 to -0.79)	-0.11* (-0.19 to -0.02)	-0.81*** (-0.85 to -0.78)	-0.08 (-0.22 to 0.05)
LHRV	-0.76*** (-0.79 to -0.73)	-0.23*** (-0.31 to -0.15)	-0.77*** (-0.82 to -0.72)	-0.15* (-0.27 to -0.02)
HFRV	-0.76*** (-0.79 to -0.73)	-0.11** (-0.19 to -0.03)	-0.76*** (-0.80 to -0.71)	-0.05 (-0.18 to 0.08)
Pulse rate	0.32*** (0.26 to 0.37)	0.36*** (0.29 to 0.43)	0.36*** (0.27 to 0.45)	0.40*** (0.28 to 0.52)
HPA				
Cortisol	0.31*** (0.21 to 0.40)	-0.31*** (-0.39 to -0.23)	0.21 (-0.02 to 0.44)	-0.22*** (-0.35 to -0.08)
DHEA-S	0.30*** (0.21 to 0.39)	-0.06 (-0.13 to 0.01)	0.22 (-0.01 to 0.45)	-0.00 (-0.11 to 0.11)
Inflammation				
CRP	0.55*** (0.45 to 0.65)	0.55*** (0.48 to 0.62)	0.55*** (0.32 to 0.77)	0.59*** (0.46 to 0.73)
IL-6	0.39*** (0.30 to 0.48)	0.53*** (0.45 to 0.60)	0.32*** (0.17 to 0.47)	0.59*** (0.48 to 0.71)
Fibrinogen	0.56*** (0.46 to 0.66)	0.37*** (0.29 to 0.45)	0.59*** (0.42 to 0.76)	0.36*** (0.23 to 0.49)
sE-Selectin	-0.01 (-0.10 to 0.09)	0.37*** (0.30 to 0.44)	-0.08 (-0.23 to 0.06)	0.33*** (0.21 to 0.44)
sICAM-1	0.09 (-0.01 to 0.20)	0.24*** (0.16 to 0.32)	0.16 (-0.00 to 0.32)	0.23*** (0.10 to 0.37)
Cardiovascular				
Pulse pressure	0.83*** (0.80 to 0.86)	0.09* (0.02 to 0.16)	0.86*** (0.80 to 0.91)	0.23*** (0.11 to 0.35)
SBP	0.83*** (0.80 to 0.85)	0.12** (0.04 to 0.20)	0.75*** (0.70 to 0.79)	0.30*** (0.18 to 0.41)
Glucose				
Glucose	0.90*** (0.86 to 0.94)	0.41*** (0.32 to 0.50)	0.90*** (0.84 to 0.95)	0.39*** (0.26 to 0.52)
HbA1c	0.60*** (0.52 to 0.68)	0.38*** (0.30 to 0.46)	0.50*** (0.37 to 0.63)	0.31*** (0.19 to 0.42)
HOMA-IR	0.28*** (0.20 to 0.35)	0.65*** (0.57 to 0.73)	0.25*** (0.16 to 0.33)	0.65*** (0.51 to 0.79)
Lipids				
HOMA-IR ^a	0.27*** (0.14 to 0.39)		0.37*** (0.21 to 0.53)	
WHR	0.14* (0.03 to 0.24)	0.43*** (0.37 to 0.49)	0.20* (0.04 to 0.35)	0.38*** (0.27 to 0.49)

Continued on next page

TABLE 3. (Continued)

	Overall Bifactor Model		Medication-Free Bifactor Model	
	System Loadings, Loading [95% CI]	AL Loadings, Loading (95% CI)	System Loadings, Loading (95% CI)	AL Loadings, Loading (95% CI)
HDL	-0.45*** (-0.58 to -0.32)	-0.32*** (-0.42 to -0.22)	-0.56*** (-0.72 to -0.40)	-0.26** (-0.45 to -0.06)
LDL	0.26*** (0.19 to 0.34)	0.01 (-0.08 to 0.11)	0.39*** (0.27 to 0.50)	0.09 (-0.06 to 0.25)
Triglycerides	0.73*** (0.60 to 0.86)	0.37*** (0.25 to 0.49)	0.67*** (0.54 to 0.80)	0.31*** (0.13 to 0.49)

AL = allostatic load; CI = confidence interval; SNS = sympathetic nervous system; E = epinephrine; NE = norepinephrine; PNS = parasympathetic nervous system; SDRR = standard deviation of beat-to-beat intervals; RMSSD = root mean square of successive differences (RMSSD) of beat-to-beat intervals; LFHRV = low-frequency spectral power; HFHRV = high-frequency spectral power; HPA = hypothalamic-pituitary-adrenal axis; DHEA-S = dihydroepiandrosterone sulfate; CRP = C-reactive protein; IL-6 = interleukin-6; sE-Selectin = soluble intracellular adhesion molecule 1; SBP = systolic blood pressure; HbA1c = glycosylated hemoglobin; HOMA-IR = homeostatic model assessment of insulin resistance; WHR = waist-to-hip ratio; HDL = high-density lipoprotein; LDL = low-density lipoprotein.

