



# The Big Five personality traits and allostatic load in middle to older adulthood: A systematic review and meta-analysis

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## ABSTRACT

Further understanding of the associations between personality traits and allostatic load (AL) may be important for predicting, addressing, and optimizing health outcomes. This review synthesized the existing literature reporting the association between the Big Five personality traits and AL in adults to identify the generalizability and robustness of relationships, potential mechanisms underlying the associations, and study characteristics that may be contributing to inconsistencies in the field. Published and unpublished empirical reports were included if at least one of the Big Five traits was examined and an AL index was constructed using at least two biomarkers in a sample of adults. The methodological plan and standardized coding guide were pre-registered and reported (<https://osf.io/rxw5a>). Based on 11 studies that met eligibility, meta-analysis of correlation coefficients indicated a small but significant positive association between neuroticism and AL, and small but significant inverse associations between both conscientiousness and openness with AL. This review identifies strengths and limitations within the field, as well as several avenues for future research.

## 1. Introduction

The interplay between physiological and psychological processes unquestionably adds a layer of complexity to the human condition. While the isolation of these processes is somewhat artificial, we presume that thoughts and emotions can influence and elicit bodily states (e.g., Campbell and Edwards, 2009; Grol and De Raedt, 2020; Sapolsky, 1999) and, likewise, that physiological conditions can influence and elicit cognitive processes and feelings (e.g., Briñol and DeMarree, 2012; Veenstra et al., 2017). At the juncture of physiological and psychological processes, emerging research suggests a link between physiological dysregulation (i.e., allostatic load; AL) and an individual's enduring behavioral and psychological tendencies (i.e., personality traits). Nuanced understanding of the relationships between AL and personality traits may be important for predicting, addressing, and optimizing health outcomes. Drawing on existing research cataloged in several

electronic databases, this review systematically identifies and synthesizes studies reporting associations between AL and the Big Five personality traits.

### 1.1. Allostatic load

Originally conceptualized as attributes of the stress response that influence disease processes (McEwen and Stellar, 1993), the AL framework aims to elucidate the mechanisms underlying (co)morbidity to identify individuals who are at greater risk of degeneration and mortality (Seeman et al., 2001). While intermittent upticks across biological systems in the context of true environmental stressors are adaptive, prolonged and cumulative physiological arousal endangers health and optimal aging processes, which is precisely what indices of AL aim to capture. Operational definitions vary between studies, but indices of AL typically include a range of biomarkers that are standardized and

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composited, whereby higher values indicate higher levels of physiological dysregulation. These biomarkers include, but are not limited to, inflammation markers (e.g., C-reactive protein), as well as assessments of hormonal (e.g., cortisol), cardiovascular (e.g., blood pressure), metabolic (e.g., cholesterol, waist circumference), and lung (e.g., forced vital capacity) functioning. Although AL conceptualizations have received some criticism (e.g., Romero et al., 2009), extensive research finds that AL is associated with many adverse health outcomes, including reduced heart rate variability (Viljoen and Claassen, 2017), as well as increased cognitive and functional decline (Karlamañgla et al., 2014; Karlamañgla et al., 2002), incidence of conditions such as chronic fatigue syndrome (Maloney et al., 2006), diabetes, hypertension, and cardiovascular disease (Juster et al., 2010; Mattei et al., 2010), and risk of all-cause and cardiovascular mortality (Parker et al., 2022). However, risk stratification based on stressors is complex, as any given social or environmental factor does not predict physiological anomalies with certainty; that is, there are individual differences in maladaptive responses to environmental stressors.

The transactional theory of stress and coping, which views stress as a transactional process between a person and their environment as opposed to a particular environmental stimulus (Lazarus and Folkman, 1984, 1987), seeks to explain the distinction. Notably, the *perception* or *cognitive appraisal* of stress, which are distinctly psychological processes, are required to *experience* stress, while the outcome of stress may manifest physiologically as increased cortisol secretion, heart rate, and blood pressure, which are conspicuously biological processes (also see Cohen et al., 1995; Cohen et al., 2016). Extensive research suggests that the perception of stress is fundamental to AL (for a systematic review, see Beckie, 2012), which leads to consideration of factors involved in patterns of perception and coping responses, such as personality traits. Although cross-context intraindividual variability in perception, emotions, and behaviors exists (e.g., how an individual perceives and subsequently behaves in response to a situation can vary extensively across any given occasion), individuals tend to be highly consistent in their pattern of responding to and interacting with their environment on average, when assessed on several occasions. Specifically, based on two weeks of five daily ecological momentary assessments, individuals tend to demonstrate a unique trend (i.e., central point) in their occasion-to-occasion behavior; at the within-person level, an individual's average behaviors and comportments are strongly associated across two weeks ( $r = 0.90$ ; Fleeson, 2001, 2004).

### 1.2. The Big Five personality traits

A common approach for measuring these enduring patterns of perception, feeling, and behaving is via assessment of the Big Five personality traits (i.e., extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience). Together, these five trait subscales are thought to represent an individual's unique constellation of behavioral and psychological tendencies, permeating numerous domains of life (McCrae and Costa, 2004). For example, extraversion is positively associated with social interactions (e.g., Argyle and Lu, 1990), neuroticism is positively associated with anxiety symptoms (e.g., Bienvenu et al., 2004), and conscientiousness is positively associated with engagement in physical activity (e.g., Bogg and Roberts, 2004). In addition to correlates of critical health behaviors important for physiological regulation, personality traits influence exposure to both quantity and type of stressors (Bolger and Schilling, 1991; Cimboric Gunther et al., 1999; Gartland et al., 2012; Iacovino et al., 2016; Leger et al., 2016), as well as the magnitude of reactivity to stressors (Bolger and Schilling, 1991; Javara et al., 2012; Mroczek and Almeida, 2004; Penley and Tomaka, 2002; Suls et al., 1998; Suls and Martin, 2005).

An individual's ongoing tendency to perceive and respond to stress in a maladaptive way may elicit a cascade of physiological reactions across neuroendocrine, immune, cardiovascular, and metabolic regulatory systems, subsequently leading to interindividual variability in

dysregulation of biological systems and poorer downstream health outcomes. Indeed, the existing literature suggests that the Big Five personality traits are associated with individual differences in many physiological outcomes, including chronic conditions (Goodwin and Friedman, 2006; Weston et al., 2015; Weston et al., 2020) and mortality (Graham et al., 2017; Jokela et al., 2013; Kern and Friedman, 2008; Wilson et al., 2004). While the mechanisms underlying these associations are not entirely clear, personality traits may contribute to individual differences in the regulation of physiological systems (i.e., differences in AL), subsequently leading to negative health outcomes. Additionally, these enduring psychological tendencies influence behavioral factors (e.g., diet, physical activity, interpersonal interactions), leading to maladaptive physiological dysregulation (e.g., hypertension, systemic inflammation), and thereby contributing to disease and mortality (Milad and Bogg, 2020). However, there is clear between-study variability in study features and researcher decisions across research investigating the associations between AL and each of the Big Five traits. This systematic review aimed to synthesize and critically analyze the outcomes of the existing literature reporting the associations between the Big Five personality traits and AL to assist in identifying which (if any) study characteristics may be contributing to inconsistencies in the field.

## 2. Method

The study justification, search strategy, and methodological approach for this research synthesis were documented and pre-registered through the Open Science Framework (OSF) (<https://osf.io/rxw5a>). We used PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses; Moher et al., 2009) to create the protocol, and the National Institutes of Health (NIH) Guidance for Assessing the Quality of Observational Cohort and Cross-Sectional Studies was used to assess the quality of articles meeting eligibility.

### 2.1. Search strategy

A comprehensive literature search was executed on January 12th, 2022, within Web of Science, PubMed, and Academic Search Complete. The full search strategy applied to each database identified any combination of the following search terms within the title, abstract, or key words: ("allostatic load") AND (personality OR extraversion OR neuroticism OR conscientiousness OR agreeableness OR openness). Due to automatic lemmatization in the PubMed database, which expands the search by adding potentially relevant subject headings to increase the search, the search strategy was modified for this database: ("allostatic load") AND (personalit\* OR extraver\* OR neurotic\* OR conscientious\* OR agreeable\* OR openness). The search identified any combination of these search terms within the title, abstract, or key words. We also executed forward and backward searches of the studies meeting eligibility. An updated search using the identical search strategy was executed on February 27th, 2023, directly prior to resubmission for publication.

### 2.2. Eligibility criteria

Empirical reports met eligibility if i) at least one of the Big Five traits was assessed; ii) an index of AL, including at least two biomarkers, was computed; and iii) the sample included adult humans (i.e., individuals who were defined as "adults" or were 18 + years old). Reports were excluded if the report was not written in English or did not include empirical investigation (e.g., narrative or theoretical papers). While inclusion of only two biomarkers within an AL index would be a very liberal definition of AL, our aim was to identify and critically reflect on all research reporting the association between AL and personality. Published and unpublished reports were eligible for inclusion.

### 2.3. Study selection

Of the original 250 citations (159 unique), 64 studies were immediately identified for exclusion, as the focus was children ( $k = 15$ ), or no novel empirical data were reported ( $k = 49$ ; e.g., commentaries). Of the 95 studies that were selected for full text screening, 81 reports did not meet eligibility criteria. This process left 12 published articles, one dissertation, and one conference proceeding that appeared to meet eligibility criteria for synthesis. However, nine of the reports used overlapping datasets: UK's Understanding Society (Barry et al., 2021; Gallagher et al., 2021); Copenhagen Aging and Midlife Biobank (CAMB; Christensen et al., 2019a; Christensen et al., 2019b); the Lothian Birth Cohort 1936 (LBC; Crook et al., 2018; Lewis et al., 2018); Midlife in the United States (MIDUS; Milad and Bogg, 2020; Turiano et al., 2015; Van Dyke et al., 2020). In four of these cases, priority was given to the report that focused on personality traits and AL, as opposed to simple adjustment for personality traits (Barry et al., 2021; Christensen et al., 2019a; Lewis et al., 2018; Van Dyke et al., 2020). An exception to this rule occurred when two reports arising from the same dataset (MIDUS) both focused on the association between personality and AL. In this case, the full-text manuscript was selected in lieu of the conference proceeding (Turiano et al., 2015). This process resulted in nine reports based on unique data, published between 2011 and 2021. The updated, identical search identified an additional 12 (7 unique) potential records, two of which met study eligibility. There were no disagreements between reviewers regarding study eligibility. A standardized coding guide was used to extract data from the reports; two researchers, T.Y. and T.L., coded each report. The original coding guide was pre-registered, and there were no deviations. See Fig. 1 for the PRISMA flow diagram visually depicting the selection process and meta-statistics.

### 2.4. Meta-analysis

A multi-level random effects approach was chosen to meta-analyze the results, as heterogeneity in effect sizes was expected beyond heterogeneity that could be explained by sampling error alone (Borenstein

et al., 2010). Further, this approach was selected as the goal was to investigate the average observed effect in the larger population of studies, and multi-level structure for meta-analysis provides the opportunity for several dependent effects to be assessed within the same model (i.e., effects are nested within studies). Meta-analytic procedures were executed in R using the Metafor package (Viechtbauer, 2010) with Maximum Likelihood (ML) applied for variance estimation, and sensitivity analyses using Restricted Maximum Likelihood Estimator (REML). Raw correlation coefficients were corrected for the slight negative bias based on work by Olkin and Pratt (1958). Sampling variances were estimated based on work by Hedges (1983), which provides unbiased estimates of the sampling variances. We report  $I^2$  and the  $Q$  statistic, which, respectively, provide the proportion of true variability of the effects relative to the total variation in observed effects and the weighted sum of squared differences between the observed effects and the weighted average effect (e.g., a measure of variation around the average).  $I^2$  (Higgins et al., 2003) is a measure of relative heterogeneity based on the studies included, and therefore should be interpreted cautiously. Random variance is likely inconsistent when the sample sizes of included studies range extensively (in this case,  $N_{range}=95-5500$ ), and  $I^2$  does not track true heterogeneity when there are disparities in sampling precision. A significant  $Q$  statistic suggests that variation between effect sizes is due to more than what is expected from sampling variability. Analytic scripts and data files are available on the OSF project page.

### 2.5. Quality assessment

The National Institutes of Health (NIH) Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies, a well-known and established tool, was used. Two reviewers (T.Y. and T.L.) evaluated study quality, and discussions resolved differing opinions.

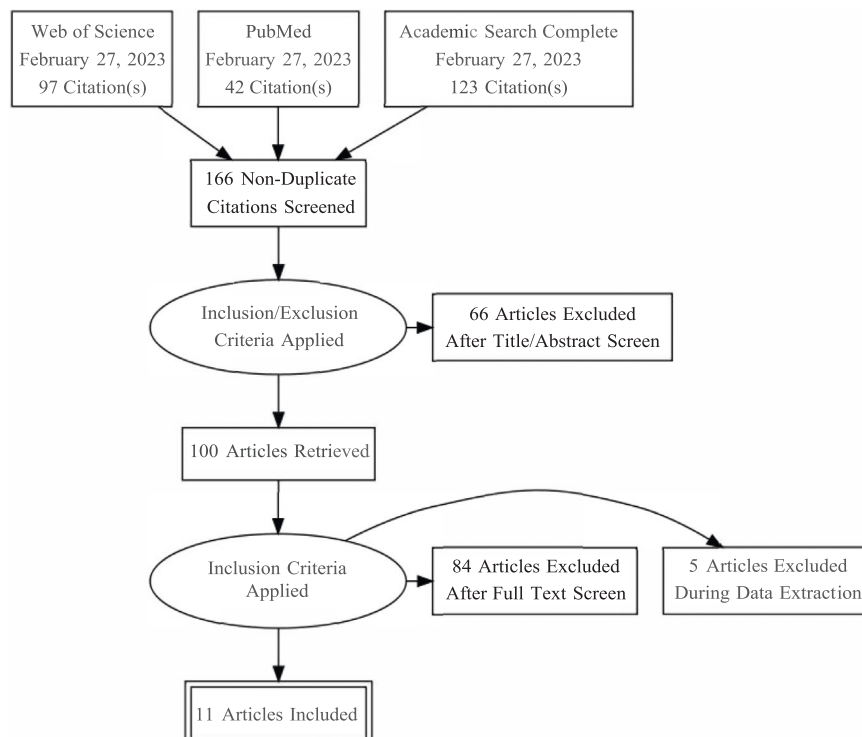


Fig. 1. PRISMA Flow Diagram.