System and AL denote the loadings of each biomarker on the specific system factor or on the common AL factor. Standardized loadings are presented for all models. *n* = 1254 for the overall bifactor models, and *n* = 486 for the medication-free bifactor model.

^a Cross loading of HOMA-IR on lipids system.

* *p* < .05, ** *p* < .01, *** *p* < .001.

TABLE 4. Estimated Latent Factor Correlations From the Final Bifactor Model

	1.	2.	3.	4.	5.	6.	7.
1. SNS	—						
2. PNS	.08	—					
3. HPA	0.34	0.07	—				
4. Inflammation	0.16	0.09	0.20	—			
5. Cardiovascular	0.10	-0.08	0.23	0.11	—		
6. Glucose	0.06	0.01	0.15	-0.14	0.06	—	
7. Lipids	-0.05	0.13	-0.09	-0.05	0.13	0.11	—
8. AL	0	0	0	0	0	0	0

SNS = sympathetic nervous system; PNS = parasympathetic nervous system; HPA = hypothalamic-pituitary-adrenal axis; AL = allostatic load. *n* = 1254 from the bifactor model.

In a recent editorial, Gallo et al. (29) argued for a need to standardize the measurement of AL and for researchers to report on the specific components of AL. We agree that the specific components of AL are important; indeed the bifactor structure suggests that specific physiological systems account for additional variance in biomarkers over and above AL. Using a method that allows both AL and specific physiological systems to be used as independent predictors or outcomes facilitates examining both systemwide (AL) and system-specific effects. We believe that using a bifactor model represents an important advance in psychosomatic research for untangling the relations between psychological factors and system-specific and systemwide physiological dysregulation.

The results were consistent with item parameter invariance for the bifactor model. The property of item parameter invariance means that the system-specific and AL factor loadings would not change regardless of the specific biomarkers measured. Item parameter invariance is an important property that underlies methods such as computer adaptive testing where not all participants are given the same questions and yet they receive comparable scores on the same underlying construct. If this result is replicated and shown reliable, it has the potential to provide a pathway to resolve discrepancies across studies due to different biomarkers being measured by deriving scores on the same underlying AL and individual system factors, even if the exact subset of biomarkers assessed varies. Another implication is that research that does not measure all 23 biomarkers can still derive a comparable AL score, opening the possibility of a “short” version of AL where fewer biomarkers are assessed to save cost or participant burden. However, one disadvantage of measuring fewer biomarkers is that it may no longer be possible to obtain a score on a particular system-specific factor. Furthermore, reducing the number of biomarkers by leaving off specific biomarkers