### 3. Results

#### 3.1. Study characteristics

The 11 eligible studies included a total of 18,942 unique participants with a mean baseline age of 59.4 ( $SD=11.8$ ) years. See Table 1 for an alphabetized list of included studies, report characteristics, and demographics. All studies used an existing dataset, except for two (Kobrosly, 2012; Otto et al., 2021). Apart from Hawkley et al. (2011), all studies included predominantly White participants (though five of these did not specifically report race).

#### 3.2. Assessment and computation of AL

Table 2 reports information regarding the various biomarkers and computation approaches for the AL indices. The quantity of biomarkers included in AL indices ranged from four (Otto et al., 2021) to 14 (Christensen et al., 2018; Christensen et al., 2019b). All studies included biomarkers representing the immune/inflammatory, metabolic, and cardiovascular systems, except for Otto et al. (2021), which only included biomarkers from the metabolic and cardiovascular systems. As four further exceptions, Gallagher et al. (2021) included a biomarker representing the neuroendocrine system (DHEA-s), while Hawkley et al. (2011) included biomarkers representing the sympathetic nervous and adrenomedullary system functioning (urinary norepinephrine and epinephrine). Hawkley et al. (2011) and Kobrosly (2012) also included assessments of cortisol (e.g., diurnal cortisol slope), which reflects hypothalamic-pituitary-adrenal (HPA) axis functioning. Finally, Richards et al. (2023) included three indicators representing lung functioning (forced expiratory volume in one second, forced vital capacity, and peak expiratory flow).

Prior to calculating  $z$  scores, some studies log transformed at least a portion of the included biomarkers to normalize their distributions. Specifically, Crook et al. (2018) log transformed CRP, fibrinogen, HbA1c, triglycerides, BMI, SBP, and DBP. Milad and Bogg (2020) log transformed CRP, IL-6, glycosylated hemoglobin, fasting glucose, insulin

resistance, and triglycerides. Stephan et al. (2016) log transformed all blood biomarkers (HbA1C, CRP, HDL, total cholesterol, and cystatin C). Furthermore, some studies selected risk category cut-offs based on sex-specific  $z$  scores for some biomarkers (e.g., waist circumference; Gallagher et al., 2021; Hawkley et al., 2011; Kobrosly, 2012) or all biomarkers (Christensen et al., 2018). Half of the studies did not note whether risk cut-offs were based on sex-specific  $z$  scores (Christensen et al., 2019b; Crook et al., 2018; Luo et al., 2022; Milad and Bogg, 2020; Stephan et al., 2016). Across studies and biomarkers, higher values typically represented high risk, except for HDL and assessments of lung function, in which low values indicated high risk. Some authors treated both high and low biomarker values as high risk (e.g., IGF-1; Gallagher et al., 2021; see Supplementary Text 1 for all exceptions).

There was extensive variation in AL scoring algorithms across studies, namely: (a) dichotomization of each biomarker based on sample-specific and/or sex-specific  $z$  scores (e.g., 0 =lower three quartiles; 1 =upper quartile), and then summation; (b) dichotomization based on existing cut-off values (Seeman et al., 1997) and/or sample-specific  $z$  score cut-off points (depending on biomarker), and then summation; (c) calculation of the within-person average across biomarker  $z$  scores (a continuous AL index); (d) parceling of biomarkers to reflect functioning across biological systems; and (e) calculation of mean absolute  $z$  scores, and then a latent variable approach using item parcels (sum of values across biomarkers, where values are the mean absolute  $z$  scores). See Table 2 and Supplementary Text 2 for further details.

#### 3.3. Assessment and computation of personality

Every study used a validated personality assessment (see Table 2). Almost half of the studies reported findings for all of the Big Five personality traits (Christensen et al., 2019b; Milad and Bogg, 2020; Otto et al., 2021; Richards et al., 2023; Stephan et al., 2016), while the remainder of studies either only assessed or only reported results regarding one to three traits. Assessment of each trait included as few as three items (Gallagher et al., 2021), and up to 26 items (Stephan et al.,

**Table 1**  
Sample Characteristics for Studies Meeting Systematic Review Eligibility.

Study	Title	Dataset	Country of origin	$N$	% Female	Mean age ( $SD$ )	Age range
(Christensen et al., 2018)	Parental socioeconomic position and midlife allostatic load: A study of potential mediators	Copenhagen Perinatal Cohort	Denmark	361	53.5	27 (4.4) / 50 (0.8)	NR
(Christensen et al., 2019b)	Big Five personality traits and allostatic load in midlife	Copenhagen Aging and Midlife Biobank	Denmark	5512	31.1	54.4 (3.6)	49–63
(Crook et al., 2018)	Apolipoprotein E genotype does not moderate the associations of depressive symptoms, neuroticism and allostatic load with cognitive ability and cognitive aging in the Lothian Birth Cohort 1936	Lothian Birth Cohort 1936	UK	1028	49.8	69.5 (0.8)	NR
(Gallagher et al., 2021)	Allostatic load and mental health during COVID-19: The moderating role of neuroticism	Understanding Society	UK	956	47.1	44.9 (13.5)	16–80
(Hawkley et al., 2011)	Mediators of the relationship between socioeconomic status and allostatic load in the Chicago Health, Aging, and Social Relations Study (CHASRS)	Chicago Health, Aging, and Social Relations	USA	208	52.9	58.4 (NR)	51–69
(Luo et al., 2022)	Personality and health: Disentangling their between-person and within-person relationship in three longitudinal studies	Swedish Adoption/Twin Study of Aging	Sweden	767 *	59.6 *	66.0 (9.0)*	45–91 *
(Kobrosly, 2012)	An epidemiologic investigation into the relationship between stress, allostatic load, and depressive disorder among older adults	Rochester Study of Healthy Minds and Bodies	USA	125	66.4	76.1 (5.9)	67–94
(Milad and Bogg, 2020)	Personality traits, coping, health-related behaviors, and cumulative physiological health in a national sample: 10 year prospective effects of conscientiousness via perceptions of activity on allostatic load	Midlife in the United States	USA	1054	54.7	46.2 (11.8)	25–74
(Otto et al., 2021)	Borderline Personality Disorder in a "life history theory" perspective: Evidence for a fast "pace-of-life-syndrome"	Community clinical sample	Germany	95	100.0	25.9 (4.6)	NR
(Richards et al., 2023)	Subjective social status and allostatic load among older people in England: A longitudinal analysis	English Longitudinal Study of Ageing	UK	2926 *	55.0 *	64.0 (8.1)*	50 * –89
(Stephan et al., 2016)	Allostatic load and personality: A 4-year longitudinal study	Health and Retirement	USA	5200 *	59.5 *	66.9 (8.9)*	50–99 *

Note. UK=United Kingdom; USA=United States of America; NR=not reported. \*Reflects baseline measurement occasion.



**Table 2**  
Allostatic Load Indices and Personality Assessments.

Study	AL #	List of AL biomarkers	Computation of AL	Traits assessed	Trait scale (items)
(Christensen et al., 2018)	14	CRP, IL-6, TNF- $\alpha$ , % body fat, blood glucose, BMI, HbA1c, HDL, LDL, total cholesterol, triglycerides, waist/hip ratio, DBP, SBP	Sex-specific $z$ scores→Cut-off points for each biomarker based on sex-specific upper quartile→Composite score ranging 0–14	E, N	EPQ (101 total)
(Christensen et al., 2019b)	14	CRP, IL-6, TNF- $\alpha$ , % body fat, blood glucose, BMI, HbA1c, HDL, LDL, total cholesterol, triglycerides, waist/hip ratio, DBP, SBP	$z$ scores→Cut-off points for each biomarker based on sex-specific upper quartile→Composite score ranging 0–14	All 5	NEO-FFI (12/ scale)
(Crook et al., 2018)	9	CRP, fibrinogen, albumin, BMI, HbA1c, HDL ratio, triglycerides, DBP, SBP	Log transformed biomarkers with non-normal distributions→Absolute mean $z$ scores→Summed	N	IPIP (10)
(Gallagher et al., 2021)	12	DHEA-s, CRP, fibrinogen, IGF-1, albumin, BMI, HbA1c, HDL, LDL, waist circumference, DBP, SBP	$z$ scores→Cut-off points for each biomarker based on sex-specific upper quartile or sex-specific risk or established criteria →Composite score ranging 0–12	N	FFMt (3)
(Hawkey et al., 2011)	9	Cortisol, epinephrine, norepinephrine, HbA1c, HDL, total cholesterol, waist circumference, DBP, SBP	Computed $z$ scores (sex-specific $z$ scores for some biomarkers) →Average across $z$ scores	E, N, A	Big 5 PI (20/ scale)
(Luo et al., 2022)	7	Blood sugar, HDL, total cholesterol, triglycerides, waist/hip ratio, DBP, SBP	Computed $z$ scores→Average across $z$ scores	E, N	EPI (9/scale)
(Kobrosly, 2012)	7	Average diurnal cortisol slope, IGF-1, IL-6, waist/hip ratio, resting heart rate, DBP, SBP	1) clinically-relevant cutoffs for each biomarker→composite score based on count, ranging 0–10; 2) calculation of quartiles based on distribution of each biomarker using data drawn from NHANES→composite score based on whether an individual exceeded the 75th percentile of each biomarker	N	NEO-FFI (74 total)
(Milad and Bogg, 2020)	10	CRP, fibrinogen, IL-6, fasting glucose, HbA1c, HDL, HOMA-IR, triglycerides, waist/hip ratio, pulse	Log transformed some biomarkers→Parceled biomarkers to reflect functioning within inflammation, glucose, and lipid systems	All 5	Big Five Adjectives (4/ scale)
(Otto et al., 2021)	4	BMI, waist/hip ratio, DBP, SBP	Used cut-off values reported by Seeman et al. (1997) AND sample-specific $z$ score cut-off points based on quartiles→Composite score ranging 0–4	All 5	NEO-FFI (12/ scale)
(Richards et al., 2023)	13	CRP, fibrinogen, BMI, fasting blood glucose, HbA1c, HDL/total cholesterol ratio, triglycerides, waist circumference, DBP, SBP, FEV1, FVC, PEF	Coded biomarkers based on clinical cut-offs or high-risk quartiles (and doctor decision)→Separated by system (cardiovascular, inflammation, metabolic, body fat, lung function)→Composite score ranging 0–5	All 5	MIDI (25 total)
(Stephan et al., 2016)	8	CRP, cystatin C, HbA1C, HDL, total cholesterol, waist circumference, DBP, SBP	Log transformed some biomarkers→ $z$ scores→Averaged across all $z$ scores	All 5	MIDI (26 total)

*Note.* Biomarkers are listed by order of system and in alphabetical order within the system: neuroendocrine (DHEA-s), hypothalamic-pituitary-adrenal axis functioning (average diurnal cortisol slope/cortisol), sympathetic nervous/adrenomedullary system (epinephrine, norepinephrine), inflammatory (CRP, IGF-1, IL-6, TNF- $\alpha$ ), metabolic (BMI, HbA1c, HDL, HOMA-IR, LDL), cardiovascular (DBP, SBP), and lung function (FEV1, FVC, PEF). DHEA-s = dehydroepiandrosterone sulfate; CRP=high sensitivity C-reactive protein; IGF-1 = insulin-like growth factor one; IL-6 = Interleukin 6; TNF- $\alpha$  = tumor necrosis factor- $\alpha$ ; BMI=body mass index; HbA1c=glycated/glycosylated hemoglobin; HDL=high density lipoprotein; HOMA-IR=homeostasis model assessment-estimated insulin resistance; LDL=low density lipoprotein; DBP=diastolic blood pressure; SBP=systolic blood pressure; FEV1 =forced expiratory volume in one second; FVC=forced vital capacity; PEF=peak expiratory flow; E = extraversion; N = neuroticism; A=agreeableness; EPQ=Eysenck Personality Questionnaire; NEO-FFI=NEO-Five Factor Inventory; IPIP=International Personality Item Pool; FFMt=Five-Factor Model traits; Big 5 PI=Big Five Personality Inventory; MIDI=Midlife Development Personality Inventory; EPI=Eysenck Personality Inventory.

2016). Across studies, items were assessed according to 5-point, 7-point, or 9-point scales, except for the EPQ, in which response options are dichotomous (0 =no; 1 =yes). Internal reliability estimates for trait scales were acceptable to good across studies and traits (see Supplementary Text 3). Personality variables were computed as the sum (Christensen et al., 2018; Christensen et al., 2019b; Gallagher et al., 2021; Luo et al., 2022; Otto et al., 2021) or average (Hawkey et al., 2011; Kobrosly, 2012; Milad and Bogg, 2020; Richards et al., 2023; Stephan et al., 2016) of subscale items. Richards et al. (2023) further computed  $z$  scores for the trait subscales. Kobrosly (2012) assessed neuroticism on two occasions and used the within-person mean neuroticism score for analyses. Finally, Crook et al. (2018) modeled neuroticism as a latent variable using item parcels (sum of different item responses).

### 3.4. Analytic approach and qualitative report of the results

Extensive variability in analytic strategies were used to examine the relationships between traits and AL. Personality traits were examined as potential mediators or moderators of the association between AL and an outcome variable. AL was also examined as a potential mediator of the association between personality traits and an outcome variable. Studies additionally examined the direct associations or direct lagged effects

between traits and AL, along with several potential mediators or moderators of the associations. The following paragraphs provide a more detailed explanation of the analytic approach across studies, as well as the primary findings reported by each study.

#### 3.4.1. Personality traits as mediators

Hawkey et al. (2011) examined traits as potential mediators of the association between socioeconomic status (SES) and AL. Adjusting for gender and ethnicity, partial correlations indicated that none of the personality traits were significantly correlated with SES or AL; therefore, the researchers did not further investigate the role of personality traits in subsequent mediation analyses. Likewise, Christensen et al. (2018) examined potential mediators (including extraversion and neuroticism) on associations between socioeconomic position (SEP) and AL. Although extraversion was positively associated with AL, neither extraversion nor neuroticism mediated the association between SEP and AL (2018). Similarly, Otto et al. (2021) compared differences in psychological constructs (including personality traits) between female participants diagnosed with Borderline Personality Disorder and healthy controls on *fast pace-of-life syndrome*, as well as the extent to which this syndrome predicted AL. Results suggested no differences in personality traits between groups; as such, no further analyses were executed to examine mediating associations between traits, fast pace-of-life syndrome, and

AL. In contrast, Richards et al. (2023) examined several potential mediators (including the Big Five personality traits) of the association between AL and subjective social status. Lower conscientiousness, extraversion, and neuroticism, as well as higher agreeableness and openness, were associated with higher AL. Furthermore, adding the Big Five personality traits to the model attenuated the relationship between AL and subjective social status.