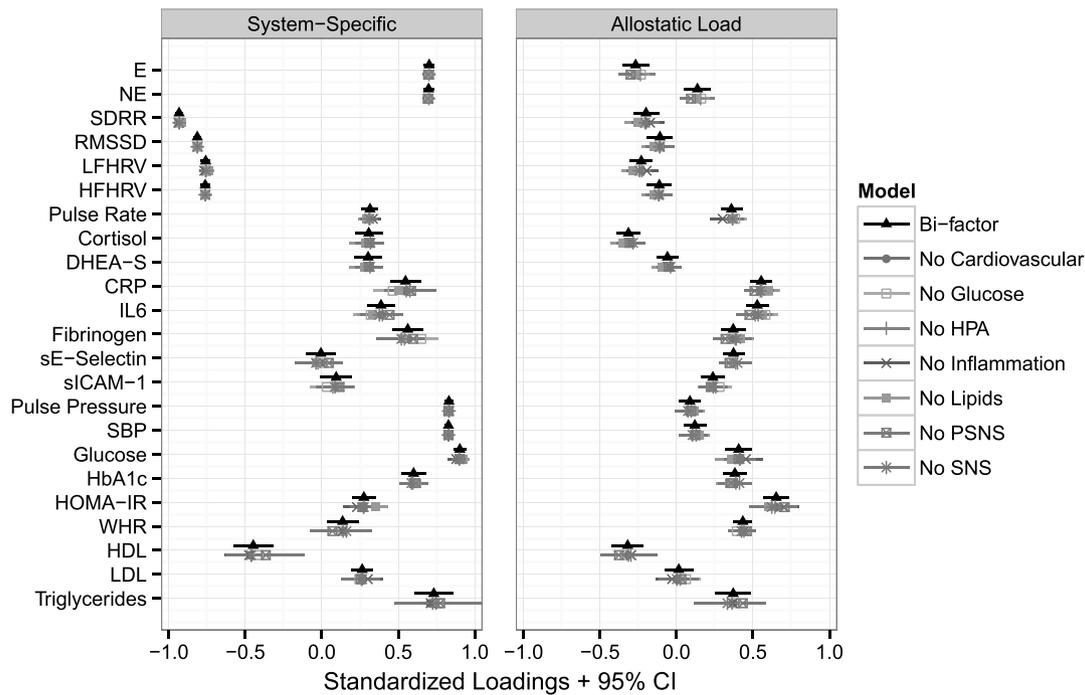


FIGURE 3. Item parameter invariance plot. Standardized loadings with 95% CIs for the overall bifactor model are shown in black triangles. Results from seven “reduced” models where each system was systematically dropped are shown slightly below the results from the overall bifactor model. The overlap in points and confidence intervals shows that the standardized loadings for the remaining biomarkers do not change substantially when biomarkers for any one system are dropped. CI = confidence interval; E = epinephrine; NE = norepinephrine; SDRR = standard deviation of beat-to-beat intervals; RMSSD = root mean square of successive differences (RMSSD) of beat-to-beat intervals; LFHRV = low-frequency spectral power; HFHRV = high-frequency spectral power; DHEA-S = dihydroepiandrosterone sulfate; CRP = C-reactive protein; IL-6 = interleukin-6; sE-Selectin = soluble E-selectin; sICAM-1 = soluble intracellular adhesion molecule 1; SBP = systolic blood pressure; HbA1c = glycosylated hemoglobin; HOMA-IR = homeostatic model assessment of insulin resistance; WHR = waist-to-hip ratio; HDL = high-density lipoprotein; LDL = low-density lipoprotein; HPA = hypothalamic-pituitary-adrenal axis; PNS = parasympathetic nervous system; SNS = sympathetic nervous system.

or whole systems will reduce the reliability of both the common AL factor score and system-specific scores. To recommend which biomarkers should be measured to optimally measure AL, future research is needed to examine the relationships between AL scored from different biomarkers and other constructs such as stress, physical functioning, morbidity, and mortality.

We found that for the bifactor model, results were consistent with what would be expected if it was invariant between men and women, which is consistent with prior research on AL comparing women and men (13), as well as across age groups.

Limitations of the current study should be noted. The sample was predominantly white, with fewer African Americans and small numbers of other ethnicities represented. In addition, only basal levels of biomarkers were assessed; future research is needed to examine relations among functional measures of biomarkers (e.g., inflammatory response to antigens). Finally, when testing measurement invariance where the model fit is compared across subgroups of the sample, many subgroups were small, and

in these multiple group models, the overall sample size was small compared with the number of parameters and complexity of our measurement model. However, with 1254 participants, this is one of the largest studies with extensive biomarker data available.

The study also has several important strengths. The current study comprehensively assessed seven physiological systems using 23 biomarkers. The use of many biomarkers ensures that each of the seven systems is measured by more than one biomarker, allowing us to differentiate effects shared across systems and effects unique to systems. Another strength is the broad age range from 34 to 84 years. Finally, the current study used careful statistical analyses including the following: accounting for clustering in twins and siblings in the MIDUS data, nonnormality of the biomarkers, missing data, and investigating alternative theoretical models.

In conclusion, across 23 biomarkers in MIDUS, we found evidence for a common AL factor, as well as for seven system-specific factors, and this model held across age groups and sex. Although our findings were consistent

with a model where AL was invariant across subpopulations and invariant to dropping biomarkers from any one system, these results do not preclude the possibility that the measurement of AL may differ importantly by the sample or population being studied. Nevertheless, they do point to the robustness of AL, and perhaps suggest that apparently disparate sets of biomarkers used in many studies may actually be more comparable than expected. Future research is needed to examine the predictive effects of AL and specific systems on health. Future research could also explore whether for specific outcomes, such as particular diseases, or for different predictors, such as chronic or acute stress, different profiles emerge across the common AL factor and system-specific factors. To standardize the measurement of AL as Gallo et al. (29) suggest, further work is needed to reach consensus on how to define “optimal” measures of AL and specific physiological systems (e.g., predict disease incidence or mortality, and predict functioning), and then to develop and validate sets of biomarkers for each system and for AL overall—work that is challenging given the great diversity of samples and populations studied. Nevertheless, findings that the bifactor model was consistent with item parameter invariance, if replicated, open the intriguing possibility that just as in computer-adaptive testing where not all participants complete the same questions, yet can be given comparable scores, it may be possible to obtain comparable AL scores from different sets of biomarkers and perhaps begin to resolve concerns about the challenge interpreting the AL literature when measurement is inconsistent.

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