3.4.2. AL as a mediator

Crook et al. (2018) examined whether AL mediated the association between neuroticism and cognitive outcomes, finding that neuroticism and AL had small-to-moderate negative associations with cognitive functioning for individuals with and without an APOE ε4 allele. However, AL did not mediate the associations between neuroticism and cognitive impairment or cognitive decline. Kobrosly (2012) conducted a path analysis to examine the associations among neuroticism, AL, life

stress, SEP, social isolation, and depressive symptoms. Results revealed that neuroticism was positively and strongly associated with social isolation and depressive symptoms, but the association between neuroticism and AL was not examined directly in path analyses. Gallagher et al. (2021) examined the extent to which AL prior to the pandemic was predictive of mental health during the pandemic, and whether the associations were moderated by neuroticism. Findings suggested that the association between AL and poor mental health during the pandemic were exacerbated in individuals with moderate and high levels of neuroticism (2021).

3.4.3. Associations between AL and traits

Christensen et al. (2019b) examined sex-stratified associations between personality traits and AL, adjusting for all traits and several covariates (e.g., sociodemographic factors, health-related behaviors). Results suggested that conscientiousness and openness were inversely

Forest Plots of the Bivariate Correlation Coefficients Between Personality Traits and Allostatic Load Across Studies Meeting Eligibility

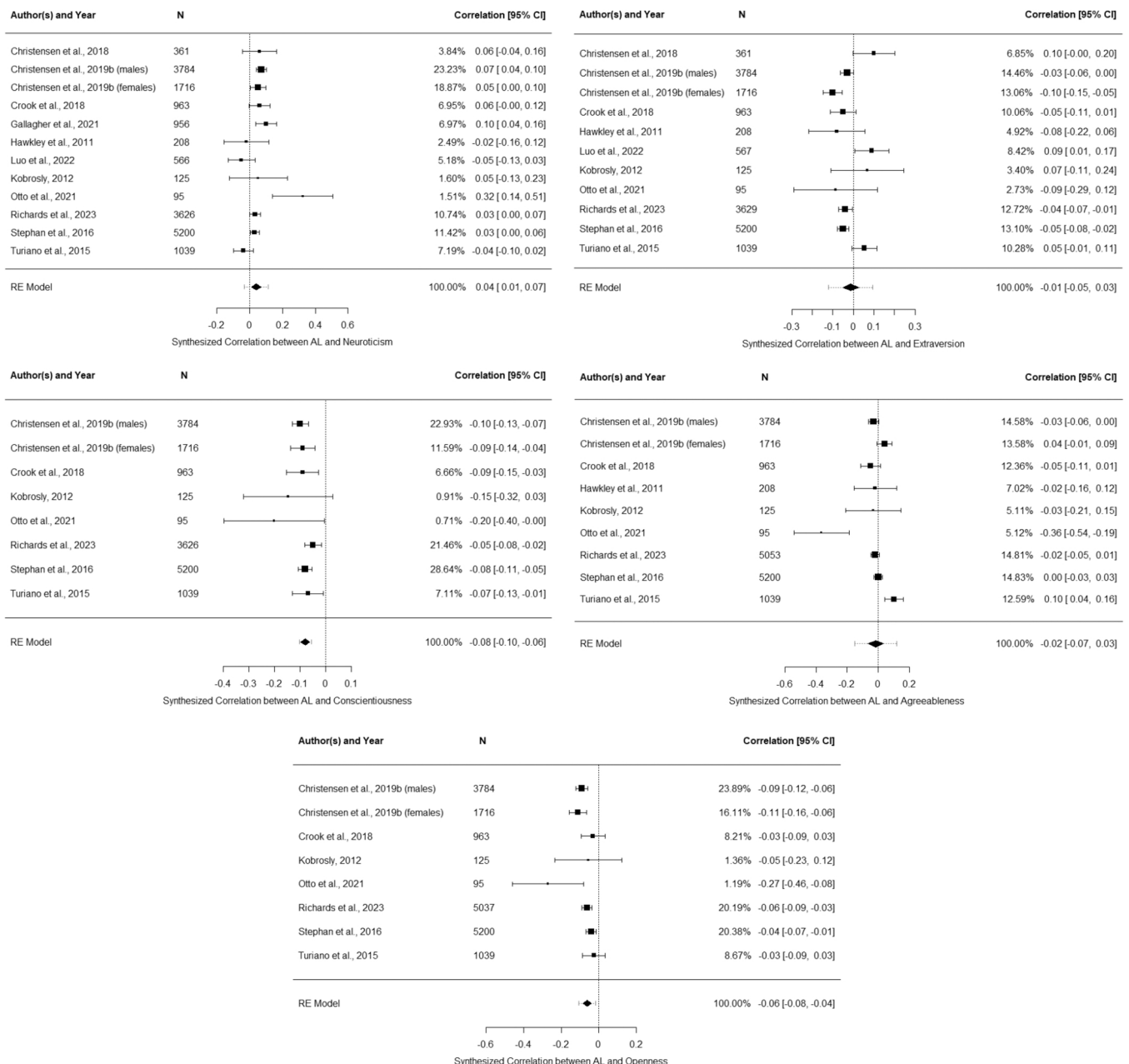


Fig. 2. Forest Plots of the Bivariate Correlation Coefficients Between Personality Traits and Allostatic Load Across Studies Meeting Eligibility.

associated with AL for all participants, while extraversion was positively associated with AL in male participants only. However, the AL-extraversion and AL-openness associations were attenuated after adjusting for sociodemographic factors. Milad and Bogg (2020) examined the direct and indirect effects (via coping styles and health behaviors) of personality traits at baseline on a latent measurement model of AL 10 years later. Results suggested that higher extraversion was prospectively associated with higher AL, that higher conscientiousness was prospectively associated with lower AL, and that both associations were mediated by greater perceptions of being active, such that higher perceptions of activity were protective against heightened AL for individuals high in extraversion and conscientiousness. Similarly, Stephan et al. (2016) examined the extent to which sociodemographic variables moderated associations between AL and personality traits, as well as change in personality traits. Results suggested that higher AL was associated with lower extraversion, higher neuroticism, and lower conscientiousness, as well as declines in extraversion, conscientiousness, and agreeableness, over four years (2016). Finally, Luo et al. (2022) examined potential lagged effects between AL and traits (neuroticism and extraversion) over up to five occasions at approximately three-year intervals. Neither extraversion nor neuroticism was linked to AL at the within-person or between-person levels.

#### 3.4.4. Meta-analytic results

We fit a series of five multi-level meta-analyses to synthesize the overall association between AL and each Big Five trait with bivariate correlation coefficients as the unit of effect size. See Supplementary Text 4 for details regarding the identification of effects across studies. The included reports ( $K=11$ ) yielded a total of 48 effects. Fig. 2 depicts funnel plots of the individual and synthesized effects.

The overall association between neuroticism and AL was very small and significant ( $r = 0.04$ , 95%CI[0.01, 0.07],  $SE=0.02$ ,  $p = .01$ ;  $k = 11$ ), suggesting that individuals higher in neuroticism tended to have more physiological dysregulation. There was significant heterogeneity in effect sizes ( $Q_{11} = 29.23$ ,  $p < .01$ ), and the proportion of true variability of the effects relative to the total variation in observed effects was moderate ( $I^2=61.10\%$ ). The overall association between conscientiousness and AL was small and significant ( $r = -0.08$ , 95%CI[-0.10, -0.06],  $SE=0.01$ ,  $p < .01$ ;  $k = 7$ ), suggesting that individuals higher in conscientiousness tended to have better physiological regulation, with minimal heterogeneity in effect sizes ( $Q_7 = 7.21$ ,  $p = .41$ ;  $I^2=10.56\%$ ). The overall association between openness and AL was small and significant ( $r = -0.06$ , 95%CI[-0.08, -0.04],  $SE=0.01$ ,  $p < .01$ ;  $k = 7$ ), suggesting that individuals higher in openness tended to have better physiological regulation, though there was significant heterogeneity in effect sizes ( $Q_7 = 16.48$ ,  $p = .02$ ;  $I^2=43.39\%$ ).

The overall associations between AL and extraversion ( $r = -0.01$ , 95%CI[-0.05, 0.03],  $SE=0.02$ ,  $p = .52$ ;  $k = 10$ ), as well as AL and agreeableness ( $r = -0.01$ , 95%CI[-0.7, 0.03],  $SE=0.03$ ,  $p = .50$ ;  $k = 8$ ), were not significant, suggesting no consistent relationships between these traits and AL. There was also significant heterogeneity across effect sizes for extraversion ( $Q_{10} = 34.62$ ,  $p < .01$ ;  $I^2=78.90\%$ ) and agreeableness ( $Q_8 = 36.90$ ,  $p < .01$ ;  $I^2=87.83\%$ ).

Figures depicting funnel plot asymmetry for publication bias are reported for the AL-neuroticism and AL-extraversion correlations (see Supplementary Figure 1); however, these plots should be interpreted cautiously given that at least 10 effect sizes are required to distinguish chance from true asymmetry (Sterne et al., 2011), which is also why funnel plots are not reported for conscientiousness, openness, or agreeableness. Use of REML (as opposed to ML) as the variance estimator did not meaningfully change the effect size or  $p$  value for any of the personality trait-AL associations.

#### 3.4.5. Quality assessment

A table outlining the quality assessment of included studies is reported on the OSF project page (<https://osf.io/rkxas/>). Several criteria

were fulfilled by all studies, though only one study (Kobrosly, 2012) fulfilled every relevant quality assessment criterion. Nevertheless, the quality of studies was deemed to be quite high overall, with nine reports receiving “good” ratings and only two receiving “poor” ratings. Gallagher et al. (2021) was deemed poor as i) the number of participants that met eligibility for analyses was extremely reduced compared to the total sample ( $N = 10,175$  to  $N = 956$ ), resulting in possible bias, ii) blood pressure (BP), which is particularly prone to measurement imprecision (e.g., Juraschek et al., 2020) was only measured once, iii) demographic characteristics of the sample were not clearly reported (e.g., education was dichotomized as “college education” versus “high school or less”), and iv) the AL index computation was unclear (i.e., an independent researcher could not replicate the approach). Otto et al. (2021) was deemed poor because i) only four biomarkers in the AL index were used, which likely reflects a narrowly defined metabolic syndrome as opposed to AL, and ii) the Borderline Personality Disorder (BPD) patient group and the control group were not drawn from the same population, and the researchers did not measure any socioeconomic characteristics; as such, any between-group differences in primary predictors (e.g., neuroticism, childhood adversity and trauma, aggression, chronic stress) may not reflect differences due to BPD status.

## 4. Discussion

The current systematic review and meta-analysis details the various approaches researchers have used to investigate the relationships between the Big Five and AL among adults ( $K=11$ ). Meta-analytic results suggest a positive association between neuroticism and AL, inverse associations between conscientiousness and AL and openness and AL, and no overall significant associations between extraversion or agreeableness and AL. These results should be interpreted with caution, as the meta-analyses were not well-powered.

The positive association between neuroticism and AL is unsurprising, as AL is thought to reflect maladaptive physiological responding as a result of heightened stress perceptions (McEwen and Stellar, 1993). Characterized by anxiety, depressive symptoms, and a propensity toward negative emotionality (Eysenck and Eysenck, 1985; McCrae and Costa, 2004), neuroticism is associated with heightened vulnerability to stressors, including greater exposure and more intense reactions to perceived stress (Bolger and Schilling, 1991; Craske, 1999; Suls et al., 1998; Suls and Martin, 2005). In combination with the existing research, the current findings highlight opportunities for interventions aiming to decrease physiological dysregulation by addressing stress perceptions and responses, particularly for those high in neuroticism. For instance, associations between neuroticism and negative affect may be mediated by threat appraisals (Schneider, 2004); neuroticism is associated with threat perception, negative affect, and poor task performance, but individuals high in neuroticism may only experience more negative affect and perceptions of stress in the context of threat appraisal (e.g., the perception of inadequate coping resources relative to the demands required by the situation). As such, interventions aiming to decrease AL may target individuals who are high in neuroticism, focusing on developing skills for reappraising situations that are perceived as threatening.

Conversely, individuals higher in openness may be more resilient to stress. Openness is characterized by cognitive flexibility, curiosity, and intellectual engagement (Costa, 2008; McCrae and Sutin, 2007). Individuals high in openness may approach potentially stressful situations with greater flexibility and adaptability; these individuals, who tend to appreciate varied emotional experience, may also evaluate environmental stressors as appealing opportunities to indulge in alternative perspectives. Consistent with these postulations, research suggests that openness is related to greater coping capacity in the face of stress (Penley and Tomaka, 2002), as well as higher average positive affect, which is mediated by lower threat appraisal (Schneider et al., 2012). Notably, openness can change; research suggests that interventions have

increased openness to experience, either purposefully (e.g., via openness to action training; [Stieger et al., 2020](#)) or unintentionally (e.g., via cognitive training; [Jackson et al., 2012](#)). Consistent with [Stephen et al.'s \(2016\)](#) findings that openness declines when individuals exceed a high level of cumulative physiological dysregulation, future research investigating whether increases in openness lead to better physiological regulation would improve our understanding of the causal relationship between openness and AL.

Finally, the significant inverse association between conscientiousness and AL is consistent with both empirical research and theoretical frameworks of conscientiousness, which is characterized by competence, dutifulness, self-discipline, and diligence ([Costa et al., 1991](#)). For instance, the Invest-and-Accrue model of conscientiousness proposes that individuals high in conscientiousness devote current resources (e.g., time, energy, assets) to maximize future gains, which subsequently contributes to positive outcomes across various domains, including improved physiological health ([Hill and Jackson, 2016](#)). Likewise, the existing literature consistently reports that conscientiousness is positively associated with health-promoting behaviors and inversely associated with risky behaviors (for a meta-analysis, see [Bogg and Roberts, 2004](#)). Indeed, [Milad and Bogg's \(2020\)](#) findings (i.e., higher perceptions of activity were protective against higher levels of AL, but only for individuals high in conscientiousness) exemplify the conscientiousness-AL link: individuals high in conscientiousness tend to engage in healthier behaviors, which leads to better physiological regulation. Notably, our meta-analysis reflecting the relationship between conscientiousness and AL was distinguished by the least amount of heterogeneity in effects, providing more confidence in the reliability of the synthesized effect.

The null effects for extraversion and agreeableness match the individual study estimates well. There was a relatively inconsistent spread of effects for these traits, with positive, negative, and null correlations, which is also reflected in the meta-analytic summaries and heterogeneity statistics.

#### 4.1. Variability across eligible studies

While the reports varied across primary study characteristics (e.g., sample size, study design, country of origin), the most prominent heterogeneity was observed in the AL algorithm approaches. For instance, one researcher stratified all biomarkers by sex prior to computing  $z$  scores, others only sex-stratified some biomarkers (e.g., waist circumference), and many did not sex-stratify any biomarkers, despite well-established sex-differences in many of the measured physiological biomarkers, including CRP ([Khera et al., 2009](#)), IGF-1 ([Austad and Bartke, 2015](#)), BP ([Ji et al., 2020](#)), BMI ([Flegal et al., 2016](#)), triglyceride synthesis ([Lonardo et al., 2019](#)), and cholesterol metabolism ([Palmisano et al., 2018](#)). Research also suggests sex-differences in cortisol responses to stress ([Kudielka and Kirschbaum, 2005](#)) and between DHEA-s and adverse health outcomes ([Goldman and Gleib, 2007](#)). Although traditional AL index computations do not include recommendations regarding sex-stratification, the extensive body of research documenting sex-differences in both levels of biomarkers and associated outcomes implies the importance of stratifying biomarker scores by sex prior to computing AL risk scores. Extensive researcher decisions were further evidenced across the various operational definitions of “high risk” and the components of AL indices included across each study. Finally,  $z$  score standardization is a limitation, as the definition of risk is inherently sample specific, such that any given individual might be categorized as meeting high risk on a given biomarker in one sample, but not another.

Concern regarding the fidelity of AL indices has been raised by several reviews (e.g., [Johnson et al., 2017](#); [Juster et al., 2010](#)). Without an established standardized method, researchers must make extensive decisions in their approach, leading to the observed between-study differences in computed constructs (i.e., [Silberzahn et al., 2018](#)) and hindrance of the development of AL as a target for clinical intervention.

Together, the widespread variability in algorithm scoring approaches may have resulted in somewhat distinct indices of AL, limiting the cross-study comparative validity of the AL variables. Given this variability, the extent to which the magnitude and/or significance of associations between the Big Five traits and AL are affected by varying operational definitions of AL across studies remains unclear (i.e., similarities in approaches may have facilitated evaluation of differences in outcomes). However, as there is no gold standard in measurement and computation of AL, researchers are forced to make decisions based on best judgment, and all studies synthesized biomarkers based on previous research and theoretical conceptualizations of AL.

Extensive variability was also evident in the analytical approaches used to assess the relationships between personality traits and AL, which highlights the inherent challenges of empirically examining the relationships between physiological and psychological constructs. That is, mediation and moderation models aim to refine, understand, and make causal inferences about constructs ([Wu and Zumbo, 2008](#)), and the cross-study heterogeneity observed in analytic approach reflects the complex interplay between physiological and psychological processes, as well as differences in theoretical understanding of how these processes affect one another.

Finally, cross-sectional assessments may not sufficiently capture the interplay of personality traits and AL as people change and develop across the lifespan. Importantly, biological wear-and-tear accumulates over time, leading to changes in physiological dysfunction over time (e.g., [van Deurzen and Vanhoutte, 2019](#)). Likewise, the existing literature documents individual differences in intraindividual change and variability in personality across development (e.g., [Graham et al., 2020](#); [Stephan et al., 2016](#)). Indeed, if AL-Big Five associations change over time, as was demonstrated by [Stephan et al. \(2016\)](#), findings may differ between the 11 eligible reports due to capturing the relationships at different points across development. Similarly, [Luo et al. \(2022\)](#) reported correlation coefficients representing trait-AL associations across five measurement occasions, which varied over time (e.g.,  $r = 0.01$  to  $0.10$  for extraversion). However, these associations did not appear to change systematically, given null between- and within-person associations between AL and either neuroticism and extraversion, though the sample was relatively small ( $N = 566$ ). Future research using repeated measurements may be especially important for elucidating associations between the Big Five and AL.

#### 4.2. Limitations reported by eligible studies

Various limitations were highlighted across the included studies (see [Supplementary Table 1](#)). For instance, many authors noted deviations in available biomarker measurements as a limitation (e.g., missing HPA-axis biomarkers). Not including a specific biomarker or an entire category of biomarkers may have implications for the construct validity of AL indices, and authors typically posited that access to more biomarker assessments was ideal for capturing AL. Future work investigating the minimum number and type of biomarkers for predictive validity would enrich the field.

Interestingly, some limitations were rarely highlighted. For instance, several biomarkers are subject to physiological variation and measurement imprecision ([McCormack and Holmes, 2020](#)): based on two serial assessments, glucose and HbA1c vary 2–5% based on measurement imprecision alone, and this variation increases to 6–10% when also accounting for natural biological variation; HDL and LDL cholesterol and triglycerides fluctuate 2–5% between two serial measurements due to measurement imprecision, which increases to 11–20% and 31–40%, respectively, when also accounting for natural biological variation ([2020](#)). Likewise, BP can often be substantially higher (i.e., white coat hypertension) or lower (i.e., masked hypertension) in the presence of a medical practitioner, compared to typical/resting BP. While most studies recorded BP at least three serial times to improve precision, few studies assessed biomarkers on repeated occasions, and only [Kobrosly](#)



(2012) repeatedly assessed biomarkers on a short-term scale to improve reliability (e.g., intraindividual means of IL-6 and IGF-1, collected at three occasions within a year). Given potential imprecision and biological variability, AL biomarkers (which were predominately assessed by a single assessment in a single context), may not provide the most accurate representation of physiological dysregulation.

The generalizability of the results is also questionable. Apart from [Hawkey et al. \(2011\)](#), all samples included predominantly European/White participants with relatively high SES, and authors rarely mentioned the broader implications of prevalent sampling bias. For example, studies examining personality and AL among primarily European/White samples often did not account for the inherent differences between individuals of different races, such as differential waist-to-hip ratio cut-offs ([Lear et al., 2010](#)) or disparate creatinine production influencing cortisol measures ([Hawkey et al., 2011](#)). Furthermore, these homogenous samples likely do not adequately account for differences in the experiences of individuals with lower levels of education and SES, who may experience greater day-to-day stress and therefore be at an increased risk for accumulating AL. Indeed, research indicates that Black individuals ([Van Dyke et al., 2020](#)) and those with lower education levels and SES ([Hawkey et al., 2011](#); [Merkin et al., 2009](#)) have significantly higher AL. Recruiting more diverse samples is critical for improving our understanding of how personality plays a role in the exacerbated accumulation of AL across diverse individuals and populations.

#### 4.3. Current study strengths and limitations

This is the first systematic review and meta-analysis to synthesize associations between the Big Five personality traits and AL. We adhered to PRISMA protocols to ensure thorough and transparent reporting, which included pre-registering our data collection procedures, research design, and analytic plan. The only deviation was our use of the NIH guidelines for the quality assessment of included articles. We also executed our search within several electronic databases and completed systematic forward and backward searches of the eligible studies. However, alternative terms reflecting AL may exist (e.g., dysregulation burden), potentially limiting identification of all relevant reports. Similarly, we chose to focus on the Big Five model of personality, though additional models or aspects of personality may be relevant to physiological dysregulation. Given our search terms (e.g., personality, neuroticism, extraversion), this review would have identified articles using alternative models of personality (e.g., HEXACO, Eysenck's Personality Inventory) if they had been published. However, future work should aim to synthesize research reporting the relationships between AL and additional aspects of personality not captured by the Big Five, such as temperament, rumination, aggression, or perceived control.

As a further strength, we also included both published and unpublished reports and effect sizes, and studies that did not focus predominantly on the association between personality traits and AL, thereby reducing the probability of publication bias. Finally, the current meta-analysis is not well-powered ( $K=11$ ), as a sample size of 20–25 independent effects sizes is ideal for a random-effects meta-analysis ([Valentine et al., 2010](#)). Therefore, the current results should be interpreted with caution.

#### 4.4. Future directions and conclusions

Although this review focused on the associations between the Big Five traits and AL, a primary concern regarding the heterogeneity in AL indices appears to be an issue across all AL research. Lack of precision in standard recommendations for AL indices may lead to differences in findings and conclusions due to researcher decisions (as well as the unethical opportunity for cherry picking results). Development and uptake of clear, rigorous guidelines for the assessment of biomarkers and computation of AL indices would unquestionably facilitate comparisons

across studies. Yet, the associations that are reported throughout the existing literature are, to some extent, conceptual replication, which may be appreciated as a strength rather than a weakness. That is, the literature is fairly ubiquitous in finding a robust association between AL and adverse outcomes, despite extensive heterogeneity in operational definitions. Similarly, the studies that were excluded due to data redundancy (i.e., using identical samples as studies meeting eligibility) primarily report consistent associations between traits and AL, despite differences in analytic approaches and AL algorithms. Apart from a positive association between agreeableness and AL (which was attenuated to non-significance when adjusting for health behaviors and chronic conditions; [Turiano et al., 2015](#)) the findings from the eligible reports align with those from the reports that were removed to avoid redundancy. Specifically, differences in sample characteristics, participant eligibility, or adjusting for specific covariates did not appear to systematically affect associations between traits and AL across the 11 studies.

To prevent bias in results due to researcher decisions, some studies repeated their analyses using various calculations of AL or including additional biomarkers (e.g., [Richards et al., 2023](#)). A handful of existing studies have aimed to identify the optimal approach for AL scoring algorithms ([Johnson et al., 2017](#); [Li et al., 2019](#); [Seplaki et al., 2005](#)). Despite inconsistencies in efforts to identify the AL computation approach with the best predictive validity, the consensus appears to be [Seeman et al. \(2010\)](#) approach for AL scoring algorithm ([Johnson et al., 2017](#); [Li et al., 2019](#)). While these recommendations provide critical information for future research, a systematic investigation of differences in quantity and breadth of biological systems included within AL indices may provide further assistance in delineating clear recommendations for the ideal AL index approach. Specifically, investigation of differences in the predictive ability of AL based on the biomarkers or biological systems included within AL indices may provide more nuanced information regarding risk stratification. For instance, the included studies differed in the total number of AL biomarkers measured (i.e., 4–14), as well as represented biological systems (i.e., 2–5). It is unclear whether particular biomarkers are critical for inclusion within an AL index, or whether more biomarkers across multiple systems provides a stronger index of dysregulation. In particular, when using the count of high risk sample-specific cut-offs, the treatment of biomarkers as equal may diminish the predictive validity of the index. Importantly, [Hawkey et al. \(2011\)](#) examined AL as a latent variable, and examined whether risk differed across subsamples for various biological systems. Findings indicated that the effects of SES on AL are specific to certain systems (i.e., cardiovascular and obesity factors) in middle to older adulthood, suggesting that there are likely differences in the importance of dysregulation across particular biological systems across outcomes.

In the absence of precise recommendations, researchers should continue to clearly document procedures for determining high risk categories to ensure transparency and the ability to replicate computations of AL indices. Likewise, stratifying biomarkers by sex prior to determining risk categories may be important, given the wealth of research suggesting sex-differences across many of the biomarkers typically included within AL indices. Finally, AL is theorized to reflect wear and tear on the body by consolidating markers of physiological dysregulation across biological systems ([McEwen and Stellar, 1993](#)). However, risk profiles were predominantly based on biomarker levels (i.e., measured at only one occasion), rather than naturally measured dysregulation. Future research may assess within-person variability in biomarkers using intensive measurement designs – to capture day-to-day fluctuations in physiological regulation across various contexts – and subsequently examine whether intensive AL indices overlap with traditional AL indices.

The included studies investigate a wide range of factors that may be involved in the associations between personality traits and AL, particularly SES/SEP. Two studies suggest that traits do not mediate associations between AL and SES/SEP ([Christensen et al., 2018](#); [Hawkey et al.,](#)

2011); however, other work finds that traits attenuate the association between AL and subjective social status (Richards et al., 2023), suggesting that personality may be important for understanding the relationships between AL and perceived economic circumstances and social standing. Thus, the role of personality traits on relationships between AL and subjective versus objective measures of socioeconomic status warrants further research to investigate the extent to which these represent study-specific findings or true differences. Further, associations between AL and some traits (conscientiousness, openness) may be attenuated by sociodemographic factors (i.e., education, occupational social class; Christensen et al., 2019b). However, Stephan et al. (2016) found that AL was associated with personality change in non-Hispanic individuals and those with higher education, though the sample was 89.6% White and highly educated. The studies meeting eligibility for this review predominantly focus on White/European samples, which provides tremendous rationale for future research drawing on more diverse samples to further investigate the role of ethnicity and SES on associations between personality traits and AL.

Finally, additional mechanisms linking personality traits and AL remain fairly unclear. Interestingly, no study identified by this review focused explicitly on perceived stress as a mediator between personality traits and AL, which is another excellent opportunity for future research. Similarly, and consistent with Milad and Bogg (2020), future research should further explore coping styles and health behaviors as potential mechanisms underlying associations between AL and personality traits.

As the first systematic review and meta-analysis to comprehensively identify and assess studies reporting the association between the Big Five personality traits and AL, we synthesized the existing literature qualitatively and quantitatively. Our meta-analyses suggest that individuals who are higher in neuroticism, or lower in conscientiousness or openness, tend to have more physiological dysregulation. These results suggest that high neuroticism may be a risk factor, while high conscientiousness and openness may be protective factors, for high AL. With only 7–11 independent effects included in each meta-analysis, these results should be interpreted with caution. Further, while Milad and Bogg's (2020) findings suggest that the perception of leading an active lifestyle was a mediating pathway by which extraversion and conscientiousness were associated with greater physiological resilience, the mechanisms underlying associations between personality traits and AL remain relatively unclear. However, given the robust associations between high AL and several adverse health outcomes (e.g., physical and cognitive impairment, disease, chronic conditions, and mortality), identifying risk factors and correlates of AL, such as personality traits, may facilitate the development of personality-informed interventions aiming to foster optimal aging processes across the lifespan by mitigating physiological dysregulation.

#### Author note

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#### Data Availability

Links for data and code are available on OSF and have been referenced within the manuscript.

#### Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.neubiorev.2023.105145.

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